Knowledge-Based Economy in Developing Countries: Measurements and Impacts

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Summary

The traditional factors of production, such as land, labour, and capital, have typically determined a nation's comparative advantage. However, in the context of a global Knowledge-Based Economy (KBE), a nation's prosperity is now determined by its knowledge assets. This transition to a KBE offers endless advantages and is desirable for all countries. However, developing countries face significant challenges in adopting this new development paradigm, where knowledge is the key driver of economic growth. Yet, to effectively measure the extent to which a country is considered knowledge-based on the international level, a robust framework is needed. Although the burgeoning literature, existing KBE measurement frameworks have limitations and may not accurately reflect the progress and efficiency of the transition to a KBE, especially in developing countries. Consequently, relying on these frameworks can lead to misleading policy directions that hinder the necessary rapid transition in developing countries.

This thesis aims to fill the gap in understanding the KBE within developing countries through an extensive analysis. To achieve this, the thesis begins by reviewing the conceptual and theoretical literature on the KBE. It then critically examines existing measurement frameworks and empirical studies related to the KBE, specifically evaluating their suitability for developing countries. In response to the limitations found, a new and more effective measurement framework is proposed. This framework focuses on input-output indicators across four dimensions of the KBE: acquisition, distribution/dissemination, production, and utilization. Notably, it utilizes a non-parametric approach known as Data Envelopment Analysis (DEA), which differs from conventional econometric analysis. The DEA empirical results are then compared with those obtained from other existing KBE measurement frameworks, allowing for a comprehensive assessment of the advantages offered by DEA.

Based on the DEA empirical findings, knowledge production is identified as the weakest aspect, despite its utmost importance among the four KBE dimensions. As a result, this thesis places special emphasis on enhancing innovation development in selected developing countries through effective innovation policies tailored to their specific circumstances and utilizing country-specific innovation policy instruments.

Declaration

This work has not been previously accepted in substance for any degree and is not being concurrently submitted in candidature for any degree.

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STATEMENT 1

This thesis is the result of my own investigations, except where otherwise stated. Where correction services have been used, the extent and nature of the correction is clearly marked in a footnote(s). Other sources are acknowledged by footnotes giving explicit references. A bibliography is appended.

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Dedication

In loving memory of my dear and unforgettable father, Abdelsattar Abdelmawgoud, may your soul find eternal peace.

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Abbreviations

ABS	Australian Bureau of Statistics
ANOVA	Analysis of Variance
APEC	Asia-Pacific Economic Cooperation
BCC	Banker, Charnes, and Cooper
CCR	Charnes, Cooper, and Rhodes
CEC	Commission of the European Community
CERI	Centre of Educational Research and Innovation
CRS	Constant Returns to Scale
DDF	Directional Distance Functions
DEA	Data Envelopment Analysis
DEAP	Data Envelopment Analysis Program
DFA	Distribution Free Approach
DIKW	Data-Information-Knowledge-Wisdom
DMU	Decision Making Unit
DMUs	Decision Making Units
DTI	Department of Trade and Industry of the UK
EIS	European Innovation Scoreboard
EMS	Efficiency Measurement System
EU	European Union
FDI	Foreign Direct Investment
FEs	Fixed Effects Model
G8	Group of Eight
GCC	Gulf Cooperation Council
GCI	Global Competitiveness Index
GDP	Gross Domestic Product
GII	Global Innovation Index
GKEI	Global KE Index
GMM	Generalized Method of Moments
GNI	Gross National Income
HDI	Human Development Index
ICT	Information and Communication Technology
ICTs	Information and Communication Technologies
IDI	ICT Development Index
INEXSK Model	Infrastructure, Experience, Skills, Knowledge Model
IPR	Intellectual Property Rights
ISI	Information Society Index

K4D	Knowledge for Development
KAM	Knowledge Assessment Methodology
KBE	Knowledge-Based Economy
KBEI	Knowledge-based Economy Index
KBEs	Knowledge-Based Economies
KE	Knowledge Economy
KEI	Knowledge Economy Index
KI	Knowledge Industries
KI	Knowledge Index
KII	Knowledge-Intensive Industries
KTI	Knowledge and Technology-Intensive
LP	Linear Programming
MBRF	Mohammed bin Rashid Al Maktoum Foundation
MED	Ministry of Economic Development of New Zealand
MENA	Middle East and North Africa
MPI	Malmquist Productivity Index
MPSS	Most Productive Scale Size
MTI	Ministry of Trade and Investment of Singapore
NAC	National Academy of Science of the US
NIC	National Innovation Capacity
NIS	National Innovation System
NRI	Networked Readiness Index
OECD	Organization for Economic Cooperation and Development
OLS	Ordinary Least Square
OTE	Overall Technical Efficiency
PCA	Principal Component Analysis
PHH	Pollution Haven Hypothesis
PISA	Program for International Student Assessment
PPI	Progressive Policy Institute
PTE	Pure Technical Efficiency
R&D	Research and Development
REA	Regional Economic Architecture
REs	Random Effects Model
RIS	Regional Innovation System
RTS	Return-to-Scale
S&E	Science & Engineering
S&T	Science & Technology
SBM	Slacks-Based Measure

SE	Scale Efficiency
SFA	Stochastic Frontier Approach
SIS	Sectoral Innovation System
SKEI	Sustainable Knowledge Economy Index
SMEs	Small and Medium Enterprises
SPRU	Science Policy Research Unit
SSA	Sub-Saharan Africa
TFA	Thick Frontier Approach
TFP	Total Factor Productivity
TIS	Technological Innovations Systems
UK	United Kingdom
UKFM	Unified KE Forecast Map
UNDP/RBAS	United Nations Development Programme/Regional Bureau for the Arab States
UNECE	United Nations Economic Commission for Europe
UNESCO	United Nations Educational, Scientific and Cultural Organization
US	United States
VRM	Variant Radial Measure
VRS	Variable Returns to Scale
WB	World Bank
WBI	World Bank Institute
WCY	World Competitiveness Yearbook
WDI	Worldwide Development Indicators
WEF	World Economic Forum
WGI	Worldwide Governance Indicators
WIPO	World Intellectual Property Organization

Chapter 1

Introduction

1.1 Background and Motivation

Since the time of Adam Smith, knowledge has played a crucial role in driving economic growth. However, in today's economy, the utilization, production, and distribution of knowledge have become even more important, resulting in a faster-paced environment. An extensive literature has recognized this shift from agricultural and industrial economies to knowledge-based economies (KBEs) (inter alia O'Donovan, 2020). While there is no widely accepted official definition, various international bodies have published definitions to clarify the meaning of KBE. These definitions all revolve around the idea that knowledge is a fundamental driver of economic development, although they differ in how they quantify the magnitude of this economy (Dahlman & Andersson, 2000). One commonly used definition by the Organization for Economic Cooperation and Development (OECD) describes KBE as "the economies that are directly based on the production, distribution, and use of knowledge and information." (OECD, 1996).

There are numerous reasons for transitioning into a KBE, supported by substantial theoretical and empirical justifications. Accumulating knowledge is positively correlated with economic growth (inter alia Aubert & Reiffers, 2003; Trewin, 2002; World Bank, 2007a). Additionally, knowledge not only facilitates economic growth but also drives societal and economic structural transformation (Trewin, 2002). The relationship between competitiveness and the KBE is also interconnected. The World Economic Forum (WEF) publishes a "Growth Competitiveness Index" that considers indicators of institutional environment, technological performance, and macroeconomic stability. Multiple empirical studies, as mentioned in Aubert and Reiffer (2003), have elaborated on the positive relationship between Middle East and North Africa (MENA) countries readiness in the KBE and their level of economic development. Furthermore, the global economy has undergone notable changes, shifting towards more knowledge and technology-intensive economies. These global trends underscore the inevitability of the transition to a KBE, considering the new global forces, as discussed in detail in the chapter two.

For developing countries, the KBE or knowledge revolution presents significant challenges and opportunities. The World Bank (2007a) emphasizes that developing countries need to adopt a new development paradigm where knowledge is the primary driver of economic growth. These countries not only need to build more efficient domestic economies but also capitalize on economic opportunities beyond their borders. However, as highlighted by numerous scholars (Gyekye & Oseifuah, 2015; Nour, 2014a), developing countries have yet to fully leverage the vast and infinite global knowledge resources available to them.

Given the aforementioned considerations, developing countries must pursue a larger-scale and accelerated transition to the KBE. The initial step in this transition involves measuring the knowledge base. Accurate measurement of the KBE is crucial for informing effective knowledge policies and expediting the transition process (Khumalo, 2006). However, a key question arises: Can we measure a country's knowledge base? And if so, what aspects should we measure and how? The international community has been engaged in an ongoing debate regarding the appropriate measurement framework for the KBE, primarily due to the numerous challenges involved in measurement. One particularly difficult aspect is how to measure knowledge itself, given its broad and multifaceted nature. Additionally, challenges arise in selecting suitable indicators to measure each significant aspect of the KBE (Kriščiūnas & Daugėlienė, 2006).

In response to this persistent debate, various international organizations have introduced KBE measurement frameworks. The World Bank (WB), OECD, Asia Pacific Economic Cooperation (APEC), and the Australian Bureau of Statistics (ABS) have developed prominent KBE frameworks. These frameworks aim to assess the contribution of the knowledge base to economic development and provide policymakers with guidance to expedite the transition to a KBE.

However, shortcomings in the existing measurement frameworks have been identified, raising concerns about their suitability for accurately assessing the transition process. This identification of shortcomings represents a significant gap in the existing literature that requires attention. Consequently, KBE measurement has gained renewed interest among scholars and organizations (Arundel et al., 2008; Goodridge, 2014; Karahan, 2012; Trewin, 2002). Moreover, the discontinuation of the widely used KBE methodology developed by the WB in 2012 without notification further emphasizes the need for alternative measurement approaches.

1.2 Research Objectives

Considering the previous discussions and identified gaps in the literature, this thesis aims to accomplish the following objectives:

1. Investigate the strengths and weaknesses of existing measurement frameworks for the KBE and this will be addressed in chapter three.
2. Introduce a new measurement framework specifically tailored to the socioeconomic characteristics, challenges, and opportunities of developing countries, with a focus on policy implications and this will be explored in the first empirical chapter, namely chapter four.
3. Evaluate which dimensions of the KBE require the highest policymakers' attention, in the form of investment needed, and policies required to support the development of this dimension, based on the empirical results. This will be evaluated in the first empirical chapter, namely chapter four.
4. Utilize the other widely used methodologies by international organizations such as the World Bank to assess the current status of developing countries in their transition to the KBE and this will be evaluated in the second empirical chapter, namely chapter five.
5. Compare the results obtained from the existing measurement frameworks with the results derived from the new policy-focused measurement approach to evaluate its merits and this will be evaluated in the second empirical chapter, namely chapter five.

6. Based on the empirical findings in chapter four, highlight the underperformance of the innovation dimension, and emphasize the need to promote innovation. Therefore, innovation development through an effective innovation policy based on country-specific instruments in a representative group of developing countries, namely selected developing countries in the MENA region, will be investigated in chapter six.

7. Formulate key policy measures necessary to facilitate the transition process towards establishing a KBE in developing countries and this will be summarised in chapter seven.

To achieve these objectives, the following research questions will be addressed:

1. How effectively do the current KBE frameworks explain the KBE in the context of developing countries? This question will be addressed in chapters three and five.
2. Does the (Data Envelopment Analysis) DEA method address the existing gaps in the literature regarding KBE measurement in developing countries? This question will be answered in chapter four.
3. Based on the empirical analysis using DEA, what actions can be taken to accelerate the transition process towards the KBE in developing countries? This question will be answered in chapter four.
4. What is the current status of the KBE in developing countries, and which measurement approach provides the most accurate assessment? This question will be answered in chapter five.
5. How can policymakers promote effective innovation policies in their respective countries? This question will be addressed in chapter six.

Given the above-stated research objectives, this thesis comprises six chapters employing qualitative methods such as descriptive statistics, econometric tools, and non-parametric analysis. The three main essays in this thesis are on main theme and each seeks to develop the existing body of empirical evidence but uses a range of different econometrics techniques to investigate several under-explored issues. However, each essay is structured similarly: providing motivation, highlighting the most important elements of the literature, developing a methodology, and presenting the main results. Formally, the layout of the thesis can be described as follows, after this introductory chapter:

Chapter Two is a conceptual framework and relevant literature chapter. It begins by introducing the concept of knowledge, including its characteristics, types, and aspects. The second part focuses on the conceptual framework of the KBE, discussing its definitions, characteristics, pillars, motivations, and highlighting the differences between a KBE and a traditional economy. The third part traces the evolution of KBE theories and explores global trends that underscore the inevitability of transitioning to a KBE. *Chapter Three* delves into KBE measurement. The first part explores the rationale for measuring the KBE, identifies challenges in measurement, presents existing KBE measurement frameworks, and outlines criteria for a reliable measurement framework. The second part examines the empirical literature on KBE measurement. This chapter concludes with a critical analysis of existing measurement frameworks and underscores the need for a new KBE measure.

Chapter Four, which represents the first empirical contribution, introduces an alternative policy-focused KBE framework, which delineates input-output indicators across four dimensions: knowledge acquisition, knowledge production, knowledge distribution, and knowledge utilization. This measurement framework employs a non-parametric approach called DEA. DEA employs linear programming techniques to identify efficiency frontiers and was originally developed to assess the performance of non-profit organizations with complex relationships between multiple inputs and outputs. The chapter considers the suitability of KBE measurement for developing countries, given data limitations, socio-economic peculiarities, development challenges, and priorities in these countries. It introduces DEA, discusses its application in the KBE context, and addresses methodological considerations. The chapter also examines prior empirical studies using DEA, presents radial DEA models, and non-radial DEA models, and compares various DEA models to identify the most suitable one. It concludes with empirical results and related policy recommendations.

Chapter Five, which represents our second empirical contribution proceeds as follows. It empirically investigates the KBE in developing countries by comparing KAM in 2020, and the GII in 2020 with the DEA results in 2020 to determine which approach is more relevant for analysing the KBE in developing countries and to provide insights for improving future analysis.

Chapter Six, which represents the third empirical contribution, focuses on innovation. According to the World Bank Institute (WBI), there are four pillars of the KBE, namely economic incentive, and institutional regime; education; information and communication technologies, and innovation. Within these four pillars, innovation is regarded as the most crucial pillar for the transition into the KBE (inter alia Kontolaimou et al., 2016). KBE is now widely accepted as the direction in which all countries are moving (inter alixa Omar, 2019). Central to this KBE is innovation, which is regarded as the most crucial pillar for transition into this KBE (This recognized importance of innovation among scholars and policymakers for KBE transition and long-run economic growth has raised researchers' wide interest in the mechanisms explaining the national innovation performance i.e., identifying its drivers. Despite the rich literature on innovation determinants theoretically and empirically, it is still not well defined (inter alia Bate et al., 2023). In the context of developing countries, they are lagging developed countries in terms of the four KBE pillars, with the innovation pillar being the worst relative to the other three pillars of KBE (inter alia Phale et al., 2021). Further, despite the importance of innovation in the developing countries context, little academic attention has been paid to an in-depth diagnostic analysis to the situation in these countries (Arshed et al., 2022). Thus, more studies are still needed to fully capture what drives the innovation process in developing countries. Therefore, chapter six explores the literature on innovation policy, with a special emphasis on boosting innovation development in selected developing countries. This is done by an empirical analysis of innovation drivers in developing countries in the MENA region using the Generalized Method of Moments (GMM) estimator. Finally, *chapter seven* highlights the main research findings emanating from this thesis and provides policy implications and recommendations. This chapter also identifies some suggestions for future research.

Therefore, these three empirical chapters will provide answers to these above-stated questions and will be able to provide suggestions and guidelines for policymakers in these developing countries. An important contribution to the literature can be made, whether it is the application of DEA in KBE assessment; the introduction of the most productive scale size and peer countries; the KBE dimension requiring the highest investment to speed up the KBE transition; the KBE measurement framework that is suitable for developing countries context and finally the introduction of national innovation policy that suits developing countries' context.

1.3 Research Contributions

This thesis begins by comprehensively and systematically reviewing the conceptual, theoretical, and empirical literature for the KBE in chapters two and three. It then advances an original contribution in chapter four by presenting a comprehensive analysis to assess the relative efficiencies of developing countries during their transition processes toward a KBE through the application of, contrary to the usual econometric analysis, a non-parametric approach, namely the DEA. To the best of the researcher's knowledge, no other study exists that applies a quantitative technique like DEA to a large sample like developing countries and to mainly concentrate on measuring the KBE relative efficiencies in developing countries. Performance assessment studies in the DEA literature can be methodologically divided into two basic approaches with distinct features, namely radial and non-radial measures. Despite the significance of radial DEA measures, they have some drawbacks in a lot of real-world circumstances. Of these restrictions, ineffective DMUs must modify their inputs and/or outputs proportionately to become frontier nations. In contrast, inputs and outputs may not always vary appropriately in real-world circumstances and this is the main significance of non-radial DEA measures (Tone, 2016). Therefore, the uniqueness of the DEA chapter arises from not only employing DEA for KBE assessment in developing countries using the basic radial DEA models, as most of the prior DEA-based studies for KBE assessment have done, but also by employing the non-radial DEA models in developing countries, which has superiority over radial DEA model, and this is explained in-depth in chapter four. This is done with consideration to all KBE dimensions to assess the latter's merits, namely the non-radial DEA models, and to deal with the form's shortcomings, namely the radial DEA models to opt for the best DEA model for KBE assessment.

The empirical and theoretical literature review shows that the Knowledge Assessment Methodology (KAM) is a widely recognized measurement framework for KBE assessment, but it stopped in 2012. Therefore, KAM is replicated for 2020 in chapter five and then compared with DEA results and Global Innovation Index (GII) results in the same year to opt for the most robust measure for KBE assessment.

Additionally, innovation is regarded as the most crucial pillar for the transition into the KBE. However, in the developing countries context, these countries are lagging behind developed countries in terms of the four KBE pillars, with the innovation pillar being the worst relative to the other three pillars of KBE. This has been empirically investigated in many studies and observed by the DEA results in chapter four. Furthermore, despite the importance of innovation in the context of developing countries, little academic attention has been paid to an in-depth diagnostic analysis of the situation in these countries. Therefore, chapter six systematically captures what drives the innovation process in developing countries. In this chapter, the innovation and institution nexus is carefully investigated as the previous empirical studies had conflicting findings and left some important details regarding the correct specification of the relationship between institutional quality and innovation development. Finally, an econometric analysis is conducted at the country level to identify the innovation determinants from a broad national perspective.

Chapter 2

Conceptual Framework and Relevant Literature

2.1 Introduction

The concept of a KBE - or knowledge economy (KE)- has gained significant attention in recent years, as countries around the world have sought to transition from traditional manufacturing and resource-based economies to ones driven by knowledge and innovation. Despite the widespread interest in the KBE, there remain fundamental questions about what exactly a KBE is, and why countries should aim to transition to such an economy. This chapter aims to address these questions. The current chapter provides a comprehensive overview of the conceptual framework and theoretical foundations of the KBE. More specifically, the chapter is organized into three main sections.

The first section explores the concept of knowledge in detail, including its characteristics, types, and aspects. The second section provides a historical background on the development of the KBE, including various definitions, characteristics, pillars, and motivations for the transition to this economy. Additionally, the second section summarizes the main differences between the KBE and traditional economies. The third section of this chapter focuses on the theoretical foundations of the KBE and its relationship to growth theory. It also outlines the global economic trends that nations must adopt if they wish to remain competitive in the global economy, as well as the motivations for transitioning to a KBE.

Overall, this chapter provides an in-depth exploration of the conceptual framework and theoretical literature on the KBE, shedding light on the key features of this economy and the reasons why it has become a critical area of study for policymakers, academics, and economists alike.

2.2 Conceptual Framework

2.2.1 The Concept of Knowledge

2.2.1.1 Data-Information-Knowledge-Wisdom

To understand the concept of the KBE - the primary focus of this thesis - it is essential to first gain an understanding of the term “knowledge” and its relationship to related terms such as information, data, and wisdom. However, the literature has defined these terms in various ways, with Zins (2007) identifying 130 different definitions created by 45 academics. Therefore, before defining the term “KBE”, this chapter will provide a brief overview of the definitions and relationships of these key terms.

While there is a significant amount of literature on the distinctions between data and information, as well as knowledge and wisdom, there is no clear and widely accepted definition for each of these terms. Scholars such as Baskarada and Koronios (2013); Hossain (2015); Oxley et al. (2008); and Rowley (2007) have made efforts to provide precise and accurate definitions for these concepts. However, despite these efforts, the definitions of these terms remain contested and vary widely in the literature.

Additionally, the terms “information” and “knowledge” are sometimes used interchangeably in the literature, which can cause confusion[1]. To avoid this confusion, this chapter will adopt a simple and widely recognized model from the knowledge management and information science literature to define these terms. This approach will help clarify the differences between the various terms and provide a solid foundation for understanding the concept of the KBE.

(1) For example, the United Nations Educational, Scientific and Cultural Organization (UNESCO) report (2005) stated that: *“The rise of the global information society has allowed a considerable mass of information or knowledge to be disseminated via the leading media. However, the different social groups are far from having equal access and capacity to assimilate this growing flow of information or knowledge*” (Bindé, 2005: p.160).

Figure (2.1): The Knowledge Pyramid.

Source: Hey (2004, p.3)

To achieve this goal, this chapter employs the Data-Information-Knowledge-Wisdom (DIKW) hierarchy, also known as the knowledge pyramids. This model, which was best articulated by Russell Ackoff and other system theorists in Ackoff's seminal paper in 1989, has been widely discussed in the literature (Frické, 2018; Sharma, 2008) and is commonly used in the knowledge management and information science fields. The DIKW hierarchy will serve as a useful framework for understanding the distinctions between these key terms and for analyzing the nature of the KBE.

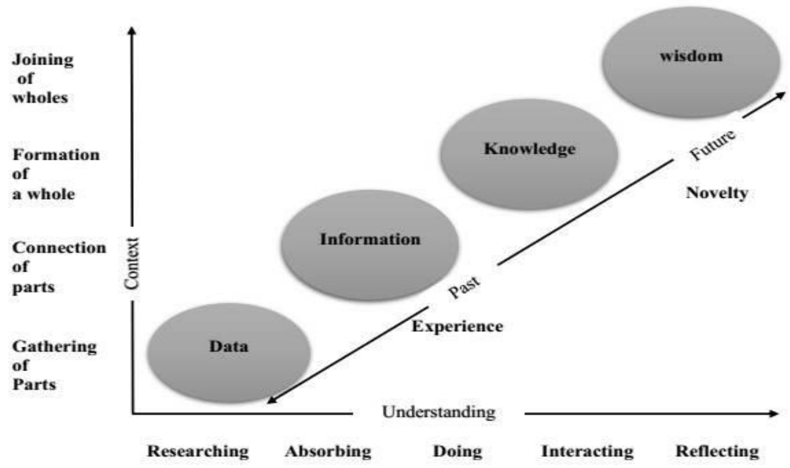
Figure (2.1) illustrates the DIKW model, which demonstrates how the human mind transforms raw data into information, knowledge, and wisdom respectively. At the first level of this model, there is data. While data is the first requirement to achieve any meaningful result, raw data does not provide any meaning on its own as it lacks context and interpretation. In other words, data is ”know-nothing” (Frické, 2018) and consists of symbols that represent the properties of a specific object (Hippe & Fouquet, 2018).

Information, on the other hand, provides answers to questions such as who, where, when, and what. In other words, information is data that has been placed in a specific context and given meaning by establishing relationships and connections between different data points. Each layer or element in the DIKW model adds certain attributes to the previous layer (Hey, 2004).

Moving on to the third level of the DIKW model, knowledge refers to the appropriate and accurate collection of information that makes it useful and valuable. For information to be considered knowledge, it must add value by being organized and structured in a particular way. This means that knowledge seeks to address the question of “know-how” Knowledge can be acquired in three different ways: from a person, from experience, or through instruction (Hippe & Fouquet, 2018).

The fourth and highest level of the pyramid is wisdom, which refers to the practical application of knowledge acquired at the previous level to answer the question of “know-why” (Baskarada & Koronios, 2013). Wisdom adds value through judgement and the ability to make informed decisions (Hippe & Fouquet, 2018). Finally, it is worth noting that the DIKW model can be viewed from three different perspectives, namely context, understanding, and time perspectives, as illustrated in Figure (2.2).

Figure (2.2): Three Perspectives for the Knowledge Hierarchy.



Source: Hey (2004, p.3)

Viewed from a contextual standpoint, the DIKW model represents a progression from gathering and collecting components (data), to connecting these parts (information), forming a whole (knowledge), and finally merging and joining these wholes (wisdom). From the standpoint of understanding, the process begins with research, followed by absorption, doing, interacting, and ultimately reflection. Furthermore, from a time perspective, the levels of the DIKW model are governed by the past, with data, information, and knowledge being rooted in historical context. In contrast, wisdom focuses on the future and emphasizes the importance of using past experiences and knowledge to make informed decisions that will impact future outcomes (Hippe & Fouquet, 2018)[2].

2.2.1.2 Characteristics of Knowledge as an Economic Good

The literature shows that Machlup (1962) was the first to study knowledge as an economic good, and he differentiated between three types of knowledge goods. The first type is knowledge as an investment good, which refers to knowledge goods that can be used to pay off in the future. These goods are considered an investment because they increase productivity and can lead to economic growth. Examples of knowledge as an investment good include education, scientific research, and applied technical research. The second type of knowledge good is knowledge as a consumption good, which refers to goods that provide immediate pleasure to the recipient. Examples of knowledge as a consumption good include comic books and arts. Finally, knowledge for intermediate use, such as in market research or financial analysis, produces knowledge with a mediation objective and is not considered a final product, but rather a cost of producing the final good (Leppälä, 2015; Machlup, 1962).

Knowledge, as an economic good, has three distinct properties that differentiate it from tangible goods. Stiglitz (1999) argues that these properties have fundamental implications for the organization and functioning of the KBE and can impact the formation of public policy. The first property of knowledge is that it is non-excludable, meaning that in practice it is difficult to control knowledge privately or make it exclusive to the entity that produced it, unless it is kept secret. This is due to the fluid and portable nature of knowledge, which makes it challenging for a firm to control its knowledge compared to its machines. This is because leaks and spillovers of knowledge are likely, allowing it to escape from the producing entity to other entities that can use it freely. The term “positive externalities” is used in the literature to express the positive impact on a third party that can benefit from knowledge spillovers without financial or other types of compensation (Foray, 2004).

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(2) It goes outside the scope of this chapter to critically analyse DIKW pyramids. However, Rowley (2007) did this critical analysis.

The second characteristic of knowledge is that it is non-rival, which means that the use of existing knowledge is unlimited in both time and among different users (Foray & Mairesse, 2001). Thus, depletion of the stock of knowledge due to its use is impossible (Brinkley, 2006). The term “infinite expansibility” is sometimes used interchangeably with “non-rivalry” by Coyle and Quah (2002), as cited in Gunay and Kazazoglu (2016, p.10).

The final characteristic of knowledge is that it is cumulative, which means that existing knowledge is a necessary component for creating new knowledge. Thus, positive externalities provide the foundation for knowledge accumulation and collective progress (Foray, 2004).

2.2.1.3 Different Types of Knowledge

Pedersen (2008) argues that it is crucial not only to distinguish between what is considered knowledge and what is not, but also to have a taxonomy that distinguishes between different types of knowledge. This is essential for analysing the role of knowledge and knowledge creation in the economy. Lundvall and Johnson (1994) similarly emphasize the importance of such a taxonomy because it enables the integration of economically relevant knowledge in new ways and allows for transactions with different types of knowledge.

The most widely used classification for types of knowledge is the one proposed by Lundvall and Johnson (1994), which divides knowledge into four categories. This classification has been documented and widely used by numerous studies, including OECD (1996); Pedersen (2008); Piech (2004), and Rim et al. (2019).

“Know-what” refers to knowledge of facts or descriptions, such as the number of people living in a country, or the ingredients needed to make a cake. This type of knowledge is like what is generally referred to as information because it can be divided into smaller units or bits. It is a crucial type of knowledge in many fields, including law and medicine, and experts must have a significant amount of it to perform their jobs effectively (OECD, 1996). This knowledge can be obtained from various sources, such as books, lectures, and database access (Gorji & Alipourian, 2011).

"Know-why," according to Lundvall (2016), "refers to scientific knowledge of principles and laws of motion in nature, the human mind, and society"(p.4). It is essential in reducing the likelihood of mistakes during trial-and-error operations and contributes to the technological progress of various industries. Institutions like research labs and universities are responsible for creating and disseminating this type of knowledge. Firms can deal with these specialized organizations directly through contacts and cooperative activities or indirectly by hiring scientifically trained workers.

"Know-how" refers to the necessary skills or practical abilities to perform tasks. This type of knowledge is usually created and stored within a single firm or organization, and sharing and combining elements of know-how can be done through industrial networks. In Nelson and Romer (1996) conceptual classification, "know-how" is equivalent to wetware.

"Know-who" involves "information about who knows what and who knows how to do what" (OECD, 1996). It entails the development of unique social ties that enable access to experts and effective utilization of their knowledge (Lundvall, 2002). This form of knowledge is becoming increasingly significant in economies where skills are broadly distributed. Modern managers and organizations must utilize this type of knowledge to deal with the increase in the rate of change. Compared to other categories of knowledge, this type is more internal to the organization (Lundvall & Nielsen, 2007).

Another closely connected taxonomy of knowledge is the one presented by Conceicao and Heitor (1999) and Nelson and Romer (1996) as they provided further classification. Conceicao and Heitor (1999) argued that knowledge can be differentiated by what it is not. This means that what is "not human" is not knowledge. The "not human" category comprising physical goods, infrastructure, natural resources, and raw materials. They then divided knowledge into "ideas" and "skills", whereas Nelson and Romer (1996) used the terms "software" and "wetware". Ideas or software refer to codified (overt) or explicit knowledge that can be stored, organized, systematized, and written outside the human brain. Examples of software knowledge include text in books or images in films.

Conversely, skills or wetware refer to tacit or implicit knowledge that is sorted in the human brain and cannot be separated from a human being. This type of knowledge involves skills, experience, intuition, and judgment that people develop through their personal and professional lives.

It is also important to note that all the classifications of knowledge mentioned earlier share similar fundamentals which can be summarized as shown in Table (2.1).

Table (2.1): Types of Knowledge

Author (s)	Types of Knowledge			
Lundvall and Johnson (1994)	Know-what	Know-why	Know-how	Know-who
Nelson and Romer (1996)	Software	Software	Wetware	Wetware
Conceição and Heitor (1999)	Ideas Codified (Explicit)	Ideas Codified (Explicit)	Skills Tacit (Implicit)	Skills Tacit (Implicit)

2.2.1.4 Aspects of Knowledge

The process of knowledge flow consists of four main phases, according to Dahlman and Andersson (2000) as cited in Piech (2004) and Trewin (2002). These phases are knowledge acquisition, knowledge production (creation), knowledge dissemination (distribution), and knowledge utilization. Each phase plays a crucial role in economic development, but the intensity of each phase may differ.

Knowledge acquisition is the first phase and can be influenced by numerous factors at both the individual and organizational levels. Bratianu (2015) suggests that a company's absorptive capacity, organizational context and structure, inter-firm alliances, and learner's intention and capacity are essential elements of knowledge acquisition at the organizational level[3]. A country with a weak research and development (R&D) sector may also develop through knowledge acquisition acquired through foreign direct investment (FDI) and the potential technological transfer connected with it.

(3) Detailed explanation for each element is available in Bratianu (2015)

Knowledge production is the second phase and is carried out through R&D and the implementation of innovation activities. Knowledge dissemination, the third phase, is fundamental to achieve technological and economic development. It involves the transfer of technology and knowledge throughout the economy, and education is considered the primary method for distributing knowledge in a society (Saudi Arabian Ministry of Economy and Planning, 2010).

Finally, knowledge utilization is the fourth phase and involves the use of knowledge in creating new products and services. The development of the R&D sector, technology transfer, and the implementation of knowledge in business processes through the development of a National Innovation System (NIS) are all essential factors for economic development (Piech, 2004).

2.2.2 The Knowledge-Based Economy: Background and Motivation

2.2.2.1 Historical Background to the KBE

The literature on the KBE is extensive and multifaceted, encompassing a range of names, interpretations, approaches, and forms of the concept. Peters (2001) emphasized the importance of comprehending these diverse aspects as they offer a historical context to this policy concept, examine its ideological interpretations, and highlight efforts to connect it with the broader global economy. However, delving into the various attempts made by theorists is beyond the scope of this chapter. Instead, this chapter will provide illustrative examples from the abundant literature on the subject.

Godin (2006) and Powell and Snellman (2004) have classified this body of literature into different periods, identifying three major research areas within the broader concept of KBE. The first line of thought focuses on exploring the relationship between economics and knowledge. Intellectuals, futurologists, and information economists like Von Hayek (1937; 1945) contributed to this exploration.

By the early 1960s, scholars started examining the role of emerging science-based industries and their impact on social and economic transformations. They recognized significant changes in the structure of the economy, characterized by a gradual expansion of non-agricultural and non-industrial sectors. Consequently, this new economy was defined as a replacement for the old one, often referred to as a post-industrial economy. However, there was a misconception during this period, as scholars mistakenly perceived it as a service-based economy (Abramson, 2006).

Bell (1973); Machlup (1962); Noyelle (1990); and Romer (1990) as referenced in Powell and Snellman (2004) supported this approach. Their key idea revolves around the crucial role of theoretical knowledge as the primary driver of innovation. Additionally, the works of pioneers in the new growth theory can be incorporated into this approach, as they emphasize the importance of knowledge in economic growth.

A closer examination of Machlup (1962) work reveals his comprehensive understanding of the main characteristics of the KBE. He introduced the term "knowledge-based industry" after observing that the number of knowledge-producing occupations had surpassed that of other occupations. Machlup also studied the creation and dissemination of knowledge in the United States during that time. Moreover, Gary Becker's (1964; 1993) focused on analysing human capital in relation to education (Batagan, 2007).

Furthermore, Peter Drucker (1969), a management theorist, placed emphasis on the concept of the "Knowledge Worker" and laid the foundation for the field of "knowledge Management". Drucker is credited with coining the phrase "the knowledge economy" in his 1969 book, "The Age of Discontinuity" (Drucker, 1969). In November 2001 edition of The Economist, Drucker declared that the future society would be a knowledge society, with knowledge workers constituting the majority of the workforce and knowledge being the primary resource. He identified three key characteristics of this society: borderlessness, as knowledge travels faster and with less effort than money; upward mobility, due to widely available formal education; and the possibility of both failure and success, as everyone can acquire the means of production and necessary skills, but not everyone will succeed (Batagan, 2007).

Bell (1973) sociology of post-industrialism emphasizes the significance of theoretical knowledge, new science-based industries, the transition from manufacturing to services, and the emergence of a new technical elite. Bell argues that post-industrial societies generate higher levels of wealth compared to industrial societies. Alain Touraine (1971) also discussed the concept of the “Post- industrial Society” and proposed a “programmed society” governed by a “technocracy” that controls information and communication (Peters, 2022). Mark Granovetter (1973, 1983) theorized the role of information in the market, focusing on weak ties and social networks (Robertson, 2008).

In 1977, Marc Porat wrote a comprehensive nine volume dissertation that measured the size of this emerging economy and referred to it as an “information economy.” Porat is credited with being the first to use this term, describing an economy where information-related work surpasses work in other sectors. In 1967, based on Porat’s measurements, 53% of the US workforce was engaged in information work. Porat further categorized the information economy into the “primary information sector,” which involves creating or handling information (e.g., scientists and writers), and the “secondary information sector,” where workers are involved in non-information tasks in non-information firms and industries (Porat, 1977).

Furthermore, discussions on knowledge-based production in relation to the “third wave economy” were presented by futurist Alvin Toffler in 1980 (Peters, 2010). Lyotard (1984) described the postmodern condition, characterized by the diffusion of knowledge by Western nations, marked by the complexity, dispersion, and contingency of knowledge. Coleman (1988) examined the relationship between social capital, human capital, and economic development. Harvey (1989) articulated the widespread transition from Fordist to flexible accumulation in modern capitalism. Romer (1990) argued that technological change drives growth, highlighting the significance of knowledge. These pioneers in the new growth theory contribute to the understanding of knowledge’s role in economic growth.

In the 1990s, the second line of thought focused on the importance of learning, ongoing innovation within businesses and firms, and the factors behind successful knowledge production and transfer.

Scholars such as David and Foray (1995); Drucker (1993); Stiglitz (1999); Lundvall and Johnson (1994), Nonaka and Takeuchi (1995); OECD (1996); and Prusak (1997) explored these aspects. They also examined the social arrangements that could enhance or constrain knowledge generation and distribution (Godin, 2006). To clarify, the OECD (1996) introduced an influential model of the KBE based on Romer's work. Stiglitz (1999) developed "Education for development programs" and the "World Bank knowledge for development program" (K4D) emphasizing knowledge as a global public good (Peters, 2001). There were also debates among writers in the 1990s regarding whether the KBE operated differently from the past, given unexpected developments in macroeconomic and financial markets.

The third line of thought, represented by writers like Brynjolfsson and Hitt (2000) and Gordon (2000), delved into analysing the contribution of knowledge-intensive sectors to productivity growth. With some stretching, the World Bank (2003) report defined a KBE as "one primarily relying on ideas and technology rather than physical abilities, raw materials, or cheap labour" (p.18).

By 2005, the concept of the KBE had become an umbrella term, with Berglind Asgeirsdottir (OECD Deputy Secretary-General), stating in her opening remarks at an OECD/NSF conference on "Advancing knowledge and the knowledge economy" that the development of the knowledge economy relies on four main pillars: "innovation, new technologies, human capital, and enterprise dynamics" (Robertson, 2008; p.7).

In a study by Aparicio et al. (2023), they assert that the period from 1991 to 2020 represents the foundation for the paradigm shift towards the KBE. They identify two distinct periods of KBE evolution. The initial period spans from 1991 to 2005 and is characterized as the starting point for KBE progression in the research field. The subsequent period, starting from 2006, is identified as the expansion period, representing almost 88% of the total volume of publications. This study also provides a more recent bibliometric literature review on the development of scientific research related to the KBE.

Overall, the literature on the KBE encompasses diverse perspectives and periods of analysis. It includes discussions on theoretical knowledge, new industries, the transition to services, the emergence of a technical elite, information economies, the role of innovation and learning within firms, the influence of social capital, and the impact of knowledge-intensive sectors on productivity. The concept of the KBE has evolved over time and is considered a key driver of economic growth and development in contemporary societies.

2.2.2.2 Definitions of the KBE

In various journals, articles, reports, and speeches by policymakers, different definitions of the term KBE have been introduced[4]. Appendix (I) provides over 30 definitions based on the researcher's knowledge. Upon reviewing this appendix, it becomes evident that the KBE definitions proposed by international organizations and scholars are relatively similar. For example, the definitions put forth by the OECD align with those proposed by the WB. Additionally, the APEC sought to expand the definition of the KBE by emphasizing the importance of knowledge for wealth creation and employment across all industrial sectors. According to APEC's definition, a KBE is not solely dependent on high-tech industries but can encompass all industries, including so-called "old economy" sectors like agriculture (Trewin, 2002). The United Nations Economic Commission for Europe (UNECE) attempted to provide a more precise definition by elaborating on the driving forces of the KBE. However, while these definitions highlight the crucial role of knowledge as an engine for economic growth, they differ in terms of the scope of the economy (Dahlman and Andersson, 2000).

It is important to note that despite the multitude of definitions, there is no coherent or universally accepted definition for the term, as pointed out by numerous scholars (inter alia Al-Rahbi, 2008; Bano & Taylor, 2015; Brinkley, 2008; Hadad, 2017). This definitional problem is also evident in the existing KBE literature. As Smith (2002a) states " *The weakness or even complete absence of definition is actually pervasive in the literature... this is one of the many imprecisions that make the notion of 'knowledge economy' so rhetorical rather than analytically usefu*l" (p. 7). Many other writers have echoed this sentiment,

(4) There are various academic journals specialized mainly in KE namely, the Journal of the Knowledge Economy, Review of Knowledge Economy, Journal of Knowledge Economy and Knowledge Management, Management Dynamics in the Knowledge Economy, the International Journal of Learning and Intellectual Capital, and Journal of intellectual capital. Aparicio et al. (2023) cited the updated and the most predominant Journals, studies, and fields of KE.

with Livingstone and Guile (2012) noting the absence of precise, quantifiable definitions and Godin (2010) highlighting the KBE's status as a buzzword in academic and official discourse.

One example of this definitional problem is the OECD's definition of KBEs as "*those which are directly based on the production, distribution, and use of knowledge and information*" (OECD, 1996, p.7). This definition appears to encompass everything and nothing, as all economies rely on knowledge to some extent. It is challenging to imagine that all these economies are directly based on knowledge if it refers only to the production and distribution of knowledge and information products.

Another fundamental definitional problem relates to the cognitive or epistemological characteristics of knowledge, which inherently defy precise pinning down. Winter (1987) argues that "knowledge is a slippery object," and the Centre for Educational Research and Innovation (CERI) report as cited in Brinkley (2006) describes knowledge as capricious, sticky, slippery, intangible, tacit, and heterogeneous.

To this end, we could conclude that Smith (2002a), among many other studies, failed to present a more precise definition for the KBE, although Smith (2002a) succeeded to illustrate the definitional problems for the term in-depth.

However, having a clear answer to the question of what this KBE is; is crucial because it allows to map the size of this economy. How fast it is growing, what indicators used to reflect the intensity of this economy, and what is the knowledge force? What is the knowledge-based firm and what are the policy implications for government, firms as well as individuals? It will enable also to gauge more accurately some of the rationale for the KBE, such as the claim that knowledge investment surpasses that of physical capital (Brinkley, 2008).

Despite these definitional challenges, Smith (2000) identifies four basic approaches to how the concept is introduced in the economic literature. The first approach emphasizes that knowledge is a more significant input to production, both qualitatively and quantitatively, compared to the past. The OECD, for instance, states that "*the role of knowledge... has taken on greater and paramount importance... all OECD economies are moving towards a KBE*" (Carlaw et al., 2006; p.671). Similarly, Peter Drucker argues that knowledge is becoming the primary factor of production, surpassing capital, and labour (Carlaw et al., 2006; p.671).

The second approach posits that knowledge is more valuable as a product than it has been in the past. The emergence of new economic activities centred around the exchange of knowledge goods supports this view (Smith, 2000). The third approach focuses on the belief that codified knowledge holds greater value as a component of economically relevant knowledge bases (Lundvall, 2006). Finally, the fourth approach highlights that KE is built upon technological changes in information and communication technology (ICT) because these advancements have an impact on both the costs and physical restrictions associated with information gathering and distribution (Smith, 2000).

In this chapter, the commonly used definition by the World Bank (2007a) is adopted, which states that a KBE is "*an economy in which knowledge is acquired, created, disseminated, and used effectively to enhance economic development*" (p.23). This definition is employed for its widespread usage, simplicity, and consistency with the measurement framework utilized later in this thesis. Moreover, it is worth noting that different terms are frequently used interchangeably in studies to refer to various aspects of the KBE, often treating them as synonyms[5] (inter alia Al Majali & Almomani, 2020; Aparicio et al., 2023; Azzman Shariffadeen, 2009; Brinkley, 2006; Hadad, 2017).

Beniger (1986), as cited in Godin (2006), have introduced numerous buzzwords between 1950 and 1984, including terms like KE, KBE, age of information, post-traditional economy, third industrial revolution, the information economy, digital economy, virtual economy, networked economy, net economy, internet economy, new economy, modern economy, weightless economy, post-industrial economy, and high-speed economy (Amirat & Zaidi, 2020). However,

(5) It is worth noting that some studies and reports provide some major differences for these technical terms. For example, the UNECE 2002 under the title "What do we mean by the knowledge-based economy?". Differentiate between KBE, digital economy, and networked economy (ECE, 2002, P.vii). However, mainstream studies used these terms synonymously.

Hadad (2017) argues that the terms KE and KBE are currently the most commonly used by international organizations and policymakers. These terms represent the concept of an economy driven by knowledge for economic development. As a result, this chapter will use these mainstream terms, namely KE/KBE, to maintain consistency.

In some rare studies, a clear distinction between the two terms KE and KBE. For example, Leydesdorff (2012) argues that these terms differ from an analytical standpoint. Leydesdorff (2012) suggests that codified knowledge is a key factor for economic growth and development in the KBE, while the emphasis in the KE is on knowledge workers. Thus, tacit, and embodied knowledge become crucial for economic growth.

Furthermore, it is important to clarify that the term "knowledge Economy" can be defined in two distinct ways. Firstly, it can refer to an economic sector within larger economy, where knowledge itself becomes a valuable product (Graham et al., 2017). For instance, Sukharev (2021) conducted an evaluation of the intensity of the KE sector in the European Union. Secondly, the KE can be understood as an economy in which knowledge serves as a tool to enhance all sectors. In this context, the costs associated with knowledge are embedded in the increased value of products and services resulting from its application. This implies that knowledge is utilized to achieve economic benefits, such as in R&D, software development, or the pharmaceutical industry (Vadra, 2017).

Moreover, it is worth noting that the concept of the KBE can be seen as an advanced phase of the KE, as stated in the Arab Knowledge Index report (2015). In the KBE, the application of knowledge extends to various economic and social activities, creating an economy that is built on knowledge and science (Mohammed bin Rashid Al Maktoum Foundation (MBRF) and United Nations Development Programme/Regional Bureau for the Arab States (UNDP/RBAS), 2015).

This chapter adopts the widely used definition of the KE provided by the World Bank (2007a), which states that "*it is an economy where knowledge is acquired, created, disseminated, and effectively utilized to enhance economic* *development*" (p.23). This definition is employed in this thesis for several reasons, including its common usage, simplicity, and consistency with the measurement framework utilized later in the study.

2.2.2.3 Characteristics of the KBE

Based on the previously presented definitions of the KE, it is possible to identify its distinctive characteristics[6]. Peters (2001), Tocan et al. (2012) and Hadad (2017) have introduced favourable attributes of the KE that differentiate it from the old economy in several key aspects.

Firstly, the KBE is an economy of abundance/accumulation, instead of the old economy characterized by scarcity or shortage. Thus, if in the past, resources used to be diminished while using, in the KBE, knowledge, which is the main resource of the KBE, is not depleted and does not decrease when used. Knowledge multiplies as it is shared, developed, and expanded through its application.

The second characteristic of the KE is the annihilation of distance. In this economy, the impact of physical location is reduced. The use of ICT enables seamless global operations and facilitates access to virtual marketplaces, commercial centers, and organizations. These virtual platforms offer advantages in terms of speed and agility. Furthermore, in the KE, human capital capabilities play a crucial role in determining value. Therefore, investing in human capital is of fundamental importance in this economy, as it relies on knowledge workers rather than traditional workers found in the old economy. Moreover, knowledge, when incorporated into systems or procedures and contextualized, holds greater inherent value than when confined to individual minds.

Another characteristic of the KE is the de-territorialization of the state. This implies that the KE operates beyond national boundaries, making it challenging or even impossible to impose laws, barriers, and taxes solely on a national basis. This is because knowledge flows to places with the highest demand and the fewest restrictions.

(6) To the best of the researcher's knowledge, the following references provide characteristics of the KBE: (APEC Economic Committee, 2000; Brinkley, 2006; Hadad, 2017; Houghton & Sheehan, 2000; OECD, 1996; Smith, 2000; Żak 2016). All these references are almost the same in providing complementary characteristics to the KE.

Lastly, the KE places high importance on local knowledge. The value and pricing of goods and services in the KE are heavily influenced by specific contextual circumstances. The same knowledge can have varying values for different individuals and at different times.

Additionally, knowledge-intensive goods and services may command higher prices compared to relatively similar goods with less embedded knowledge.

2.2.2.4 Pillars of the KBE

To leverage the transformative power of the knowledge revolution and the accompanying economic and technological changes, countries need to re-evaluate their development strategies. The foundation of these strategies should primarily revolve around pro-knowledge and pro-innovation policies. According to the World Bank Institute (WBI), these strategies and policies should be built upon what is referred to as the four pillars of the KBE, also known as core drivers, elements, pillars, or pylons. These four fundamental pillars are derived from studies conducted by the WB, which draw insights from the successful transition of KBEs[7].

The pillars, as stated in Chen and Dahlman (2005), are as follows: "*Economic incentive and institutional regime*," which refers to *Economic incentive and institutional regime: that provides good economic policies and institutions that permit efficient mobilization and allocation of resources and stimulate creativity and incentives for the efficient creation, dissemination, and use of existing knowledge"* (p.4). Additionally, these policies and institutions should stimulate creativity and provide incentives for the effective creation, dissemination, and utilization of existing knowledge. This implies that economic actors must be motivated to utilize existing knowledge efficiently and to generate new knowledge.

This concept encompasses various issues and policy areas, including the macroeconomic framework, trade regulations, labour markets, the financial

(7) Chen and Dahlman (2005) provided a detailed description of each KE pillar and supported empirical literature that emphasized the importance of these pillars as crucial determinants for long-term economic growth. Additionally, confirmative econometric evidence is sketched out in World Bank (2007a)

system, and governance. A "knowledge-conducive" economic regime is characterized by minimal price distortions. For example, an economy that embraces international trade without protectionist policies fosters competition, which, in turn, encourages entrepreneurship. It is also important to maintain stable and low inflation rates, manageable government spending and budget deficits, a relatively free pricing system, and a stable exchange rate that accurately reflects the currency's value. Additionally, the financial system should effectively allocate resources to sound and efficient investment opportunities while being capable of reallocating assets from failed investments to more promising ones (World Bank, 2007a).

Similarly, a "knowledge-conducive" institutional regime implies the presence of an effective and transparent government with minimal corruption. It also requires a legal system that upholds the rule of law and safeguards intellectual property rights. In the context of the KBE, protecting intellectual property rights is essential for the transition to occur successfully. Without robust and enforced intellectual property rights, researchers and scientists lack incentives to create new knowledge. Additionally, a weak system of intellectual property rights protection severely hampers the dissemination of new knowledge.

The second pillar of the KBE is characterized as having "educated and skilled workers who can continuously upgrade and adapt their skills to efficiently create and use knowledge" (Chen & Dahlman, 2005; p.4). A highly skilled and educated workforce plays a critical role in enhancing total factor productivity, leading to economic growth by effectively creating, disseminating, utilizing, and acquiring knowledge.

Education and training systems encompass various components such as basic and secondary education, higher education, vocational training, and lifelong learning. Basic education is fundamental as it enhances individuals' ability to use information effectively. However, secondary, and higher education are particularly crucial for technological innovation and the adaptation of foreign technologies to be employed in domestic production. These levels of education equip individuals with the necessary knowledge and skills to drive technological advancements and successfully apply them in various sectors.

In this manner, the weight assigned to each segment of education will differ depending on the level of development in a country and on the population age. Basic education, for example, will receive more attention and hence more weight at low levels of development. In contrast, lifelong learning has the highest weight in the context of the current knowledge revolution that requires adaptation of knowledge and know-how. This means that the knowledge revolution forces countries to cover a wide range of educational levels, even when these countries are at low levels of development, to catch up with developed countries and to remain competitive.

The third pillar of the KBE is characterized by "*an effective innovation system of firms, research centres, universities, consultants, and other organizations that can keep up with the knowledge revolution, tap into the growing stock of global knowledge, and* assimilate *and adapt it to local needs*" (Chen & Dahlman, 2005; p.4). An innovation system comprises institutions, rules, and practices that shape how nations produce, share, and apply knowledge.

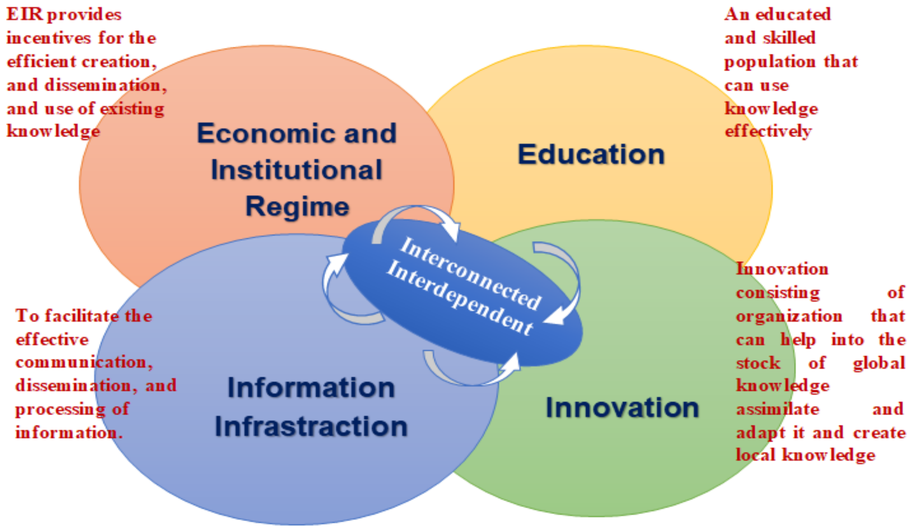
Universities, research centres (both public and private), and policy think tanks are integral institutions within the innovation system. Additionally, the government and non-governmental organizations play a crucial role in the NIS if they contribute to the production of new knowledge. In the transition to a KBE, an effective innovation system is essential. It provides an environment that supports and fosters R&D, which leads to the creation of new products and knowledge. R&D is a primary source of technical progress, which, according to economic theory and empirical literature, is a key driver of productivity growth (Bučar, 2003). Thus, an effective innovation system is indispensable for fostering technical progress and driving productivity growth in the KBE.

The fourth pillar of the KBE is characterized by "*a modern and adequate information infrastructure that can facilitate the effective communication, dissemination, and processing of information and knowledge*" (Chen & Dahlman, 2005; p.4). The information and communication technologies (ICTs) infrastructure of a country, as defined by the World Bank (2003), encompasses the accessibility, reliability, stability, and efficiency of computers, phones, television and radio sets, and the various networks connecting them. A robust ICT infrastructure significantly reduces costs, overcomes geographical barriers, and provides easy access to information. Consequently, ICTs have revolutionized the transfer of information and knowledge on a global scale. This, in turn, leads to reduction in uncertainty, increased number of transactions, improved productivity, and subsequent economic growth are among the benefits brought about by ICTs.

In addition, Aubert and Reiffers (2003) introduced a fifth pillar that encompasses intangible elements influencing a society's ability to function efficiently. These elements include the formulation of a vision, the level of self confidence and trust within society, and the relevance of guiding values.

It is important to note that all the pillars of the KBE are interconnected and interdependent, as illustrated in Figure (2.3).

Figure (2.3): The Overlap Between KBE Pillars.



Source: Aubert (2006, p.8)

2.2.2.5 Motivations for Transition into a KBE

The motivations for transitioning to a KBE are numerous and supported by various studies and reports (Amirat & Zaidi, 2020; Hadad, 2017; Toimbek, 2022). The KBE is seen as a catalyst for economic growth, productivity enhancement, innovation, wealth creation, job opportunities, competitiveness, and comparative advantages. These discussions and debates are backed by empirical studies, as discussed below. Additionally, the KBE is considered a driver for comprehensive integration among Arab countries (ESCWA, 2014) and a means to achieve sustainable development (Rezny et al., 2019; Sabau, 2010).

Numerous empirical studies highlight a positive relationship between knowledge accumulation and economic growth. For example, a WB econometric study in 1999 compared the per capita Gross Domestic Product (GDP) of Ghana and Korea over a 50-year period and found that a significant portion of the differences in growth were attributed to intangible sources such as knowledge capital (World Bank, 2007a). Driouchi et al. (2006) conducted a regression analysis covering the period from 1995 to 2001 and concluded that knowledge is a fundamental driver of economic growth. They also emphasized that countries' varying economic performance could be attributed to investments in education, R&D, information technology, and economic policies affecting FDI, all of which are pillars of the KBE. Poorfaraj and Keshavarz (2011) analysed panel data from 16 developing countries between 2000 and 2008, finding a positive and significant relationship between knowledge and economic growth.

Studies by Sepehrdoust and Zamani Shabkhaneh (2015) and Barkhordari et al. (2019) explored the impact of KBE components on growth performance in MENA countries. Both studies demonstrated that institutions, human capital and research, infrastructure, and business sophistication are pillars of the KBE that correlate with significant and positive economic growth in MENA countries. Similarly, Asongu and Kuada (2020) noted that knowledge has emerged as a major factor driving economic growth and development. Oluwatobi et al. (2020) highlighted the success of developing economies like China and South Korea in catching up with developed countries by making knowledge the key driver of economic development. Recent studies by Elhini and Mourad (2022) and Mohamed et al. (2022) also found significant positive relationships between KBE indicators and economic growth. Elhini and Mourad (2022) empirically evaluates the relationship between KBEs and economic growth in 16 countries of Asia-Pacific region from 2011 to 2018 and founded that a significant and positive relationship between KBE pillars such as education and innovation on economic growth. Further, Mohamed et al. (2022) examined the impact of KBE indicators on economic growth for 20 developing countries over the period from 1996 to 2020 and articulated that 93% of changes in economic growth in these countries are attributable to KBE.

Transitioning to a KBE is associated with job creation and economic diversification, as documented in studies by Lightfoot (2011); Nour (2014b). Moreover, knowledge is recognized for its potential to drive structural transformation in economies and societies, bringing about changes in work patterns, production processes, and the introduction of new goods and services (Trewin, 2002). Aubert and Reiffers (2003) observed a strong correlation between a country's overall knowledge economy readiness index and its level of development measured by GDP per capita. This relationship can be justified by two different approaches.

First, investment in KE related variables in past times attribute significantly to growth performances measured by total factor productivity. Second, the higher the level of development, the greater is the ability to invest in most areas of the KE and the greater is the opportunity to construct an adequate economic and institutional framework to take the most benefits of them. Further, Toimbek (2022) provided a diagnostic analysis for KBE in Kazakhstan and considered the KBE as the platform for sustainable development.

Furthermore, the KBE is closely connected to competitiveness. The WEF's Growth Competitiveness Index (GCI), which includes variables for technological performance, institutional appropriateness, and macroeconomic stability, shows that there is a strong correlation between the ranking in the growth competitiveness index and the ranking for the knowledge economy index (Aubert & Reiffers, 2003). Shiryaev et al. (2016) emphasized that the KBE is an essential resource for driving socio-economic transformation, provided that human capital development and the diffusion of scientific knowledge are prioritized. Širá et al. (2020) examined the relation between KBE indicators and sustainable competitiveness in EU countries and found that the pillars of the KBE positively affect a country's competitiveness, leading to greater sustainability.

Additionally, the KBE is closely linked to poverty reduction and unemployment reduction. A recent study by Zeb (2022) demonstrated that the

KBE in 45 Asian countries between 2000 and 2019 contributed to boosting business sectors, eradicating poverty, and reducing unemployment.

Given all these motivations, the KBE is recognized as a pivotal element in various development policies aiming for economic transformation and societal advancement. It is an essential element in European policy debates since the Lisbon summit of the European Union Council in March 2000. As various development policies have aimed to transform the Union by 2010 into "the most competitive and dynamic KBE in the world capable of sustainable economic growth with more and better jobs and greater social" (Udovič & Bučar, 2008, p.31).

In conclusion, the motivations for transitioning to a KBE are supported by numerous studies and reports, which emphasize its positive impact on economic growth, productivity, innovation, job creation, competitiveness, poverty reduction, and societal development. Empirical evidence highlights the positive relationship between knowledge accumulation and economic performance, while the KBE is seen as a catalyst for structural transformation and a driver of sustainable development. The KBE is closely intertwined with competitiveness and has implications for reducing poverty and unemployment. Its significance is reflected in policy debates and initiatives aiming to foster KBEs.

2.2.2.6 Differences Between Traditional Economy and KBE

To gain a deeper understanding of the KBE, Table (2.2) provides a concise overview of the transformations resulting from the transition to a KBE. The KBE differs significantly from the traditional economy across various dimensions. One of the key differentiators is the shift in the determinants of economic activity, with the KBE being driven by dynamic markets operating in the shadow of global competition and a reliance on innovation and knowledge as fundamental factors of production.

Moreover, the relationship between the business sectors and the state is transformed in the KBE. In the traditional economy, the state imposes regulations, commands, and controls based on its economic requirements and intentions. In contrast, the KBE features an enabling state that offers market tools, flexibility, and cooperation to support firms in their innovation and growth endeavours.

Furthermore, the workforce in the old economy typically possesses job-specific skills, focusing on performing specific tasks. In contrast, the workforce in the new economy is characterized by highly skilled employees who possess the ability to adapt and thrive in a rapidly changing environment. Continuous education and training are essential in the KBE, enabling employees to leverage their cognitive abilities rather than relying solely on manual labour.

Overall, the transition to a KBE brings about fundamental changes in economic dynamics, the role of the state, and the skills and capabilities of the workforce. These transformations reflect the shift towards a more dynamic, knowledge-driven, and innovative economic system.

Table (2.2): The Main Differences Between the Old Economy and the New Economy.

	Old (Traditional) Economy	New (KBE)Economy
Economy-Wide Characteristics		
Markets	Stable	Dynamic
Scope of Competition	National	Global
Organizational Form	Hierarchical, Bureaucratic	Networked, Entrepreneurial
Structure	Manufacturing core	Services core
Source of Value	Raw materials, physical capital	Human and social capital
Potential Geographic Mobility of Business	Low	High
Competition between Regions	Low	High
Business		
Organization of Production	Mass production	Flexible production
Key Factor of Production	Capital/Labor	Innovation/Knowledge
Key Technology Driver	Mechanization	Digitization
Source of Competitive Advantage	Lowering cost through economies of scale	Innovation, quality, speed along whole supply chain (time to market), and cost
Importance of Research/ Innovation	Low- moderate	High
Relations with other Firms	Go it alone	Alliances and collaboration, outsourcing
Consumers		
Tastes	Stable	Changing rapidly
Workforce		
Principal Policy Goal	Full employment	Higher wages and incomes
Skills	Job- specific skills	Broad Skills and Cross-Training
Education Needs	A craft skill or degree, one-off requirement	Lifelong learning
Workplace Relations	Adversarial	Collaborative
Nature of Employment	Stable	Marked by risk and opportunity
Government		

	Old (Traditional) Economy	New (KBE)Economy
Business-Government Relations	Impose regulations	Assist firm's innovation and growth
Regulation	Command and control	Market tools, flexibility
Government Services	Nanny state	Enabling state

Source: Compiled from Atkinson and Coduri (2002), and Carlaw et al. (2006)

2.3 Literature Review on the KBE in Growth Theories

In addition to the motivations discussed earlier, it is important to recognize the notable changes occurring in the global economy that signify a shift towards more knowledge and technology-intensive economies. This section aims to highlight some key observations, known as stylized facts, about the worldwide trend towards knowledge-intensive economies, along with the societal transformations accompanying these changes. Subsequently, the theoretical foundations of the KBE within various growth theories will be presented.

The first notable observation is the increasing significance of knowledge as a critical driver of economic growth and development. Traditional factors of production, such as land, labour, and capital, are being complemented and in some cases surpassed by knowledge as the primary source of competitive advantage and innovation. This shift is evident in the rising share of knowledge-intensive industries and sectors in many economies, reflecting the growing importance of intellectual capital and intangible assets (O'Donovan, 2020).

Furthermore, the transformation towards knowledge-intensive economies is accompanied by profound changes in human societies. These changes include shifts in the nature of work and employment, with a greater emphasis on knowledge-based occupations, cognitive skills, and adaptability. Additionally, there is a growing need for continuous learning and skill upgrading to keep pace with rapidly evolving technologies and knowledge requirements. These changes have implications for education and training systems, labour markets, and social dynamics (Rabie, 2016).

To understand the theoretical foundations of the KBE, it is essential to explore various growth theories. These theories provide frameworks for explaining the relationship between knowledge, innovation, and economic growth. For instance, endogenous growth theory emphasizes the role of knowledge accumulation, technological progress, and innovation in driving sustained economic growth. The KBE aligns with the core tenets of endogenous growth theory by recognizing knowledge as a key determinant of productivity and emphasizing the importance of investments in human capital, R&D, and knowledge diffusion.

Other growth theories, such as the new growth theory and the innovation-driven growth theory, also provide insights into the dynamics of knowledge-intensive economies. These theories highlight the importance of innovation, knowledge spillover, and the role of institutions in fostering economic growth and technological advancement.

By exploring these theoretical foundations, we can gain a deeper understanding of the factors and mechanisms that underpin the transition towards knowledge-intensive economies and their implications for sustainable economic development.

2.3.1 Transformation in Human Societies

Throughout human history, significant transformations have shaped the course of civilization. The first major transformation was the advent of agriculture, which brought about a shift from hunter-gatherer societies to settled farming communities. The second transformation occurred with the industrial revolution in the 18th century, marking a period of rapid industrialization and technological advancements. However, the most profound transformation to date is the knowledge revolution, which emerged in the latter half of the 20th century (Rabie, 2016).

The knowledge revolution is characterized by unprecedented progress in scientific research, technological innovation, and the widespread dissemination of information. This revolution has fundamentally changed the dynamics of production and economic growth. As highlighted by Azzman Shariffadeen (2009), information has become the new critical resource, surpassing the traditional factors of land and labour in terms of its importance in driving production and economic development.

Moreover, O'Donovan (2020) argues that we are currently in the era of knowledge-led growth, where knowledge is the key driver of future prosperity. The advancements in science and technology, along with the increasing availability and accessibility of knowledge, have created opportunities for innovation, productivity enhancement, and economic advancement. The ability to generate, acquire, and effectively utilize knowledge has become a crucial factor for countries, organizations, and individuals to thrive in the modern era.

As such, the knowledge revolution represents a significant transformation in human civilization. It has replaced traditional factors of production with information as the primary driver of economic growth and prosperity. This era of knowledge-led growth highlights the central role of knowledge in shaping the present and future trajectory of societies and economies.

2.3.2 Global Trends in the World Economy

2.3.2.1 New GDP Composition: The Leading Role of the Service Sector

According to the classification used by the WB in the Worldwide Development Indicators (WDI) database, the GDP is divided into three main sectors: agriculture, industry, and services. The agriculture sector encompasses activities related to farming, fishing, and forestry. The industry sector includes mining, manufacturing, energy production, and construction. The service sector comprises government activities, communications, transportation, finance, and other private economic activities that do not involve the production of tangible goods.

In 2020, the agriculture sector accounted for approximately 4.4% of the world's total economic production. The industry sector held a larger share, contributing around 26.3% to the global GDP. However, it is the services sector that takes the lead, representing approximately 66% of the total GDP. This indicates that the services sector plays a dominant role in the world economy, surpassing the contributions of the agriculture and industry sectors.

When analysing the breakdown of value added in the GDP structure, it becomes evident that the services sector continues to hold a prominent position compared to the other sectors of the economy. Its substantial contribution to GDP highlights the importance of services such as government activities, communication, transportation, finance, and various other private economic activities.

Overall, the data demonstrates the significant role played by the services sector in the global economy, with agriculture and industry sectors contributing relatively smaller shares to the overall GDP[8].

2.3.2.2 Global Trends in Knowledge and Technology-Intensive (KTI) Industries

KTI industries play a crucial role in the global economy, encompassing both service and manufacturing sectors. These industries are classified into 15 categories based on the OECD classification and are closely linked to science and technology (S&T). The KTI industries include knowledge-intensive services industries, which consists of five high-technology and five medium-high-technology manufacturing industries[9].

In terms of their economic contribution, the KTI industries have a significant value-added output of $24 trillion, representing approximately one-third of the world's GDP in 2016. Among these KTI industries, the commercial knowledge-intensive services sector holds the largest share, accounting for 15% of the global GDP. Following closely behind are the public knowledge-intensive services, contributing 9% to the GDP. The medium-high-technology manufacturing industries

(8) **Source:** World Bank national accounts data, and OECD National Accounts data files; available at: http://wdi.worldbank.org/table/4.2#, Last updated date: 06/30/2022.

(9) **Five knowledge-intensive services industries;** include high technology either in their services or in the delivery of their services. Three of these—financial, business, and information-services (including computer software and R&D)—are generally commercially traded. The other two services include education and health care which are publicly regulated. **Five high-technology manufacturing industries;** spend a large proportion of their revenues on R&D and make products that contain or embody technologies developed from R&D. These are aircraft and spacecraft; pharmaceuticals; computers and office machinery; semiconductors and communications equipment. **Five medium-high-technology manufacturing industries;** spend a relatively large proportion of their revenues on R&D. These are motor vehicles and parts, chemicals excluding pharmaceuticals, electrical machinery and appliances, machinery and equipment, and railroad and other transportation equipment. These industries spend a relatively lower proportion of their revenue on R&D compared to high-technology manufacturing industries. However, medium-high technology manufacturing industries produce many products that incorporate advanced and science-based technologies. For instance, cars and trucks contain sophisticated sensors and software to prevent accidents, optimize engine performance, and maximize fuel economy.

constitute the third-largest share, contributing 4% to the global GDP. The high-technology manufacturing industries have the smallest percentage, with only 2% of the global GDP[10].

These statistics, provided by the National Science Board (2018), highlight the economic significance of KTI industries and their impact on the world economy. The dominance of knowledge-intensive services industries, along with the contributions of high-technology and medium-high-technology manufacturing industries, underscores the role of knowledge and technology in driving economic output and development.

It is noteworthy that the share of developed countries in KTI is greater than that of developing economies. One possible reason could be their much higher share of knowledge-intensive services. However, KTI shares vary between developed countries with United States to have the highest KTI share among developed economies (38%). This is because the United States share in commercial knowledge-intensive services is higher than the average for developed countries. Moreover, the United Kingdom and Japan constitute the second highest share with 36% of GDP (National Science Board, 2018).

For developing countries, though, the share of KTI varies considerably. Reasons for these disparities, among many other reasons, could be the differences in the stage of development for these countries; the level of income per capita and the size of their high-technology and medium-high-technology industries.

Based on the science and engineering (S&E) report in 2018, China has the largest share among developing economies (35%) because of its relatively large shares in medium-high technology manufacturing industries and commercial KI services industries. Other countries, for instance, Mexico, India, Russia, and Indonesia have KTI shares ranging from 19% to 22%. These shares are lower than the average for developing economies.

(10) Providing comparable data to this indicator is misleading because the 2018 edition of science and engineering indicators has expanded the definition of KTI industries to include medium-high-technology manufacturing industries. In previous Science and engineering indicators editions, KTI consisted of only 10 categories of industries namely, five knowledge-intensive services industries and five high-technology manufacturing industries.

2.3.2.3 Changes in the Labour Market

Recognizing the importance of a highly skilled workforce in a KBE, governments are actively competing to attract top talent and promote the mobility of high-skill individuals. This trend is evident in various indicators related to S&E workers, who represent the specialized segment of the workforce, as well as in the number of bachelor's and doctoral degrees awarded in S&E fields, the mobility of international students, and the estimated number of researchers involved in generating new knowledge.

For instance, the global number of bachelor's degrees awarded in S&E fields exceeds 7.5 million, based on the most recent estimates from 2016. Notably, the growth in this indicator has been particularly robust in several parts of Asia. In fact, approximately half of these degrees were earned in just two Asian countries: India (25%) and China (22%). It is worth highlighting the significant increase in the number of bachelor's degrees awarded in China between 2000 and 2014, which experienced a remarkable growth rate of over 350%. This surge in China's bachelor's degree attainment far surpasses the growth observed in many other European and Asian regions (National Science Board, 2018).

These statistics underscore the global competition for talent and the concerted efforts made by countries to develop a skilled workforce capable of driving knowledge creation and innovation in a KBE. The substantial increase in the number of bachelor's degrees, particularly in rapidly developing regions such as Asia, indicates the emphasis placed on higher education and the recognition of its role in fostering a knowledge-intensive economy.

2.3.2.4 Public Attitudes and Increased Awareness of KBE

The robust engagement and development in the KBE are evident through various indicators, as highlighted in the S&E reports series. These indicators provide insights into the American population's attitudes, serving as an example of the broader trend. Five key indicators were considered in the report: interest in new scientific discoveries, basic scientific knowledge, belief in the opportunities created by science, confidence in the scientific community, and support for science funding.

According to the report, a significant percentage of Americans, exceeding 40% of total respondents, have shown a consistent level of “very interested” in new scientific discoveries in recent years. Similarly, there has been a slight increase in Americans’ basic knowledge of science over time. Moreover, a relatively high percentage of Americans agree that S&T can create new opportunities, and there is a strong belief in the importance of funding scientific research. These attitudes have remained at notable levels compared to previous years (National Science Board, 2018).

In conclusion, these trends observed in the global economy highlight the inevitability of transitioning to a KBE for countries to remain competitive and thrive. The indicators discussed demonstrate the active engagement, growing knowledge, and support for scientific advancements, all of which contribute to the development and success of a KBE.

2.3.3 Theoretical Background for the Relationship Between Knowledge and Economic Growth

The evolving trends in the global economy have prompted economists to re-examine economic theories and models to align with the current reality. A key area of focus in this analysis is the exploration of the foundations of economic growth. Two main forms of economic growth are typically identified: catching-up growth and cutting-edge growth.

Catching-up growth refers to the process by which countries can accumulate wealth and achieve prosperity by adopting technologies, ideas, and management methods that have already been developed by more advanced nations. In this approach, these countries do not need to invent or invest in new ideas but rather replicate and apply existing knowledge. Examples of countries that have successfully implemented this catching-up growth strategy include South Korea, Singapore, Indonesia, Malaysia, and China. On the other hand, cutting-edge growth involves the development of innovation and the generation of new knowledge. Japan serves as a notable example of a country that has achieved cutting-edge growth. It is evident that developing new knowledge is more challenging compared to adopting existing knowledge (Cowen & Tabarrok, 2009).

Growth theories can be broadly categorized into four main theories: classical growth theory, neo-classical growth theory, new growth theory, and evolutionary growth theory. Among these theories, the new growth theory and the theory of evolutionary growth explicitly highlight the importance of knowledge in economic growth. These theories are often referred to as theories of the KBE, as they recognize the central role of knowledge (Cortright, 2001). However, it is important to note that economists have long acknowledged the significance of knowledge in economic growth, as further elaborated in the subsequent paragraphs.

2.3.3.1 The Classical Growth Theory

The classical growth theory encompasses the contributions of renowned scholars such as Adam Smith, Ricardo, Malthus, and Marx. Adam Smith, in his seminal work "*An Inquiry into the Nature and Causes of the Wealth of Nations*" published in 1776, emphasized the significance of knowledge and new ideas. Smith illustrated this point through the example of a pin factory, highlighting the concept of division of labour. According to Smith, division of labour allows for specialization in the production process, leading to increased productivity and capital accumulation. This notion of increased productivity as a key driver of the KBE aligns with the understanding of the division of labour (Gürak, 2005).

However, the optimistic view of growth expressed by Adam Smith was countered by the more pessimistic perspectives of many classical economists. For instance, Malthus argued that growth is contingent upon effective demand. Yet, he held a pessimistic outlook on long-term growth due to his assertion that population growth outpaces output growth (Weil & Wilde, 2009). Ricardo emphasized the role of land as the foundation of growth and posited that profits serve as the source of capital accumulation. He further argued that when the rate of profit nears zero, a state of recession ensues, resulting in zero growth. Ricardo also underscored the significance of political stability and culture as non-economic factors influencing economic growth. Lastly, Marx discussed the crises arising from surplus production. According to Marx, capitalism generates internal forces that drive constant technological changes, which can have adverse effects on economic growth (Gürak, 2005).

As such, the classical growth theory encompasses the ideas put forth by scholars like Adam Smith, Ricardo, Malthus, and Marx, highlighting the importance of knowledge, division of labour, population dynamics, land, profits, political stability, culture, and the impacts of surplus production and technological change on economic growth.

In 1890, Alfred Marshall introduced two significant ideas in economic literature: economies of scale and market size. Marshall emphasized the power of knowledge as a crucial engine of production, enabling humanity to harness nature and fulfil our wants (Marshall & Marshall, 1920). He is also credited with the modern concept of "Industrial District," referring to specialized industries located in specific regions. Industrial districts, also known as agglomerations, localizations, or clusters, were observed as real-world phenomena during that time and were able to maintain competitiveness over long historical periods. Marshall argued that knowledge within businesses was regionally specific, rooted in the local labour force, institutions, and organizations. The sharing of knowledge within and between firms was seen as a significant contributor to the production of goods and services, thereby increasing the country's income and prosperity. This idea is exemplified in cases such as Route-128 and the South Korean 35 Chaebol cluster, where economies of scale and the introduction of ICT have facilitated the development of sizable high-tech clusters surpassing market size (Belussi & Caldari, 2009; Lundvall, 2004).

The Keynesian perspective, influenced by John Maynard Keynes, emphasized effective demand as the engine of economic growth. Keynesian analysis focused on achieving equilibrium with full employment and understanding the mechanisms through which an economy could return to this state. Increasing output through more division of labour was seen to enhance productivity. Technological change was not given adequate consideration as the correlation between effective demand and growth was assumed (Foray, 2004; Gürak, 2005).

The Austrian School, in the early 20th century, recognized the role of knowledge as an engine of economic growth. Austrian economist Fritz Machlup highlighted the importance of knowledge production for economic growth and assessed the knowledge intensity of various economic sectors in the United States. This perspective aligns with the transition to a KBE (Chiang Lin, 2007).

Another influential Austrian economist, Joseph Schumpeter, emphasized the combination of new knowledge as a fundamental driver of innovation and entrepreneurship. Innovation plays a central role in the KBE. Schumpeter introduced the concept of "Creative Destruction" in which economic growth occurs through knowledge production and innovation. He argued that companies failing to innovate would eventually exit from the market (Nicholas, 2003).

In 1974, Nobel laureate Friedrich Hayek stated in his lecture that people learn by doing and acquire new knowledge through the competitive market process. This discovery of new knowledge contributes to economic growth. The Austrian school places great importance on free markets. It is argued that a free market economy naturally transitions towards a more KBE (Cader, 2008).

2.3.3.2 The Neo-Classical Growth Theory

By the late 1950s and 1960s, the neoclassical growth theory emerged, with the Solow growth model as its foundation. This model relied on several assumptions and concepts. Firstly, it assumed that all economic agents are rational and have similar preferences, resulting in the same marginal propensity to consume, save, and invest. However, their decisions differ based on their budget constraints. Secondly, the production function for all firms consisted of two factors of production—labour and capital as determinants of output. Capital was subject to the law of diminishing returns, while labour remained fixed. Thirdly, technology was treated as an exogenously determined factor outside the model, added as a constant to the production function (Kurz et al., 2003).

According to the neoclassical theory of growth, in the short term, capital accumulation plays a complete role in driving economic growth. However, in the long term, the Solow model predicts either steady-state conditions or no economic growth. In this view, long-term growth does not depend on intrinsic characteristics of the economy, such as financial and economic policies, or the actions of economic agents, such as their investment or savings. Instead, it is driven by external factors, mainly technical progress originating from outside the economic system. This technical progress is considered a key driver for transitioning to a KBE (Solow, 1956).

The Solow model's implication for economic theory is that all nations will eventually converge to the same level of capital and income per capita. This conclusion assumes similarity in preferences among economic agents, resulting in the same consumption, savings, and investment decisions (Dowrick & Rogers, 2002).

However, the reliance on the concept of diminishing returns and the neglect of the behaviour of economic agents have left many practitioners unsatisfied with neoclassical growth theory in its current form (Kriščiūnas & Daugėlienė, 2006). Furthermore, Solow model assumed convergence between countries irrespective of their wealth or size. Nevertheless, when the model was tested by economists, empirical results showed that the model is not valid in low-income countries (Gentzoglanis, 2000).

To provide a more realistic understanding of the sources of economic growth, it is important to consider factors beyond capital accumulation in the long run, such as human capital and R&D. Additionally, we must acknowledge that there is convergence between countries in their economic growth rates due to intrinsic characteristics that vary across countries. These arguments laid the foundation for the development of a new theory called endogenous growth theory, also known as the new growth theory (Banerjee & Duflo, 2005).

2.3.3.3 The New Growth Theory

New growth theory provides valuable insights into the ongoing transition from a resource-based economy to KBE. It emerged in the late 1980s as a response to the limitations of neoclassical growth theory. Pioneered by Paul Romer (1986,1990) and Lucas (1998,1993), enhanced by Helpman and Grossman (1991), and Aghion and Howitt (1992), this theory integrates the growth of countries and individual enterprises with economic processes that generate and disseminate new knowledge (Cortright, 2001).

The distinguishing features of new growth theory can be summarized as follows. Firstly, it recognizes technological progress and knowledge as outcomes of economic activities. Unlike previous growth theories that treated technology as given or influenced by factors outside of market forces, new growth theory is "Endogenous" in nature. It incorporates technology into models of how markets operate by integrating it into the neo-classical production function, which now includes labour, capital, and technology as factors of production (Bardhan, 1995).

Secondly, unlike physical goods, knowledge and technology in new growth theory exhibit increasing returns. This means that knowledge-driven growth is characterized by the absence of diminishing returns. Ideas can be shared and used indefinitely, leading to expanding returns to knowledge and driving the growth process (Cortright, 2001).

It is important to note that different pioneers of new growth theory proposed various growth mechanisms. However, they all treat knowledge and its related variables as endogenous factors. For example, Lucas emphasizes the role of incremental learning for sustained growth. On the other hand, Romer (1990), Helpman and Grossman (1991), and Aghion and Howitt (1992) argue that investment in R&D leads to innovation, which serves as the source of economic growth. The economic incentive for innovation stems from the partially excludable nature of knowledge through intellectual property rights (Sabau, 2010).

Furthermore, all models within new growth theory acknowledge the presence of uncertainty. However, this uncertainty is weak in the sense that while the outcome may be uncertain, the result is ultimately certain. This assumption aligns with the positive relationship between R&D and innovation, where higher investment in R&D increases the likelihood of successful innovation discovery and consequently higher growth potential (Cortright, 2001).

Finally, although new growth theories make significant contributions to the growth literature, they have limited capability in addressing the dynamic nature of the economy driven by innovation, knowledge, and technology. This is where evolutionary theories of economic growth come into play (Cortright, 2001).

2.3.3.4 Evolutionary Economic Growth Theories

Evolutionary economic growth theories, also known as system theories, aim to explain how wealth is created through knowledge. These theories encompass various approaches, including the Neo-Schumpeterian long wave theory, the technology gap approach, Nelson and Winter's evolutionary theorizing, and the national and regional innovation system framework (Metcalfe & Foster, 2010).

One of the main differences, and might be the deepest, between neo-classical theory and evolutionary theory is that unlike the neo-classical theory that viewed the economy as unchanged or possibly undertakes well anticipated changes, the evolutionary theory considered the economy as in a process of continuous changes with economic activities that are completely unfamiliar to actors (Nelson, 2008).

The concept of the NIS is considered a crucial pillar for the KBE according to the World Bank. Evolutionary theories emphasize that innovation, technological advancements, and organizational changes are key drivers of long-term economic growth. They challenge the notion of a static market and argue that the market is in a constant state of change. Therefore, firms must innovate to adapt to the evolving conditions of the environment (Trewin, 2002).

2.4 Summary of the Chapter

This chapter commenced by providing an explanation of the conceptual framework for the KBE along with its theoretical foundations.

Following an introduction to the concept of knowledge, its characteristics as an economic good, and its types and aspects, this chapter investigated the diversified perspectives around the KBE concept that evolved over time under the main theme that knowledge is a crucial driver for economic growth and development in all countries. Additionally, it is concluded that the numerous proposed definitions of the KBE by different international organizations and studies reveal that there is no universal definition for this concept with the WB definition being the commonly used definition in most studies.

This chapter also explained the four pillars of the KBE, namely economic and institutional regime, ICT, education, and innovation. These four KBE pillars as proposed by the WB are interconnected and interdependent. Furthermore, KBE has numerous motivations, it has a positive impact on economic growth, productivity, competitiveness, job creation, and poverty reduction. All these motivations are extensively supported by theoretical justifications and empirical evidence. That is why KBE is now reflected in policy debates and initiatives to foster its transition.

To this end, it could be observed that the transition to a KBE leads to fundamental changes in economic structure that significantly differ from that of the traditional economy in various areas.

The second section of this chapter started by clarifying the notable changes in the global economy that highlight the central role of knowledge and emphasize the inevitable transition towards a KBE. These ongoing trends in the global economy led to a re-examination of economic theories and models to align with reality. A key area of focus in this regard is the evolution of knowledge in the different growth theories, namely the classical growth theory, the neo-classical growth theory, the new growth theory, and the evolutionary growth theory. It is observed from these theories that the importance of knowledge in economic growth is clearly and explicitly represented by the new growth theory and the theory of evolutionary growth, but this does not mean that economists realize the importance of knowledge as explained in detail in the last section of this chapter.

Chapter 3

KBE Measurement: Theoretical and Empirical Literature Review

3.1 Introduction

This chapter focuses mainly on the "How" question to the KBE. That is how to transit to a KBE. This chapter is made up of two constituent parts. The first part starts by justifying the importance of KBE measurement followed by the measurement challenges. Then, the diversified views in the literature about how a KBE can be measured and what indicators should be included are demonstrated as well. The structure of an appropriate framework and its criteria is then presented. Finally, the concepts, and current methodologies in the literature for mapping and assessing a KBE in any country are presented prior to introducing the current diversified introduced models by international organizations and interested scholars for KBE assessment.

The second part of this chapter shows the existing empirical literature on KBE assessment. This is done by dividing the prior empirical literature into different groups based on the methodological approach adopted. Following this a critical analysis of these methodologies is presented to evaluate the pros and cons of each assessment methodology.

3.2 Measurement Frameworks for the KBE

3.2.1 The Rationale Behind Measuring the KBE

Given the advantages of the KBE, mentioned earlier in the previous chapter, the transition to a KBE is inevitable in all countries and there are tremendous enthusiasms and aspirations for transition into a KBE in all countries at different regions with different stages of development and with diversified economic, institutional, and social characteristics. Thus, for countries to reap the benefits of the KBE, it is constrained by understanding what is happening in any economy which is certainly determined by the extent and the quality of available knowledge assessment measures (OECD, 1996). Therefore, monitoring and evaluating the overall KBE performance has become a hot area for research in past years and continues to the present day as observed later in this section. To this end, the core concern of many international organizations, academics, scholars, policymakers, and other stakeholders is to develop an assessment framework to quantitatively assess the level of a KBE, its progress, and its dynamics.

Meanwhile, the first step for transitioning into a KBE in any country is to measure it. Generally speaking, to measure is to label any objects and phenomena by numerical symbols using specified rules. Matošková (2016) introduced four diversified levels of measuring depending on their strength. Firstly, a nominal categorization simply means sorting data into mutually exclusive categories, for instance, male and female. In this case, each item can be represented by a single category and then all items can be categorized. Additionally, rather than naming the genders by “male” or “female”, the numerical marks of 0 or 1 could be used instead. Therefore, the nominal level of measuring means numbering individual items or categories. These numerical marks mean nothing but the names of the given categories.

Secondly, the ordinal, which means giving the variable a relative value in comparison with others, rather than measuring the absolute values of given variables. Thirdly, the interval, which aims to separate items into categories on a scale with points that lay at the same distance from each other, and this is done based on the existing knowledge of the researcher. Additionally, the user can use numbers to be added and subtracted but not multiplied or divided. For instance, temperatures measured in °C. Finally, the ratio, which means assigned numeric values indicate the amount or level of characteristics that they in fact measure. In this case, there is a natural zero. Possible examples could be measuring length, weight, and time. In this case, the values can not only be added but also multiplied and divided. For example, as states, four kilometres is twice as far as two km.

In the area of a KBE, knowledge measurement simply means the assessment of an enterprise, industry, economic sector, a city, region, or nation to create access, assimilate, diffuse, and use knowledge (Kriščiūnas & Daugeliene, 2006). However, creating such a measurement for the KBE is an ever-presenting challenge and a complex task as it depends mainly on how KBE is defined and on other methodological issues for instance, specific statistics to the KBE (Godin, 2006). This complicated process of KBE measurement is acknowledged by many studies (inter alia Lagzouli et al., 2020 ; Ojanperä et al., 2019). Notwithstanding, these numerous merits associated with KBE measurement, it may remain a vague concept unless consolidated with a robust measurement tool (Rezny et al., 2019).

Further, the mission to quantify knowledge effectively will undoubtedly prompt effective knowledge policies for governments around the world by identifying the ways through which knowledge can be observed, distributed, stored, and used (Piech, 2004). Furthermore, measuring a KBE allows for deciding on the new dynamics of economic growth, which is driven by knowledge, setting the pace of development and allows for passing into a KBE. Additionally, measuring a KBE allows for identifying the countries' advantages and weaknesses relative to their partners through assessing the level of performance and comparing it with different countries (Lagzouli et al., 2020). It also can certainly achieve accountability and validation against objectives set and allows for healthy competition (Khumalo, 2006).

Neef (2009) argues that knowledge not only stimulates and increase economic growth, but also can lead to structural changes (which is different from the incremental changes that all economies are constantly faced) in an economy and subsequently society. This is reflected in many changing aspects of the economy such as the rapidly changing nature of worker towards high-skill workers and the rapid growth in the service sector.

For organizations, measuring an organization's knowledge allows benchmarking it against other organizations and allows for comparing the development inside the organization during a specific period of time (Matošková, 2016) Last but not least, KBE measurement influences the frame of thinking for policy makers by focusing attention on specific issues, benchmark performance, and setting pro-knowledge policies and strategies (Kuznetsov & Dahlman, 2008).

Nonetheless, a question of whether it is possible to measure the knowledge base of an economy or not should be considered. In addition, if the answer to this question is yes, then, what should be measured to reflect the country's transition into a KBE and how to measure this transition?

In the literature, many attempts and initiatives have been done as evidenced in the tremendous research conducted in this ongoing debate (Chen & Dahlman, 2005; Trewin, 2002). Though, there is no clear consensual answer to this question given the challenges in introducing a KBE measurement framework. These challenges include developing a proper framework, choosing the indicators, determining the assessment methodologies, searching for the required data, and measuring knowledge itself. These challenges will be discussed in some detail below.

3.2.2 Challenges Regarding the Measuring of the KBE

Transition into a KBE depends mainly upon an effective and proper measurement approach. Lagzouli et al. (2020) indicated that "most knowledge phenomena are very difficult to observe". Therefore, Lagzouli et al. (2020) suggested studying the challenges associated with measuring this discipline should be paid the highest attention prior to introducing its main indicators of measurement. Moreover, Lagzouli et al. (2020) concluded four major challenges which hinder the scope of analysis during KBE measurement; notably: (1) a KBE is an insensible phenomenon to a large extent because it has a tacit state which is specific to each person. (2) introducing a stable framework for converting inputs into outputs in a KBE is a big dilemma; (3) difficulties associated with measuring the available stock of knowledge and (4) the special character of knowledge obsolescence and depreciation.

Additionally, Arundel et al. (2008) emphasized that the existing frameworks do not consider the future challenges that could affect the KBE in the future of which the changing environment of innovation strategies.

Further, the existing knowledge measurement literature provides numerous methodologies relating to assessing the transition towards a KBE. Nonetheless, it has certain shortcomings if we take into consideration the required data, indicators, and frameworks to monitor progress of any country towards the transformation into a KBE. Furthermore, measuring knowledge itself represents a hampering factor in the knowledge measurement literature. This can be explained as follows:

3.2.2.1 Problems with Existing Data for the KBE

Current KBE data has certain limitations in aspects related to its quality, reliability, funding, coverage, periodicity, consistency, as well as availability. For instance, in developing countries data collection is a critical factor because statistical agencies do not have the required resources to collect such data. Other problems may be related to different conceptual and methodological approaches for data collection among statistical agencies. For example, in the ICT domain (as a crucial pillar for KBE), the definition of "internet user" varies between different countries because the frequency of data differs whether it is daily, weekly, or monthly. Another issue is related to the lack of inclusion of appropriate questions in surveys that should include all aspects related to the particular data to be measure. For example, data on internet access is usually collected through household surveys. Nonetheless, this aspect is often ignored and if included information about cost and distance is usually misleading due to untruthful answers, survey sponsorship bias or language bias (Khan, 2003).

3.2.2.2 Problems with the Required Indicators for the KBE

Economic indicators are used to describe the performance of an economic system. By providing aggregate value of goods and services and the rates of change in these aggregates such as production, consumption and GDP, traditional economic indicators guide policy makers and leads to effective economic policies. However, a KBE is working differently from the traditional economy and hence, these traditional indicators fail to describe the economic performance other than the aggregate values. For instance, there are systematic constraints to the creation of intellectual capital accounts in parallel to the accounts of traditional fixed capital (Daugėlienė, 2004).

In this manner, Shapira et al. (2006) stated that direct measurement is uncommon in a KBE because it is a complex phenomenon, but rather only proxies and indirect estimates of a KBE because knowledge contains formal (codified) forms and informal (tacit) forms. Further, Hossain (2015) pointed out that KBE indicators can capture the production of knowledge only, neither the shape nor the spread and use of knowledge. Thus, what we have until today are indirect and partial indicators of the growth in the knowledge base.

Additionally, OECD (1996) postulated that there are four principal reasons why knowledge indicators, however carefully constructed, cannot approximate the systematic comprehensiveness of traditional economic indicators. Of these reasons, there are no stable formulae or “recipes” for translating inputs into knowledge creation into outputs of knowledge. Additionally, transforming inputs into knowledge creation are hard to map because there are no knowledge accounts analogous to the traditional national accounts. Further, there are no prices as knowledge lacks a systematic price system that would serve as a basis for aggregating pieces of knowledge that are essentially unique. Finally, new knowledge creation is not necessarily a net addition to the stock of knowledge, and obsolescence of units of the knowledge stock is not documented. That is why improved indicators for the KBE are still needed and poses a great challenge.

As a contribution in this regard, a set of indicators are currently used as proxies for the KBE, but none of these indicators are ideal. They can be served as a starting point for analysing the KBE (Industry Analysis Branch of the Department of Industry and Resources, 1999).

Additionally, Passerini (2007) argued that the ongoing KBE measurement research still spans diversified directions but are interrelated. Therefore, Passerini (2007) asked for more integration through international, multinational, and organizational partnerships to reconcile and introduce actual standards for the evaluation and the assessment of the knowledge-based growth.

3.2.2.3 Problems with Measuring Knowledge

One of the fundamental obstacles to the measurement process of the KBE is measuring knowledge itself. The OECD (1996) report contended that “at the heart of the KBE, knowledge itself is particularly hard to quantify and also to price" (p.29). Carter (1996) as quoted in Industry Analysis Branch of the Department of Industry and Resources (1999) declared that it is difficult to give a price to knowledge as regards what we do with normal goods and services due to three reasons, namely sellers do not "give up" the knowledge that they sell. Knowledge is automatically and permanently "vested" in whoever acquires it; potential buyers have no use for additional units of knowledge identical to what they already have; and buyers cannot really appraise the knowledge that they might acquire without acquiring it.

In a similar vein, Kahin and Foray (2006) maintained that there are no units of knowledge like a currency unit in the system of national accounts. Additionally, there is nothing parallel to purchasing power parities that allows for comparisons across space or price indices for comparison over time. Further, there is nothing comparable to the concepts of current and constant currency units that could allow for comparisons of the economic system over time. Along the same lines, knowledge is not a traditional economic input like labour or capital. To clarify, in the case of adding traditional inputs to the stock of economic resources, then, the economy grows according to the traditional production function. However, new knowledge affects economic performance by influencing and changing the production function itself. This is because new knowledge provides product and process options that were unavailable previously. Consequently, it is impossible to construct a production function for knowledge to describe the relationship between inputs and outputs (Daugėlienė, 2004).

Furthermore, a certain proportion of knowledge is kept in people's minds and hence it is an unknown proportion of knowledge i.e., implicit, or uncodified knowledge (Cowan et al., 2000). That is why, Daugėlienė (2004) argued that knowledge stocks and flows, knowledge distribution and the relation between creation and economic performance is still "virtually unmapped".

To summarize, for knowledge to be measured in an effective manner, statisticians should give knowledge its own units like weight and length that have their own units, only then it is possible to say how much knowledge one needs to implement a particular task (Kriščiūnas & Daugeliene, 2006; Trewin, 2002).

In contrast, Steedman (2002) articulated that it is impossible to measure the KBE because it is hard and impractical to measure the knowledge itself. Therefore, the Steedman (2002) questioned about the measurability of knowledge and declared that new growth theory which is based on "the stock of knowledge to be cardinally measurable" is misleading. Further, Kahin and Foray (2006) maintained that knowledge is immeasurable and if it can be measured, this would be highly challenging. Similarly, Piech (2004) declared that the problem of knowledge measurability is not related to the lack of required data but to the lack of proper theory that is needed to develop accurate conceptual categories of a KBE and if this happens KBE could be measured precisely.

Nonetheless, the existing KBE literature showed that measuring a KBE has gained tremendous importance and there is a constant dialogue among international organizations, scholars, and statistical units to measure a KBE in a proper way and they have produced numerous indexes, frameworks and models as will be shown later in this section.

3.2.3 Two Lines of Thought Concerning KBE Measurement

Given the aforementioned challenges and after investigating the current KBE literature, it is obvious that the literature presents two points of view concerning KBE measurement. On the one hand, studies carried out by Batagan (2007); Godin (2006), and Smith (2002a) emphasized the immeasurability of knowledge and hence of the KBE. A study by Rezny et al. (2019) argued that phenomena such as a KBE which is mainly based on unmeasurable variables such as knowledge are difficult to bring to the data and therefore the model continues to be theoretical. Additionally, Godin (2006) acknowledged the historical role played by OECD as a think tank for its members to find a measure for the KBE. Yet, Godin (2006) asserted that the proposed indicators used to measure the KBE were previously developed and measured by OECD years ago and suddenly subsumed under the concept of the KBE.

Over and above that, these employed indicators failed to capture neither the shape nor the weight of the distribution and use of knowledge, but rather its production. In the same line, Smith (2002a) demonstrated that the development of specific indicators for a KBE failed as the concept of a KBE is far from being fruitful analytically but a rhetorical artifice. However, this line of thought, namely knowledge immeasurability, is very limited in the literature as only rare studies agree with this thought and this is obvious in the continuous trails for KBE assessment.

On the other hand, the KBE literature offers numerous KBE measurement attempts and proposals which continues till nowadays and have been introduced by international organizations, scholars, researchers, and research institutes. For instance: OECD, APEC, ABS, the European Union (EU), Progressive Policy Institute of the US (PPI), Commission of the European Community (CEC), Ministry of Trade and Investment of Singapore (MTI), National Academy of Science of the US (NAC), Ministry of Economic development of New Zealand (MED), Department of Trade and Industry of the UK (DTI) and the WBI, and recently the joint initiative between the United Nations Development Program (UNDP) and the Mohammed Bin Rashid Al Maktoum Knowledge Foundation (MBRF).

All these measures have one common trait; that is, they tried to develop a KBE framework to assess the extent of individual countries' knowledge base and to implicitly guide policymakers. Additionally, they used a range of indicators i.e., a "suite of indicators" that varies from one edition to another within the same institution or from one institution to another.

However, all these previously developed attempts are not without flaws as observed later in this chapter. But, before presenting the existing KBE frameworks, it is crucial to understand the types of measurement frameworks as well as the structure of what we can judge to be a robust framework.

3.2.4 Type of Frameworks

3.2.4.1 Conceptual Framework

It is considered a conceptual map in which statistics are organized and grouped in a logical manner. It is sometimes called a statistical framework because it deals with a specific topic and includes a set of rules and conceptual information like classifications, standards, definitions, and actors. Education statistics, training statistics or ICT statistics could be possible examples of conceptual or statistical frameworks (Trewin, 2002).

3.2.4.2 Descriptive Framework (Presentation Framework)

A descriptive framework, as its name suggests, tries to describe a subject using available statistics while not trying to view these statistics within the context of a conceptual framework. In addition, the scope of such a framework is much wider than the conceptual or statistical framework. This means that the parts formulating this framework can be statistical frameworks (some of which already exist). Another issue is that this framework, as opposed to the statistical framework, does not deal with concepts. For example, designing a conceptual framework for education statistics is a possible example to the presentation framework (Trewin, 2002).

3.2.4.3 Suite-of-Indicators

In this case, a set of indicators is used collectively to describe the specified subject, for instance, indicators of the KBE in this chapter, have been gathered and connected according to different aspects of the subject. Nowadays, most statistical agencies and tremendous research work utilizes this approach to portray data on the KBE (Trewin, 2002).

3.2.4.4 A single–Index

Theoretically, it is possible to construct an index if a suite of indicators has been decided upon. The main merit of such an index is that it can be used to reflect the intensity of knowledge in an economy and allows for comparative analysis between different countries. However, the disadvantage of this index is that it can be over simplified and hence leads to misinformed representation of the intensity of knowledge in an economy.

This problem arises because indicators used to construct an index must be given appropriate weight, and this mainly depends on the availability of a generally agreed model that defines and prioritizes key elements of the KBE (Trewin, 2002). This is because, before constructing such an index, it is crucial to determine which data should be used? What are the appropriate weights that must be assigned to them? How does the index deal with changes over time? (Piech, 2004).

3.2.4.5 Direct measurement Approach

In this approach, it is possible to assess a KBE through the economy's input/output framework. In this approach, the traditional sectors for inputs and outputs of knowledge should be developed. Then, linkages between these traditional sectors should be analysed to assess the degree of knowledge transfer and dependence. Certain conceptual and methodological constraints should be dealt with if this approach is applied (Trewin, 2002).

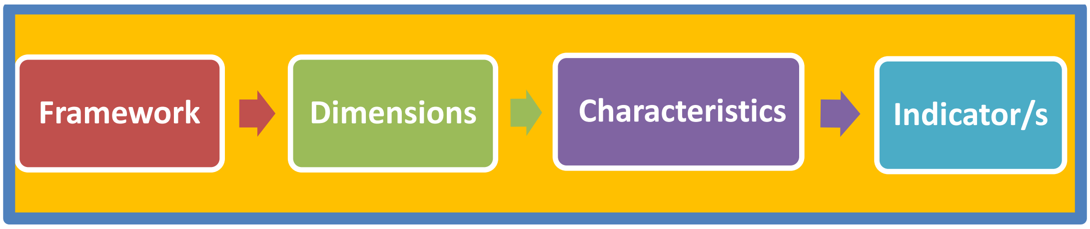
3.2.5 Structure of a Good Measurement Framework

Before elaborating on the existing frameworks, it is crucial to understand firstly the structure of an appropriate robust framework for the KBE to be able to assess the literature gaps in the existing frameworks. Then, use these gaps as starting point to develop proper measure for the KBE in the following chapters.

A good framework must have dimensions that indicate the main components of KBE. Within each dimension are characteristics. Then, indicators are selected to give measures to the characteristics as illustrated in the following Figure (3.1).

Based on Figure (3.1), to develop a well-structured statistical picture of knowledge in an economic and social manner, proper statistics must be gathered within a framework which must have certain criteria. It should be structured in a logical and understandable manner; developed in the light of relevant theory and empirical evidence; widely accepted by policymakers and other users; unbiased in its choice of statistical indicators so that, for instance, it does not show a group of indicators selected to suit a particular purpose or argument. Finally, be comprehensive; whether relevant statistics exist for all framework elements (thus, enabling any gaps in available statistics to be readily identified) are the required criteria for an orderly statistical framework of KBE.

Figure (3.1): Structure of a Proper Framework for Measuring the KBE.



Source: Trewin (2002).

This statistical framework should consist of dimensions which are defined as the main components (pillars) of the KBE. For example: ICT, education, and innovation. For each dimension, specific characteristics should be included. A characteristic is defined as an aspect of the dimension, which has been used to further describe the dimension and give it some structure by splitting it into more understandable elements. These characteristics are neither mutually exclusive nor intended to comprehensively describe each dimension. For example, ICT infrastructure, ICT demand and ICT access are the possible characteristics of the ICT pillar.

For each characteristic, one or more statistical indicator should be introduced. Indicators are introduced and precisely chosen to provide a measure of the characteristics. Most characteristics are populated by one or more than one statistical indicator.

The following criteria describe the characteristics of a good indicator; being relevant to the characteristic it is intended to describe (including policy-relevant); being supported by reliable and timely data; being sensitive to the underlying phenomenon that it purports to measure; being intelligible and easily interpreted; preferably be available for several time periods including recent periods; and for the objective of international comparison, preferably be available for other countries to be able to provide benchmarking analysis.

In this regard, it should be highlighted that for some characteristics, there are inadequate or no possible indicators. In this situation, the characteristic is included but the lack of an appropriate indicator should be mentioned. For example: ICT infrastructure, number of internet users and telephone lines. For some other characteristics, the most appropriate indicators will change over time.

For example, access to mobile phones is currently of interest as an indicator of household use of ICTs (Trewin, 2002).

3.3 Diversity of the Knowledge Assessment Models

Nowadays, it is possible to distinguish between different methodological approaches to measure the KBE. The most notable systematic trials are those developed by Piech (2004) and Daugėlienė (2004). Both writers divided the existing KBE models into two groups based on the standpoint of analysis as follows:

3.3.1 Proposed Models of Comprehensive KBE Assessment

These models use both qualitative and quantitative methods of study. As its name suggests, these models are performed to determine the potential of knowledge acquisition, creation, dissemination, and usage in the country. Therefore, their crucial purpose is to evaluate the business and economic condition of the specified country and then develop strategic solutions based on the level of development for the KBE in the country being analysed. Such models are mainly based on the presentation of dozens of selected indicators. Additionally, data in these models are gathered and given normalized value (i.e., scale from 0-10) to enable comparison between different indicators.

The essential elements of KBE or as it should be called the characteristics of the KBE are analysed. In these models, the first analysed dimension is the context dimension or the economic incentive and institutional regime i.e., state management situation; the stability of the state's market as well as the financial system. Further, the second analysed dimension is the human capital dimension, which is concerned with the potential of human capital development. Furthermore, the third analysed dimension is the ICT infrastructure mainly its production and usage. Finally, the innovation system dimension i.e., the assurance of innovation policy and the entrepreneurial activity tendencies in the specified country. As for differences between these comprehensive models, they differ in determining the scope of this KBE. They also differ in the indicators used to measure each pillar.

The models of comprehensive KBE assessment are presented for example, by

OECD (starting from 1996), Atkinson and Court – New Economy index (starting from 1998), WB (starting from 1998 and modified in 2004), APEC (starting from 1999), ABS (starting from 2000), experts of Harvard University (starting from 2000), UNECE (starting at 2002) and more recently the UNDP and the MBRF (starting from 2015). However, so far, the measurement frameworks promulgated by OECD, APEC, EU, and WB, are viewed by many studies such as Al Shami et al. (2011); Leon (2017) as the mainstream measurement frameworks. Table (3.1) show a snapshot presentation to the mainstream KBE frameworks and a description of the main measurement indicators. Other proposed frameworks and the mainstream frameworks are presented in-depth in Appendix (II).

What is noteworthy in that all these prior proposed frameworks on assessing the level of a KE, is that they attempted to introduce a comprehensive set of indicators for KBE characteristics and based on them, they developed their different assessment methodologies.

Table (3.1): The Advantages and Disadvantages of the Frameworks Developed by OECD, APEC, EU and WBI.

Publisher	Name of the framework	Date	Countries coverage	Advantages	Limitation
OECD	The Knowledge-Based Economy	1996	29	High consideration of human and social development indicators	Limited data accessibility and not user-friendly / reusable scorecards
	Technology and Industry Scoreboard OECD	1999, 2001, 2003(every two years)	35		
WB	Knowledge Assessment Methodology	1999 Stopped in 2012	146	User-friendly model readily accessible to the public	Limited prediction models and difficult multi-year data aggregation
EU	DESI: Digital Economy and Society Index	2015, 2016	28	Measurement framework developed within a systematic strategic planning process	Ambitious and broad plan that may not be actionable or sustainable in a short time frame.
APEC	Towards Knowledge-Based Economies in APEC	2000	21	Suits the context of their own economies	Only chose the indicators that were available for APEC Countries.

3.2.2 Models of Sectorial Assessment

In the sectorial assessment, the assessment of knowledge expression is issue oriented. In this case, the identification of penetration level of one KBE characteristic is the object of assessment. The assessment could be directed towards any KBE pillar, for instance, the ICT, R&D, human resources, patents and so on.

These models use quantitative methods of study. In these models, the penetration level of one or several characteristics of KBE could be assessed. In another way, these models focus on only one pillar of the KBE. That is, they are issue oriented models. Additionally, the measurement framework could be oriented to macro-level assessment or micro-level assessment or both levels of assessment.

These assessment models mostly are based on the one index principle. Once a set of indicators has been decided upon, it is theoretically possible to create an index to reflect the intensity with which an economy is knowledge-based. The use of a single figure index if it is possible and valid; could facilitate benchmarking and comparative analyses and could become an important indicator of economic performance. However, before an index can be developed, each indicator would require an appropriate weight to be assigned to it. This in turn relies on the existence of a sound and generally agreed model which defines and prioritizes key elements of a KBE.

As Mohnen and Dagenais (1998) noted, a major obstacle in constructing an index from a compilation of survey data is how to combine various measures of the same concept. This problem is compounded when the index is used over time, as the framework on which it is based needs to change to remain relevant. According to the ABS method, a single index would present an over-simplified and possibly misleading representation of the extent to which an economy or society is knowledge-based (Trewin, 2002).

Nonetheless, an essential feature of these models which makes them different from models of comprehensive assessment is the methodology of model's application. Some of them are econometric models such as Benhabib and Spiegel (1994; 2000). The application of these is based on mathematical statistical calculations. Others are designed for the assessment of potential of knowledge usage such as (KI; Machlup methodology) or knowledge creation and dissemination such as (Information Society Index; INEXSK and others) (Daugėlienė, 2004).

Theoretically, there is a possibility to classify models of sectorial KBE assessment. Classification could be based on the assessment orientation or specification as in Table (3.2).

Specific assessment that is oriented on subject include indexes such as the GCI, Science Citation Index, Regional Economic Architecture (REA) method (basically concerned with the assessment of human capital dimension with deep point on employment and skills indicators), Human Development Index (HDI) belong to this category (Daugėlienė, 2004).

Basic assessment is based on one index to express all knowledge characteristics. The result of this calculation is a single coefficient. However, the weakness of this assessment method is concerned with the problematic identification of the penetration level of different knowledge expression characteristic. Knowledge-based Economy Index (KBEI) and Global KE Index (GKEI) and the knowledge index could be assigned to this group.

The third group is assessment orientated to ICT infrastructure, in which Indexes calculation is concentrating on the issues correlated with ICT usage in all activity forms. In the scientific literature, four types of such indexes exist: F. Machlup Assessment Methodology (1962), Information Society Index (ISI) (Gifford, 1999), Networked Readiness Index (NRI), INfrastructure, EXperience, Skills, Knowledge model (INEXSK Model) (Mansell, Wehn, 1998) (Daugėlienė, 2004). Appendix (II) presented in-depth explanation to these indices.

Table (3.2): Groups of Models of Sectorial Knowledge Assessment.

Models of Micro Knowledge Assessment		
Specific assessment (Oriented on subject)	**Basic Assessment based on one index (all knowledge characteristics)**	**Assessment orientated to ICT infrastructure**
Growth Competitiveness index (GCI) Science Citation Index (Small, Garfield, 1985) Regional Economic Architecture (REA) Human Development Index (HDI) Knowledge Index (KI) Nelson-Phelp's technology spread model (1990) Greenwood, Hercowitiz, Krussel Investment to the technology development model (1997) Benhabib, Spiegel development of finance and impact of human capital on the growth of economy model (1994;2002)	Knowledge-based Economy Index (KBEI) Global Knowledge-based Economy Index (GKEI)	F. Machlup Assessment Methodology (1962) Information Society Index (Gifford, 1999) Networked Readiness Index, NRI INEXSK Model (Mansell, Wehn, 1998)

Further, it is key to stress, that it is theoretically possible to distinguish the KBE assessment models as two separate instruments for assessment, but in practical use, they are tightly connected.

3.4 Empirical Literature on KBE Assessment

The empirical literature on KBE assessment is vast given that there is no widely accepted measurement tool at the international level as well as the numerous enthusiasms for transition into a KBE in all countries.

As can be observed in the coming paragraphs, a wide use of the WB methodology, namely KAM is distinguishable in numerous empirical studies and reports that are employed for KBE assessment and still many studies acknowledge that this methodology is the most frequently applied one for KBE assessment as manifested by studies such as ,inter alia, Leon (2017).

Furthermore, recent empirical studies still utilize this methodology even though it stopped in 2012 without any updates. Other recent studies are still grounded on KAM but with different approaches to assess the KBE. Alternative studies used KAM to introduce a new index for the KBE or may use KAM besides other indices to provide a more holistic analysis of the KBE assessment as detailed below.

Therefore, this empirical review is divided into two main sections, namely the empirical studies that uses KAM even those studies with some edits to the original KAM methodology and the next main section focuses on other methodologies for KBE assessment, however, KAM is not among them as seen in the following paragraphs. Table (3.4) classifies the existing empirical literature on KBE assessment. Finally, a critical analysis of the existing KBE measurement frameworks is introduced and the gaps in existing empirical studies are presented prior to reaching main conclusions.

Table (3.3): Empirical Literature on KBE Measurement.

<table>
<tr><th colspan="6">Empirical Studies Used KAM</th></tr>
<tr><th rowspan="2">Studies that employed KAM at the country or regional level.</th><th rowspan="2">Recent studies that employed KAM</th><th colspan="4">Studies Grounded on KAM</th></tr>
<tr><th>Studies based on KAM, but with Different Approaches</th><th>Studies based on KAM to develop a New Index</th><th>Studies based on KAM besides Other Indices</th><th>Studies based on KAM for Micro Analysis</th></tr>
<tr><td>Asongu (2017)
Asian Development Bank (2007)
Asian Development Bank (2014)
Aubert and Reiffers (2003).
Rahimić and Kožo (2009)
Bashir (2013a)
Council (2007)
Dahlman and Aubert (2001)
Dahlman and Utz (2005)
Gorij and Alipourian (2011).
Hvidt (2015).
Kaur and Singh (2016)
Murat et al. (2017)
Nour (2014b)
Qamruzzaman and Ferdaous (2014)
Shahabadi et al. (2017)
Suh and Chen (2007)</td><td>Asongu and Andrés (2020)
Asongu and Odhiambo (2019)
Asongu et al. (2020 a, b)
Cavusoglu (2018)
Madbouly et al. (2021)
Rezny et al. (2019)
Wirba (2022)
Zelinska et al. (2020)</td><td>Amirat and Zaidi (2020)
Andres et al. (2021)
Chen (2008b)
Nurunnabi (2017)
Parcero and Ryan (2017)
Skrodzka (2016)
Tchamyou (2017)
Taghizadech and Ahmadi (2019)</td><td>Affortunato et al. (2010)
Al Shami et al. (2011)
Garcia (2020)
Leung (2004)
Ojanperä et al. (2019)
Popov and Kochetkov, (2019)
Tyshchenko, (2013).</td><td>Bakırcı (2018)
Burdenko and Mudrova (2018)
Ahmed and Alfaki (2013)
Ahmed and Al-Roubaie (2012).
Krasnokutskaya (2012)
Nour (2014a)
Nour (2015)
Bryl (2012)
Aliyev (2021)</td><td>Al-Busaidi (2020)</td></tr>
<tr><th colspan="6">Empirical studies used other Methodologies for KBE Assessment, but KAM was not among them.</th></tr>
<tr><th>Studies based on Existing Frameworks/ Indices (KAM not among them).</th><th>Studies Used Different Approaches Other than KAM for KBE Assessment</th><th>Studies Used Different Approaches for Introducing a New Index but KAM was not among them</th><th colspan="3">Studies Used Input-Output Approach</th></tr>
<tr><td>Almoli and Tok</td><td>Ben Hassen (2020)</td><td>Arvanitidis and</td><td colspan="3">Afzal (2012 b, e)</td></tr>
</table>

Empirical Studies Used KAM					
Studies that employed KAM at the country or regional level.	**Recent studies that employed KAM**	**Studies Grounded on KAM**			
		Studies based on KAM, but with Different Approaches	**Studies based on KAM to develop a New Index**	**Studies based on KAM besides Other Indices**	**Studies based on KAM for Micro Analysis**
(2020) Alnafrah and Mouselli (2019) Demir et al. (2015) Lagzouli et al. (2020) Tadros (2015)	Shen et al. (2016) Shapira et al. (2006) Nachef et al. (2014) Chen (2008 a)	Petrakos (2011) Chen (2010) Dima et al. (2018) Donlagic et al. (2015) Hossain (2015) Mêgnigbêto (2018). Širá et al. (2020)	Karahan (2012) Bashir (2013a, b) Lee (2001)		

3.4.1 Empirical Studies Used the KAM

Considering the current empirical KBE literature, tremendous empirical studies and reports have employed the WB methodology, namely KAM as will be observed in the coming paragraphs. These studies are divided into three main sub-parts, namely studies that employed KAM at country or regional level; then recent studies that applied KAM methodology without any amendments and finally studies that used KAM but with different approaches. Among these studies are the following. More comprehensive elaboration to the studies presented in this empirical section is available in appendix (III).

3.4.1.1 KAM for KBE Assessment at the Country or Regional Level.

Numerous empirical studies and reports employed the WB methodology (KAM); among these studies are those that utilized KAM for comprehensive KE assessment at country level such as: Qatar (Council, 2007); Korea (Suh & Chen, 2007); Japan (Shibata, 2006); India (Dahlman & Utz, 2005); China (Dahlman & Aubert, 2001); Bangladesh (Qamruzzaman & Ferdaous, 2014); Saudi Arabia (Nour, 2014b); and Iran (Gorji & Alipourian, 2011).

In a similar manner, other studies used KAM for a group of countries. For instance, Bashir (2013a) assessed the KBE in 42 Islamic countries in 2012 using

KAM. Rahimić and Kožo (2009) assessed the position of Bosnia and Herzegovina on its development towards a KBE. Moreover, KAM was the main methodology to analyse the core components of the global KBE in six Asian countries, namely Thailand, Singapore, Malaysia, Korea, India, and China by the Asian Development Bank (2007). Similarly, KAM was employed by the same institution to calculate the performance of the KBE in four countries, namely Republic of China, India, Indonesia, and Kazakhstan as in Asian Development Bank (2014).

Further, KAM was employed to provide comparative analysis for two countries as evidenced in the study by Alizadeh and Salami (2015) which compared the status of Iran and Turkey from the perspective of the KBE. Last but not least, KAM was used to assess the performance of the Gulf Cooperation Council (GCC) countries in their transformation to a KBE by Hvidt (2015). Similarly, Murat et al., (2017) evaluated the position of OECD countries in the KBE using KAM in 2012. Shahabadi et al. (2017) examined the effect of KE components on income inequality for 16 selected Islamic countries during the period 1995– 2012.The study followed the World Bank methodology in determining the variables that serve as a proxy for KE components. The study concluded that these Islamic countries must adopt demand and supply side policies to construct a framework for the KBE.

Additionally, Researchers Kaur and Singh (2016) investigated inter-country differences among 42 selected developing economies by employing the KAM through its aggregate index, namely KEI. They examined the correlation between KEI and the level of economic development for selected developing economies through regression analysis. Finally, they demonstrated the impact of the KBE on the economic growth for the sample of countries. It is worth mentioning that; though this study has been published in 2016, the analysis has been implemented at four points in time notably: 1995, 2000, 2005 and 2012. This means that analysis had stopped in 2012 due to data availability. Asongu (2017) assessed the KBE progress in Africa by comparing its dynamics within African countries to measure the best and worst performers based on fundamental characteristics of the continent’s development.

At the regional level, some studies employed KAM for KBE assessment at the regional level. For instance, evaluating the performance of the KBE in the Middle East and North Africa was the main concern of the study presented by Aubert and Reiffers (2003).

3.4.1.2 Recent Studies Used KAM for KBE Assessment

The popularity of KAM is obvious in the numerous new studies that employed KAM even after it stopped without further notifications since 2012; among them the studies presented by scholars such as Asongu and Andrés (2020); Asongu and Odhiambo (2019); Asongu et al. (2020 a, b); Cavusogluv (2018); Madbouly et al. (2021); Rezny et al. (2019); Wirba (2022); Zelinska et al. (2020), among many other scholars.

To clarify more, benchmarking the Ukrainian economy in comparison with the Polish economy and assessing the regional development of the KBE in Ukraine through comparing its regions was the main idea of a study conducted by Zelinska et al. (2020). Through utilizing KAM, an in-depth analysis for each region (22 regions) in Ukraine for the four pillars of the KE and the calculation of the KEI was conducted over the period 2015-2017. Based on this analysis, it was quite possible to identify the "leading" regions, the "persecutors" regions, regions with relatively slow fluctuations, the "outsiders" or "anti-leaders" regions and the "risk group" regions. Some policy recommendations have been drawn up to faster the development of a KE in the Ukrainian economy, among them; the urgent need for a high-quality education system and ongoing professional training to management staff.

Further, the paths of a KBE in countries of Sub-Saharan Africa (SSA) and MENA were the main issue in a study carried out by Asongu and Andrés (2020). The study utilized all the four pillars of the World Bank's methodology i.e., KAM, namely economic incentives, innovation, education, and information infrastructure. Then, panel data was used to investigate whether cross-country differences in SSA and MENA countries in the KE are increasing or decreasing. The analysis was conducted for only 21 African and Middle East countries due to data availability constraints. The main conclusion drawn from this study was that countries of SSA and the MENA countries with low levels of KE dynamics were catching-up with their counterparts where the progression of a KE was higher.

Furthermore, the speeds of integration and time required to attain full (100%) integration were computed. The study estimated this required time for full integration to be between four and seven years. Finally, some policy implications were discussed based on the empirical results.

The aforementioned approach of recent studies is consistent with many other studies such as Asongu (2017); Asongu and Odhiambo (2019) and Asongu et al. (2020 a, b). To clarify, in a study for KE assessment, Asongu and Odhiambo (2019) systematically reviewed the literature to set up exactly the required policies and strategies with which African countries can faster their march towards building KBEs. A pilot study which has been consolidated within three pillars of the World Bank’s framework; notably: (I) education and skilled population, (ii) economic incentives and institutional regime and (iii) ICT has been utilized to draw up insights into the diversified strands of a KBE. Then, these insights were subsequently grouped under the three pillars analysed in the study. The study concluded that African countries are lagging other regions of the world in their transformation toward KBEs.

Additionally, a study by Rezny et al. (2019) was dedicated to gaining an understanding whether the KE could solve the problem of resource scarcity and climate disruption or not. It was carried out using KAM and through examining the relationship between KEI, consecutive economic growth rates and other indicators reflecting resources consumption, namely material footprint.

Furthermore, studying the overall level of preparedness in Northern Cyprus during its switch to a KBE was the main issue in a study carried out by Cavusoglu (2018). This has been done by calculating the KEI and the KI of the KAM methodology and comparing it with other countries. The methodology results revealed that the KEI of Northern Cyprus was less than Turkey and Southern Cyprus in 2012, but slightly more than the average index of lower middle-income countries. Additionally, education and ICT indexes of Northern Cyprus were higher than its competitors and the global average. On the other hand, the other two indices, namely economic incentives and institutional regime and innovation were relatively low.

A much more recent study introduced by Asongu and Andrés (2020) implemented the KBE assessment analysis over a period from 1996–2010, although the study is published in 2020. Similarly, a latest study published by Wirba (2022) assessed the position of Cameroon in its transformation to a KBE by using KAM even though the analysis stopped in 2012 indicators for KEI and KI although Wirba (2022) stated that the main objective was to provide an analysis of the current situation of KBE with a focus in the role of higher education.

To conclude, it is quite notable that, though these previous studies have been published recently and they used the KAM without any edits. However, the analysis in most of these studies stopped in outdated period due to data limitation. Obviously, this negatively affects the novelty and validity of the research and hence cast doubts on its policy recommendations. Other updated studies tried to detect this outdated KAM limitation by relying on the methodology dimensions but collected data manually from their sources or other sources. An example of this direction is the study of Madbouly et al. (2021); they acknowledged the drawback of KAM and thus collected data from the global competitiveness report to the same KAM's Pillars to investigate the position of Gulf Cooperation Council (GCC) countries in the period from 2010 to 2017.

3.4.1.3 Other Studies Grounding on KAM

Over and above that, investigating the KBE measurement literature reveals that other studies conducted their analysis grounding on KAM, but with different approaches and with different sets of indicators to assess the KBE. Another direction of these studies is employed to propose a new index for KBE or to use KAM besides other indices to give a much more holistic analysis to of KBE assessment. Lastly, scholars used KAM to provide micro analysis for the KBE. Most of these studies are discussed briefly in the coming paragraphs and presented in depth in the related appendix (III) as follows.

3.4.1.3.1 Studies Based on KAM, but with Different Approaches

It is relevant to clarify that attempts have been made to assess the KBE using KAM as a base but with a different set of indicators and different methodological approaches such as studies implemented by Amirat and Zaidi (2020); Andres et al. (2021); Chen (2008b); Nurunnabi (2017); Parcero and Ryan, 2017; Skrodzka, 2016; Tchamyou (2017);Taghizadech and Ahmadi (2019) and Vinnychuk et al. (2014).

For instance, Parcero and Ryan (2017) assessed the performance of Qatar and United Arab Emirates in their achievements towards becoming KBEs. A comparison against 17 benchmark countries using a four pillars' framework was implemented. The study mainly used the KAM pillars, yet with a different set of indicators. Parcero and Ryan (2017) defined clearly each indicator used, sources for each indicator, the year used as well as the descriptive statistics for each indicator. In the same year, Tchamyou (2017) evaluated the contribution of KBE in 53 African countries from 1996 to 2010 using KAM pillars but with different techniques, namely Principal Component Analysis (PCA) and panel instrumental variable fixed effect to calculate the contribution of the KBE.

Additionally, Skrodzka (2016) assessed the differences in the development level of the KBE in the European Union countries (EU-27) in two periods 2000 and 2013 using KAM and the soft modelling method. Further, Nurunnabi (2017) studied in detail the indicators of the KBE in Saudi Arabia for the purpose of introducing a framework for KBE assessment in this country and then defined these KBE indicators as human capital, education, ICT, employment, and innovation. Furthermore, Vinnychuk et al. (2014) aimed at defining the required indicators that can describe the key determinants of a KBE based on time series data for the years 1996-2011 for four countries, namely Ukraine, Poland, Germany, and Lithuania.

Furthermore, Amirat and Zaidi (2020) evaluated the position of Saudi Arabia from the lens of KAM methodology but with different indicators. Chen (2008b) utilized the knowledge assessment scorecards developed by the World Bank and used the path analysis with observed variables model to introduce the causal modelling for the KBE. Furthermore, Taghizadech and Ahmadi (2019) classified the KBE indicators to assess its impact on long-term economic growth in Iran using KAM dimensions but with different methodological consideration to attain the study objectives. The study also used ARDL bound tests to investigate the convergence between these KBE indicators.

In another approach to predict the scores of the knowledge economy index, Andres et al. (2021) used machine deep learning neural network approach for 71 developing and emerging countries during 1995–2017. The study concluded that their results were robust, and the World Bank can apply their approach until a substitute for KAM exists.

3.4.1.3.2 Studies Based on KAM to Develop a New Index

Other studies undertaken based on existing frameworks (KAM among them) to develop a new index for the KBE. Among these studies were Affortunato et al. (2010); Al Shami et al. (2011,2012); Garcia (2020); Leung (2004); Ojanperä et al. (2019); Popov and Kochetkov (2019) and Tyshchenko (2013).

To clarify more, establishing "Sustainable Knowledge Economy Index" was the main concern of a study executed by Garcia (2020). This index was defined as an amalgamation of many indices presented by the World Bank and the European Bank for Reconstruction and Development. It combines the KE variables with the agriculture output. The justification for the integration of the agricultural output in the construction of the KBE index is that it is mandatory to make the newly constructed knowledge economy index sustainable. However, this index was computed for only one year (2006) since most of the data was available for that year.

In a similar way, introducing the Russian regional knowledge economy index was dedicated to a study carried out by Popov and Kochetkov (2019); by taking KAM as a reference point, the study divided the data under three categories: innovation and technology, science and education and ICT. Then, three sub-indexes were built, and each category is divided into inputs and outputs except for ICT because Popov and Kochetkov (2019) stated that they had only usage indicators. The justification for the chosen variables under each sub index has been mentioned in the study as well. The study informed some policy recommendations for Russia. A similar study to Popov and Kochetkov (2019) was done by Tyshchenko (2013) to build a model for the KBE in Ukraine. The study was grounded on the same indicators under three dimensions, notably innovation, education, and ICT.

Another similar study was done by Affortunato et al. (2010) which had been conducted at local level. Grounding on the WB and OECD frameworks, the study introduced regional KBE indicators to assess the development of KBE at local level. Furthermore, due to the high visibility of KAM, a study by Ojanperä et al. (2019) was based on KAM with minor changes. The study paid the highest attention to the construction of a digital knowledge economy index, and empirically applies this index to Sub-Saharan African counties. The study added a fifth sub-index that includes indicators of participation and digital content creation of knowledge resources.

Al Shami et al. (2011) introduced the unified KE forecast map (UKFM) to forecast the KBE in the future as the majority of the developed composite indicators only assess the past performance. The proposed map is based on aggregating five complexes i.e., multi-dimensional composite indices, KEI, ICT Development Index (IDI), GII, and GCI and the World Competitiveness Yearbook (WCY). Then, the output of this UKFM could be used to forecast and visually combine scores for any country. This model could not predict values for the KBE in developing economies as the scores are usually missing or not reported by one or more of the used indicators. Yet, Al Shami et al. (2011) planned to enhance the analysis and extend this study to do comparisons with other advanced forecasting methods such as panel data analysis or also known as time series cross-sectional analysis to assess the strengths and weakness of this proposed model, but no future work has been done.

Additionally, introducing a framework for assessing the KBE in Hong Kong, China has been the main concern for a study conducted by Leung (2004). The study started by reviewing three of the existing KBE frameworks introduced by international organizations, namely OECD, APEC, and the WB. Grounding on these frameworks, the study proposed a KBE measurement framework that best suits the situation in Hong Kong with greater attention to the issues and challenges during the developing KBE indicators. The proposed framework defined a set of knowledge-related indicators, about 80 indicators, which are then categorized and organized under four KBE dimensions. The chosen indicators were selected from the previously listed indicators in the international frameworks. Additionally, the chosen indicators were based on three criteria, including international comparability, availability, and relevance. Leung (2004) concluded that by mid-2005, the first full set of KBE indicators for Hong Kong would be available. Yet, no updates have been introduced to the study. Moreover, the study lacked any empirical investigation to the proposed framework.

In a similar manner, an attempt to build a unified knowledge economy competitiveness composite index was reported by Al Shami et al. (2012) using a novel approach based on fuzzy clustering model. This model can predict values for the emerging economies, whereby, not all the data is available. Grounding on four of the most well-known and reputable knowledge economy indices, Al Shami et al. (2012) combined them into a unified index that indicates the overall rate of knowledge in an economy. The indices used in the study are KEI; IDI; GCI and WCY. Nonetheless, the shortcoming of this study lies in its lack of empirical investigation.

3.4.1.3.3 Studies Based on KAM Besides Other Indices

Other studies used KAM without any edits (standardized KAM) in addition to other indices to provide a holistic and updated analysis to the KBE have been undertaken. For example, Bakırcı (2018) introduced a situation analysis to Turkey’s position in KBE. This is done through using KAM and other global indexes such as the NRI to evaluate the usage of ICT. Furthermore, Burdenko and Mudrova (2018) employed the KEI, the GII, and the HDI to assess the KE development in in Russia and in G20 countries.

Moreover, Ahmed and Alfaki (2013) investigated the distinctive role of science, technology, and innovation in the development of a KE in UAE through assessing the country’s achievements in implementing the KE pillars. The study employed KAM in addition to other international indices such as HDI, GII and GCI to provide depth analysis. Similarly, the same objective of the previously mentioned study and the same methodology has been investigated for Muslim countries in Ahmed and Al-Roubaie (2012).

Likewise, Krasnokutska (2012) contended the importance of having a measurement framework for the KBE through developing composite indexes for the KBE development. The study investigated some of the existing KBE indices and used them to identify the gap between different countries. The study concluded that the existing indexes are highly correlated. Furthermore, Nour (2014a) assessed the position of Arab Gulf countries in their passing towards KBEs as well as the challenges and opportunities through using KAM and other indices such as the GII. Similarly, Nour (2015) evaluated the existence and progress of the Arab region in their movement towards the KBE by employing KAM and other indices.

Lastly, Bryl (2012) elaborated some of the existing KE measuring indices and concluded that there is no unified way of new economy measurement at the macro level. However, high ranking within the KEI for any country usually associated with high ranks in other indices as well such as Global Innovation Index. Another more recent study presented by Aliyev (2021) used the KEI, the global knowledge index, the GCI, Global Entrepreneurship Index, and the GII to rate the position of Azerbaijan on the bases of these indices.

3.4.1.3.4 Studies Based on KAM for Micro Analysis

In the literature, there are other studies that employed KAM but at the micro level to analyse specific pillars of the KBE i.e., studies that measure only some pillars of the KE through assessing one or more of its sub-indices. As an example, ICT is considered as the enabler of a KBE by Al-Busaidi (2020), hence the mentioned study applied both quantitative analysis (using KAM) and qualitative analysis to assess the most contributing ICT indicators that progress KE development in Oman. It also investigated how the ICT pillar could be used to enhance the development of the other KBE pillars, namely economic and institutional regimes, education, and innovation pillars.

3.4.2 Other Methodologies for KBE Assessment (KAM Not Among Them)

The KBE measurement literature pointed out that more and more analytical approaches have been developed. To the best of the researcher's knowledge, the following studies attempt to introduce a new measure for KBE assessment; inter alia: studies based on existing frameworks/indices; however, KAM is not among these measurement frameworks to assess the KBE; studies that used different approaches for assessment; studies that used different approaches for introducing a new index, and finally studies that used input-output approach.

3.4.2.1 Studies Based on Existing Frameworks/ Indices (KAM Not Among Them)

Rare studies in literature used existing mainstream frameworks or indices other than KAM to assess the KBE. The work presented by Almoli and Tok (2020); Alnafrah and Mouselli (2019); Demir et al. (2015); Lagzouli et al. (2020); and Tadros (2015) could be subdivided under this category.

For instance, grounding on the OECD and the European Commission methodologies for measuring the KBE, Lagzouli et al. (2020) set their own framework for measuring the KBE in Morocco based on a set of indicators as follows: (1) indicators tracing scientific and technological activity: these indicators are categorized under four areas notably; R&D activities, patent tracking, monitoring scientific publications and measuring the degree of scientific and technological specialization. (2) indicators for measuring the contribution of human resources to the KBE. Two data sources were used in the study to assess the contribution of human resources, namely measuring the contributions of the field of education, and measuring the contribution of personal qualifications. (3) indicators tracing knowledge products to measure innovation. The study used three surveys which had different objectives that is; the “YALE 2” survey aims to study the degree of ownership of innovation; “CIS” surveys of European community and OECD countries to measure the factors influencing innovation and studying the scope and impact of technological innovation in the enterprise; and The SESSI survey, which presents the skills required for companies to innovate. (4) ICT diffusion measurement indicators, in which; the study utilized the “Network Readiness Index” which has been developed by the World Economic Forum to rank countries according to their capacity to exploit ICT and the level of digitization of their economies. Based on the proposed frameworks, Morocco’s position has been identified. It has been found that, though the multiple assets that Morocco has; the country is lagging its rivals in the development of the KBE, especially in the level of its educational system, its R&D

results and in terms of its innovation indicators. Obviously, the limitation of this study lies in its limited empirical investigation as the study was conducted in only one country. Future studies could include more countries at different developmental levels.

Similarly, Almoli and Tok (2020) evaluated the performance trends for Qatar in its turning to a KBE. Almoli and Tok (2020) highlighted the strengths, weaknesses, challenges as well as public policies related to KBE through using three global indices, namely GCI, GII and Global Entrepreneurship Index. Alnafrah and Mouselli (2019) differentiated between indicators for knowledge society and KBE and then utilized the GII to assess the performance of Russia using the data of GII in 2014. Furthermore, Demir et al. (2015) ranked Turkey's position in the knowledge society by using the United Nations Public Administration Network (UNPAN)'s Knowledge Society Index. Other studies such as Tadros (2015) used the NRI, the GII for selected countries (GCC countries and the BRICS countries), key science, technology, and innovation indicators and the "Doing Business 2015: Going beyond Efficiency." to analyse the KBE, the information society and innovation ecosystem.

3.4.2.2 Studies Used Different Approaches Other Than KAM for KBE Assessment

In the light of the foregoing debate, the literature highlighted another trend in assessing KBE. In this trend studies used different approaches for KBE assessment. For instance, Ben Hassen (2020) investigated the current situation of the KBE in Qatar and Lebanon through reviewing the literature (scholarly literature, written documents, and governmental reports) and through in-depth interviews and questionnaires with stakeholders. Shen et al. (2016) defined the KE as a new economic sector in China and introduced sectoral assessment to the size of this "new" economic sector in the total economy through using a big data approach.

Shapira et al. (2006) assessed Malaysia's progress towards the development of KBE at the micro level (sectoral assessment) using a survey to more than 1800 Malaysian firms in 18 manufacturing and services industries. Nachef et al. (2014) used a fuzzy approach to build a model that best suits Qatar in its transition to a

KBE and in line with Qatar National Vision 2030. Chen (2008 a) tried to construct a unified model for KBE indicators using exploratory factor analysis, principal component analysis and confirmatory factor analysis. Chen (2008 a) divided the KBE indicators under five categories, namely information infrastructure, the business environment, the country's human resources, the country's innovation system and some performance indicators.

3.4.2.3 Studies Used Different Approaches for Introducing a New Index (KAM Not Among Them)

Furthermore, another trend of studies aimed to introduce a new index or framework for KBE assessment that is not grounded on KAM. Donlagic et al. (2015) introduced a measurement framework for the development of KBE in Bosnia and Herzegovina by building a questionnaire survey which focuses mainly on medium and large enterprises in Bosnia and Herzegovina. Hossain (2015) implemented a comparative analysis for the KBE indicators in the Cooperation Council of Arab States of the Gulf through building a model for the KBE that combines 26 indicators of KBE under five categories, namely education/talent, economic and institutional regime, innovation, digital economy globalization. Then, the study employed an analysis of variance (ANOVA) to calculate standard deviation, mean, and confidence interval. Additionally, ANOVA is used to compare countries. Chen (2010) developed a short form KBE Scorecards to evaluate the KBE competitiveness globally. Arvanitidis and Petrakos (2011) presented an Economic Dynamism Composite Indicator to assess the knowledge-driven economic dynamism worldwide. Nonetheless, all these proposals and trials are not widely applicable and lacks empirical application.

Other studies touched the KBE measurement indirectly to attain the stated objective of the study. For instance, Širá et al. (2020) examined the interconnections among KBE, competitiveness, and sustainability through a multi-criteria evaluation of countries. The TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method was used to achieve the study objective. However, since the objective in this literature is to see how KBE is measured, thus the level of development of KBE was evaluated according to these selected indicators: tertiary education as a percent of population, R&D

expenditure as a percent of gross domestic product, total amount of patents per million populations, and the score in the 12th pillar of the GCI.

Further, studying the impact of various KBE indicators on countries competitiveness in the EU was investigated by Dima et al. (2018). Pearson coefficients and panel data regression are employed throughout the study for the empirical analysis. Countries competitiveness was the dependent variable and measured by the GCI whereas six independent variables are used as proxies for KBE, namely R&D expenditure as a percentage of the GDP, tertiary education attainment (percentage of the population with tertiary education (levels 5–8), aged 15 to 64 years), lifelong learning (the percentage of people aged 18 to 64 who stated that they received education or training in the four weeks preceding the survey),GDP per capita, energy intensity (gross inland consumption of energy divided by GDP: kg of oil equivalent per 1000 EUR), and debt to equity (financial sector leverage, %). Moreover, studying the correlation between the transmission power in six OECD countries and some indicators used to assess the development of a KBE was the main concern of a study presented by Mêgnigbêto (2018). In this study, six indicators are used as proxies for the KBE, notably gross domestic expenditure for research and development, number of researchers, the growth rate of GDP, GDP per capita, HDI and total factor productivity.

3.4.2.4 Studies Used Input-Output Approach

Finally, another more effective approach was employed by these studies, namely Afzal and Lawrey (2012 b, e); Karahan (2012); Bashir (2013 a, b); Lee (2001) KBE assessment. Such an approach introduced a policy-focused KBE framework which select appropriate indicators from the current KBE frameworks then divided these indicators under “input” and “output” indicators for the four KBE dimensions, namely “Knowledge Acquisition”, “Knowledge Production”, “Knowledge Distribution” and “Knowledge Utilization”. Input indicators reflect investment or capacity building efforts for each dimension towards the development of a KBE whereas the output indicators identify the degree of KBE that a country has. Thus, output indicators illustrate the impact of input indicators or performance of a country towards a KBE (Karahan, 2012). Such a classification analyses the dynamic of a new KBE economy in a more effective manner rather than having a set of diversified indicators.

Furthermore, this kind of classification sheds light on the economic policies that support a KBE much more. For instance, Lee (2001) determined the position of Korea in its move towards the KBE through building indicators for the KBE in terms of inputs and outputs. Afzal and Lawrey (2012 e) developed a measurement framework that divided input-output indicators of a KBE under four categories to assess the KBE in Brunei Darussalam, a resource-based country. Similarly, Afzal and Lawrey (2012 b) used the same methodology to construct a policy focused framework for the KBE in five ASEAN countries. Furthermore, Karahan (2012) presented a more effective and comprehensive statistical approach for the KBE in Turkey by comparison with OECD countries and some cases of European Union countries. Moreover, Bashir (2013a) used the same approach to assess the position of Pakistan and other Asian countries in their direction towards KBE. It is relevant here to note that, comparing the two methodologies for KBE assessment in Pakistan using KAM and “Input-Output” methodologies, it is concluded that Pakistan position is explained in a better way using the input-output approach (Bashir, 2013 a, b).

After presenting the empirical literature, it is concluded that given the lack of an internationally recognized measurement tool and the widespread support for transitioning KBEs in all nations, the empirical literature is abundant on KBE assessment. The predominant approach adopted in almost all these studies is the use of KAM in one way or another to develop a measure for the KBE. This calls for urgent research in this area, namely: measuring the KBE.

3.5 Critical Analysis to the Limitations in Existing KBE Frameworks and Defining Gaps in Empirical Literature

3.5.1 Limitations in Current KBE Frameworks

After confirming the importance of KBE measurement, the challenges during the measurement process and the various measurement attempts, a critical analysis to the mainstream frameworks should be presented which will highlight all observed gaps in the KBE measurement literature that call for more research work to fill in these gaps.

Despite the previously mentioned numerous attempts to find a measure for KBE, not internationally consensual and agreed framework for measuring a KBE has been introduced. This unfortunate conclusion is confirmed by many studies such as Mêgnigbêto (2018) and Guaita Martínez et al. (2020).

Many issues and concerns raised by these studies suggests that there are certain disadvantages associated with these frameworks as observed in this chapter. As a general note, Bashir (2013a) affirmed that of the numerous KBE frameworks developed by international organizations, most of them confirmed four core dimensions for the KBE; notably knowledge acquisition, production, distribution, and utilization, and used a large set of structural and qualitative indicators in their frameworks. However, none of these frameworks explicitly divide the KBE indicators under these four core dimensions. Moreover, none of them tried to measure the efficiency with which the knowledge inputs are transformed into knowledge outputs.

In a similar way, Cader (2008) confirmed that the existing literature introduced few consistent methodological underpinnings to assess the knowledge level of a firm, region or economy and criticized the current indices for being "data-driven" i.e. using the available data across countries rather than "conceptually–driven" i.e. being based on a model of knowledge acquisition and use and relationships to innovation and economic performance" (p.120). Cader (2008) also underlined the fact that the majority of the indices are only available at the national level. That is why Cader (2008) concluded that measuring knowledge is an incredibly difficult task and the perfect criterion for knowledge measurement has yet to be found.

Similarly, Shapira et al. (2006) contends that the international KBE measurement proposals and the other alternatives are conditioned by the fact that the chosen indicators under each proposal are those whose availability is ensured in all the countries involved in the analysis. A good example of this limitation in the current frameworks is the APEC framework.

Al Shami et al. (2011) confirmed that KBE indices have severe shortcomings, among them: (1) for most indicators there are no clear functional relationships, (2) little information is available concerning how these indicators relate, (3) data aggregation methods proved to be challenging, and (4) positive bias in most of the results as most of the used data was unbalanced data with the majority of them not available, therefore discarded and substituted by zero values in the data matrix. Further, Al Shami et al. (2011) admitted that there is redundancy in most of the reputable knowledge economy indices. Although these indices look different in names and purpose, their results are almost similar with respect to knowledge performance and countries' ranking. Therefore, Al Shami et al. (2011) tried to build a unified index through aggregating four of the widely used indices into one index by using fuzzy clustering. Yet, there is no empirical analysis to support the suggested index.

On the other hand, AlShami et al. (2012) criticized the numerous composite indicators which have been created so far at both micro and macro levels as they are inconsistent because they created different ranking and scores which is controlled by and mainly depend on the nature and type of assessments. Furthermore, they are not able to forecast where a KBE is moving soon; they only assess the past performance. Additionally, they have inherited two disputed points with respect to the weighting scheme that comes first while being examined at a specific time is the second problem highlighted (Mimis & Georgiadis, 2013).

In a similar vein, concerning indicators and data issues, researchers Cherchye et al. (2011) introduced a composite index for KBE assessment with imprecise data. Cherchye et al. (2011) admitted that most of the KBE frameworks promulgated by international organizations i.e., European Commission came up with a composite index for assessing countries' performance in the development of a KBE. Although such composite index has many advantages as it is straightforward in its interpretation by the public, media, academics, experts, journalists, policymakers etc., it has many disadvantages that cast doubt on its credibility. This is because many issues arise while constructing such an index; among them: What is the definition of the phenomenon at issue? What are the required indicators to be included? How they should be aggregated to construct a model or a framework? How the index provider could be able to deal with low quality or imprecise data? How to establish the weights of partial indicators? How to avoid redundant information? As a solution followed in most cases, when dealing with issues such as missing data, the provider of the index substitutes the last available data for each country or neglects the specific indicator for the concerned countries. Certainly, all the afore-mentioned questions and solutions lessened up-to–date benchmarking internationally and impeded the reliability in the construction of the composite index.

Adding to the aforementioned issues, the distinctive role of constructing composite indicators for assessing complex and multidimensional phenomenon that cannot be expressed in a single simple indicator, such as KBE is encapsulated in Guaita Martínez et al. (2020). Such composite indicators are crucial for policy makers as it is possible to synthesize in a single data all information contained in several variables about different aspects of a given issue, the KBE in this situation. The literature offered numerous proposals to measure countries' progress for KBE. Yet, the number of methodological proposals is very limited, with limited attention paid to the analysis of how each of them can be adjusted to different contexts and concrete needs of countries. Additionally, the selected indicators are constrained by the quality of the statistical sources especially in less developed countries.

Moreover, Trewin (2002) confirmed that the international proposals for KBE assessment lacked any solid theoretical base or empirical evidence. They can only be seen as a "descriptive" or "presentation". To clarify, as confirmed by the Australian Bureau of Statistics (2002) in Trewin (2002), these frameworks are using a large set of statistical indicators to define a specific subject, i.e., KBE. These indicators are then grouped and organized according to a specific purpose previously stated by the international organization, while not trying to view these indicators through a context of a statistical framework. However, classifying the KBE indicators as inputs and outputs is crucial to understand the dynamics of this economy. Studies carried out by Afzal and Lawrey (2012 a, b); Cader (2008); Leung (2004); suggested the same point of view.

Leung (2004) added to the previous shortcoming that there are certain deficiencies with the set of indicators used in the measurement frameworks, inter alia: (I) wide range of indicators are used and vary considerably from more than 130 to only 20; (ii) although some indicators look different from each other, they are not completely mutually exclusive and (iii) there is no international standard for KBE indicators which is essential to allow for international benchmarking. Therefore, Leung (2004) suggested international cooperation to develop a set of indicators for such international comparison as a top priority.

Further, Karahan (2012) stressed that effective measurement of KBE is conditional on building a reliable composite index, the data available, and the ability of composite indicators to capture a complex reality such as the KBE. Karahan (2012) added to these limitations: the descriptive nature of the international framework, the challenging issue of how to combine various measures of the same concept and how to determine the interaction among them. As a solution, Karahan (2012) stressed that the effective classification of indicators such as input, and output is a must to set “causal connection” among the indicators not like the conventional classification of international organizations which set different statistical indicators and grouped them according to different aspects.

Affortunato et al. (2010) demonstrated that the analysis of this area of research is always far from utilizing a direct approach and sometimes biased. This is due to many reasons; chief among them is the inability to establish a production function and using mismatched indicators in most cases of assessment. Consequently, scholars are forced to identify all society’ characteristics and select only those ones that indicate the relationship between knowledge and economics. Moreover, comparing the developed KBE indicators by OECD with its KBE definition depicts a bias on the side of the mechanisms for knowledge production. Thus, Affortunato et al. (2010) suggested that focusing on measuring KBE at the local level of KBE measurement rather than the international one could partly solve the KBE measurement challenges. Finally, Affortunato et al. (2010) came up with regional knowledge economy indicators. Yet, there is no empirical investigation into these indicators.

Likewise, Tyshchenko (2013) criticized the rating methodologies of international organizations and the international focus of previously developed frameworks, and highlighted that the regions specific approach should be paid the highest attention. Therefore, Tyshchenko (2013) introduced a methodological approach which is based on the calculations of integrated indicators with entropy methods and regions positioning in three-dimensional KBE components, namely innovation, education, and ICT.

Within this ongoing debate to find out a consensual international framework to the KBE, Fen and Chaudhry (2006) as cited in Afzal and Lawrey (2012b) noted that a large number of KBE variables are suggested by international organization such as OECD, APEC, WBI and ABS. These organizations assert that investing in these KBE indicators is crucial to becoming a KBE. Thus, the indicators in each KBE dimension might be changed and replaced with others over time because of the constant changes in KBEs. Put differently, as the economy develops, indicators used in the past may no longer be applicable at present or in the future. That is why the KBE indicators must be flexible, rather than being rigid in nature.

Another study conducted by Alguliyev and Aliyev (2017) introduced a comparative analysis of the different frameworks related to the level of development of an information and knowledge economy and their methodological approaches. Alguliyev and Aliyev (2017) argued that international organizations have implemented quantitative and qualitative assessment for its penetration; though, they suffer from methodological defects and application difficulties.

Among these flaws, Alguliyev and Aliyev (2017) paid much more attention to the disunity in conducting comparative analysis as well as the diversified structure and content of these indices. Moreover, Alguliyev and Aliyev (2017) gave an example to one of the measurement indicators which suffers from deficiencies; namely investment in knowledge; it is evaluated by experts of OECD as a collection of national expenses for education, R&D, and software. Obviously, this indicator is not completely reflective of the conditions of investment in knowledge. A similar criticism has been introduced by a more recent study dedicated to Rim et al. (2019) as they suggested that current KBE literature lacks a unified view of a KBE because numerous studies relate to the definition of KBE and the assessment of its level has been carried out in different ways.

Additionally, one more up-to-date study by Rezny et al. (2019) underlined the outstanding role played by OECD in various areas related to the KBE with a comprehensive science, technology and industry scoreboard consisting of a set of 260 variables in its last edition in 2013. Yet, some shortcomings in the empirical investigation of this framework have been found. As, some variables are far from being internationally comparable but rather only experimental. Additionally, data limitation has hindered its robustness as data is available only for the last one or two years for some cases. Finally, the framework is oriented only to OECD countries with insignificant attention to other countries. Thus, Rezny et al. (2019) employed the KAM provided by the World Bank Institute, as it allows for a better variant, with other methodologies to attain the objectives of the study. But, from our point of view, this analysis is outdated. The paper was published in 2019 and the KEI was calculated for the period from 1995 to 2012. Obviously, this affects the credibility and novelty of research results.

Moreover, a study conducted by Asongu and Odhiambo (2019) confirmed that the current literature has failed to introduce a logical structure for the policies and strategies with which policymakers could enhance the KBE in developing countries and more specifically in Africa.

Summad et al. (2018) provided a criticism for most of the international frameworks. For instance, the APEC framework only chooses those indicators that were available in the context of their own countries. Obviously, this tended to limit the choice of indicators. The WB framework is criticized for the chosen indicators in the education pillar. That is the educational dimension which is assessed through a sub- index consisting of the average of three statistical-based variables, namely average years of schooling, gross secondary enrolment rate, and gross tertiary enrolment rate. However, such data might not be available at the regional level. Moreover, the average years of schooling are not a good indication for the level of literacy and numeracy in a society. Consequently, this could lead to a misleading picture of a country's capabilities for the transition into a KBE. Additionally, both the ABS framework and the WB framework are criticized for not introducing a systematic process on how to guide a transition process towards a KBE given the contextual factors that are highly specific to each country.

Similarly, it has been explained by Afzal and Lawrey (2012 a, b, c, d) that all the state-of-the art KBE frameworks are built using the available data and lack rigorous theoretical basis. Therefore, using these methodologies internationally for all countries in different regions, with different stages of development and with diversified institutional, social, and economic characteristics will be fallacious and result in inconvenient pro-KBE policies and strategies. Afzal and Lawrey (2012 a, b, c, d) criticized the existing frameworks, for instance, the OECD framework is criticized for not considering the inputs and outputs of the new growth theory in any significant manner; but rather it selected only variables under five KBE pillars. Additionally, the case studied economies in the APEC framework were chosen primarily based on available data. Thus, this framework loses the soundness to be applicable for other countries. Afzal and Lawrey (2012 a, b, c, d) in the mentioned studies also highlighted the fact that the existing KBE frameworks (for instance World Bank, OECD, ABS and APEC frameworks) suffer from several flaws related to the indicators that reflect the national and regional innovation system, although it constitutes an integral part of the overall KBE. Moreover, there are no acceptable quantitative measurement techniques to benchmark the knowledge acquisition, production, distribution or dissemination and utilization dimensions hence available frameworks implicitly guide policymakers. Moreover, each framework has a specific purpose related to the needs of the organization's member states. For instance, the World Bank has developed the KAM to show a country's readiness to become a KBE, while the OECD focuses solely on innovation performance in its framework. Furthermore, the above-mentioned studies assured that investing in the proposed large set of variables would be financially unrealized, unsustainable, and unfocussed for countries, especially developing countries.

Therefore, it would be better for governments to know the KBE factors that are best contributing to a country's progress. Furthermore, the historical approach to the evolution of the KBE concept is missing in the existing frameworks; something which we believe to be important when it comes to understanding the knowledge-based growth phenomenon in creating wealth of nations. For developing countries, not only may this approach be theoretically questionable, but rather it is impossible given the lack of consistent data in many developing countries. The scope of KBE is vast, but the analytical tools, precise theoretical background, and development process of indicators for mapping and measuring KBE performance are loose at best (Kriščiūnas & Daugeliene, 2006).

Similarly, according to Chen (2008 a) measuring knowledge is a complex process. Additionally, the conventional economic indicators such as GDP and GNP are no longer appropriate to assess the KBE performance due to neglecting the socio-cultural factors as well as the environmental protection. Put differently; the traditional economic indicators face many challenges and suffer many critiques as they do not have knowledge of input-output variables and lack measurable knowledge of pricing databases. Therefore, KBE as a broad concept must be measured from all dimensions of knowledge notably: creation, acquisition, distribution, and utilization.

In a more detailed investigation, Chen (2010) contended that many countries had introduced KBE development plans with various indicators which were different from each other's in the description of indices, and measured categories and variables until now. Some of these indicators came up with complicated scorecards characterized by abundant information, improper construct factors and biased weight allocation. Additionally, these indicators are lacking certain criteria such as robustness, conciseness, accuracy, and efficiency. The study argued that KAM is the most popular measurement with a framework consisting of seventy-two variables organized under five measured categories. On the other hand, it suffers from asymmetric allocation and high degree of overlapping for some measured indicators. Therefore, simplifying these indicators could contribute to the degree of conciseness and effectiveness of KBE assessment.

To conclude, critically analysing the existing KBE frameworks, it could be possible to present some deficiencies in the existing frameworks have been noted that cast doubts on their relevance for proper assessment (not reflect the extent and efficiency) of the transition process. Of these limitations, we could simply conclude that there is no generally acceptable framework at the international level. Additionally, it would be financially unsustainable and unfocused for developing countries to invest in large number of KBE indicators proposed by the mainstream frameworks. Further, each framework has a specific purpose for instance the OECD focuses on innovation performance in its framework.

Furthermore, there are no agreed quantitative measurement techniques to benchmark the knowledge dimensions. Current measurement frameworks refer to static knowledge not the dynamics of the KE as well as existing frameworks being descriptive in nature. Moreover, KAM has stopped in 2012 without notification. Applying the current frameworks in developing countries is not only theoretically impossible but rather impossible to be applied given the lack of consistent data in developing countries.

In summary, although many measurement frameworks have been proposed for KBE, these approaches have many problems, stemming from a wide set of issues ranging from data reliability to underlying philosophical considerations and from ethics to the intra-organizational division of power. With this critique in mind, a step further is needed to develop a new measurement technique for the KBE.

3.5.2 Gaps in Existing Empirical KBE Literature in the Context of Developing Countries

For developing economies, the knowledge revolution presents both challenges and opportunities as written by many studies of which Shapira et al. (2006). Further, studies such as Al-Busaidi (2016); Nour (2014c) ; Nurunnabi (2017); Parcero and Ryan (2017) and practitioners in Arab countries highlighted the inevitable need for Arab countries to take serious steps to transit to a KBE. Nonetheless, the international frameworks for KBE assessment; not only may be theoretically questionable, but it may simply be impossible to apply given the lack of consistent data in many developing countries. Moreover, study conducted by Asongu and Odhiambo (2019) confirmed that the current literature has failed to introduce a logical structure for the policies and strategies with which policy makers could enhance the KBE in developing countries and more specifically in Africa.

Additionally, the concern in this thesis is in introducing appropriate measure for KBE, as the existing frameworks (OECD, APEC, ABS and WBI) do not have sufficient focus to measure KBE in developing countries. For instance, the comparison in KAM is undertaken for a group of 146 countries, most of them are developed economies with little attention to developing economies.

Furthermore, several literature reviews such as Roztocki and Weistroffer (2015) have confirmed that most KBE studies are conducted in developed countries; hence, there is a great need for investigations in the context of less developed economies. Even the literature lacks studies on KBE pillars. A welcome exception is the study by Kaur and Singh (2016) that touched the approach of KBE measurement in developing countries.

In conclusion, if the mainstream KBE frameworks are to be beneficial as a policy tool it is crucial to build a more rigorous approach to enhance their significance than exists at present. There is certainly more and more work to be done in this area of research. Additionally, for developing countries, there is an urgent need for a new measure in these countries. This is the motivation to build a generalizable measurement framework to measure the KBE in developing countries in the subsequent chapter.

3.6 Summary of the Chapter

The main objective of this review for the empirical literature is to participate in the ongoing debate related to the KBE measurement. Although during the last 20 years multiple studies have been conducted and numerous works have been written on KBE measurement, one widely accepted measurement method has not been arrived at.

This chapter concluded that existing gaps still exist in both the theoretical literature of KBE assessment as well as the empirical application in developing countries and calls for more research work to fill in these gaps. It inevitably requires a new measurement framework for KBE in developing countries as will be introduced in the next chapter.

It ended up by concluding that there are some deficiencies in existing KBE measurement frameworks that cast doubts on their relevance for proper assessment of the KBE. Of these limitations, the existing measurement frameworks do not reflect the extent and the efficiency of an economy.

This measurement problem is much more vexing in developing countries given the lack of data. Thus, the main conclusion derived from this chapter is that there is an urgent need for a measure to KBE transition especially in developing countries context. That is why, this is going to be the focus of the next chapter.

Chapter 4

KBE Efficiencies in Developing Countries: A DEA Approach

4.1 Introduction

There is a wide consensus among scholars and policymakers that knowledge is indispensable to long-term economic growth and development (inter alia Nordhaus & Romer, 2018; Romer, 1994). Additionally, for developing countries, there is an urgent need to transition to a KBE at a faster pace to reap its benefits. This is confirmed by a substantial body of research that has been focused on productivity-led economic growth and its determinants as in Klevenhusen et al. (2021), among others. For instance, a recent study by Mohamed et al. (2022) examined the impact of KBE indicators on economic growth for 20 developing countries over the period from 1996 to 2020 and found that 93% of changes in economic growth in these countries were attributable to the KBE.

Additionally, policymakers cannot be able to manage what cannot be measured and this emphasizes the inevitable need for developing a performance measurement system. This is because performance measurement is an essential step for any country/organization as it provides valuable information regarding its production processes that in turn could help both the worst and the best performers to make further improvements for various types of efficiency. Thus, performance measurement has gained thoughtful importance among countries due to its importance as well as the existing large development disparities between countries (Shewell & Migiro, 2016).

Measuring the knowledge-based economic performance of all countries is no exception. Unfortunately, it is still a challenging task in and of itself.

For developing countries, this problem continues to be a much more problematic challenge given the lack of consistency of KBE measures as well as the missing values that hamper policy formation and any future research in this area. Therefore, this chapter advances an original contribution by presenting a comprehensive analysis to assess the relative efficiency of developing countries during their transition processes toward KBEs.

To attain the aforementioned objective and contrary to the usual econometric analysis, the application of a novel analysis on this topic using a non-parametric approach, namely the Data Envelopment Analysis (DEA) is utilized. To the best of the researcher's knowledge, no other study exists that applies a quantitative technique like DEA to a large sample like developing countries and to be mainly concentrated on measuring the KBE relative efficiency in developing countries. Further, most of the prior empirical literature, as will be observed later in the literature section of this chapter (section 3), is directed toward developed countries with little attention paid to developing countries and if included in the analysis, the number of developing countries is very small compared to the whole sample size of countries under assessment. Additionally, the unique nature of the work in this chapter arises from not only employing DEA for KBE assessment in developing countries using the basic radial DEA models (CCR and BCC) as most of the prior DEA-based studies for KBE assessment did but also by employing the non-radial DEA models in developing countries. This is done with consideration to all KBE dimensions to assess the latter's merits and to deal with the form's shortcomings to opt for the best DEA model for KBE assessment.

Thus, first, this chapter uses the traditional radial DEA models, namely output-oriented CCR and output-oriented BCC to present a comparative assessment of KBE efficiency in developing countries in 2020. Then, the traditional super-efficiency model is used to discriminate between efficient countries and to provide a full ranking for all developing countries along with the target-setting analysis for further improvements. Second, this chapter applies a non-radial approach, namely slack-based models and super-SBM models for the same objectives.

In this chapter, eight inputs and five outputs are used as proxies for the four KBE dimensions which have theoretical underpinning and are available for all developing countries. To this end, this chapter could be beneficial for researchers, analysts, and policymakers in different governments who are interested in the KBE through raising their awareness of DEA salient features, of which will determine areas for potential improvement and where greater investments in KBE could be defined. This will in turn enhance KBE dimensions in their economies and hence faster the transition process to a KBE through improved performance.

The remainder of this chapter is organized in a logical sequence as follows. It starts by a brief introduction to the DEA approach, its history, its main concept, the different efficiency measures in literature, and how efficiency is measured, together with the DEA basic models and their main extensions. Then, a survey of related empirical literature through presenting notable studies that employed DEA methodology to measure the relative efficiency of a KBE, or its dimensions are outlined. Further, this chapter depicts the empirical radial DEA models, their main specification, countries included in the sample, the set of input and output variables used as a proxy for KBE dimensions, the models' orientation as well as the empirical results.

Additionally, non-radial DEA models are employed for the same sample and by the same methodological considerations for comparability purposes. Finally, the empirical results of all models are compared before summing up and offering concluding remarks to different stakeholders along with study limitations and future research.

Findings from this chapter will provide some suggestions and guidelines for policymakers in developing countries. An important contribution to the literature can be made through the application of DEA in KBE assessment. Using this approach allows us to overcome the problem of KBE measurement and comparison issues among neighbour countries. The shortcomings of existing KBE frameworks in addressing the efficiency scores, presenting the most productive scale size, and identifying the best practice for countries to emulate can be dealt with by applying appropriate methodologies and theoretical backgrounds.

4.2 Conceptual Literature on DEA

4.2.1 The Origin of Data Envelopment Analysis

DEA is a linear programming-based technique for relative/comparative efficiency measurement. It assesses efficiency for any unit/organization relative to other comparable units/ organizations but not in an absolute sense (Thanassoulis, 2001). Likewise, Cooper et al. (2004) defined DEA as "a relatively new" "data orientated" approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs, hence after[1]) which convert multiple inputs into multiple outputs".

This means that DEA calculates the comparative efficiency with which these DMUs could execute the transformation process of converting their inputs to their outputs. These DMUs are homogeneous or mutually comparable units (Marti et al., 2009) i.e., belonging to the same technology (Cook et al., 2015). Further, these DMUs perform the same function, by consuming the same inputs (in different quantities) to create the same outputs (in different quantities). Further, these inputs and outputs are measured in the same manner but in varying amounts from one DMU to another (Benítez et al., 2021). Basically, DEA was initially utilized to assess performance measurement in non-profit organizations but extended to profit organizations as well. In such organizations, the existence of multiple inputs and outputs makes comparisons difficult (Kim & Lee, 2018).

In operations research literature, DEA was originally introduced by Charnes, Cooper, and Rhodes (CCR) in their influential paper "Measuring the efficiency of decision-making units" which incorporates technologies characterized by constant returns to scale (Charnes et al., 1978). Subsequently, Banker, Charnes, and Cooper (BCC) popularized the DEA concept by extending the CCR model to a more realistic model that accommodates technologies exhibiting variable returns to scale (Banker et al., 1984).

However, the origin of the DEA concept has its main roots in the neoclassical production theory and dates to the early 1950s, regardless of its wide introduction within the operations research literature. Economists are concerned with measuring and improving the efficiency of economic systems since the origin of economics as a scientific discipline (Škare and Rabar, 2016). Such necessity arises from the importance of efficiency being an indispensable source of economic development and its role in evaluating the productivity of resources

(1) In DEA literature, A DMU is defined as an entity concerned with utilizing resources (inputs) to obtain favourable outcomes (outputs). It could be profit or non-profit organizations, countries, manufacturing units, universities, shops, police stations, schools, banks, hospitals, tax offices, etc. (Lozić, 2022).

used by the government (Mihaiu et al., 2010). Koopmans (1951) used linear mathematical programming of maximizing an objective function subject to a set of constraints in economic analysis (Cooper et al., 2004).

Koopmans defined a technical efficient point in which the producer cannot be able to produce more of any output of one good without producing less of the output of another good or by using more of some input. Koopmans's definition is similar to Pareto optimality to a large extent, known as the Pareto-Koopmans definition for technical efficiency. Additionally, Debreu (1951) and Shephard (1953) refined this definition due to its inappropriateness in the application as being only theoretical. Debreu (1951) introduced a coefficient of resources utilization to be used as a measure of technical efficiency from an output perspective whilst, Shephard (1953) introduced the same concept from an input direction and measured the technical inefficiency by the radial distance of a producer from a frontier or unity (Ray, 2004).

Later, in 1957, Farrell's seminal paper " The measurement of productive efficiency" empirically investigated the concept introduced by Shephard (1953) on actual input and output data and developed a measure for technical efficiency and decomposes the overall economic efficiency into two multiplicative components of technical efficiency and allocative (price) efficiency (Farrell, 1957). According to Farrell, a DMU is said to be efficient when it is impossible to enhance any of its input or output without worsening some other input or output. However, Farrell dealt with examples with single output and single input only which is not realistic in real world situations (Førsund & Sarafoglou, 2002). By 1958, linear programming became an acceptable method for efficiency measurement in different approaches to economic analysis by Dorfman, Samuelson, and Solow. According to Ray (2004), these writers combined game theory, input-output analysis, and linear programming.

In 1978, a breakthrough was made by Charnes and his co-authors as they identified the limitations of traditional efficiency analysis and refine the pioneering work of Farrell, after approximately two decades, to include real situations with multiple inputs and outputs and developed a non-parametric efficiency measurement technique named DEA.

The basic idea behind DEA is data so it is an empirically based methodology that could eliminate the need for assumptions and shortcomings of traditional efficiency measurement approaches (Rabar, 2017); which are presented briefly in subsequent paragraphs.

4.2.1.1 Traditional Efficiency Analysis

Historically, traditional efficiency analysis has been done by applying different approaches including ratio analysis, cost-benefit analysis, and regression analysis (Alrashidi, 2016). Though, none of these traditional measures are satisfactory for assessing efficiency due to serious limitations. Among these shortcomings is the inability to form an explicit functional relationship between inputs and outputs on the various factors in public sectors, private sector companies, or in non-profit organizations (Pakhnenko et al., 2018).

Of these conventional approaches, ratio analysis of efficiency assessment takes the lead which is simply the ratio of output to input. This means that the more output per unit of input, the greater the efficiency. Further, if the greatest possible output per unit of input is attained, then it is unbelievable to be more efficient without adopting new technology or without implementing other changes in the production process (Sherman & Zhu, 2006). Thomas et al. (2011) indicated that ratio analysis is a well-known technique and calculated R&D efficiency as the ratio of R&D outputs to inputs. Similarly, Chun et al. (2015) assessed R&D efficiency using ratio analysis. Furthermore, the GII is issued annually and aimed at assessing the innovation efficiency of different countries by calculating the ratio of average innovation outputs to average innovation inputs (Dutta et al., 2020).

However, ratio analysis requires a priori set of weights to transform all indicators into a common measure for performance evaluation. Further, ratio analysis cannot operate with situations having multiple inputs and outputs. Additionally, although, ratio analysis is one of the simplest techniques for measuring technical efficiency by using different indicators as ratios, scholars should evaluate different ratios simultaneously to get an estimate of the overall efficiency. Otherwise, calculating only partial indicators for efficiency will lead to misleading results (Thanassoulis et al., 1996).

A second possible approach for measuring efficiency is regression analysis. Although regression analysis is a well-known technique as well, it has serious shortcomings. With regression analysis, it is not easy to incorporate the data structure of multiple outputs into its computational process (Bowlin, 1998). Additionally, specifying a functional form that links inputs to outputs on a prior basis is a must for regression analysis, though this is challenging in complex issues such as in cases of assessing R&D efficiency. Han et al. (2016) declared that it is inconvenient to prescribe the R&D production function because it is unknown; additionally, the nature of the relationship between inputs and outputs is difficult to set up. Furthermore, most of the empirical (observational) data sets cannot comply with the necessary statistical assumptions required by regression analysis (Alrashidi, 2016). Finally, with regression a general tendency approach or average performance; not the optimal performance is considered. Thanassoulis (1993) articulated a comprehensive comparison between DEA and regression analysis along with a detailed explanation to its advantages and disadvantages.

A third conventional approach is a cost-benefit analysis which could deal with multiple outputs and inputs as it measures all costs and benefits flowing from an activity. After that, aggregates all these values, and finally assesses each activity based upon the aggregated scalar score (Rabar, 2017). However, a key limitation associated with cost-benefit analysis is involved in the process of aggregation especially when the activity is usually characterized by many different units of measurement (Womer et al., 2006). Additionally, it is challenging to distinguish clearly between efficient and inefficient activities. Fortunately, this analytical capability is easily accomplished by DEA application as observed later in this chapter (Karami Khorramabadi et al., 2020). Interested readers could refer to Ray (1984) who presented a detailed analysis of the theory and practice of cost-benefit analysis.

4.2.1.2 Modern Efficiency Analysis

Modern efficiency analysis, on the other hand, often called efficiency frontier analysis, can be split into two subdivisions, namely parametric and non-parametric methods. The Non-parametric methods include the DEA and the Free Disposal Hull (FDH).

These methods calculate the scores of efficiencies accurately based on the empirical efficiency frontier; in form of the most pessimistic piecewise envelop all the observed inputs and outputs of the DMUs (objects of analysis) (operating units) under investigation (Rabar, 2017). However, the parametric methods include the Stochastic Frontier Approach (SFA), the Thick Frontier Approach (TFA), and Distribution Free Approach (DFA). They present an estimate of the efficiency scores stochastically. Hjalmarsson et al. (1996) presented a detailed comparison between DEA, DFA, and SFA. As opposed to the non-parametric methods, in parametric methods, the user must define in advance a functional form of transforming resources (inputs) into outcomes (outputs).

In addition, the non-parametric methods measure the technological (technical) efficiency (meaning minimizing inputs at a given level of output; or maximizing outputs at a given level of inputs). Though, the parametric methods measure overall economic efficiency, which is a broader term than technical efficiency as it measures the optimal level and structure of inputs and outputs based on market prices (Vincova, 2005). Therefore, choosing a certain level and structure of inputs and outputs to minimize cost or maximize profit is a must to be economically efficient. This means that economic efficiency needs technical efficiency along with efficient allocation. Additionally, technical efficiency requires inputs and outputs data only; however, economic efficiency requires price data as well. To this end, DEA is an appropriate alternative approach to the econometric approach of stochastic production function given its features (Ray, 2020).

Therefore, this chapter adopts the main non-parametric method which is the DEA to assess the relative efficiencies of developing countries in their transition to a KBE. DEA has been chosen by many scholars over other methods for comparative performance assessment due to its unique and powerful advantages. For instance, many studies such as Zelenyuk (2020), among others argued that DEA is the most extensively applicable technique in the literature and has gained greater attention by many researchers. Additionally, Carayannis et al. (2016) signified DEA as the most prominent method to combine the innovation factors and could calculate NIS effectiveness.

Over and above that, its empirical results are not comparable with other techniques due to the number of outputs being restricted to only one output in the other techniques such as SFA or regression analysis (Karadayi & Ekinci, 2019).

Furthermore, with DEA, one single real number of relative performance efficiency for the KBE is introduced. This single measure can be used as a guide for diversified decisions in a KBE (Klevenhusen et al., 2021). Additionally, in the KBE, most of the variables and the processes that form the KBE are developed by complex interactions i.e., they are poorly understood and are difficult to be modelled. Arundel et al. (2007) contended that in such a situation without a clear theoretical model, without a definite production function linking inputs and outputs, and in an uncertain world, DEA being a flexible estimator, outperforms SFA.

Additionally, input and output prices are not always available in a KBE especially when dealing with the service sector like education; with DEA having an efficiency measure without requiring the use of market prices is possible (Wang & Huang, 2007). Moreover, the KBE is a multidimensional phenomenon i.e., it has many characteristics which can be expressed by diversified proxies of inputs and outputs. Further, it is difficult to set a prior functional form between inputs and outputs in the KBE (Hoff, 2007). Last but not least, DEA can manipulate multiple variables regardless of their market values and non-linearity (therefore fulfilling the criteria of the KBE dataset utilized in this chapter); each of these variables can be expressed in different units of measurement (again, fulfilling our dataset that represents various dimensions of KBE with different input and output indicators) (Charnes et al., 1997).

Before presenting the empirical literature that employed DEA for KBE efficiency assessment; the coming paragraphs introduces the DEA main concept, its models, and their extensions, how it works, its advantages and weaknesses, and its applications in many contexts and in diversified fields.

4.2.2 DEA Concept

Before going through the concept of DEA, it is important to stress that research fields such as economics and operational research agree on mutual interests. One of the prominent areas of interest is performance measurement.

In the literature, there are two different measures of performance whether by productivity analysis or by assessment of efficiency for any DMUs. These two terms (productivity/efficiency) are closely related and are used as synonymous in many studies (Thanassoulis, 2001). However, the former term is a descriptive measure, but the latter is a normative measure. Productivity is defined by Asia Productivity Organization as "Productivity = Efficiency + Effectiveness = Doing things right + Doing the right things" (Roghanian et al., 2012). Additionally, the productivity of a DMU or a firm is measured by ratio analysis which is the ratio of output to input. In this case, the production technology used is not necessarily known. However, efficiency is measured by comparing actual output produced from a given input with the maximum attainable quantity of output. In that case, production technology must be known (Ray & Chen, 2015).

In the DEA literature, studies that are concerned with evaluating the productivity of DMUs through the DEA technique can be divided into two categories: I) productivity assessment using productivity indicators or II) productivity assessment through efficiency and effectiveness. DEA is mainly concerned with the efficiency of DMUs, and the effectiveness is not considered in its assessment process (Esmaeeli et al., 2021). Therefore, from now on, this study deals with efficiency, not with productivity. Carayannis et al. (2016) maintained that efficiency measurement has gained considerable attention over the last years, especially in the aftermath of the recent economic crises as well as the need for efficient use of public money.

DEA is an empirically based methodology that calculates the relative efficiency score by comparing the total weighted outputs to the total weighted inputs through carrying out a linear programming equation for each DMU in the analysed sample without requiring the specification of any functional form between inputs and outputs. It does so through a comparison with the best DMU in the sample to calculate a real relative efficiency score. This efficient frontier is empirically constructed based on the best observed DMUs, and any deviations from this frontier serve as the basis for DMUs benchmarking. Therefore, DEA eliminates the need for some prior assumptions and limitations of traditional efficiency measurement approaches (as in the regression approach). For instance, there is no need for any specific and predetermined functional form linking inputs and outputs, thus the problems of model misspecification are omitted (Ray et al., 2015).

In DEA, the production possibility frontier (in short: the frontier) is built empirically by the observed values of the DMUs that are efficient. All efficient DMUs have an efficiency score of 100% or 1 relative to the rest of the other DMUs under investigation (Zhu, 2015).

In case of having a DMU located in the interior part of the “piecewise” “best practice” frontier, this means that this DMU is inefficient and, this inefficiency is measured by the distance from the point that represents its input and output combination to the corresponding reference point located on the efficient frontier. This inefficient DMU has an efficiency score of less than one but greater than zero. Moreover, the inefficiency may be attributed to output shortages and/or input surpluses. Further, this inefficiency can be solved by reaching a projected efficient point located on the frontier (Manoharan et al., 2009).

DEA has been given the name “envelopment” because of the way the production possibility frontier “envelops” the set of observations that represent the performance of all DMUs in the analysis to locate a frontier where the best performing DMUs are located in this frontier. Then, this frontier is used to assess the relative performance of other DMUs i.e., as a base for benchmarking (Ramanathan, 2003).

Further, unlike, index number approaches, weight flexibility is possible in DEA analysis i.e., weights for input and output variables are formulated within the DEA model as it is determined by the linear programming model itself which determines the optimal weights for inputs and outputs that are needed to maximize the efficiency without requiring a priori setting. In other words, weights are objectively determined by observed data not subjectively determined based on the estimation of their importance from the analyst’s point of view (Osman, 2013).

Thus, DEA is sometimes called an extreme point method as it compares each DMU with only the best DMUs under investigation and the core concern of DEA lies in finding these best DMUs using mathematical linear programming (Vera & Kuntz, 2007). It is also called the boundary-based nonparametric efficiency assessment model (Alamtabriz & Imanipour, 2011).

4.2.3 How Does DEA Work?

Concerning its working, Charnes et al. (1978) operationalized it, through Linear Programming (LP) using the simplex method; the notion of using empirical data from operating units (DMUs) to measure their comparative efficiency. The simplex method is defined as a computational procedure (an algorithm) for solving a linear programming problem. This is done through an algebraic procedure in which a series of repetitive operations are used to attain the optimal solution (Gale, 2007). Through different phases, an efficiency analysis utilizing DEA could be applied by first: defining and selecting the DMUs in the analysis. Second: determining the most appropriate inputs and outputs factors that will enter the analysis. Third: choosing the suitable DEA model depending on the modelled phenomenon. Fourth: selecting the model orientation. Fifth: choosing the DEA software that best fits the DEA model (s) of interest. Six: analysing the outcomes of the proposed DEA model (Tarnawska & Mavroeidis, 2015).

Thanassoulis and Silva (2018) argued that DEAs' mechanism of working can be best understood if it is dealt with it as an advanced extension of key performance indicators. It is worth mentioning, before explaining each phase, to contend that there are basic conditions that must exist while using DEA, such as positivity property, isotonicity property, and homogeneity of DMUs. Bowlin (1998) presented a detailed elaboration of these essential conditions.

Concerning the first and the second phase in the application of DEA, these are two obligatory steps before proceeding with any DEA analysis. Such methodological considerations must be dealt with accuracy; because DEA results are highly sensitive to the sample size (number of DMUs) as well as the inputs and outputs used in the analysis. Moreover, if the number of DMUs decreases or the number of inputs and outputs combination increases, the discrimination ability and accuracy of DEA with respect to the performance of DMUs would decrease (Khezrimotlagh et al., 2021). Thus, the first step is to determine the coverage of the analysis i.e., to set the number of DMUs that will enter the analysis, these DMUs are homogenous which simply means that each uses the same input and output measures, however, in varying amounts from one DMU to another (Dyson et al., 2001).

Broadly speaking, DEA assigns valuable guidelines regarding the relative efficiency of the sample units (DMUs) under investigation when the number of DMUs selected for comparison is significantly larger than the sum of the number of inputs and outputs being considered.

As for the determination of input and output variables; prior to applying the DEA model, setting the methodology for selecting the most suitable inputs and outputs that will enter the DEA analysis is mandatory. This step is critical because the efficiency scores are to a large extent sensitive to the set of input and output variables. This is confirmed by many studies such as Smith (1997) ,among others, as they obtained different results in the efficiency scores dependent on variable selection. Additionally,, Cooper et al. (2007) argued that inappropriate selection leads not only to misleading results but also hinders the technique's ability to introduce meaningful results. Though, in DEA's literature, such selection methodology has gained only limited attention as there are no specific guidelines and there is no consensus on how best to select the variables regarding the input-output combination (inter alia Wong, 2021).

In the DEA literature, most of the existing empirical studies simply treat the input and output variables as "givens" then go on to deal with the DEA analysis without providing any justification for the chosen inputs–outputs combination such as Klevenhusen et al. (2021) and Juřičková et al. (2019). This is because many scholars argue that the selection process of the variables has been done before by the decision-makers and politicians. Then, they proceed as if the selection process is a correct one and there is no reason to doubt it as explained in Cook and Zhu (2007).

On the other hand, some studies have tried to handle this issue and are devoted to the selection of variables in DEA with no agreement on how best to select the variables for instance; Chen et al. (2021) and Sharma and Yu (2015). Fernandez-Palacin et al. (2018) portrayed historically the main contribution of the studies that discussed the selection of variables in DEA since 1982 whether using classical statistical methods or methods that are based on efficiency. Further, Nataraja and Johnson (2011) provided different guidelines for variable selection techniques and how to choose the best fit methodology. Practically speaking, Avkiran et al. (2008) articulated that for a meaningful DEA analysis, the researchers need to select those inputs and outputs that should considered as key drivers (for the inputs) and key objectives (for the outputs) to the analysed DMUs. Additionally, Parkan (1987) stated that the number of selected input variables should be chosen to be greater than or equal to the number of output variables. Another issue during the determination of data structure is how to combine all necessary variables in the case of multidimensional phenomena. Zelenyuk (2020) provided diversified methods for data aggregation before any DEA analysis.

It is noteworthy here that DEA analysis can be applied to different types of data. It could be applied in cross-section through comparing many DMUs at one point in time; or as a time-series through assessing the performance of a particular DMU over time; or as panel data, through combining cross-section as well as time–series data in which a relative efficiency score is calculated for several DMUs over time (Australia, 1997).

Regarding the DEA models, the basic traditional DEA models are the one developed in 1978 by Charnes and his co-author and is named after as CCR model and the other model is the one developed by Banker and his co-author and is named as BCC model. These two DEA models are called radial DEA models and provide radial efficiency measures. Each radial DEA model has its characteristics, uses, and led to different efficiency scores. Thus, selecting the most appropriate radial DEA model is one of the most crucial steps before carrying out the DEA analysis and the decision-maker must set in advance the required objectives/needs before selecting the DEA model to be applied for efficiency assessment. Both models deal with known data (Dehnokhalaji et al., 2022). The mathematical specifications for the most widely cited DEA model, applied in this study, is presented in Appendix (IV).

Though, the main difference between both models is the treatment of returns to scale (constant or variable). While the former assumes constant returns to scale (CRS), the latter (BCC model) assumes variable returns to scale (VRS).

In the CCR model, the relationship between inputs and outputs is exhibiting a constant return to scale i.e., when an increase in the inputs results in a proportional increase in the output. Further, the efficiency of a DMU can be calculated as the maximum ratio of weighted outputs to weighted inputs, subject to a constraint that the same efficiency ratio for all DMUs must be less than or equal to one.

The CCR DEA model is to a large extent restrictive in realistic real-world situations as it measures the technical efficiency of a DMU relative to a production technology characterized by constant returns to scale everywhere in the production frontier (Cooper et al., 2004).

The CCR model calculates an overall (comprehensive) technical efficiency for each DMU, in which, as its name suggests, the internal factors controlled by the decision-maker (technical efficiency) as well as the external factors that are determined by the scale size of the DMU (scale efficiency) are aggregated into a single value (Luptacik, 2010). Therefore, a DMU is a CCR efficient, if it is both scale and technical efficient. This means that the CCR model measures scale and technical efficiency. Moreover, the CCR model assumes CRS, and therefore, the size of the DMU is not considered to be relevant in evaluating its relative efficiency. In other words, small DMUs can produce outputs with the same ratios of input to output as large DMUs can. This is because, under CRS assumption, there are no economies or diseconomies of scale present, so doubling all inputs will lead to a doubling in all outputs (Australia, 1997).

On the contrary, the BCC DEA model is more flexible and the assumption of constant returns to scale is relaxed to include technologies exhibiting increasing, constant, or diminishing returns to scale at different points on the production frontier. This means that the BCC model is built on the assumption of VRS in which an increase or a decrease in inputs or outputs does not result in a proportional change in outputs or inputs respectively. Additionally, the BCC model measures only the pure technical efficiency (managerial efficiency), a measure of efficiency without scale consideration. It does so by only comparing a DMU to a unit of a similar scale. Therefore, a DMU is a BCC efficient if it is only technically efficient. Therefore, the efficiency score obtained using the BCC model is greater than or equal to the score obtained using the CCR model (Reddy, 2015).

Further, in the CCR model, both output and input orientation measures of technical efficiency are identical. But this is not the case with the BCC model.

The BCC model is appropriate for use when the DMUs do not operate under optimal size conditions. In this case, scale efficiency is calculated as CCR efficiency divided by BCC efficiency (Visbal-Cadavid et al., 2017) and indicates the potential productivity gain achieved from the optimal size of a DMU (Raheli et al., 2017). To this end, it is obvious that DEA analysis differentiates between different types of efficiency depending on the applied model. Graphical explanation for the different types is available in Ray (2019). Other types of efficiency include price efficiency and dynamic efficiency, etc. as in Thanassoulis (2001).

Numerous scholars such as Dellnitz et al. (2018) have confirmed that these two radial DEA models have gained the most prevalence in DEA model formulation. Further, Dellnitz et al. (2018) reported that the correct choice between both models is to a large extent a difficult decision. Even though, Han et al. (2016) indicated that a BCC model is not convenient in tracing the change in total factor productivity. Additionally, Podinovski and Thanassoulis (2007) argued that a CCR model brings better discrimination among analysed DMUs.

In the DEA literature, following the basic radial DEA models, numerous developments have emerged such as new DEA models and more advanced DEA extensions. These models and extensions are explained in-depth in Charnes et al. (1994a), among others. Of these advanced models, and without being exhaustive into in-depth analysis, DEA advanced models include but are not limited to non-radial DEA models such as the additive DEA model as in Khodabakhshi et al. (2010), which is a non-oriented DEA model i.e., input reductions and output increases is possible at the same time. Nonetheless, it does identify the inefficient DMUs but without providing an efficiency score (Bardhan et al., 1996).

It is worth mentioning that it is mandatory to differentiate between two variants of model metrics, namely radial and non-radial models. Radial DEA models are given this name because of the proportional (radial) movement toward the frontier. That is the meaning of radial and is referred to as the measuring way of evaluating the degree of efficiency through proportional reduction for all inputs, or the proportional increase for all outputs so that the inefficient DMU becomes efficient. These radial models are represented by CCR and BCC models which are based on proportional changes in the levels of inputs and/or outputs. On the other hand, non-radial DEA models are the models that do not maintain the proportional movement within inputs and within outputs toward the frontier i.e., models that define all possibilities of disproportionate movements in inputs and outputs to reach efficiency, though specific slacks for each input or output. These advanced non-radial DEA models tackle the shortcomings of the previous traditional radial DEA models and includes different models such as the additive model, the multiplicative model, the range-adjusted measure, and the slack-based measure. The interested reader could refer to Tone et al. (2020) for more clarification with graphs. Other more advanced DEA models include the Russell measure of efficiency models as in Salahi et al. (2019), the preference structure model as in Zhu (1996), the range-adjusted measure of efficiency model as in Cooper et al. (1999), the super-efficiency models as in Andersen and Petersen (1993), the cross-efficiency models as in Doyle and Green (1994), the Fuzzy DEA models as in Emrouznejad et al. (2014) and, Network DEA models as in Färe et al. (2007), etc.

As for the extensions, DEA's scholars introduced many valuable enhancements to DEA's literature as, but without providing comprehensive details to it to save space in this chapter, it could be possible to incorporate uncontrollable (or non-discretionary) inputs and/or outputs as for instance in Zarbakhshnia and Jaghdani (2018) and the ability to set and impose restrictions on the weights for inputs and/or outputs or to add prior knowledge as for example in Pourhabib Yekta et al. (2018), among others.

Further notable extensions developed in DEA's literature include the presence of categorical (ordinal) inputs and/or outputs as illustrated in Karadayi and Ekinci (2019); the introduction of a two-stage DEA efficiency analysis as in Ibrahim et al. (2021); presenting a three-stage DEA analysis as in Ribeiro et al. (2021); the possibility to take into account the presence of undesirable factors as defined in Ramli and Munisamy (2013) and lastly the possibility to incorporate machine learning algorithms with DEA models to predict the efficiency scores or to add new DMUs without reconducting the analysis as in Zhu et al. (2020).

It is worth mentioning here also that in DEA literature, there are two versions for each DEA model, namely the "envelopment model" and the "multiplier model". For each envelopment model, there is an associated" dual" model, often referred to as the "multiplier" model. This model provides further information in the form of "weights" assigned to each input and output. These weights are referred to as "multipliers" in the DEA's literature to ensure that they are not predetermined values such as the weights used in the construction of index number of prices, productivities, or cost, etc. That is, the weights in DEA are determined from the data by this multiplier model for each of the DMUs that are being assessed (Sherman & Zhu, 2006).

Regarding the model's orientation, in DEA literature, there are three orientations for DEA models, namely the input-orientation, the output-orientation, and the non–orientation. The DEA models with input orientation are directed toward cost minimization (input conservation) whilst the output-oriented models focus on output maximization (augmentation). Finally, the non-oriented DEA models (or mixed) model assumes both an increase in outputs and a decrease in inputs at the same time (Cooper et al., 2007). In these models, the expected problem of selecting which orientation to apply can be bypassed (Škare & Rabar, 2016).

Cullinane et al. (2005) indicated the appropriateness of both orientations and maintained that input-oriented models are more applicable in the case when the output is fixed for a short time span and hence the main concern is how to use inputs efficiently. However, output-oriented models; present a much more applicable analytical scenario when inputs are considered as given and hence the main objective of economic agents and/or policymakers is maximizing productivity performance over a longer time span i.e., in the medium or long-run future.

In a similar manner, Foddi and Usai (2013) indicated that input–orientation is related to operational and managerial issues and entails short-term objectives, whereas the output-orientation is closely related to planning and macroeconomic strategies and thus span over a long-time horizon. Thanassoulis (2001) pinpointed that selecting the orientation depends mainly on the degree of controllability for inputs or outputs. Output orientation is convenient in situations when outputs are controllable for instance schools have more control in their outputs i.e., the attainments levels of students and little control over its inputs i.e., students' background. However, the input orientation is appropriate when inputs are more controllable. As an example, hospitals have more control over their inputs i.e., the number of doctors and beds compared with its outputs such as the number of patients needing medical treatment.

In many analytical situations, there is no clear-cut priority in choosing between the different model's orientations. As a rule, in practice, select the orientation that yields a lower measure of efficiency under the VRS assumption. With constant returns to scale, the technical efficiency scores from the two orientations would be the same for the DMU (Cheng, 2014).

In DEA modelling, a linear programming model should be solved for each DMU in the analysis. This optimization procedure in DEA serves to ensure that each DMU being evaluated is given the highest score possible by maximizing its relative efficiency ratio subject to constraints (that all efficiency measures must be smaller than or equal to one) while at the same time maintaining equity for all other DMUs (Tan et al., 2008). Thus, DEA is called an extreme point technique (Kuntz & Vera, 2007). Certainly, this step is too long and makes the calculation of relative efficiency score a problematic task. Benítez et al. (2021) argued that numerous theoretical models have been advanced in DEA literature, yet they are not extensively employed due to the lack of proper basic tools i.e., DEA softwares and much work needs to be done to fill the gap between theoretical DEA models and practice. Nonetheless, at the present time, there are many commercial and non-commercial specialist DEA softwares and DEA websites that could be utilized to estimate the relative efficiency score for all DMUs in one DEA model whether conventional or fuzzy models (Charnes et al., 1994b). These softwares are considered lifesavers; they reduce the potential of any human error, though have their limitations (Iliyasu et al., 2015). Examples include but are not limited to; DEA online Solver, Data Envelopment Analysis Program (DEAP), and Efficiency Measurement System (EMS) (Barr, 2004, Daraio et al., 2019).

Recently, Benítez et al. (2021) provided a detailed description of all available DEA software's. However, their most common limitation is that their access required the researcher to pay for it and hence of limited use. It is worth mentioning that there are other software that are not directed to DEA models only as they have the capacity to conduct linear programming and can be customized to execute DEA models for instance, the programming language R as in Wilson

(2008) and Iliyasu et al. (2015) or MATLAB as in Álvarez et al. (2016) and Zhang and Shi (2019). All these non-specific DEA software's incorporate packages to assess efficiency using DEA models. Though, it is not easy to learn such programming languages and their codes to execute any DEA model (Benítez et al., 2021). Appendix (V) presents the latest programs; software and websites for DEA applications that the writer of this thesis is aware of.

4.2.4 DEA Advantages and Drawbacks

DEA has been developed over time as being the most potent approach for comparative efficiency measurement because of the intrinsic merits it possesses over other measurement techniques (Zelenyuk, 2020). The DEA outcomes provide useful guidelines for policymakers as it developed ranking for the DMUs by their relative efficiency score. To elaborate more, The DEA efficiency score has an upper bound of 1 (100% efficient) (best performance) (frontier units) and a lower bound of 0 (inefficient) (lesser performance) (non-frontier units). Therefore, this relative efficiency score for each DMU can be viewed as an integral measure of their performance. In other words, DEA produces a scalar measure of relative efficiency for DMUs under evaluation (Sun, 2002).

Further, DEA outcomes allow identifying the sources and amounts of relative inefficiency in each input and output for every single DMU being evaluated. Additionally, with DEA, the possible ways of improvement for inefficient DMUs can be introduced. It does so by determining target input and/or output levels i.e., the optimal level (required change) of inputs and/or outputs that should be used to obtain the best level of inputs and/or outputs depending on the chosen model orientation. These target input-output levels would make efficient DMUs to be Pareto-efficient and provide a subset of efficient peer DMUs that inefficient DMUs could emulate to improve their performance and become efficient. A DMU is considered a DEA Pareto efficient if it cannot increase any output or reduce any input without increasing other input or reducing other output. These recommended improvements with determining targets are identified with respect to a reference set identified by the closest efficient DMUs and all this (sources, amounts, possible improvements) is introduced for every input and output. Thus, this efficiency ranking is more than just an index number (Bowlin, 1998).

Additionally, the changes in efficiency over time can be done through the Malmquist Productivity Index (MPI) which is the most frequently used method and calculates the relative efficiency of DMUs at different periods of time and could be employed in different areas of research. Therefore, DEA introduces a relative efficiency analysis from static and dynamic perspectives (Liu & Huang, 2022). Another possible method, however, not commonly used, to tackle the changes in efficiency over a longer time span is window analysis (Wang et al., 2021). Over and above that, in DEA models, researchers can consider various external factors (in the form of environmental variables) that are not under managerial control and could considerably affect a DMU'S performance to give a more precise efficiency analysis (Mazzocchitti et al., 2016). Additionally, the DEA method can be used for forecasting the efficiency scores of DMUs, by generating fuzzy data sets (imprecise data) for future time as in Kafi et al. (2021).

Finally, the robustness and effectiveness of DEA over other techniques have been investigated by diversified ways of observation, simulations, and hypothetical data sets using previously known efficiencies and inefficiencies. Of these studies, Nyhan and Cruise (2000) assessed the superiority of DEA by comparing it with two other comparative performance measurement techniques, namely the ratio analysis and the regression analysis. They concluded that DEA outperformed other techniques in incorporating an optimizing principle, not an averaging principle. It is also produced improvement targets for inefficient providers and identifies best practice providers that can be used as a model for operational improvement.

It is worth mentioning that the outcomes obtained from any DEA model must be treated with caution as it is very sensitive to the choice of inputs and outputs as well as the sample size (see Cooper et al. (2004)) for detailed sensitivity analysis in DEA models). Thus, if a variable is omitted from the DEA analysis despite its importance, then the resulting efficiency scores are misleading (Yao & Han, 2010). Consequently, the afore-mentioned explanation and features of this frontier methodology make obsolete the conventional methods of efficiency measurement.

Nonetheless, there are major limitations related to DEA methodology that should not be omitted from consideration. First, DEA efficiency scores can be strongly biased by the statistical noise i.e., random irregularity in data/ unexplained variability and outlier DMUs (Sickles & Zelenyuk, 2019). However, such shortcomings could be dealt with; scholars such as Dharmapala (2021) has introduced different ways to detect outliers in DEA. Second: DEA efficiency scores can be seriously influenced by the content of the DMU sample (when adding each new object of analysis, it is necessary to recalculate the entire system). Third: DEA efficiency scores by DEA cannot be cleared from statistical noise. Fourth: a small sample size and an overly large set of input and output variables seriously biases the efficiency scores (Alirezaee et al., 1998). Fifth, DEA produces efficiency scores with respect to the best practice under the investigated sample units. Therefore, it is not applicable to compare the efficiency scores between two different studies (Australia, 1997).

In the present time, there is tremendous growth of DEA both theoretically and in practical application in diversified fields (Clermont & Schaefer, 2019). For instance, at the micro-level; most scholars employed DEA for microeconomic assessment such as efficiency evaluation at the industry level. Spitsin et al. (2022) estimated the technical efficiency of high technology industries in 1150 Russian companies from static and dynamic perspectives by applying DEA, malmquist productivity index and tobit regression models over the period from 2013 to 2017. In a like manner, Raab and Kotamraju (2006) measured the efficiency of high-tech industries in 50 states of the United States using the DEA additive model in 2002. While, Chen et al. (2006) used CCR and BCC DEA models to estimate the efficiency of six high-tech industries in Hsinchu Science Park, Taiwan, in 1991–1996 and Lu et al. (2010) extended the analysis to calculate the efficiency of 194 high-tech enterprises in Taiwan using two-stage DEA model and Tobit regression model.

This extensive use is obvious in the increased number of publications every year. Since its introduction by Charnes et al. (1978), many bibliographies on DEA applications have been reported in the DEA literature such as Liu et al. (2016), among others. A most cited scholarly survey in DEA applications has reported that in the last four decades within the period from 1978 to 2016 around 10,300 journal articles are published by the end of 2016 (Emrouznejad & Yang, 2018). A much more recent systematic literature review from 2003–2020 was introduced by Rostamzadeh et al. (2021); they identified eight major areas of DEA applications with the transportation and service sectors to be the highest. Further, this study ended by emphasising the great capabilities of DEA as a methodology for performance assessment for various decision and policy making units in which the production function between outputs and inputs are hard to be obtained. As a matter of fact, an instant Internet search by Google for DEA produces no fewer than 6,730,000 entries in 0.69 seconds[2].

In conclusion, it makes sense for researchers and policymakers to use the DEA method over more conventional efficiency evaluation techniques due to the aforementioned features. Furthermore, DEA's benefits have outweighed its drawbacks.

4.2.5 DEA for KBE Assessment

After presenting all the previous DEA literature, it could be possible to define diversified advantages of DEA for KBE assessment. DEA introduces a systematic efficiency score as an integral number. This means that all KBE components are weighted objectively and simultaneously according to an objective function criterion. Additionally given the ability to include multiple output variables in the DEA analysis, all aspects of KBE performance can be considered by using several output variables (instead of only one in other performance measurement techniques). Furthermore, DEA is much more practical, thanks to its high accessibility in the case of lack of data availability. It is also a units-invariant method and thus useful for combining different types of goals and setting different targets and activities in comparison with most econometric methods.

Thus, with DEA, it is possible to have an efficiency score for KBE, determine sources and amounts of inefficiency for inefficient DMUs, conduct a target setting analysis for inefficient countries to be frontier countries or target setting for efficient countries to be Pareto-efficient, trace efficiency changes over time, and forecast efficiency scores for the analysed DMUs.

(2) This search is done by the researcher on 2 June 2022 at 2 AM.

4.3 Empirical Literature for KBE Measurement Using DEA

The theoretical literature on non-parametric efficiency analysis encompassed two strands of thought. On the one hand, the so-called Charnes–Cooper school identified radial DEA models as a non-parametric alternative to econometric models using empirical input and output data. On the other hand, the Afriat School is built on the neo-classical theory of production economics and makes use of aggregate functions such as production, cost, revenue, and profit functions. It uses both observed data as well as information about prices. Therefore, by using the neo-classical theory as the analytical framework, the different DEA models could be presented theoretically (Ray, 2020).

Thanks to DEA's merits and its adaptability as well as the characteristics of the country's performance assessment phenomenon; DEA has dominated this field where it is challenging to know the form of the frontier relations a priori, and in cases when there is an imperative need to incorporate various aspects/characteristics of an economy in the form of multiple inputs and outputs to provide a realistic indication for efficiency assessment. In the existing literature, numerous studies have been conducted to assess countries' macroeconomic and development performance for different regions, cities, and nations. To save space while writing up this chapter, this literature review is fourfold. First, a review of studies on evaluating countries' efficiencies is introduced in Appendix (VI); it presents a sample of DEA literature in assessing countries' efficiencies. It is also advisable to see Škare and Rabar (2016) for previous studies concentrated on the macroeconomic performance assessment. Second, studies which apply DEA to assess KBEs are explored as well. Third, the existing empirical studies in each KBE dimensions are introduced. Finally, the fundamental limitation in existing empirical studies is concluded.

In the area of KBE, despite previously stated DEA's merits, the application of DEA to measure KBE efficiency is not widely used in empirical research to date. Such KBE assessment is crucial for all countries to reap the full advantage of the new prospects introduced by the Fourth Industrial Revolution, which is mainly driven by the transition to KBEs (Droit, 2005). Though, Mutanov et al. (2020) emphasised that modelling the performance of KBE at the regional level is limited. In the same line, Tan et al. (2008) indicated that the application of non-parametric techniques such as DEA is still quite rare in comparison to the application of parametric technique which utilizes econometrics to build an index for KBE measurement. Appendix (VII) listed the few existing empirical studies that employed DEA to assess KBE performance.

By critically examining these empirical studies, it is obvious that research on the assessment of KBE efficiencies using DEA is still limited, despite its significance for future development. To clarify, existing research publications on KBE measurement using DEA are to a large extent scattered and fragmented with Afzal and his co-authors having the highest share in publications. It is also obvious that the study by Afzal and Lawrey (2012 a) presented an overview to the input and output variables selected for the DEA analysis by various studies in the KBE assessment.

Furthermore, by going through the very limited empirical studies that tried to assess the efficiency of KBEs, it can be noted that it was limited only to Radial DEA models (i.e., the traditional input/output oriented CCR and BCC models) and treated the economy as a black box (a whole system). This is done with the assumption that the processes involved consist of one stage; this means that the production process is like a black box, in which the input variables are transformed within this box to produce the output variables (Zhong et al., 2021). Of these empirical studies, Prokop et al. (2018) signified that the level of development of KBE in any country depends on all its determinants. This means that not only is the effectiveness of the innovation system crucial but also the effectiveness of its other determinants, namely economic and institutional regime, education of population and information and communication technology. Thus, the study quantifies the determinants of the KBE in providing its intended macroeconomic effects by means of DEA analysis for 28 EU countries in the years from 2011 to 2015. The DEA guidelines showed that only a minority of the EU countries in the sample were efficient over the investigated period and certainly possessed varying levels of a KBE.

Furthermore, other studies devoted their attention to trace the efficiency changes over time and classified these changes into two components, technical component, and production component. Thus, these studies utilized the

Malmquist productivity index as in Firsova et al. (2022) and Mutanov et al. (2020). Mutanov et al. (2020) designate the KBE performance for the regions of Kazakhstan in the period from 2007 to 2017 using the Malmquist Productivity Index in DEA. Additionally, to the best of our knowledge, the only study that employed a Non-radial DEA model (additive model) is the Afzal and Lawrey (2012a) as it evaluated the KBEs Performance in ASEAN through the application of DEA additive efficiency model. However, a gap in literature pertains with respect to the use of more advanced DEA modelling such as Slack-Based Measure (SBM), and network DEA which takes into consideration the many sub-processes within this KBE, and thus could introduce an in-depth and advanced analysis to this economy.

Regarding the KBE dimensions, it is observed that the empirical literature for measuring the efficiency of innovation systems using DEA, as representative for knowledge production dimension, is to a large extent widely applied. One reason could be that the structure of the KBE can be best explained by endogenous growth models; in which innovation is the main driver for sustainable growth (Cullmann et al., 2009). This is also confirmed by many previous researchers who pinpointed that the knowledge production dimension innovation pillar is the most impactful dimension among the other three dimensions in both developing and developed countries (Phale et al., 2021). Most of the knowledge production studies are manifested in appendix (VIII) which unveiled DEA as an appropriate tool for measuring the efficiency of the national, regional, and sectoral innovation systems. Furthermore, a more comprehensive comparative review of literature, though not up to date, on this matter was carried out by Kotsemir (2013). The scholar has reviewed 11 studies focusing on the choice of DMUs, input and output variables, and the applied DEA models.

To this end, broadly speaking, the existing empirical literature can be divided into three different categories.

First, studies that measure the efficiency of the NIS. It is worth mentioning here that most of these studies devoted their attention to developed countries with little exceptions. As an exception, a study introduced by Choi and Zo (2019) focused on NIS in developing countries. Furthermore, Attia (2015) paid attention to NIS in Egypt. Second, studies that measure the efficiency of the Regional

Innovation System (RIS). Where, Third, studies that measure the efficiency of the Sectoral Innovation System (SIS) as, for instance, in Yang and Li (2021).

Apart from innovation studies, R&D efficiency has acquired considerable attention. This attention is justified by the importance of R&D policies and investments as a base for creating new knowledge and promoting innovation (Gavurová et al., 2019). Further, R&D efficiency measures have become an indispensable objective of management targeting improved productivity (Cook & Seiford, 2009). Additionally, the ground-breaking studies done by Rousseau and Rousseau (1997, 1998) have identified the potential of DEA analysis in the assessment of R&D activities.

Empirically, this attention is manifested in the prior studies devoted their main objective to relative efficiency analysis of R&D whether in industry (Chun et al. , 2015), Organisations (Hoseini et al., 2021), Science parks (Zuo & Chen, 2014), Universities (Ismail et al., 2014), Companies (Kalai, 2019) ; and even at the national level (Wang & Huang, 2007) as well . Other studies devoted their attention to the potential of R&D efficiency by utilizing DEA such as Karadayi and Ekinci (2019); among many others. These studies have provided enough confirmative evidence and most of them are elaborated in-depth in Appendix (VIIII).

As for the knowledge distribution dimension, few studies utilized DEA to assess ICT or education efficiencies. For instance, Đsmail (2008) evaluated the performance of ICT sectors for KBE in selected OECD countries using DEA and Malmquist TFP index in the period from 1980 to 2003. Diskaya et al. (2011) introduced performance benchmarking through DEA Analysis and MPI on the telecommunication sector during the period of global crisis 2007-2010 in Turkey and Group of Eight (G8) countries. Lozić (2022) employed DEA for ICT assessment as well. Aristovnik (2014a) investigated the efficiencies of the information society and the R&D sector at the regional level using DEA. Additionally, Aristovnik (2014b) employed DEA for the efficiency assessment of the higher education systems at national level. To the best of our knowledge, other KBE dimensions, namely knowledge acquisition and knowledge utilization do not utilize the DEA methodology.

It is worth noting that in the above previous studies, the major flaw observed in them was that the majority of studies paid attention to the KBE frontier countries i.e., developed countries with quite rare attention to later comer economies i.e., developing countries. Further, surprisingly, it is noted that none of the existing literature comprehensively addresses the efficiency assessment of KBEs in developing countries. This commentary note is consistent with the conclusion presented by Phale et al. (2021). Only some exceptions were found in Mutanov et al. (2020); Zhuparova et al. (2019) and Yakici Ayan and Pabuçcu (2018) as elaborated in depth in appendix (VII).

Summing up, numerous studies employed DEA to measure the efficiency of knowledge production dimension. Nonetheless, limited studies conducted this analysis on KBE dimensions as a whole and almost no studies for KBE efficiencies in developing countries. Therefore, this background empirical literature yields a fertile scenario for the implementation of DEA to analyse KBE efficiencies in developing countries.

Additionally, this study endeavours to fill the research gap by presenting major contributions to the DEA literature through (1) introducing DEA as a tool for KBE assessment with a salient feature, (2) Applying the traditional radial DEA models, namely the CCR and BCC models in developing countries, (3) conducting a non-radial DEA analysis by employing SBM and Super-SBM for developing countries, and (4) determining the best DEA model that could be used as a tool for KBE assessment.

4.4 Radial DEA Analysis

4.4.1 Methodological Considerations Before Applying DEA Analysis

Prior to applying any DEA model, different methodological considerations should be dealt with before applying the DEA analysis. These steps include determining the number of DMUs that will enter the DEA analysis, selecting the proper combination of inputs and outputs and setting the model orientations are among these considerations.

4.4.1.1 Determination of DMUs

The main concern of this study is to assess the KBE performance in developing countries in 2020. Many international organizations such as the WB, IMF, WTO, and the UN have introduced country classification systems and segregated countries based on diversified criteria (Nielsen, 1959; United Nations, 2020). However, The WB classification by income group is the one applied in this chapter because it is the most used classification in many studies. Additionally, this classification is consistent with the most widely used KBE methodology; that is the KAM developed by the WB.

Additionally, as a rule of thumb, in any DEA application, the number of DMUs should be at least three times the number of inputs and outputs used in the analysis (Shao et al., 2021) . Other studies such as Bowlin (1998); Golany and Roll (1989) recommended different rules. Though, the afore-mentioned rule is the most widely applied rule. See Sarkis (2007) for further clarification.

In this study, the number of developing countries in 2020 according to WB classification as in appendix (X) is 135 developing countries. However, our final sample includes only 65 countries i.e., the number of DMUs is sixty-five, given data availability and DEA rules, as determined in appendix (X). Further, the previous rule of thumb is fulfilled in this study as the DMUs number (65) is greater than three times the selected variables for all KBE dimensions, as shown in the coming paragraphs, multiplied by three (65 > 3 × (8 (inputs) + 5 (outputs)). The justification for the selected variables and the number of DMUs is explained in the coming paragraphs. Thus, the DEA models proposed in this chapter conform to the number of DMUs requirements.

4.4.1.2 Determination of Input and Output Variables

In the area of a KBE, the input variables outline the resources available, investments (capacity-building efforts) for each knowledge dimension toward KBE transformation. It includes monetary and non-monetary indicators. In other words, knowledge inputs could be described as the resource environment required for knowledge development (Tan & Hooy, 2007). On the other hand, the output variables define the degree of KBE that a country has or the country's achievements from utilizing the knowledge inputs. This means that the output variables elaborate the economic impact of these inputs by measuring the amount of existing knowledge or through evaluating 6the performance of a country towards a KBE. Most output variables are technology-oriented and include monetary and non-monetary indicators as explained in Karahan (2012), among others. These input and output variables should have logical cause-effect relationships and be complementary to each other (Tong & Liping, 2009). It is noteworthy that Nurunnabi (2017) is one of the most comprehensive studies that summarized almost all KBE components and their indicators from past KBE studies; yet without subdivision into inputs and outputs indicators and within the context of only one country, namely Saudi Arabia.

Before applying the DEA model to assess KBE performance, it is crucial first to determine the conceptual framework for the KBE (Afzal & Lawrey, 2012 c, e). After that, setting the methodology for selecting the most suitable inputs and outputs for the DEA analysis. Thus, in this chapter, the conceptual and policy-focused KBE framework is based on the WB definition of the KBE. This definition is the most widely used and the most comprehensive definition in the literature and covers most of the KBE dimensions (Amirat & Zaidi, 2020).

Additionally, the final selection of inputs and outputs are those having theoretical underpinnings, included in the prior empirical literature along with data availability for all countries in the sample. Table (4.1) presents the most used proxies in the prior empirical literature for KBE under each knowledge dimension and their segregation into inputs and outputs. While Table (4.2) shows the final selection of eight inputs and five outputs applied in the employed DEA models.

Among the studies which are utilized to back up the possible proxy indicators for KBE assessment are Afzal and Lawrey (2012a, b, c, d); Siddiqui and Afzal (2022), among many others mentioned in-depth in appendix (VII). Additionally, these inputs and outputs are not only the commonly used variables under each knowledge dimension in the prior empirical studies but also, are those used by the international frameworks for KBE assessment as OECD, WB, and ABS.

However, if all the previously used indicators for KBE assessment are collected, an un-ended list of proxies which can be segregated into KBE inputs and outputs variables could be introduced. On the other hand, although DEA works best with larger numbers of DMUs, the inclusion of many inputs and /or outputs in the DEA analysis will lead to having a greater number of efficient units, i.e. the number of DMUs that are likely to be given a score of 100% will be high and hence the discrimination power of the applied DEA model will not do a good job (Su et al., 2020). Cooper et al. (2007) contended that having inaccurate number of DMUs in proportion to the number of inputs /outputs combination will introduce a large portion of the DMUs as efficient. Thus, the efficiency discrimination among DMUs will be lost. In another perspective, the number of degrees of freedom will increase with the number of DMUs and vice versa; decrease with the number of inputs and outputs (Khezrimotlagh et al., 2021). This argument is supported by the earlier contribution by Golany and Roll (1989) who maintained that the inputs/outputs selection is crucial for DEA to work effectively.

To this end, it is crystal clear that selecting the most appropriate inputs and outputs to enter the DEA analysis out of numerous KBE variables is of paramount importance and will lead to DEA results with an exact number of efficient DMUs. However, the well-established empirical literature on the assessment of KBE efficiency, as presented previously in section three, shows challenges with the choice of variables and sometimes scholars treated KBE variables as given.

Given this paramount importance of variable selection in any DEA analysis, unfortunately, in DEA literature, there are no strict rules on how best to select the most relevant input and output variables. However, there are several practical guiding principles and methods used which are considered additional (non-DEA) analysis to help the researcher select the best data structure for DEA analysis. One of these guidelines, though it is just a rough idea, is that the number of selected input variables must be greater than or equal to the number of output variables (Parkan, 1987). On the other hand, concerning the reduction methods that could help in selecting the most appropriate DEA structure, correlation matrix[3]; principal component analysis[4] and beta coefficient technique are the

[3] To clarify, correlation analysis can be applied to select the most relevant input/output factors that will be used in the analysis. For instance, if two inputs are highly correlated, then they perhaps represent the same thing and hence one of them could be excluded from the analysis Bastani et al. (2021).

[4] Another method for reducing the inputs and output variables is PCA. Zhu (1998) presented PCA as a complementary approach to DEA. PCA helps the decision maker to liberate data from redundancy and hence minimize the data structure of DEA variables into certain principal components which in turn leads to the possible minimum loss of information and hence, helps in increasing the discrimination power of DEA models. Many studies have employed this methodology due to its usefulness. For

commonly used methods among many others.

If the previous guideline to all these commonly used KBE variables is applied, then 18 inputs and 12 outputs could be used in the DEA analysis, so the rule of having inputs number greater than that of outputs is satisfied. However, the second rule which is related to the number of DMUs in comparison to the total number of inputs and outputs is not satisfied because of missing data in our collected dataset. As presented in Table (4.1), the magnitude of the missing data in the whole data for the collected variables is high as indicated in parentheses in Table (4.1). Therefore, several trials have been done to opt for appropriate number of inputs, outputs and DMUs[5].

Table (4.1): Most Commonly Used Indicators under Each Knowledge Dimension Along with Data Availability in the Dataset.

KBE Dimensions	Inputs	Outputs
Knowledge Acquisition	Transparency (135/135) Government Effectiveness (135/135) Rule of Law (135/135) Regulatory Quality (135/135) Foreign direct investment, net inflows (% of GDP) (132/135) Easy of doing a business (130/135) Trade openness (Exports+ imports)/GDP (129/135)	Human Development Index (HDI) (131/135) Real GDP Growth (129/135) Competitiveness (87/135)
Knowledge Production	R &D expenditure as % GDP (90/135) Intellectual Property Rights (IPR) (86/135)	Scientific and technical publications (134/135)

instance, Garcia (2020) presented a Sustainable Knowledge Economy Index (SKEI) by using a PCA to minimize 26 KBE variables to a few dimensions which makes it easy to assess KBE in developing and less-developed countries. Furthermore, Amirat and Zaidi (2020) and Zeb (2022) demonstrated the usefulness of PCA analysis in sorting out the problem of multi-collinearity and reducing the KBE indicators to solve the issue of over-parameterization in multidimensional phenomena such as the KBE.

[5] Firstly, in this analysis, it is attempts to sort out the issue of missing data and thus executing a DEA analysis for the whole sample of developing countries (135 developing countries) by filling in missing data with different methods of dealing with missing data. It is obvious from the very beginning of this chapter that the basic idea behind DEA is data. Therefore, missing data hinders any trials for accurate calculation of relative efficiency scores. Though, in the DEA literature, many approaches could be used to deal with missing data. For instance, Kao and Liu (2007) introduced a comprehensive explanation for ways to sort out missing data. One of the most used approaches is to delete the DMUs with missing data, though this approach is criticized for two reasons; deleting DMUs with missing values leads to the loss of information that these deleted DMUs have. It also brings about an overestimation of relative efficiencies for the remaining DMUs under evaluation. A fuzzy DEA approach could be another effective alternative to deal with missing data. While the analysis aims to evaluate KBE efficiency in all developing nations, it excludes countries with missing data. In the dataset, out of 135 countries, only 40 developing countries have complete data. The DEA conclusion, however, contradicted logic as all nations are regarded as frontier nations—that is, as efficient nations with a 100% efficiency score. One explanation for this would be that the DEA application rule of thumb, that the number of DMUs should be greater than 3*(inputs +outputs) is not satisfied, because in the dataset, at least 90 nations = 3*(18 inputs + 12 outputs) with a complete data set are needed. Therefore, to solve the problem of having a dataset that includes at least 90 nations, there are two possible approaches: either use impute missing data, or reduce the number of inputs and outputs.

KBE Dimensions	Inputs	Outputs
	Researchers in R&D (per million people) (80/135)	Trademarks application, total (111/135) Patents Granted per million people (87/135)
Knowledge Distribution	Education expenditure as % GDP (130/135) Net enrolment ratio at secondary school (123/135) ICT Access (117/135) ICT Price Basket (113/135)	percentage of households with a computer (131/135) School enrolment, tertiary (% gross) (130/135) Government Online Service Index (127/135) ICT use (117/135)
Knowledge Utilization	FDI net outflows % GDP (131/135) Knowledge transfer rate (129/135) Intellectual property payments (121/135) High-Tech Imports, % of Total Trade (102/135)	High-tech Exports % of manufactured exports (109/135) Medium and high-tech manufacturing value added (% manufacturing value added) (96/135)

Table (4.2): Final Selection of Key Influence Factors and Their Proxy Input-Output Indicators.

Dimensions	Inputs	Outputs
Knowledge Acquisition	Foreign direct investment, net inflows (% of GDP) Easy of doing a business	Real GDP Growth
Knowledge Production	R &D expenditure as % GDP Intellectual Property Rights (IPR)	Scientific and technical publications Patents Granted per million people
Knowledge Distribution	Education expenditure as % GDP ICT Access	Percentage of households with a computer
Knowledge Utilization	Knowledge transfer rate Foreign direct investment, net outflows (% of GDP)	High-tech Exports % of manufactured exports

Because this chapter aimed to include as many as possible of the developing countries, different missing data algorithms[6] are employed using XLSTAT, statistical software for Excel, but the DEA efficiency scores were still not plausible as almost all countries (130 countries out of 135) are defined as efficient countries. In this case, the DEA result is consistent with Charles et al. (2019) and Ray (2020) who argued that the sample size can be an issue of great importance in determining the efficiency scores for the evaluated units, empirically, when the use of too many inputs and outputs may result in a significant number of DMUs being rated as efficient. Likewise, Cheng (2014) argued that in real-world situations when the number of DMUs is often fixed, the only way to improve the

(6) XLSTAT provides different methods in dealing with missing data such as: using a mean imputation method; using a nearest neighbour approach, or replace missing values with a given numeric value, Using the NIPALS algorithm; using an MCMC multiple imputation algorithm, or using the EM (Expectation-Maximization) algorithm for data following a multivariate normal distribution. A detailed explanation of each algorithm is available in the user guide when the package is installed on the computer from this website: https://www.xlstat.com/en/.

discrimination power of the DEA is by reducing the number of inputs or outputs[7]. In this DEA analysis, only actual data are used in the analysis without any missing data computations.

Thus, choosing the most appropriate variables out of many KBE variables is crucial. This is done in this chapter by applying the beta coefficient technique (explained in depth in the appendix (XI)) to select the most contributing indicators for KBE in developing countries. The beta coefficient technique is commonly used in the DEA analysis for selecting the most critical inputs and outputs variables owing to the lack of clear criteria of how to choose the inputs and outputs variables as in Afzal and Lawrey (2012a, b, c); Amirat and Zaidi (2020) and Lu et al. (2010). A standardized beta coefficient simply compares the strength of the effect of each individual independent variable to the dependent variable. The higher the absolute value of the beta coefficient, the more the effect (Bring, 1994)." In our DEA analysis, eight inputs and five outputs are kept as a result of applying the beta coefficient technique (see table 4.2).

To conclude, for the primary selection of inputs and outputs, the prior literature on KBE is considered to preserve research consistency with previously mentioned empirical studies, as well as data availability in developing countries. At the same time, the selected input-output KBE variables are chosen under the

(7) In this study, several methods have been applied to minimize inputs and outputs as follows; I did random choices from the commonly used variables in the literature. However, I found that the distinguishing ability of the model slightly increased but still unrealistic results in the sense that the efficiency score does not reflect the actual performance of these countries in transition to a KBE. i.e., efficient countries are the smallest countries in the sample in terms of their performance. (This is the case when I applied the DEA model on the whole sample (135 countries) with missing data imputation or the small sample with actual data without missing data computation (40countries). I also used a dimensionality reduction method known as principal component analysis for each knowledge dimension after following the conclusion presented in Nataraja and Johnson (2011) and I did the analysis, using the XLSTAT package on Excel, eight times for the inputs and outputs that are used as a proxy for each knowledge dimension. I took the first component as a representative for each dimension to represent the whole data set. So, to this end, I have 4 principal components for the inputs and 4 principal components for the outputs. But, in the principal component analysis, you either choose to delete missing observations or to choose an estimation method for the missing observation. The problem is that the efficient countries are the ones with the highest number of missing values (the result of my DEA analysis was that countries such as Korea, Dem. People's Rep, American Samoa, Venezuela, and Afghanistan are defined as efficient). I tried also to use the variables in the first principal component with the highest squared cosines, but still to a large extent the same result. Another trial is that I did a regression analysis and I considered only the less correlated inputs and outputs one time and the high correlated inputs another time as there is no clear guideline in DEA literature about whether to use high correlated or less correlated variables, but still, the efficient countries are small countries in their performance similar to my study (Mauritania, Ethiopia, Myanmar, Chad) compared to other countries in the analysis.

assumptions previously introduced in the ABS framework (Trewin, 2002). However, the final selection of inputs and outputs in this chapter is restricted by data availability. This is because the data availability issue is a hampering issue in KBE assessment especially in developing countries. To elaborate more, OECD databases offer, to a large extent, the most comprehensive indicators for KBE, though; they do not include most of the developing countries. Therefore, the final selection is theoretical, and data driven as well. That is, these inputs and outputs are part of the commonly used variables i.e., have a theoretical base, used in the prior empirical studies related to DEA application and KBE assessment, used by international frameworks for assessing the KBE and are available for most developing countries. Additionally, this selection is guided by the theoretical principles of DEA, and the latest selection is finalized based on data availability for developing countries in 2020.

Another criterion in the determination of inputs and outputs is that due to the nature of the selected inputs and outputs, comparisons between countries are made on a yearly basis. Given the previous discussion and guidelines, and after previously mentioned trials, this study finally opts for eight inputs and five outputs in the employed DEA models as observed in Table (4.2). The theoretical and empirical justification for many of these variables and their effect on economic development is presented in many studies such as in Kassicieh (2010) and studies included in appendix (VII). Additionally, this final selection of inputs and outputs is also consistent with the theoretical principles in DEA literature. So, the rule which requires that the number of selected input variables (eight variables in this study) must be greater than or equal to the number of output variables (five variables in this study) is satisfied and the rule of 3 times the number of inputs and outputs is also applied. Appendix (XII) presents a detailed description of the selected variables along with data sources.

For the knowledge acquisition pillar, FDI is the first chosen input variable and is used as a proxy for knowledge acquisition. FDI is of a paramount source of technology transfer and the necessary capital to upgrade their existing one. FDI provides substantial financial capital, technological know-how, enhanced management skills and managerial expertise; and hence allows for growth and offers many development opportunities to the recipient (host) economies. That is why many countries especially developing ones follow policies to encourage inward FDI to reap the advantage of the technology transfer that it entails (Liang et al., 2021; Mohamed et al., 2022). In FDI literature, there is a large and ongoing body of work on the impacts of FDI on economies as in Liang et al. (2021); Bruhn et al. (2020); Adhikary (2017); Chen (2017a); Rehman (2016); Iamsiraroj (2016); Khaliq and Noy (2007); among others.

The second used proxy for knowledge acquisition is the ease of doing a business score developed by the WB group as an indication of a simple business environment in which friendly regulations for businesses and stronger protections of property rights exist. Therefore, in this DEA analysis, FDI and ease of doing business as input variables. While real GDP growth is the only output variable in the knowledge acquisition dimension. This indicator is used in many studies as a proxy for knowledge acquisition such as Amirat and Zaidi (2020).

Concerning the knowledge production dimension, most of the studies on the assessment of knowledge production or innovation systems efficiency, reveal problems with the choice of variables. These studies exhibit quiet little similarity regarding the input variables as they used more than one variable of the following: R&D expenditures as a proxy of investment; the number of R&D personnel as a proxy of human capital; the intellectual property rights to reflect the prerequisite environment required for any innovation activity as in Juřičková et al.(2019); Roman (2010); Lu et al. (2014); Foddi and Usai (2013); Zemtsov and Kotsemir (2019); Wang and Huang (2007); among others. For a more exhaustive treatment of the knowledge production variables, the reader can refer to Kotsemir (2013) for more details.

On the other hand, scientific and technical publications and patents granted per million people are the commonly used variables to approximate the output variables by many studies as they represent the skillfulness of any country in terms of their investment in various innovation aspects. Scientific and technical publications refer to the number of scientific publications published in scientific journals and books. This indicator has been used in many prior empirical studies and more specifically when examining developing economies position in innovation as in Thomas et al. (2009; 2011); Rousseau and Rousseau (1998); Hu et al. (2014); Aristovnik (2012a); Oluwatobi et al. (2020); Lee et al. (2009); Han et al. (2016), among others.

However, scientific and technical publications as a proxy for knowledge production have been somewhat criticized for many reasons of which measurement problems and language bias (Cullmann et al., 2009). Thus, unlike the other three KBE dimensions, we added two outputs for this dimension because of the mentioned criticism of scientific and technical publications.

Patent activity is the second proxy for knowledge production in this study. It is also one of the most popular output variables in literature to approximate innovative output; to mention but a few Han et al. (2016); Cullmann et al. (2009); Johansson et al. (2015); Thomas et al. (2009; 2011); García-Valderrama et al. (2009); Aristovnik (2012a); Roman (2010); Rousseau and Rousseau (1997; 1998); Hu et al. (2014); Lee et al. (2009); Lee and Park (2005). However, trademarks as an indicator for country-specific knowledge spillovers and circulation of new knowledge; is not a widely used variable. To the best of the researcher knowledge, Choong and Leung (2021); Avilés-Sacoto et al. (2020), and the global innovation index are some of the limited studies that employed this variable in the KBE assessment.

Therefore, R&D expenditure as % GDP and Intellectual Property Rights (IPR) are used here as the input variables. While scientific and technical publications per 1000 of the population and patents granted per million people are used as the output variables. It is important to stress here that, most of the previous studies used time lag between inputs and outputs in assessing innovation or knowledge production (Prokop et al., 2018). However, in this chapter, there is no reason to use this lag because this chapter aimed at assessing the performance of all knowledge dimensions not the production dimension.

As for the knowledge distribution dimension, it includes all forms of disseminating or diffusing knowledge by way of ICT and the transmission of knowledge by way of education. For education, education expenditures as % GDP is used as the input variable and for ICT, ICT Access is used as the input indicator Aristovnik (2012 b). On the output side, the percentage of households with computers is used as the only output variable due to data availability. These input and output proxies are used in previous empirical studies such as Afzal and

Lawrey (2012 b, e).

Finally, for the knowledge utilization dimension, knowledge transfer rate, and FDI net outflows as a percentage of GDP are used as inputs variables. University–industry collaboration or knowledge transfer rate is a distinguishing characteristic of the KE. A study by El Hadidi and Kirby (2017) highlighted the difference forms of this collaboration with key drivers to this collaboration.

Although the impact of outward investment flows is less researched, there is growing evidence that this outward investment can boost a country's investment competitiveness and put firms under continuous pressure to innovate. Thus, countries are using it as a channel for sustainable growth and a catch-up strategy to utilize existing knowledge and technology. Firms investing abroad must cope with competitive pressure to conduct R&D, upgrade production processes, boost managerial skills, innovate, and access wide distribution networks (Schwab, 2018). On the other hand, the output proxy for knowledge utilization dimension is high-technology exports as a percentage of manufactured exports. This output proxy reflects the products with high R&D intensity, such as in aerospace, computers, etc. and is used as the output variable. Many scholars used this variable such as Lee and Yoon (2015), Roman (2010), Aristovnik (2012a), Saljoughian et al. (2013), Boon et al. (2014), among others used this as an output variable.

4.4.1.3 Data Collection

To conduct this DEA analysis, the WB online database as indicated in appendix (XII) is employed. Data collected was cross-sectional data as it was collected for all developing countries in 2020 or the closest available year. This means that, due to data availability, some of the data came with a time lag.

For instance, data for ICT access is mostly form 2017 or before. Additionally, stemming from the available data for all inputs and outputs for each country even with a time lag, the sample size has been reduced to only 65 countries from the whole 135 developing countries in the 2020 data. This data limitation is consistent with the conclusion presented by Andres et al. (2021), who argued that disparity among KBE measurement frameworks as well as missing data specifically in developing and emerging countries continue to exist in the evolving literature and restrict any policy formation trials and further research.

4.4.1.4 Descriptive Analysis for the Selected KBE Variables

A statistical descriptive analysis for all considered input and output variables, including mean, standard deviation, minimum value, and the maximum value was carried out on the sample data as exhibited in Table (4.3) using SPSS software. It is worth to stressing that these descriptive statistics are done just for explaining the data and show only the distribution of variables but are not included in the main DEA analysis (Lu et al., 2014).

The descriptive statistics enumerated for the selected inputs and outputs demonstrated that the developing countries are not very homogeneous as there is great variability of the data. This heterogeneity is mainly due to the highest variation between developing counties in knowledge transfer rate and ease of doing a business from the input side, and the scientific and technical publications, percentage of households with a computer from the output side. It is also noticed that there is a wide variance in the minimum and maximum values of the units in all sets of input and output variables. Certainly, this pattern is plausible as the sample countries are at different stages of KBE transition. Thus, these countries have significantly different KBE achievements. Additionally, standard deviation is relatively large in comparison with mean in case of FDI net inflows, FDI net outflows, real GDP growth, patent granted and high-tech exports which indicates the skewness of distributions and/or outliers. However, standard deviation is less than the arithmetic means for all other variables which indicates to a large extent a small variation between developing countries.

Concerning the degree of correlation between inputs and outputs which is a crucial issue as it has a great impact on the robustness of the applied DEA model. Thus, a correlational analysis for the chosen inputs is presented by the correlation matrix in Table (4.4) using the same utilized software, namely SPSS. Abd El-Fattah (2011) argued that if very high correlations (higher than 0.95) are found between an input variable and any other input variable (or between an output variable and any of the other output variables), this input or output variable may be thought of as a proxy for the other variables. On the other hand, if an input variable has a very low correlation with all the output variables (or an output variable has a very low correlation with all the input variables) this may indicate that this variable does not fit the model.

Table (4.3): Descriptive Statistics for the Selected Input and Output Variables.

Variable	Observations	Minimum	Maximum	Mean	Std. deviation
Input Variables					
Ease of doing a business	65	41.288	83.734	64.433	9.934
Foreign direct investment, net inflows (% of GDP)	65	-11.625	17.457	2.872	3.834
R & D expenditure as % GDP	65	0.011	2.141	0.409	0.377
Intellectual Property Rights (IPR)	65	2.730	5.390	3.839	0.580
Education expenditure as % GDP	65	1.821	9.410	4.245	1.485
ICT Access	65	2.140	7.550	4.774	1.465
Knowledge transfer rate (university to industry)	65	16.670	68.300	38.979	9.657
FDI net outflows % GDP	65	-1.140	3.920	0.482	0.842
Output Variables					
Real GDP Growth	65	-11.000	6.100	-3.511	3.859
Scientific and technical publications per 1000 pop	65	18.540	528263.250	16782.058	67959.951
Patents Granted per million people	65	0.000	14.460	0.892	2.098
percentage of households with a computer	65	1.000	83.800	31.806	24.164
High-tech Exports % of manufactured exports	65	0.013	62.247	8.922	12.131

Evidently, the matrix of correlation coefficients between the study variables showed that most of the variables have moderate correlation coefficients (not too high or too low) to each other. Therefore, as there is no evidence of a very high correlation between the input variables (nor between the output variables); this is a reasonable validation of the presented DEA models in this study as explained in Aristovnik (2014b) and Moutinho et al. (2021).

Table (4.4): Correlation Matrix for the Study Variables.

Correlation Matrix (Pearson(n)):													
	Ease of doing a business	**FDI net inflows**	**R & D Exp.**	**IPR**	**Education Exp.**	**ICT Access**	**Knowledge transfer rate**	**FDI net outflows**	**Real GDP Growth**	**Scientific publications**	**Patents Granted**	**households with a computer**	**High-tech Exports (%)**
Ease of doing a business	1												
FDI net inflows	0.161	1											
R & D Exp.	0.432	-0.056	1										
IPR	0.432	-0.146	0.343	1									
Education Exp.	0.008	0.087	0.194	0.165	1								
ICT Access	0.677	0.086	0.421	0.309	0.087	1							
Knowledge transfer rate	0.450	0.115	0.437	0.676	0.060	0.323	1						
FDI net outflows	0.122	0.074	-0.034	0.046	-0.016	-0.024	0.287	1					
Real GDP Growth	-0.225	0.017	0.212	-0.150	-0.230	-0.253	-0.023	-0.019	1				
Scientific publications	0.229	-0.076	0.674	0.177	-0.058	0.133	0.294	0.008	0.176	1			
Patents Granted	0.419	-0.034	0.751	0.309	-0.012	0.389	0.448	0.016	0.066	0.845	1		
households with a computer	0.555	0.016	0.425	0.277	0.003	0.902	0.197	-0.020	-0.115	0.175	0.403	1	
% High-tech Exports % of manufactured exports	0.292	0.065	0.274	0.325	-0.072	0.219	0.469	0.169	-0.021	0.245	0.386	0.195	1

4.4.2 Appling Radial DEA Models

4.4.2.1 The DEA Models

Because inputs/outputs variables used as a proxy for KBE dimensions are not conventional/traditional factors of production i.e., they may exhibit constant returns to scale, increasing returns to scale, or decreasing returns to scale. This means that prior knowledge of the production frontier characteristics could not be determined previously. This theoretical proposition is empirically proved by Klevenhusen et al. (2021) who affirm that there is no clear guideline in the literature on whether these returns are constant or varying. Therefore, in this DEA analysis, the two radial DEA models are employed to evaluate the relative KBE efficiencies for 65 developing countries in 2020. The first model is the CCR model and is employed to assess the overall technical efficiency (OTE); whereas to estimate the pure technical efficiency (PTE) and scale efficiency (SE) as two components for the overall technical efficiency, the second model which is the BCC model is applied as well.

4.4.2.2 Model's Version

The version of the models in this DEA analysis is the "envelopment model" because the concern is with the relative efficiency scores, not the "weights" assigned to each input and output.

4.4.2.3 Model's Orientation

In this DEA analysis, the concept of KBE efficiency is used to mean how big the output of the knowledge economy in a specific country is compared to the facilities/investments/resources the country has. In other words, the output-orientation is applied in this DEA analysis by considering that the resources invested in the KBE dimensions (for example: in education, ICT, innovation) for a specific country are given and thus the objective of the decision-maker is to maximise achievements/outcomes from these KBE inputs/resources to improve the position of developing countries in the KBE.

It should be noted that in this situation, the objective is to maximize output (KBE outputs) rather than reducing KBE inputs to achieve efficiency. This is because it is not advisable to reduce input variables of KBE in developing countries as there is an inadequacy in many KBE inputs such as education expenditures and R&D expenditures in most developing countries compared to developed countries. Thus, it is more sensible, from a practical view to consider the output-oriented DEA model that will determine exactly by how much a decision-maker output quantities can be proportionally increased without affecting the amounts of resources (inputs) that a specific country has. This output orientation is consistent with many prior works such a Afzal and Lawrey (2012 a, b, c, d). However, this is contrary to Prokop et al. (2018) who used N input-oriented approach.

Another justification for choosing the output orientation is that macro-economic objectives rather than short term objectives are the main concern of this chapter, and in this case the researcher should follow the output orientation rather than the input orientation. Furthermore, given that the KBE inputs used in this chapter are all favourable input variables, it is not logical to seek reduction in these inputs because increasing these KBE inputs not decreasing them is needed, on contrary to what is supposed to happen if the input-orientation is employed.

4.4.2.4 Software Used

All the DEA estimates are obtained using Ultra Max DEA. It is worth noting the great diversity of models implemented in Ultra Max DEA software as well as its ease of use as it comes in a folder and do not require any installation. This software offers two versions to users: (1) Max DEA Basic, which is free of charge and allows running basic and limited DEA models under different orientations and returns-to-scale with no limit of DMUs, and (2) Max DEA Ultra, which is the commercial version in which a wide variety of advanced DEA models and extensions are available. Iliyasu et al. (2015) introduced further details.

4.4.2.5 Required Adjustments to the Selected Inputs and Outputs Data

During the collection stage of data, multiple imputations have been proposed to meet the basic conditions of applying the DEA analysis. As observed in the introductory section, negative values and zero values are not permitted in radial DEA models (Sarkis, 2007). In DEA’s literature, there are different ways of dealing with negative numbers and the other required adjustments before applying any DEA modelling. For instance, Mohamad (2007) normalised all the indicators used in his study because some indicator's values were negative, i.e., in the rate of growth and inflation indicators. Lin et al. (2019) confirmed that methodologies for dealing with negative data have grown in use with so many contributions from DEA scholars. However, given that the software employed is Ultra Max DEA; thus, negative values in either inputs or outputs are dealt with automatically (Cheng, 2014). The default way of dealing with negative values in Ultra Max DEA is called the Variant Radial Measure (VRM) and is introduced by Cheng et al. (2013). In this approach, original values are replaced with absolute values to quantify the proportion of improvements to attain the frontier. This method can be extended to all types of distances i.e., non-radial models. As for zero value, it must be avoided in inputs and outputs. The best solution to deal with zero values is to delete the DMUs with zero values or to delete the input or output variable with zero values. Whether to accept or to reject zero values depends on model orientation as well as model type (Cheng, 2014). To this end, it is worth mentioning here to contend that DEA results are highly sensitive to the selection of inputs and outputs used in the analysis. Certainly, other input and/or output data would probably yield different DEA results.

4.4.3 Empirical Results for the Radial DEA Analysis

4.4.3.1 Overall Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency Scores

In this section, the efficiency scores obtained from the output oriented CCR and BCC models have been reported. There are three types of efficiency scores of great importance to this DEA analysis, namely overall technical efficiency (OTE), pure technical efficiency (PTE), and scale efficiency (SE). Along with these three types of efficiency, returns to scale (RTS) levels can be calculated as well.

These three types of efficiency scores are all continuous scores ranging from 0 to 1 whereas RTS is a categorical ordinal variable with three diversified levels, namely decreasing, increasing, and constant. Table (4.5) presents these scores for 65 developing countries in 2020. Since the applied models' orientation is output, therefore the technical output efficiency refers to the degree to which the output levels of the country concerned can be increased through improved performance, without any additional inputs/ resources (Thanassoulis, 2001).

With respect to the CCR Model, as shown in columns 2 and 3 of Table (4.5), there is a considerable variation among developing countries regarding their overall technical efficiency scores with most of these countries being inefficient. Of the sample countries, there are only around 32% (21 Countries) that turned out to be efficient and form the efficiency frontier whereas the remaining countries about 68% (44 Countries) are inefficient. Among these inefficient countries, Kenya is found to be the most inefficient country as its efficiency score is only 25.76%. On the other hand, North Macedonia is the least inefficient country with an efficiency score of approximately 98.98%.

Furthermore, the average of the technical efficiency scores is 74% for the 65 developing countries (see Table (4.6) for descriptive statistics of the OTE scores). Additionally, this result reveals that the magnitude of overall technical inefficiency among developing countries turned out to be on average, about 62%. Additionally, among the 44 inefficient countries, 25 inefficient countries have an efficiency score below the average overall technical inefficiency score (0.62) and only 19 inefficient countries have an efficiency score above the average overall technical inefficiency score. To this end, it is also suggested that developing countries can, on average, able to produce 1.35 times (i.e., 1/0.74) as much as outputs from the same level of input by adopting best practice technology. Notwithstanding, this potential increase in outputs from adopting best practice technology varies from one country to another.

Concerning the BCC model, which does not consider the scale size of the country, hence it calculates only the PTE. This is shown in columns 4 and 5 of Table (4.5). Thus, to assess whether the inefficiency is a result of inefficient production processes, or a result of unfavourable conditions caused by the size of the country, BCC model is also employed, which is built on the assumption of VRS, recall that the CCR model is built on the assumption of CRS. Thus, in other words, this model calculates the pure technical efficiency which measures the efficiency rating when scale effects are eliminated. Table (4.7) presents descriptive statistics for the PTE. Among 65 observed developing countries, 52% turned out to be efficient which means that none of these countries have the scope for further improvement in outputs by using the same level of inputs; while 48% of the developing countries are inefficient with a maximum relative efficiency score of 96% assigned to Russian Federation and a minimum score of 28% for Kenya. This means that there is room for about 48% of the developing countries to improve their purely technical (managerial) efficiencies as apart from purely technical limits. This result is not surprising as in general, the scores of the BCC model are a bit bigger than that of the CCR model due to the different proposed assumptions on which each model is built.

However, the two different results of the BCC and CCR models conform to each other. This empirical evidence is already proved by many other empirical studies such as Klevenhusen et al. (2021). In this study, for instance, Kenya is the most inefficient country in both models. Furthermore, the average PTE is 84%. This indicates that given the scale size of the country, each country can on average increase its outputs by 16% of its observed output levels without proportional increase in its input level. It is also evident that countries such as Argentina, Bulgaria, Burundi, Ukraine are overall technically inefficient (OTE less than 100%), but they are pure technically efficient. Thus, in these countries, inefficiency is caused by scale size. In other words, these countries could convert their inputs into outputs with 100% efficiency; however, on the other hand, they are overall technically inefficient because of their unfavourable scale size.

Regarding the scale efficiency, as shown in column 6 and 7 of Table (4.5), it is defined as the ratio of CCR Score to BCC Score. This score provides an indication of whether the size of the country influences its overall technical efficiency or not. The scale efficiencies in developing countries reveal that this ratio equal to one for 21 countries which indicates that these countries are operating at optimum scale size, and thus are scale efficient countries. The remaining 44 countries are not scale efficient. This means that most of the developing countries (about 68%) are scale inefficient indicating that a scale inefficiency problem really does exist among developing countries. Further, the average scale efficiency score reported for all countries is 88% which means that developing countries on average could increase its scale efficiency by 12% beyond its best practice average target levels under the BCC model, if these countries were to operate at OTE.

Furthermore, Mozambique has the most scale inefficiency of 33% as calculated in Table (4.5). It is also observed that the overall technical efficiency (OTE, mean=0.74) is decomposed into pure technical efficiency (PTE, mean=0.84) and scale efficiency (SE, mean =0.88) as shown in Tables (4.6), (4.7), and (4.8). This result reveals that the overall technical inefficiencies of the KBE across developing countries are primarily due to their pure technical inefficiencies rather than the scale inefficiencies. Therefore, this result provides a confirmative guideline to policy makers in developing countries as they must pay attention to their managerial inefficiency firstly, and then proceed to enhance their scale efficiencies.

As for the returns to scale, to address efficiency, it is crucial to differentiate the impact of the scale from the gains of efficiency. When scale economy is taken into consideration, countries with increasing or decreasing returns to scale can change their scale to achieve constant returns to scale, which is equivalent to technical efficiency. The DEA results show that only 21 countries are exhibiting constant returns to scale. But 38 developing countries show increasing returns to scale, indicating that these developing countries operating at IRS which are greater than their CRS and can consider further expanding the economic scale to enhance the competitive advantage. Additionally, only 6 developing countries have decreasing returns to scale, indicating that in these countries the percentage for the increment in outputs fell behind that in inputs. To this end, it is observed that 44 = (38+6) developing countries have the possibility to change their scale to achieve constant returns to scale and achieve technical Efficiency.

Table (4.5): Overall Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency Scores for Developing Countries.

DMU	**Overall Technical Efficiency Score (CRS)**	**Overall Technical inefficiency Score**	**Pure Technical Efficiency Score (VRS)**	**Pure Technical Inefficiency Score**	**Scale Efficiency Score (SE)**	**Scale Inefficiency Score**	**Returns to Scale (RTS)**
DEA Model	**CCR Model**		**BCC Model**		**CCR Model Score / BCC Model Score**		
Albania	0.51	0.49	0.72	0.28	0.71	0.29	Increasing
Algeria	0.68	0.32	0.81	0.19	0.83	0.17	Increasing
Angola	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Argentina	0.98	0.02	1.00	0.00	0.98	0.02	Increasing
Armenia	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Azerbaijan	0.87	0.13	0.88	0.12	0.99	0.01	Increasing
Botswana	0.46	0.54	0.46	0.54	0.99	0.01	Increasing
Brazil	1.00	0.00	1.00	0.00	1.00	0.00	Constant

DMU	Overall Technical Efficiency Score (CRS)	Overall Technical inefficiency Score	Pure Technical Efficiency Score (VRS)	Pure Technical Inefficiency Score	Scale Efficiency Score (SE)	Scale Inefficiency Score	Returns to Scale (RTS)
DEA Model	**CCR Model**		**BCC Model**		**CCR Model Score / BCC Model Score**		
Bulgaria	0.98	0.02	1.00	0.00	0.98	0.02	Increasing
Burkina Faso	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Burundi	0.35	0.65	1.00	0.00	0.35	0.65	Increasing
Cambodia	0.42	0.58	0.60	0.40	0.70	0.30	Increasing
China	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Colombia	0.58	0.42	0.61	0.39	0.96	0.04	Increasing
Costa Rica	0.82	0.18	0.82	0.18	0.99	0.01	Increasing
Côte d'Ivoire	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Ecuador	0.78	0.22	0.79	0.21	0.99	0.01	Decreasing
Egypt, Arab Rep.	1.00	0.00	1.00	0.00	1.00	0.00	Constant
El Salvador	0.48	0.52	0.56	0.44	0.86	0.14	Increasing
Ethiopia	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Gambia, the	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Georgia	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Ghana	0.30	0.70	0.33	0.67	0.91	0.09	Increasing
Guatemala	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Honduras	0.56	0.44	0.59	0.41	0.95	0.05	Increasing
India	0.85	0.15	0.86	0.14	0.99	0.01	Increasing
Indonesia	0.58	0.42	0.61	0.39	0.96	0.04	Increasing
Iran, Islamic Rep	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Jamaica	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Jordan	0.63	0.37	0.67	0.33	0.94	0.06	Increasing
Kazakhstan	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Kenya	0.26	0.74	0.28	0.72	0.92	0.08	Increasing
Kyrgyz Republic	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Lao PDR	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Lesotho	0.45	0.55	0.48	0.52	0.93	0.07	Increasing
Madagascar	0.52	0.48	1.00	0.00	0.52	0.48	Increasing
Malaysia	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Mali	0.29	0.71	0.46	0.54	0.65	0.35	Increasing
Mauritania	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Mexico	0.84	0.16	0.85	0.15	0.99	0.01	Increasing
Mongolia	0.93	0.07	1.00	0.00	0.93	0.07	Increasing
Morocco	0.87	0.13	0.87	0.13	0.99	0.01	Decreasing
Mozambique	0.33	0.67	1.00	0.00	0.33	0.67	Increasing
Namibia	0.47	0.53	0.48	0.52	0.98	0.02	Increasing
Nepal	0.41	0.59	0.51	0.49	0.79	0.21	Increasing
Nicaragua	0.44	0.56	0.68	0.32	0.65	0.35	Increasing
Nigeria	0.60	0.40	1.00	0.00	0.60	0.40	Increasing
North Macedonia	0.99	0.01	1.00	0.00	0.99	0.01	Increasing
Pakistan	0.56	0.44	1.00	0.00	0.56	0.44	Increasing
Paraguay	0.84	0.16	1.00	0.00	0.84	0.16	Increasing
Peru	0.60	0.40	0.64	0.36	0.94	0.06	Increasing
Philippines	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Russian Federation	0.92	0.08	0.96	0.04	0.95	0.05	Decreasing
Rwanda	0.51	0.49	1.00	0.00	0.51	0.49	Increasing
Senegal	0.52	0.48	0.59	0.41	0.89	0.11	Increasing
Serbia	0.91	0.09	0.96	0.04	0.96	0.04	Decreasing
South Africa	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Sri Lanka	0.66	0.34	0.82	0.18	0.80	0.20	Increasing
Thailand	0.64	0.36	0.71	0.29	0.91	0.09	Increasing
Tunisia	0.73	0.27	0.74	0.26	0.99	0.01	Decreasing

DMU	Overall Technical Efficiency Score (CRS)	Overall Technical inefficiency Score	Pure Technical Efficiency Score (VRS)	Pure Technical Inefficiency Score	Scale Efficiency Score (SE)	Scale Inefficiency Score	Returns to Scale (RTS)
DEA Model	**CCR Model**		**BCC Model**		**CCR Model Score / BCC Model Score**		
Turkey	0.79	0.21	0.80	0.20	0.99	0.01	Decreasing
Uganda	0.35	0.65	1.00	0.00	0.35	0.65	Increasing
Ukraine	0.97	0.03	1.00	0.00	0.97	0.03	Increasing
Vietnam	1.00	0.00	1.00	0.00	1.00	0.00	Constant
Zambia	0.35	0.65	0.48	0.52	0.73	0.27	Increasing

Source: Max DEA 8 Ultra; while technical inefficiency, pure technical inefficiency and scale inefficiency Scores are my own calculations, technical inefficiency Score = (1-techncial efficiency score) ×100; Pure Technical inefficiency Score = (1-Pure technical efficiency score) ×100 and Scale inefficiency score = ((1-scale efficiency score) ×100

Table (4.6): Descriptive Statistics for Overall Technical Efficiency Scores in the Sample.

Statistics	All countries	Efficient Countries	Inefficient Countries
Number of DMUs	65	21(Around 32% of the total DMUs)	44(Around 68% of the total DMUs)
Average overall technical efficiency	0.74	1	0.62
Minimum	0.25	1	0.25
Maximum	1	1	0.98

Table(4.7): Descriptive Statistics for Pure Technical Efficiency Scores in the Sample.

Statistics	All countries	Efficient Countries	Inefficient Countries
Number of DMUs	65	34 (About 52% of the total DMUs)	31 (About 48% of the total DMUs)
Average pure technical efficiency	0.84	1	0.66
Minimum	0.28	1	0.28
Maximum	1	1	0.96

Table (4.8): Descriptive Statistics for the Scale Efficiency Scores in the Sample.

Statistics	All countries	Efficient Countries	Inefficient Countries
Number of DMUs	65	21(32%)	44(68%)
Average scale efficiency	0.88	1	0.83
Minimum	0.33	1	0.33
Maximum	1	1	0.99

4.4.3.2 Discrimination between Efficient Countries

In the previous section, the result of the DEA analysis allows classifying the sample countries under two groups, namely efficient countries, which construct the best practice frontier, and inefficient countries which are located in the interior part of this frontier. But, as with the previous results, it is not possible to rank the efficient DMUs based on their efficiency score in principle because many different countries are defined as efficient countries. In some situations, the discrimination power of the DEA model is very poor, and most countries are defined as efficient. In DEA literature, this lack of discrimination is referred to as the “curse of dimensionality” and it has negative implications for managerial decisions and insights (Charles et al., 2019).

Therefore, in DEA literature, numerous methods have been proposed to rank the countries (DMUs) and to discriminate among efficient DMUs more effectively regardless of the size of the data set. Researchers such as Podinovski and Thanassoulis (2007) provided an in-depth review of these ranking methods. Among these methods; the reference set frequency (Kumar & Gulati, 2008); the super-efficiency models (Andersen & Petersen, 1993); and the cross-efficiency models (Liang et al., 2008); are the commonly used methods as observed in Benítez et al. (2021). However, each method has its advantages, and it also faces some problems as shown in Pourhabib Yekta et al. (2018), with the super-efficiency model being the most effective tool (Lin et al., 2019). Other methods could be utilized as presented in Ziari and Raissi (2016). In this study, the frequency count and the super-efficiency model will be applied to rank efficient DMUs.

4.4.3.3 Frequency of the Reference Set Approach

One of the ranking methods in DEA’s literature is the methodology adopted in many studies such as Chen and Yeh (1998); they used the frequency in the ‘reference set’ to discriminate between DMUs. That is, how many times an efficient country is shown up in the reference sets of inefficient countries is the frequency of that efficient country. This frequency (peer count) provides an indication of the extent of the robustness of that country with respect to other efficient countries in the DEA analysis. The higher the peer count, the more robust this efficient country has compared with other efficient countries.

Certainly, this high frequency is an indication of exemplary operating practices or a country with top performance, country with high robustness, global leader, role model or well-rounded performer (Yao & Han, 2010). Thus, countries with high frequency can be considered as a role model for other countries in the sample and can be emulated by other inefficient countries.

Additionally, the efficient countries with high frequency are to a greater extent efficient in many inputs and outputs variables of analysis and surely will continue to be efficient unless a shift in their fortune happens. On the other hand, some efficient countries may show small frequency in the DEA analysis; these countries have an infrequent combination of inputs and output and possess dissimilar characteristics with respect to other/relative countries in the DEA analysis. Consequently, these countries are to a large extent an odd country and are not considered role models to emulate by other inefficient countries. These countries are called the marginally efficient countries. Small changes in the value of inputs or outputs variables will drop these countries from the efficiency frontier. Finally, the result of the DEA analysis may exhibit countries with zero frequency. These countries are called “efficient by default” which appear seldom in the reference set and do not have characteristics that could be emulated by other countries. In other words, it is a lonely country with a special situation which is uncommon in terms of its input and outputs (Cheng, 2014) and thus cannot be considered a good example to follow.

Table (4.9) displays the times efficient countries are used as a benchmark for other inefficient countries or the frequency count for every efficient country based on the CCR DEA model, whereas Table (4.10) shows these frequencies when adopting the BCC DEA model. It also presents the categorization of these efficient countries into three categories as follows: (I) Highly Robust Countries; (II) Marginally Robust Countries and (III) Efficient Countries by default.

It is obvious that Kazakhstan, Iran, China, Angola, Ethiopia, Egypt, Mauritania, Armenia, and Côte d’Ivoire are the highly robust countries in both models and hence can be considered as a role model for other inefficient countries.

However, a super efficiency model is employed as another approach to increase the discrimination power among the highly robust countries as shown in the coming paragraphs.

The importance of the reference set is also obvious in providing information about the role models for each inefficient county. For inefficient countries, i.e., those with efficiency scores below one; DEA could identify a group of corresponding, perfect countries, efficient countries which are, in DEA terminology, collectively called the peer group. This peer group could provide guidelines to focus the decision maker's attention on a subgroup of countries referred to as the efficiency reference set countries as in Table (4.11). This efficiency reference set includes the group of peer units against which each inefficient country was found to be directly inefficient, i.e., this set is made up of efficient countries which are characterised by a KBE structure similar to the country being evaluated and thus this set of countries is a realistic term of comparison that an inefficient country being examined should emulate to enhance its performance (Sherman & Zhu, 2006). For instance, North Macedonia was found to have overall technical inefficiency in direct comparison to Armenia, Iran, and Kazakhstan.

The value in Parentheses in Table (4.11) refers to the relative weight assigned to each efficiency reference set country to calculate the overall technical efficiency score using CCR DEA model, whereas Table (4.12) presents these peer groups in case of applying BCC DEA model.

Table (4.9): Frequency Count for Efficient Countries with Categorization using the CCR DEA Model.

Highly Robust Countries	Marginally Robust Countries	Efficient Countries by default
Kazakhstan (31)	Vietnam (6)	South Africa (0)
Iran, Islamic Rep. (27)	Kyrgyz Republic (4)	Jamaica (0)
China (21)	Malaysia (4)	Georgia (0)
Armenia (18)	Gambia (3)	
Egypt, Arab Rep. (13)	Philippines (3)	
Côte d'Ivoire (12)	Burkina Faso (2)	
Ethiopia (10)	Guatemala (2)	
Angola (9)		
Lao PDR (8)		
Brazil (8)		
Mauritania (8)		

Table (4.10): Frequency Count for Efficient Countries with Categorization using the BCC DEA Model.

Highly Robust Countries	Marginally Robust Countries	Efficient Countries by default
Angola (24)	Lao PDR (6)	Argentina (0)
China (20)	Brazil (5)	Gambia (0)
Kazakhstan (19)	Burkina Faso (5)	Georgia (0)
Iran, Islamic Rep (16)	Vietnam (4)	Jamaica (0)
Ethiopia (12)	Burundi (3)	Kyrgyz Republic (0)
Egypt, Arab Rep. (11)	Nigeria (3)	Mozambique (0)

Highly Robust Countries	Marginally Robust Countries	Efficient Countries by default
Mauritania (11)	Guatemala (2)	North Macedonia (0)
Armenia (10)	Malaysia (2)	Pakistan (0)
Côte d'Ivoire (9)	Philippines (2)	Paraguay (0)
	Uganda (2)	Rwanda (0)
	Bulgaria (1)	South Africa (0)
	Madagascar (1)	
	Mongolia (1)	
	Ukraine (1)	

Table (4.11): Peer Group for Each Inefficient Developing Countries Using CCR DEA Model.

DMU	Efficiency Score	Efficiency Reference et (Lambda)
Albania	0.51	Armenia (0.03); China (0.01); Côte d'Ivoire (0.36); Iran, Islamic Rep (0.06); Kazakhstan (0.33)
Algeria	0.68	Angola (0.15); Armenia (0.04); Iran, Islamic Rep (0.63); Kazakhstan (0.02)
Argentina	0.98	Armenia (0.09); China (0.07); Iran, Islamic Rep (0.34); Kazakhstan (0.34)
Azerbaijan	0.87	Angola (0.06); China (0.00); Iran, Islamic Rep (0.11); Kazakhstan (0.76)
Botswana	0.46	Angola (0.11); Egypt, Arab Rep. (0.22); Iran, Islamic Rep (0.44); Kazakhstan (0.06)
Bulgaria	0.98	Armenia (0.21); China (0.26); Iran, Islamic Rep (0.15); Kazakhstan (0.31)
Burundi	0.35	Brazil (0.02); Burkina Faso (0.08); China (0.00); Côte d'Ivoire (0.17); Iran, Islamic Rep (0.15); Mauritania (0.04)
Cambodia	0.42	Côte d'Ivoire (0.29) ; Egypt., Arab Rep. (0.08); Ethiopia (0.09); Kazakhstan (0.11)
Colombia	0.58	Armenia (0.04); China (0.07); Côte d'Ivoire (0.01); Kazakhstan (0.69)
Costa Rica	0.82	Armenia (0.16); Brazil (0.24); Egypt, Arab Rep. (0.00); Iran, Islamic Rep (0.00); Kazakhstan (0.43); Lao PDR (0.14); Vietnam (0.03)
Ecuador	0.78	Angola (0.66); Brazil (0.13); Egypt, Arab Rep. (0.12); Iran, Islamic Rep (0.22); Kazakhstan (0.04)
El Salvador	0.48	Côte d'Ivoire (0.38); Ethiopia (0.03); Iran, Islamic Rep (0.10); Kazakhstan (0.25); Vietnam (0.03)
Ghana	0.30	Egypt, Arab Rep. (0.48); Ethiopia (0.03); Kazakhstan (0.23)
Honduras	0.56	Angola (0.20); Guatemala (0.05); Kazakhstan (0.27)
India	0.85	China (0.30); Lao PDR (0.14)
Indonesia	0.58	China (0.09); Côte d'Ivoire (0.03); Kazakhstan (0.31); Lao PDR (0.08)
Jordan	0.63	Armenia (0.20); China (0.05); Iran, Islamic Rep (0.53); Kazakhstan (0.12)
Kenya	0.26	Angola (0.22); China (0.15); Egypt, Arab Rep. (0.13); Iran, Islamic Rep (0.02); Vietnam (0.29)
Lesotho	0.45	Côte d'Ivoire (0.65); Kazakhstan (0.04)
Madagascar	0.52	China (0.00); Guatemala (0.34); Kazakhstan (0.02)
Mali	0.29	Côte d'Ivoire (0.28); Egypt, Arab Rep. (0.35); Ethiopia (0.06)
Mexico	0.84	Armenia (0.25); China (0.03); Kazakhstan (0.27); Malaysia (0.16); Philippines (0.08)
Mongolia	0.93	Armenia (0.24); Kazakhstan (0.14); Kyrgyz Republic (0.07); Lao PDR (0.07); Philippines (0.19)
Morocco	0.87	Angola (0.42); Iran, Islamic Rep (0.64); Kazakhstan (0.08); Malaysia (0.01)
Mozambique	0.33	Egypt, Arab Rep. (0.08); Ethiopia (0.08); Malaysia (0.08); Vietnam (0.29)
Namibia	0.47	China (0.01); Egypt, Arab Rep. (0.01); Ethiopia (0.08); Iran, Islamic Rep (0.33); Kazakhstan (0.17); Mauritania (0.19)
Nepal	0.41	Armenia (0.00); Brazil (0.00); Iran, Islamic Rep (0.35); Kyrgyz Republic (0.01); Lao PDR (0.12); Mauritania (0.02)

DMU	Efficiency Score	Efficiency Reference et (Lambda)
Nicaragua	0.44	Côte d'Ivoire (0.50); Ethiopia (0.00); Iran, Islamic Rep (0.05); Kazakhstan (0.25)
Nigeria	0.6	Brazil (0.03); China (0.01); Iran, Islamic Rep (0.09); Kyrgyz Republic (0.09); Lao PDR (0.06); Mauritania (0.01)
North Macedonia	0.99	Armenia (0.04); Iran, Islamic Rep (0.37); Kazakhstan (0.44)
Pakistan	0.56	Armenia (0.04); China (0.03); Gambia, The (0.31); Iran, Islamic Rep (0.17); Kyrgyz Republic (0.02); Lao PDR (0.07); Mauritania (0.082)
Paraguay	0.84	Armenia (0.04); Gambia, The (0.15); Iran, Islamic Rep (0.12); Kazakhstan (0.19); Lao PDR (0.10)
Peru	0.6	Angola (0.42); Armenia (0.05); China (0.01); Iran, Islamic Rep (0.04); Kazakhstan (0.41)
Russian Federation	0.92	Armenia (0.12); China (0.26); Iran, Islamic Rep (0.47); Kazakhstan (0.22)
Rwanda	0.51	Brazil (0.07); Burkina Faso (0.32); Vietnam (0.29)
Senegal	0.52	Egypt, Arab Rep. (0.61); Ethiopia (0.11)
Serbia	0.91	Armenia (0.14); China (0.15); Iran, Islamic Rep (0.59); Kazakhstan (0.19)
Sri Lanka	0.66	Armenia (0.19); Gambia, The (0.29); Iran, Islamic Rep (0.06); Kazakhstan (0.15); Mauritania (0.06)
Thailand	0.64	China (0.34); Mauritania (0.07); Philippines (0.37); Vietnam (0.07)
Tunisia	0.73	Angola (0.48); Brazil (0.13); Iran, Islamic Rep (0.48); Kazakhstan (0.11); Malaysia (0.03)
Turkey	0.79	China (0.26); Côte d'Ivoire (0.18); Egypt, Arab Rep. (0.07); Ethiopia (0.02); Iran, Islamic Rep (0.40); Kazakhstan (0.14); Mauritania (0.00)
Uganda	0.35	Brazil (0.08) ; Côte d'Ivoire (0.47); Egypt, Arab Rep. (0.03)
Ukraine	0.97	Armenia (0.24); China (0.06); Iran, Islamic Rep (0.33); Kazakhstan (0.29)
Zambia	0.35	Côte d'Ivoire (0.21) ; Egypt, Arab Rep. (0.31); Ethiopia (0.16)

Table (4.12): Peer Group for Each Inefficient Developing Countries Using BCC DEA Model.

DMU	Efficiency Score	Efficiency reference set (Lambda)
Albania	0.72	Angola (0.56); China (0.02); Côte d'Ivoire (0.27); Ethiopia (0.05); Iran, Islamic Rep (0.06); Nigeria (0.04)
Algeria	0.81	Angola (0.58); Brazil (0.04); Iran, Islamic Rep (0.38)
Azerbaijan	0.88	Angola (0.19); China (0.00); Iran, Islamic Rep (0.02); Kazakhstan (0.80)
Botswana	0.46	Angola (0.17); Egypt, Arab Rep. (0.68); Iran, Islamic Rep (0.05); Kazakhstan (0.04); Mauritania (0.07)
Cambodia	0.60	China (0.00); Iran, Islamic Rep (0.10); Mauritania (0.86); Vietnam (0.05)
Colombia	0.61	Angola (0.19); Armenia (0.07); China (0.06); Côte d'Ivoire (0.04); Ethiopia (0.05); Kazakhstan (0.56); Lao PDR (0.03)
Costa Rica	0.82	Armenia (0.15); Brazil (0.24); China (0.00); Egypt, Arab Rep. (0.01); Iran, Islamic Rep (0.00); Kazakhstan (0.43); Lao PDR (0.15); Vietnam (0.02)
Ecuador	0.79	Angola (0.30); Armenia (0.14); Brazil (0.09); Egypt, Arab Rep. (0.42); Kazakhstan (0.06)
El Salvador	0.56	Angola (0.47); Côte d'Ivoire (0.22); Ethiopia (0.06); Iran, Islamic Rep (0.08); Kazakhstan (0.01); Mongolia (0.08); Vietnam (0.09)
Ghana	0.33	Angola (0.23); Côte d'Ivoire (0.060); Egypt, Arab Rep. (0.424); Ethiopia (0.178); Kazakhstan (0.108)
Honduras	0.59	Angola (0.28); Armenia (0.02); Guatemala (0.51); Kazakhstan (0.05); Lao PDR (0.14)
India	0.86	Angola (0.07); China (0.30); Lao PDR (0.11); Madagascar (0.26); Mauritania

DMU	Efficiency Score	Efficiency reference set (Lambda)
		(0.26)
Indonesia	0.61	China (0.08); Côte d'Ivoire (0.20); Guatemala (0.13); Kazakhstan (0.22); Lao PDR (0.06); Mauritania (0.31)
Jordan	0.67	Angola (0.27); Armenia (0.14); China (0.05); Iran, Islamic Rep (0.49); Kazakhstan (0.04)
Kenya	0.28	Angola (0.25); Burkina Faso (0.41); China (0.12); Egypt, Arab Rep. (0.21); Ethiopia (0.01)
Lesotho	0.48	Angola (0.05) ; Côte d'Ivoire (0.60); Ethiopia (0.01); Mauritania (0.34)
Mali	0.46	Angola (0.01); Burkina Faso (0.25); China (0.00); Ethiopia (0.07); Iran, Islamic Rep (0.10); Mauritania (0.41); Uganda (0.16)
Mexico	0.85	Angola (0.31); Armenia (0.26); China (0.03); Kazakhstan (0.13); Malaysia (0.15); Philippines (0.11)
Morocco	0.87	Angola (0.18); Iran, Islamic Rep (0.73); Kazakhstan (0.05); Malaysia (0.05)
Namibia	0.48	Angola (0.15); China (0.01); Côte d'Ivoire (0.06); Egypt, Arab Rep. (0.39); Ethiopia (0.08); Kazakhstan (0.10); Mauritania (0.21)
Nepal	0.51	Angola (0.02); Brazil (0.01); Burkina Faso (0.00); Burundi (0.04); Egypt, Arab Rep. (0.29); Lao PDR (0.02); Mauritania (0.11); Nigeria (0.31); Uganda (0.21)
Nicaragua	0.68	Angola (0.35); China (0.00); Côte d'Ivoire (0.37); Ethiopia (0.05); Iran, Islamic Rep (0.03); Nigeria (0.20)
Peru	0.64	Angola (0.57); Bulgaria (0.03); China (0.00); Kazakhstan (0.29); Ukraine (0.11)
Russian Federation	0.96	Armenia (0.05); China (0.26); Iran, Islamic Rep (0.49); Kazakhstan (0.21)
Senegal	0.59	Burkina Faso (0.42); Burundi (0.13); Egypt, Arab Rep. (0.34); Ethiopia (0.11)
Serbia	0.96	Armenia (0.04); China (0.16); Iran, Islamic Rep (0.66); Kazakhstan (0.14)
Sri Lanka	0.82	Angola (0.33); Armenia (0.07); China (0.01); Iran, Islamic Rep (0.10); Kazakhstan (0.03); Mauritania (0.47)
Thailand	0.71	Angola (0.25); China (0.08); Mauritania (0.10); Philippines (0.31); Vietnam (0.25)
Tunisia	0.74	Angola (0.03); Armenia (0.10); Brazil (0.10); Egypt, Arab Rep. (0.31); Iran, Islamic Rep (0.26); Kazakhstan (0.20)
Turkey	0.80	China (0.25); Côte d'Ivoire (0.11); Egypt, Arab Rep. (0.05); Ethiopia (0.03); Iran, Islamic Rep (0.42); Kazakhstan (0.13)
Zambia	0.48	Angola (0.17); Burkina Faso (0.11); Burundi (0.32); China (0.00); Egypt, Arab Rep. (0.13); Ethiopia (0.16); Mauritania (0.12)

4.4.3.4 Super Efficiency DEA Model

In 1993, Andersen and Petersen developed a more effective approach; named the traditional super-efficiency model to characterize efficient DMUs among the other technically efficient ones and thus able to rank efficient units in a better way. Thus, this model aims to enhance the discriminating power of DEA and is one of the commonly used tools by Lin et al. (2019). The main idea behind this model is that it assesses the performance of super-efficient DMUs by excluding the DMU under evaluation from the reference set.

Mathematically, this model allows an extremely efficient unit to have an efficiency score greater than one by removing the constraint (that the efficiency score must have a value between zero and one) in the primal formulation of the radial DEA model. Thus, the calculated super-efficiency scores can be greater than one for CCR and BCC models. After that, these super-efficiency scores are employed to rank all DMUs. The linear programming for some DMUs might be infeasible (Seiford & Zhu, 1999). In such cases, the decision-maker can decide whether the program returns the score to 1 or to maintain its infeasibility[8].

Though, the DEA literature has presented a recent extension named Directional Distance Functions (DDF) to sort out this issue (Tang et al., 2020).

Additionally, DEA literature has presented new orientations; that is the modified input-oriented and modified output-oriented super-efficiency models to overcome the infeasibility issue in the traditional super-efficiency models as fully presented in Cheng et al. (2011). Other modified super-efficiency DEA models that could tackle this issue are proposed by Lin and Chen (2015), among others. To this end, the super efficiency model to a large extent eliminates some of the possible ties; though not all ties occur for efficient DMUs (Andersen & Petersen, 1993).

It is obvious that based on the super efficiency DEA model, China is the global leader for developing countries in 2020 as in Table (4.13) using the CCR DEA model. However, Angola is the global leader for developing countries in 2020 as in Table (4.14); in the case of using the super efficiency DEA model and the BCC model. Finally, it is significant here to note that the traditional super-efficiency model gives the inefficient countries the same radial efficiency score.

Table (4.13): CCR Super-Efficiency Scores and Complete Ranking of the 65 Developing Countries.

NO.	DMU	Score	NO.	DMU	Score
1	**China**	**9.38**	**37**	Thailand	0.64
2	Ethiopia	4.05	**38**	Jordan	0.63
3	Armenia	3.72	**39**	Nigeria	0.60
4	Lao PDR	3.48	**40**	Peru	0.60
5	Côte d'Ivoire	3.42	**41**	Indonesia	0.58
6	Philippines	2.47	**42**	Colombia	0.58
7	Kazakhstan	2.13	**43**	Pakistan	0.56
8	Iran, Islamic Rep	2.03	**44**	Honduras	0.56
9	Vietnam	2.02	**45**	Madagascar	0.52
10	Angola	1.86	**46**	Senegal	0.52
11	Burkina Faso	1.56	**47**	Rwanda	0.51
12	Egypt, Arab Rep.	1.24	**48**	Albania	0.51
13	Malaysia	1.21	**49**	El Salvador	0.48

(8) This can be done through the option “No optima”, then select the score =1

NO.	DMU	Score		NO.	DMU	Score
14	Guatemala	1.21		**50**	Namibia	0.47
15	The Gambia	1.19		**51**	Botswana	0.46
16	South Africa	1.14		**52**	Lesotho	0.45
17	Jamaica	1.14		**53**	Nicaragua	0.44
18	Georgia	1.03		**54**	Cambodia	0.42
19	North Macedonia	0.99		**55**	Nepal	0.41
20	Bulgaria	0.98		**56**	Burundi	0.35
21	Argentina	0.98		**57**	Zambia	0.35
22	Ukraine	0.97		**58**	Uganda	0.35
23	Mongolia	0.93		**59**	Mozambique	0.33
24	Russian Federation	0.92		**60**	Ghana	0.30
25	Serbia	0.91		**61**	Mali	0.29
26	Azerbaijan	0.87		**62**	Kenya	0.26
27	Morocco	0.87		**63**	Brazil	LP infeasible
28	India	0.85		**64**	Kyrgyz Republic	LP infeasible
29	Mexico	0.84		**65**	Mauritania	LP infeasible
30	Paraguay	0.84				
31	Costa Rica	0.82				
32	Turkey	0.79				
33	Ecuador	0.78				
34	Tunisia	0.73				
35	Algeria	0.68				
36	Sri Lanka	0.66				
Source: Max DEA 8 Ultra				**Source:** Max DEA 8 Ultra		

Table (4.14): BCC Super-Efficiency Scores and Complete Ranking of the 65 Developing Countries.

NO.	DMU	Score		NO.	DMU	Score
1	**Angola**	**49.18**		**38**	Jordan	0.67
2	Pakistan	20.09		**39**	Peru	0.64
3	China	10.82		**40**	Colombia	0.61
4	Madagascar	9.01		**41**	Indonesia	0.61
5	Armenia	8.55		**42**	Cambodia	0.60
6	Philippines	2.48		**43**	Senegal	0.59
7	Vietnam	2.18		**44**	Honduras	0.59
8	Kazakhstan	2.15		**45**	El Salvador	0.56
9	Mongolia	1.50		**46**	Nepal	0.51
10	Mozambique	1.44		**47**	Lesotho	0.48
11	Guatemala	1.42		**48**	Namibia	0.48
12	Rwanda	1.36		**49**	Zambia	0.48
13	Malaysia	1.33		**50**	Botswana	0.46
14	Egypt, Arab Rep.	1.32		**51**	Mali	0.46
15	South Africa	1.16		**52**	Ghana	0.33
16	Jamaica	1.16		**53**	Kenya	0.28
17	Paraguay	1.14		**54**	Brazil	LP infeasible
18	Georgia	1.03		**55**	Burkina Faso	LP infeasible
19	Argentina	1.03		**56**	Burundi	LP infeasible
20	Bulgaria	1.02		**57**	Côte d'Ivoire	LP infeasible
21	Ukraine	1.02		**58**	Ethiopia	LP infeasible
22	North Macedonia	1.00		**59**	The Gambia	LP infeasible
23	Russian Federation	0.96		**60**	Iran, Islamic Rep	LP infeasible
24	Serbia	0.96		**61**	Kyrgyz Republic	LP infeasible
25	Azerbaijan	0.88		**62**	Lao PDR	LP infeasible
26	Morocco	0.87		**63**	Mauritania	LP infeasible

NO.	DMU	Score		NO.	DMU	Score
27	India	0.86		**64**	Nigeria	LP infeasible
28	Mexico	0.85		**65**	Uganda	LP infeasible
29	Sri Lanka	0.82				
30	Costa Rica	0.82				
31	Algeria	0.81				
32	Turkey	0.80				
33	Ecuador	0.79				
34	Tunisia	0.74				
35	Albania	0.72				
36	Thailand	0.71				
37	Nicaragua	0.68				

4.4.3.5 Areas for Efficiency Improvement: Targets Setting Analysis

Once inefficiencies have been calculated for inefficient countries, then it is logical to undertake appropriate measures to improve the performance of these countries to reach the frontier countries. One of the DEA’s merits is that it could help policymakers to precisely assess the sources and amounts of relative inefficiency for inefficient countries in each input and output variable used in the DEA analysis, which in turn would transform these countries into efficient.

This is done by calculating the distance of inefficient DMUs from their respective (peer) (reference) groups. This distance offers extremely valuable information to decision-makers as it provides an accurate measure for the required improvements (in terms of inputs and/or outputs (reduction and/or increase) to improve the position of inefficient DMUs to “catch up” with efficient ones. The decision-makers in every specific country can then set effective country-specific goals and determine the required policy changes that will achieve these goals directly and will faster the transition of KBE from inefficient developing countries to efficient ones.

The difference between empirical (obtained from databases) and projected values (provided by DEA) for each inefficient county in every output is presented as a percentage change that must be attained by every country to be efficient as reported in Table (4.15) showing CCR results and Table (4.16) exhibiting BCC results.

It is worth mentioning that this new projected value consists of the proportional radial movement. So, the efficient target for each variable in the radial DEA model is calculated as the sum of the original value of the variable (observed data) plus the proportionate radial movement. This efficiency projection is called weak efficient projection (Cheng, 2014). Additionally, since the applied DEA is output-oriented so feasible and reasonable changes on the output side is considered.

As an example, under the CCR model, for Albania to be an efficient country, it must proportionally increase all its output by the percent of 95.8%. It is observed also that Kenya, Mali, and Ghana need the highest improvements among all developing countries as they are required to increase their outputs by 288.1%, 239.2%, and 232.6 % respectively. This result is consistent with the super-efficiency scores for these countries as they have the lowest super-efficiency scores of 0.26, 0.29,0.30 for Kenya, Mali, and Ghana.

Additionally, the same result is observed if we employed the BCC model but with slight changes in super efficiency scores and the proportionate percentage of target improvement. To elaborate, Kenya, Mali, and Ghana have a super efficiency score of 0.28, 0.33, and 0.46 respectively and must set targets for output augmentation by 256.9 % for Kenya, 202.6 for Ghana and 119.1 for Mali.

Table (4.15): Output Targets for Inefficient Countries Under the Output-Oriented CCR Model.

DMU	Y1 (A)	Y1 (PM)	Y1 (Pro.)	Y2 (A)	Y2 (PM)	Y2 (Pro.)	Y3 (A)	Y3 (PM)	Y3 (Pro.)	Y4 (A)	Y4 (PM)	Y4 (Pro.)	Y5 (A)	Y5 (PM)	Y5 (Pro.)	% Change
Albania	-3.3	3.2	-0.1	180.4	172.8	353.1	0.2	0.2	0.4	20.2	19.4	39.6	0.0	0.0	0.1	95.8
Algeria	-4.9	2.3	-2.6	5231.4	2471.9	7703.4	0.0	0.0	0.0	42.2	19.9	62.1	1.0	0.5	1.4	47.3
Argentina	-9.9	0.2	-9.7	8811.1	172.5	8983.6	1.4	0.0	1.5	64.3	1.3	65.6	5.2	0.1	5.3	2.0
Azerbaijan	-4.3	0.6	-3.7	761.4	112.2	873.7	0.3	0.0	0.3	65.0	9.6	74.6	4.3	0.6	5.0	14.7
Botswana	-8.5	10.0	1.5	280.6	331.7	612.2	0.0	0.0	0.0	27.8	32.9	60.7	0.4	0.5	0.8	118.2
Bulgaria	-4.2	0.1	-4.1	3311.3	52.6	3363.8	4.4	0.1	4.5	63.0	1.0	64.0	10.9	0.2	11.0	1.6
Burundi	-1	1.8	0.8	21.1	38.4	59.5	0.0	0.1	0.1	1.0	1.8	2.8	1.5	2.8	4.3	181.7
Cambodia	-3.1	4.2	1.1	145.7	199.3	345.1	0.0	0.0	0.0	8.0	10.9	18.9	1.2	1.6	2.8	136.8
Colombia	-6.8	4.9	-1.9	7195.0	5178.9	12373.9	0.8	0.6	1.4	37.2	26.8	64.0	9.1	6.6	15.7	72.0
Costa Rica	-4.1	0.9	-3.2	507.4	112.5	619.9	0.9	0.2	1.1	47.0	10.4	57.4	17.6	3.9	21.5	22.2
Ecuador	-7.8	2.2	-5.6	2142.2	590.5	2732.7	0.1	0.0	0.2	43.9	12.1	56.0	5.5	1.5	7.1	27.6
El Salvador	-7.9	8.6	0.7	45.4	49.6	95.0	0.1	0.1	0.1	16.7	18.2	34.9	6.4	7.0	13.4	109.1
Ghana	0.4	0.9	1.3	1276.0	2967.9	4243.9	0.0	0.0	0.1	15.8	36.8	52.6	1.1	2.6	3.8	232.6
Honduras	-9	7.1	-1.9	45.1	35.7	80.8	0.1	0.0	0.1	17.1	13.6	30.7	2.0	1.6	3.5	79.2
India	-7.3	1.3	-6.0	135787.8	23985.4	159773.2	1.5	0.3	1.8	10.7	1.9	12.6	10.3	1.8	12.1	17.7
Indonesia	-2.1	1.5	-0.6	26947.6	19382.2	46329.8	0.1	0.1	0.1	18.8	13.5	32.3	8.1	5.8	13.9	71.9
Jordan	-1.6	0.9	-0.7	2627.3	1546.6	4173.8	0.8	0.5	1.3	42.9	25.3	68.2	1.4	0.8	2.2	58.9
Kenya	-0.3	0.9	0.6	1246.8	3591.6	4838.4	0.1	0.4	0.5	8.8	25.4	34.2	4.6	13.2	17.8	288.1
Lesotho	-5.4	6.6	1.2	18.5	22.6	41.2	0.0	0.0	0.0	5.1	6.2	11.3	0.2	0.3	0.5	122.1
Madagascar	-6.1	5.5	-0.6	127.4	115.8	243.2	0.0	0.0	0.0	5.2	4.7	9.9	0.4	0.3	0.7	90.9
Mali	-1.6	3.8	2.2	90.4	216.1	306.5	0.0	0.0	0.0	4.6	11.0	15.6	1.2	3.0	4.2	239.2
Mexico	-8.3	1.6	-6.7	16345.6	3087.5	19433.1	1.8	0.3	2.2	44.2	8.3	52.5	20.4	3.9	24.3	18.9
Mongolia	-5.3	0.4	-4.9	140.9	10.8	151.7	0.7	0.1	0.8	29.7	2.3	32.0	18.9	1.5	20.4	7.7
Morocco	-6.3	1.0	-5.3	5056.8	764.8	5821.6	0.1	0.0	0.1	64.2	9.7	73.9	4.9	0.7	5.6	15.1
Mozambique	-1.2	2.4	1.2	139.3	276.9	416.2	0.0	0.0	0.0	6.7	13.3	20.0	5.6	11.2	16.9	198.9
Namibia	-8	8.9	0.9	156.3	173.7	330.0	0.1	0.1	0.3	21.2	23.6	44.8	0.5	0.5	1.0	111.1

DMU	Y1 (A)	Y1 (PM)	Y1 (Pro.)	Y2 (A)	Y2 (PM)	Y2 (Pro.)	Y3 (A)	Y3 (PM)	Y3 (Pro.)	Y4 (A)	Y4 (PM)	Y4 (Pro.)	Y5 (A)	Y5 (PM)	Y5 (Pro.)	% Change
Nepal	-2.1	3.1	1.0	792.1	1155.2	1947.3	0.0	0.0	0.1	12.7	18.5	31.2	1.2	1.7	2.9	145.8
Nicaragua	-2	2.6	0.6	43.7	56.0	99.7	0.0	0.0	0.0	13.5	17.3	30.8	1.1	1.4	2.4	128.2
Nigeria	-1.8	1.2	-0.6	5602.3	3731.5	9333.7	0.0	0.0	0.0	6.4	4.3	10.7	1.5	1.0	2.5	66.6
North Macedonia	-4.5	0.0	-4.5	493.1	5.1	498.1	0.3	0.0	0.3	69.5	0.7	70.2	4.2	0.0	4.2	1.0
Pakistan	-0.5	0.4	-0.1	12904.3	10149.7	23054.0	0.0	0.0	0.1	14.3	11.2	25.5	1.9	1.5	3.4	78.7
Paraguay	-0.6	0.1	-0.5	98.0	18.8	116.7	0.0	0.0	0.0	27.7	5.3	33.0	7.2	1.4	8.6	19.2
Peru	-11	7.3	-3.7	1629.9	1088.5	2718.4	0.3	0.2	0.5	33.1	22.1	55.2	4.1	2.7	6.8	66.8
Russian Federation	-3	0.3	-2.7	81579.4	7086.0	88665.4	3.8	0.3	4.2	72.1	6.3	78.4	13.0	1.1	14.1	8.7
Rwanda	-3.4	3.2	-0.2	169.5	162.0	331.6	0.0	0.0	0.0	2.5	2.4	4.9	10.6	10.1	20.6	95.6
Senegal	1.5	1.4	2.9	388.3	358.0	746.3	0.0	0.0	0.0	15.8	14.6	30.4	0.9	0.9	1.8	92.2
Serbia	-1	0.1	-0.9	4523.4	426.2	4949.6	2.5	0.2	2.7	74.3	7.0	81.3	4.5	0.4	5.0	9.4
Sri Lanka	-3.6	1.9	-1.7	1347.5	695.7	2043.3	0.2	0.1	0.3	23.0	11.9	34.9	1.0	0.5	1.5	51.6
Thailand	-6.1	3.4	-2.7	12513.8	6903.3	19417.0	1.0	0.5	1.5	19.3	10.6	29.9	23.6	13.0	36.6	55.2
Tunisia	-8.6	3.2	-5.4	5564.9	2082.6	7647.5	0.3	0.1	0.4	52.1	19.5	71.6	6.9	2.6	9.5	37.4
Turkey	1.8	0.5	2.3	33535.8	8856.3	42392.1	3.0	0.8	3.8	52.1	13.8	65.9	3.0	0.8	3.8	26.4
Uganda	-0.8	1.5	0.7	673.1	1259.7	1932.7	0.0	0.0	0.0	3.5	6.6	10.1	2.1	3.9	6.0	187.2
Ukraine	-4	0.1	-3.9	10379.9	361.2	10741.1	1.6	0.1	1.6	66.2	2.3	68.5	5.6	0.2	5.8	3.5
Zambia	-3	5.5	2.5	213.1	390.0	603.1	0.0	0.0	0.1	8.1	14.8	22.9	1.4	2.5	3.9	183.0

Note: Own calculations based on Max DEA 8 Ultra Y1= output 1 (Real GDP Growth); Y2 = output 2 (scientific and technical publications); Y3= output 3 (patents granted); Y4= output 4 (households with a computer), Y5= high-tech exports A= actual value; PM= proportionate movement; Pro. = projected value; % change = percentage proportionate output addition

Table (4.16): Output Targets for Inefficient Countries Under the Output-Oriented BCC Model.

DMU	Y1 (A)	Y1 (PM)	Y1 (Pro.)	Y2 (A)	Y2 (PM)	Y2 (Pro.)	Y3 (A)	Y3 (PM)	Y3 (Pro)	Y4 (A)	Y4 (PM)	Y4 (Pro)	Y5 (A)	Y5 (PM)	Y5 (Pro.)	% Change
Albania	-3.3	1.3	-2.0	180.4	69.4	249.8	0.22	0.08	0.30	20.2	7.8	28.0	0.0	0.0	0.1	38.5
Algeria	-4.9	1.1	-3.8	5231.4	1196.0	6427.5	0.03	0.01	0.04	42.2	9.6	51.8	1.0	0.2	1.2	22.9
Azerbaijan	-4.3	0.6	-3.7	761.4	107.9	869.3	0.28	0.04	0.32	65	9.2	74.2	4.3	0.6	5.0	14.2
Botswana	-8.5	9.9	1.4	280.6	328.0	608.6	0	0.00	0.00	27.8	32.5	60.3	0.4	0.5	0.8	116.9
Cambodia	-3.1	2.0	-1.1	145.7	95.5	241.3	0.01	0.01	0.02	8	5.2	13.2	1.2	0.8	2.0	65.5
Colombia	-6.8	4.4	-2.4	7195.0	4627.9	11822.9	0.79	0.51	1.30	37.2	23.9	61.1	9.1	5.9	15.0	64.3
Costa Rica	-4.1	0.9	-3.2	507.4	112.3	619.8	0.87	0.19	1.06	47	10.4	57.4	17.6	3.9	21.5	22.1
Ecuador	-7.8	2.0	-5.8	2142.2	555.4	2697.6	0.12	0.03	0.15	43.9	11.4	55.3	5.5	1.4	7.0	25.9
El Salvador	-7.9	6.2	-1.7	45.4	35.9	81.4	0.05	0.04	0.09	16.7	13.2	29.9	6.4	5.0	11.4	79.1
Ghana	0.4	0.8	1.2	1276.0	2585.7	3861.7	0.02	0.04	0.06	15.8	32.0	47.8	1.1	2.3	3.4	202.6
Honduras	-9	6.4	-2.6	45.1	32.0	77.1	0.06	0.04	0.10	17.1	12.1	29.2	2.0	1.4	3.4	70.8
India	-7.3	1.2	-6.1	135787.8	22213.5	158001.3	1.5	0.25	1.75	10.7	1.8	12.5	10.3	1.7	12.0	16.4
Indonesia	-2.1	1.4	-0.7	26947.6	17345.3	44292.8	0.07	0.05	0.12	18.8	12.1	30.9	8.1	5.2	13.3	64.4
Jordan	-1.6	0.8	-0.8	2627.3	1308.2	3935.5	0.82	0.41	1.23	42.9	21.4	64.3	1.4	0.7	2.0	49.8
Kenya	-0.3	0.8	0.5	1246.8	3203.0	4449.7	0.13	0.33	0.46	8.8	22.6	31.4	4.6	11.8	16.4	256.9
Lesotho	-5.4	5.8	0.4	18.5	19.9	38.4	0	0.00	0.00	5.1	5.5	10.6	0.2	0.2	0.4	107.2
Mali	-1.6	1.9	0.3	90.4	107.6	198.0	0.01	0.01	0.02	4.6	5.5	10.1	1.2	1.5	2.7	119.1
Mexico	-8.3	1.5	-6.8	16345.6	2962.3	19307.9	1.84	0.33	2.17	44.2	8.0	52.2	20.4	3.7	24.1	18.1
Morocco	-6.3	0.9	-5.4	5056.8	761.8	5818.6	0.13	0.02	0.15	64.2	9.7	73.9	4.9	0.7	5.6	15.1
Namibia	-8	8.6	0.6	156.3	167.8	324.1	0.13	0.14	0.27	21.2	22.8	44.0	0.5	0.5	1.0	107.4
Nepal	-2.1	2.0	-0.1	792.1	755.0	1547.1	0.03	0.03	0.06	12.7	12.1	24.8	1.2	1.1	2.3	95.3
Nicaragua	-2	0.9	-1.1	43.7	20.7	64.4	0.02	0.01	0.03	13.5	6.4	19.9	1.1	0.5	1.6	47.4
Peru	-11	6.2	-4.8	1629.9	921.8	2551.7	0.27	0.15	0.42	33.1	18.7	51.8	4.1	2.3	6.4	56.6
Russian Federation	-3	0.1	-2.9	81579.4	3009.1	84588.4	3.82	0.14	3.96	72.1	2.7	74.8	13.0	0.5	13.5	3.7
Senegal	1.5	1.1	2.6	388.3	273.7	662.0	0.02	0.01	0.03	15.8	11.1	26.9	0.9	0.7	1.6	70.5
Serbia	-1	0.0	-1.0	4523.4	204.8	4728.2	2.49	0.11	2.60	74.3	3.4	77.7	4.5	0.2	4.8	4.5
Sri Lanka	-3.6	0.8	-2.8	1347.5	288.9	1636.5	0.23	0.05	0.28	23	4.9	27.9	1.0	0.2	1.2	21.4
Thailand	-6.1	2.5	-3.6	12513.8	5151.1	17664.9	0.97	0.40	1.37	19.3	7.9	27.2	23.6	9.7	33.3	41.2
Tunisia	-8.6	3.1	-5.5	5564.9	1998.8	7563.6	0.28	0.10	0.38	52.1	18.7	70.8	6.9	2.5	9.4	35.9
Turkey	1.8	0.5	2.3	33535.8	8414.4	41950.2	3.01	0.76	3.77	52.1	13.1	65.2	3.0	0.8	3.8	25.1

Note: see Table (4.15).

4.4.3.6 Inputs and Outputs Slacks for Developing Countries

In the traditional radial DEA models, the slacks are related to further improvements i.e., possible increases in outputs and/or proposed reduction in inputs for inefficient countries that could be gained beyond that implied by the radial proportional movement (i.e., an equal proportional increase in all outputs and/or decrease in all inputs depending on the model's orientation) to reach the frontier and become efficient (Thrall, 1996). In other words, slacks are the addition of neglected portions of inefficiencies beyond the proportionate radial movement, which leads to only weak efficient projection (Cheng, 2014). Thus, having knowledge about the values of slacks; whether in inputs or outputs, for each country is crucial as it introduces additional insights into the magnitude of inefficiency for the inefficient countries.

This magnitude of inefficiency for each country is defined by the quantity of excess inputs used (underutilization of inputs) (input slack) and/or shortage in outputs produced (deficient output production) (output slack) by inefficient countries. It also gives information for the possible reduction in each individual input and/or possible output augmentation but in different proportion not in proportional movement for efficient countries to reach the optimal targets when this efficient country is relatively compared with its peer efficient countries' ultimate benchmark targets (Cooper et al., 2004).

To calculate the values of slacks, radial DEA models calculated it in two stages process. First, the efficiency scores are calculated. Then, the slack model with efficiency scores fixed is computed. In Ultra Max DEA software, the user opts for the choice of two-stage computations when slacks values are to be computed. Additionally, in most cases the values of the slacks for efficient countries are equal to zero. Thus, Table (4.17) depicts the estimated input and output slacks for all countries by employing the CCR, while Table (4.18) shows the input and output slacks for the inefficient countries only using BCC models, because the slacks for efficient countries are equal to zero.

It is noteworthy here to differentiate between DEA efficiency scores based on the value of the slacks. A DMU is said to be strongly efficient in the case of having an efficiency score of one with no slack values i.e., the value of slacks is zero for all inputs and outputs variables. Otherwise, a weak efficient DMU happens if its efficiency score is one with some non-zero slack values.

In our dataset, the calculated slacks for all efficient countries are zero under both CCR and BCC implying that they are strongly efficient. Thus, there are only inputs and outputs slacks for inefficient countries. Within these inefficient countries, positive values of slacks mean an increase (output slack), while negative values mean a decrease (input slack). In our dataset, all inefficient countries have non-zero slacks in inputs and outputs as shown in Table (4.17) and (4.18).

Finally, it could happen that even if the model is output-oriented, there will be some negative slacks in inputs which suggest a possible decrease in individual inputs but not in a proportionate radial movement (Ray, 2004). However, for some inputs, as in our case, it is not desirable to decrease these inputs. For instance, it could be acceptable to decrease the education expenditures for the same level of outputs to enhance KBE efficiency. But it may be unfavourable to accept a possible decrease in other inputs such as in the ease of doing a business score. This is because, it is unacceptable to make the business environment more restrictive. So, in this case a constraint should be added to the linear programming to deal with these inputs as discretionary inputs if the researcher needs to provide target-setting analysis for inputs and outputs simultaneously.

Hence, the inefficient country will become strongly efficient. However, if the focus is only in the output side and it is attempted to improve only outputs to their projected values, then the inefficient country will become weakly efficient (Cheng, 2014).

Table (4.17): Inputs and Outputs Slacks for Developing Countries by Employing the CCR Model.

DMU	Score	I (1)	I (2)	I (3)	I (4)	I (5)	I (6)	I (7)	I (8)	Y (1)	Y (2)	Y (3)	Y (4)	Y (5)
Angola	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Armenia	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Brazil	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Burkina Faso	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
China	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Côte d'Ivoire	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Egypt, Arab Rep.	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Ethiopia	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Gambia, the	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Georgia	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Guatemala	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Iran, Islamic Rep	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Jamaica	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kazakhstan	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Kyrgyz Republic	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Lao PDR	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Malaysia	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Mauritania	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Philippines	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
South Africa	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Vietnam	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
North Macedonia	0.99	-20.78	-3.32	0.00	-0.25	-0.57	-0.56	0.00	-1.20	4.25	18354.36	0.00	0.00	9.72
Bulgaria	0.98	-3.44	-1.89	0.00	0.00	-1.20	-0.74	-3.54	0.00	2.92	142760.26	0.00	0.00	8.26
Argentina	0.98	0.00	-0.52	0.00	-0.91	-2.10	-1.06	-6.58	0.00	9.50	47204.64	0.00	0.00	8.24
Ukraine	0.97	-5.62	-2.82	0.00	0.00	-2.56	-0.32	-12.50	0.00	2.55	35595.47	0.00	0.00	7.22
Mongolia	0.93	-18.29	-16.08	0.00	-0.09	-2.68	-0.62	0.00	0.00	0.23	751.92	0.00	0.00	0.00
Russian Federation	0.92	-4.39	-0.79	0.00	0.00	-1.11	-0.21	-5.64	0.00	3.46	69609.38	0.00	0.00	1.97
Serbia	0.91	-3.72	-7.30	-0.06	0.00	0.00	-0.03	-1.34	0.00	1.70	104409.68	0.00	0.00	7.19
Azerbaijan	0.87	-7.46	-1.96	0.00	-1.64	0.00	0.00	-24.31	-1.32	1.74	6777.75	0.00	0.00	18.00
Morocco	0.87	-11.65	-2.85	-0.15	-1.66	-1.93	0.00	0.00	-0.29	5.00	25544.09	0.00	0.00	0.00
India	0.85	-40.55	-0.80	0.00	-2.54	-1.98	-1.44	-24.56	-0.21	6.65	0.00	2.62	5.88	0.00
Mexico	0.84	-12.52	-1.03	0.00	-0.66	-1.81	0.00	-5.50	-0.04	2.63	0.00	0.00	0.00	0.00
Paraguay	0.84	-20.60	-0.11	0.00	-1.09	-1.62	-0.93	0.00	0.00	0.00	6241.70	0.24	0.00	0.00
Costa Rica	0.82	0.00	-1.71	0.00	-0.60	-3.09	0.00	-2.27	0.00	0.00	15263.53	0.00	0.00	0.00
Turkey	0.79	-6.17	0.00	0.00	-0.03	-0.49	0.00	0.00	0.00	0.00	113054.59	0.00	0.00	10.97

DMU	Score	I (1)	I (2)	I (3)	I (4)	I (5)	I (6)	I (7)	I (8)	Y (1)	Y (2)	Y (3)	Y (4)	Y (5)
Ecuador	0.78	0.00	-2.91	0.00	-0.13	-0.78	0.00	-6.08	0.00	2.64	17313.83	0.15	0.00	0.00
DMU	**Score**	**I (1)**	**I (2)**	**I (3)**	**I (4)**	**I (5)**	**I (6)**	**I (7)**	**I (8)**	**Y (1)**	**Y (2)**	**Y (3)**	**Y (4)**	**Y (5)**
Tunisia	0.73	-2.29	-3.27	0.00	0.00	-3.49	0.00	-2.45	0.00	3.45	24081.63	0.12	0.00	0.00
Algeria	0.68	0.00	-1.06	0.00	-1.56	-3.31	0.00	-13.79	0.00	3.53	23035.50	0.15	0.00	1.10
Sri Lanka	0.66	-14.06	0.00	0.00	-0.76	0.00	-0.56	-13.04	0.00	0.00	1500.54	0.27	0.00	5.18
Thailand	0.64	-21.34	0.00	-0.18	0.00	-0.13	-1.20	-9.15	-2.96	0.00	161290.32	3.56	0.00	0.00
Jordan	0.63	-10.06	-1.12	-0.12	-1.88	0.00	0.00	-14.76	0.00	0.80	46274.21	0.00	0.00	5.11
Nigeria	0.60	-39.93	0.00	0.00	-2.04	-1.92	-1.72	-16.99	0.00	0.00	0.00	0.15	0.00	0.00
Peru	0.60	-11.30	-5.00	0.00	0.00	-1.97	0.00	-3.28	0.00	0.07	5476.33	0.00	0.00	8.77
Indonesia	0.58	-32.24	-1.18	0.00	-2.46	-1.30	-1.62	-31.43	-0.16	0.00	0.00	1.26	0.00	0.00
Colombia	0.58	-6.41	-2.93	0.00	-0.48	-2.16	0.00	-8.87	-0.12	0.00	25337.49	0.00	0.00	7.45
Pakistan	0.56	-20.65	0.00	0.00	-1.35	-0.29	0.00	-22.38	0.00	0.00	0.00	0.52	0.00	0.00
Honduras	0.56	-22.89	-4.14	0.00	-2.07	-3.59	-1.25	-21.30	-1.56	0.00	576.83	0.00	0.00	6.09
Madagascar	0.52	-24.93	-2.79	0.00	-1.77	-1.77	-0.61	-18.68	-0.66	0.00	0.00	0.02	0.00	1.89
Senegal	0.52	-17.15	-2.10	-0.10	-1.69	-2.32	0.00	-9.91	0.00	0.00	7641.99	0.08	13.21	1.15
Rwanda	0.51	-36.27	-1.39	-0.22	-2.11	0.00	0.00	-13.83	0.00	1.31	4983.87	0.15	7.18	0.00
Albania	0.51	-12.84	-6.66	0.00	0.00	-1.33	-0.22	-10.04	0.00	0.00	11205.98	0.00	0.00	14.62
El Salvador	0.48	-12.94	-1.26	0.00	-0.16	-0.63	-0.48	0.00	0.00	0.00	5742.30	0.01	0.00	0.00
Namibia	0.47	-13.46	0.00	0.00	-2.10	-6.87	0.00	-19.29	0.00	0.00	22451.48	0.00	0.00	5.79
Botswana	0.46	-17.88	0.00	0.00	-1.49	-4.06	0.00	-11.48	-0.14	0.00	23848.02	0.11	0.00	2.41
Lesotho	0.45	-16.58	-0.49	0.00	-0.94	-4.85	-0.85	-14.90	-1.28	0.00	219.65	0.02	0.00	8.10
Nicaragua	0.44	-1.27	-2.77	0.00	-0.13	-0.68	-0.02	0.00	0.00	0.00	3074.44	0.06	0.00	10.61
Cambodia	0.42	-18.31	-12.42	0.00	-1.28	0.00	-1.54	-16.58	0.00	0.00	1279.40	0.04	0.00	5.08
Nepal	0.41	-34.62	0.00	0.00	-1.87	-2.69	-0.71	-16.63	0.00	0.00	15081.09	0.00	0.00	0.00
Burundi	0.35	-20.57	0.00	0.00	-2.24	-3.26	0.00	-20.44	0.00	0.00	9398.33	0.00	13.15	0.00
Zambia	0.35	-28.18	-0.71	0.00	-1.15	-1.68	0.00	-5.65	0.00	0.00	3846.19	0.00	1.88	1.38
Uganda	0.35	-25.50	-2.56	0.00	-1.22	-0.71	0.00	-24.40	0.00	0.00	3312.82	0.16	0.48	0.30
Mozambique	0.33	-19.90	-11.85	0.00	-0.92	-4.01	0.00	-10.30	-0.61	0.00	3903.56	0.57	0.00	0.00
Ghana	0.30	-11.72	-3.85	0.00	-1.07	-1.31	0.00	-19.27	-0.51	0.00	2696.41	0.11	0.00	4.55
Mali	0.29	-11.53	-1.23	0.00	-0.78	-0.68	0.00	-15.38	0.00	0.00	4569.45	0.03	12.76	0.68
Kenya	0.26	-23.34	0.00	-0.20	-1.24	-2.38	0.00	-21.63	0.00	0.00	76550.84	1.70	0.00	0.00

Note: I= Inputs, Y=outputs, I(1)= Ease of Doing a Business, I(2)= FDI Inflows, I(3)=R&D Expenditures , I(4)=Intellectual Property Rights, I(5) = Education Expenditure , I(6)= ICT Access, I(7) = Knowledge Transfer Rate , I(8)= FDI Outflows; Y(1) = GDP Growth, Y(2)= Scientific and Technical Publications, Y(3)=Patents Granted , Y(4)= Households with a computer , Y(5)= High-tech Exports.

Table (4.18): Inputs and Outputs Slacks for Developing Countries by Employing the BCC Model.

DMU	Score	I (1)	I (2)	I (3)	I (4)	I (5)	I (6)	I (7)	I (8)	Y (1)	Y (2)	Y (3)	Y (4)	Y (5)
Russian Federation	0.96	-9.48	-0.86	0.00	-0.29	-1.26	-0.63	-8.13	0.00	4.20	74035.12	0.00	0.00	1.45
Serbia	0.96	-10.32	-7.40	0.00	-0.40	-0.13	-0.54	-4.33	0.00	2.92	114128.14	0.00	0.00	5.49
Azerbaijan	0.88	-4.65	-2.51	-0.07	-1.39	0.00	0.00	-23.28	-1.28	0.69	2230.69	0.00	0.00	19.81
Morocco	0.87	-15.74	-1.61	-0.04	-1.99	-1.97	0.00	0.00	-0.29	6.46	30609.99	0.27	0.00	0.00
India	0.86	-13.52	-3.34	0.00	-0.78	-0.68	0.00	-11.90	0.00	4.31	0.00	2.59	10.42	0.00
Mexico	0.85	-7.76	-2.64	0.00	-0.18	-1.50	0.00	-3.60	-0.08	0.93	0.00	0.00	0.00	0.00
Sri Lanka	0.82	-10.77	-7.70	0.00	-0.58	0.00	-1.06	-20.15	0.00	0.00	6134.57	0.00	0.00	2.32
Costa Rica	0.82	0.00	-1.70	0.00	-0.59	-3.09	0.00	-2.13	0.00	0.00	15471.09	0.00	0.00	0.00
Algeria	0.81	0.00	-3.08	-0.16	-1.22	-3.40	-0.80	-14.75	0.00	1.78	14484.40	0.09	0.00	3.03
Turkey	0.80	-10.52	0.00	0.00	-0.32	-0.71	-0.26	-2.19	0.00	0.00	113015.26	0.00	0.00	10.04
Ecuador	0.79	-0.13	-0.51	0.00	-0.04	-0.89	0.00	-2.81	0.00	4.10	8167.57	0.50	0.00	0.00
Tunisia	0.74	-4.24	-0.30	0.00	-0.09	-3.64	0.00	0.00	0.00	5.67	15701.68	0.26	0.00	0.00
Albania	0.72	-18.53	-9.84	0.00	0.00	-1.27	-1.51	-14.58	0.00	0.00	13932.93	0.00	0.00	7.58
Thailand	0.71	-20.96	-0.89	-0.63	0.00	0.00	-1.35	-15.14	-3.14	0.00	28125.71	0.00	0.28	0.00
Nicaragua	0.68	-1.85	-4.78	0.00	0.00	-0.44	-0.86	-1.56	0.00	0.00	3652.36	0.00	0.00	5.67
Jordan	0.67	-10.97	-2.56	-0.14	-1.77	0.00	-0.47	-16.05	0.00	0.00	48794.13	0.00	0.00	4.23
Peru	0.64	-12.21	-5.48	0.00	0.00	-1.67	-0.29	-3.16	-0.03	0.39	0.00	0.00	0.00	6.55
Colombia	0.61	-1.47	-3.68	0.00	0.00	-1.65	0.00	-5.93	0.00	0.00	22121.73	0.00	0.00	7.07
Indonesia	0.61	-6.66	-4.63	0.00	-0.76	0.00	-0.25	-21.11	-0.17	0.00	0.00	1.18	0.00	0.00
Cambodia	0.60	-1.15	-23.12	0.00	-0.14	0.00	-0.74	-17.63	-0.44	0.00	5547.75	0.03	0.80	0.00
Senegal	0.59	-5.85	-2.48	-0.01	-0.59	-0.31	0.00	-3.39	0.00	0.00	4237.61	0.04	0.00	11.76
Honduras	0.59	0.00	-3.63	0.00	-0.45	-2.11	-0.02	-4.94	-1.67	0.00	132.15	0.00	0.00	5.94
El Salvador	0.56	-12.95	-2.26	0.00	0.00	-0.36	-1.14	-1.46	0.00	0.00	4138.50	0.00	0.00	0.00
Nepal	0.51	-6.22	0.00	0.00	0.00	-1.17	0.00	0.00	0.00	0.00	4757.15	0.02	0.00	0.00
Lesotho	0.48	-3.15	-4.84	0.00	0.00	-4.37	-0.21	-11.29	-1.25	0.00	143.81	0.00	0.00	6.71
Namibia	0.48	-4.58	0.00	0.00	-1.12	-6.26	0.00	-12.25	0.00	0.00	10849.93	0.00	0.00	5.94
Zambia	0.48	-18.13	-3.51	0.00	-0.15	-0.37	0.00	0.00	0.00	0.00	1729.02	0.00	0.00	3.88
Botswana	0.46	-9.28	0.00	0.00	-0.51	-3.54	0.00	-3.97	-0.12	0.00	10689.47	0.15	0.00	2.93
Mali	0.46	0.00	-6.57	-0.01	0.00	0.00	0.00	-13.11	0.00	0.00	4899.24	0.00	2.75	5.19
Ghana	0.33	-4.23	-4.81	0.00	-0.45	-0.49	0.00	-14.68	0.00	0.00	2419.60	0.07	0.00	5.20
Kenya	0.28	-19.44	-1.35	-0.12	-0.45	-0.96	0.00	-19.77	0.00	0.00	61500.82	1.31	0.00	0.00

Note: see Table (4.17).

4.4.3.7 Discussion of the Radial DEA Analysis Results

4.4.3.7.1 Country's grouping based on the CCR and BCC Models

After applying the radial DEA analysis to developing countries in 2020, the following conclusion can be reached. In this case, developing countries are divided into four groups as follows:

First Group (Cluster A): Countries that attain the best overall comparative technical efficiency and pure technical efficiency under output oriented CCR and BCC models. These countries have an efficiency score of one (100%), which means that this group of countries has utilized its resources effectively to reach the maximum possible outputs. These countries account for 32.3% of the developing countries in the sample (21 out of 65 countries), namely Angola, Armenia, Brazil, Burkina Faso, China, Côte d'Ivoire, Egypt, Ethiopia, Gambia, Georgia, Guatemala, Iran, Jamaica, Kazakhstan, Kyrgyz Republic, Lao PDR, Malaysia, Mauritania, Philippines, South Africa, and Vietnam. Further, these countries have a scaling efficiency of 100% which means that there are no sources of inefficiency in this group of countries.

Second Group (Cluster B): Countries that achieve pure technical efficiency under the BCC model, but do not attain CCR efficiency and Scale efficiency. These countries have an efficiency score of 100% with respect to the BCC model but have an efficiency score of less than 100% in scale efficiency and in CCR efficiency as well. Thus, the sources of inefficiency in this group are both sides i.e., technical one and scale one. Additionally, all these countries are in the stage of increasing returns to scale which means that these countries could enhance their scale size to be efficient. This group represents 20% of the total sample (13 countries out of 65) and includes North Macedonia, Bulgaria, Argentina, Ukraine, Mongolia, Paraguay, Nigeria, Pakistan, Madagascar, Rwanda, Burundi, Uganda, and Mozambique. These countries have a CCR efficiency score of North Macedonia (0.99), Bulgaria (0.98), Argentina (0.98), Ukraine (0.97), Mongolia (0.93), Paraguay (0.84), Nigeria (0.60), Pakistan (0.56),

Madagascar (0.52), Rwanda (0.51), Burundi (0.36), Uganda (0.35), and Mozambique (0.33). These countries have also the same scale efficiency scores as the CCR efficiency scores, simply because their BCC efficiency scores are equal to 1. Therefore, these countries have the opportunity to increase their scale size by 1% for North Macedonia (0.01=1-0.99), 2% for Bulgaria (0.02=1-0.98), 2% for Argentina, 3% for Ukraine, 7% for Mongolia, 16% for Paraguay, 40% for Nigeria, 44% for Pakistan, 48% for Madagascar, 49% for Rwanda, 64% for Burundi, 64% for Uganda, and 67% for Mozambique and thus could reach the optimal scale size and hence attain the scale efficiency.

Third Group (Cluster C): This group includes countries that are inefficient under both two radial models, namely the CCR and BCC models. The scale efficiency for each country in this group is less than 100%. This means that these countries are CCR inefficient, BCC inefficient and scale inefficient as well. Thus, the sources of inefficiency for this group of countries are technical inefficiency and scale inefficiency. Therefore, these countries could adjust their scale size to reach the optimal size and become scale efficiently. Further, all these countries have attained increasing returns to scale (known as economies of scale); which means that increasing the inputs size will lead to efficiency gains. These countries constitute the largest percentage of countries as they account for 38.5% of the whole sample (25 countries from 65 developing countries). These countries are Albania, Algeria, Azerbaijan, Botswana, Cambodia, Colombia, Costa Rica, El Salvador, Ghana, Honduras, India, Indonesia, Jordan, Kenya, Lesotho, Mexico, Mali, Namibia, Nepal, Nicaragua, Peru, Senegal, Sri Lanka, Thailand, and Zambia. Among this group of countries, Kenya has the highest relative inefficiency score of (0.74) according to the CCR model and (0.72) with respect to the BCC model. On the other hand, Azerbaijan has the lowest relative inefficiency score of (0.13), and (0.12) according to the CCR model and the BCC model scores respectively. Finally, Nicaragua and Mali have the highest relative scale inefficiency score of (0.35) while, Costa Rica, Azerbaijan, Botswana, India, and Mexico all have the lowest relative scale inefficiency scores of (0.01).

Fourth Group (Cluster D): This group includes countries that are inefficient under CCR and BCC models. The scale efficiency for each country is less than 100%. So, these countries are CCR, BCC and Scale inefficient as in group (3). However, these countries have attained decreasing returns to scale (known as diseconomies of scale) which means that decreasing the inputs size will lead to efficiency gains. Thus, for these countries to be scale efficient, increasing outputs requires a decrease in inputs. These countries represent around 9.2% of the whole sample (6 countries only). Russian Federation, Serbia, Morocco, Turkey, Ecuador, and Tunisia form this group of countries. Within this group of countries, Russian Federation has the lowest inefficiency score of (0.08) and (0.04) according to the CCR and BCC models respectively, and Tunisia has the highest inefficiency score of (0.27) according to the CCR model and (0.26) with respect to the BCC model. Additionally, within this group of countries, Morocco, Turkey, Ecuador, and Tunisia have the lowest scale inefficiency of (0.01), whereas Russian Federation has the highest scale inefficiency (0.05).

4.4.3.7.2 Classification by Income

Additionally, the clustering results presented above are classified from an economic perspective, as presented in Table (4.19). The income data are extracted from the World Bank Database for the year 2020. Therefore, countries are classified into low, lower-middle, and upper-middle income groups. Generally, many cluster's member countries are distributed across the middle-income groups.

Table (4.19): Countries Clustering by Income Group Under the Radial DEA Models.

	Cluster A	Cluster B	Cluster C	Cluster D
Definition	Countries with the best overall technical efficiency and pure technical efficiency under the CCR and BCC models.	Countries that achieve pure technical efficiency under the BCC model, but do not attain CCR efficiency and Scale efficiency.	Inefficient countries under CCR and BCC models. These countries attain increasing returns to scale	Inefficient countries under CCR and BCC models. These countries attain decreasing returns to scale
Countries Included	21/65	13/65	25/65	6/65
Low-Income ($1,035 or less).	1. Burkina Faso 2. Ethiopia 3. Gambia 4. Georgia	1. Rwanda 2. Burundi 3. Uganda 4. Mozambique	1. Mali	
Lower-Middle Income ($1,036 to $4,045).	1. Angola 2. Côte d'Ivoire 3. Egypt 4. Kyrgyz Republic 5. Lao PDR 6. Vietnam 7. Philippines 8. Mauritania	1. Ukraine 2. Mongolia 3. Nigeria 4. Pakistan 5. Madagascar	1. Algeria 2. Cambodia 3. El Salvador 4. Ghana 5. Honduras 6. India 7. Kenya 8. Lesotho 9. Nicaragua 10. Nepal 11. Senegal 12. Sri Lanka 13. Zambia	1. Morocco 2. Tunisia
Upper-Middle Income ($4,046 to $12,535).	1. Armenia 2. Brazil 3. China 4. Guatemala 5. Iran 6. Jamaica 7. Kazakhstan 8. Malaysia 9. South Africa	1. North Macedonia. 2. Bulgaria 3. Paraguay 4. Argentina	1. Albania 2. Azerbaijan 3. Botswana 4. Colombia 5. Costa Rica 6. Indonesia 7. Jordan 8. Mexico 9. Namibia 10. Peru 11. Thailand	1. Russian Federation 2. Serbia 3. Turkey 4. Ecuador

4.4.3.7.3 Summing Up

Most developing countries are inefficient under both radial models. The CCR model does provide a narrow efficiency area than the BCC model within this case study. Additionally, most developing countries are scale inefficient and are operating with increasing returns to scale as well. Thus, the sources of inefficiency for most developing countries are both sided. That is most developing countries suffer from pure technical inefficiency and scale inefficiency. However, on average, their pure technical inefficiencies are greater than their scale inefficiencies. Thus, policymakers are advised to pay first attention to the managerial efficiency in these countries then focus on improving the scale efficiency.

4.5 Non-Radial DEA Analysis

4.5.1 Introduction

In DEA literature, performance assessment studies can be methodologically partitioned into two fundamental approaches with different characteristics, namely radial and non-radial measures. The former traditional (radial) measures are presented by CCR and BCC models as in section 5 of this chapter. Despite their usefulness, in many real-life situations they have certain disadvantages. Of these limitations, inefficient DMUs must seek changes in their inputs and/or outputs proportionally to become frontier countries. However, in real situations, inputs and outputs can change non-proportionally (Tone, 2016).

To clarify, both radial DEA models are constructed by assuming proportionate movement. This means a proportionate reduction in all inputs and/or proportionate augmentation in all outputs depending on the model's orientation. These suggested proportionate movements could raise the efficiency of the inefficient DMUs to the level on the frontier corresponding to the most efficient units in the dataset and thus present a radial measure of efficiency. In contrast, non-radial DEA models allow each input and output to change individually and thus allow for non-proportional movement (Avkiran et al., 2008).

The other limitation of the radial DEA models is that these models neglect the input and output slacks and thus provide overestimated efficiency scores (Wei et al., 2019). Additionally, Lin et al. (2019) maintained that conventional DEA models failed to deal with negative inputs and outputs and failed to discriminate between efficient DMUs as well. Further, Ferrier et al. (1994) added that traditional DEA models fail to satisfy Pareto Koopmans's definition of technical efficiency in which technical efficiency is equated with the DMUs in the efficient subset not relative to the isoquant as in radial measures. In other words, it provides a non-Pareto optimal solution (Wei et al., 2019).

On the other hand, the latter approach i.e., the non-radial approach has salient advantages over the radial approach as it takes into consideration the slack, by allowing inputs and output to change in different proportions and thus providing a non-radial measure of efficiency (Shao et al., 2021). This approach also presents a Pareto-efficient efficiency score. DEA Scholars introduced many non-radial measures such as the additive model introduced by Charnes et al. (1985), the Russell measure introduced by Färe et al. (1985) as in Salahi et al. (2019), the multi-directional efficiency analysis as in Asmild et al. (2003) and the slacks-based measure (SBM) introduced by Tone (2001).

Each of these measures has its advantages and disadvantages. For instance, the additive model has been criticized for not providing an efficiency score for the DMUs being evaluated. Additionally, the additive model presents the 'furthest' target for inefficient DMUs on the frontier (Cheng et al., 2013). The Russell measure is formulated as a non-linear programming model and thus has been criticized computationally for being very complicated (Panwar et al., 2022). Among these non-radial models, the SBM model is one of the famous applied non-radial models in many contexts (Lin et al., 2019) and could sort out the issue of the additive model by providing a single scalar efficiency measure. Thus, this section provides a non-radial SBM to assess KBE efficiencies in developing countries.

Theoretically, the non-radial measures of efficiency have superiority over radial measures because it satisfies Pareto Koopmans definition of technical efficiency (Ferrier et al., 1994) and empirically it is more effective as they present higher discrimination power than the radial DEA models and provide meaningful and practical results as observed in many empirical studies as in Zhou et al. (2007).

A literature review in estimating the efficiency of KBE using the SBM reveals that almost no studies exist, to the best of the researcher knowledge, except the study presented by Afzal and Lawrey (2012d). However, even in this study, the applied DEA model is the additive model with its limitations as it failed to introduce an efficiency score for each country. Thus, in this chapter, the SBM is applied in this section of the chapter in an attempt to fill the gap in the literature in this area.

4.5.2 Slack-Based Measure

As shown in the literature review, most studies have adopted the basic DEA models for performance assessment, with the main criterion that all inputs and/or outputs of a DMU must be adjusted by the same ratio to catch the efficiency frontier. However, in practice, many inefficient DMUs may be inefficient because one or more of their inputs and/or outputs are performing badly. Therefore, it is not appropriate to change all inputs and/or outputs by the same proportion. Non-radial DEA measures allow for a non-proportional reduction in each input and/or increase in each output. Therefore, the resulting DEA guidelines present reasonable insights to specific areas that need improvements. This will allow for better use of resources through adequate allocation and utilization of resources/inputs and finally lead to convergence between target and actual performance (Wu et al., 2011).

SBM uses the term slacks to reflect the excess in inputs and shortfalls in outputs and directly deals with these slacks. Since SBM focuses on inputs slacks and output slacks directly; it can detect all sources of inefficiency for the investigated DMU and provide a more accurate efficiency score. SBM introduced an efficiency score between 0 and 1. Additionally, it is units-invariant which means that this measure is invariant with respect to the units of data and a monotone decreasing with excess in inputs and decrease in output (Tone, 2001). SBM can divide DMUs into efficient and inefficient DMUs. SBM also provides projection points on the frontier for each input and/or output without assuming that their movement should be radial but rather different movements. The best performers DMUs are those denoted by a score of 1 (100% efficient) while the inefficient DMUs have a smaller score than 1.

4.5.3 Methodological Considerations Prior to Applying the DEA Analysis

In this section, for consistency and comparing purposes the same methodological considerations, the same data, and the same variables structures as those used previously in the radial DEA models (section 4.4) are followed. Thus, 65 developing countries are involved in the analysis with the same inputs and outputs framework.

Furthermore, the orientation of the SBM employed is output-oriented, instead of models with non-radial or input orientations. This is because, given the previous results of DEA analysis, it is not appropriate to provide suggestions for a reduction in inputs because many inputs such as the ease of doing business, the intellectual property rights, and the knowledge transfer rate are favourable. These input variables should be increased not decreased because their reduction would create a restrictive knowledge environment. Instead, it is more applicable to find out output decreases that cause inefficiency, without changing the input variables and thus improving KBE outputs and hence faster the transition of KBE in developing countries through the non-radial output oriented SBM model.

4.5.4 Empirical Results for the Non-Radial DEA Analysis

4.5.4.1 SBM Model under CRS, VRS and Scale Effect Scores

The results of the SBM-CRS and SBM-VRS models are calculated and are displayed in the following Table (4.20). In the non-radial DEA models, the ratio between CRS score/ VRS score is called the "scale effect", and this same ratio is called scale efficiency if the radial models are employed (Cheng, 2014). As shown in Table (4.20), there is substantial variation between developing countries regarding their overall technical efficiency scores, pure technical efficiency scores and scale effect scores, with most of the developing countries being inefficient. The percentage of efficient countries in both SBM CRS and SBM VRS models is 32% and 52% respectively. This percentage is the same as the results observed previously in the radial models. One reason for these similar results is that as shown in section 5.3.4, the efficient countries have zero slacks in inputs and outputs. Therefore, the non-radial SBM model does not have any slacks to deal with.

However, the SBM model provides more accurate efficiency scores than the over-estimated efficiency scores with the inefficient countries. For instance, the average overall technical efficiency for inefficient DMUs under the radial CCR CRS model was 0.62 compared to only 0.13 in the non-radial SBM CRS model, because the SBM model detected all inefficiency sources, as shown in Table (4.25). The same accurate efficiency scores are obtained if we compare the pure technical efficiency scores using the radial and non-radial approaches. As the average pure technical efficiency scores for inefficient DMUs was 0.66 in radial models compared to 0.11 in the non-radial model as shown in Table (4.26). Finally, the average scale efficiency/scale effect for inefficient DMUs was 0.83 and 0.65 for the radial and non-radial models respectively as shown in Table (4.25).

Up to this stage, the SBM model could divide developing countries into efficient and non-efficient ones. However, all efficient countries have an efficiency score of one (100%), which means that the SBM failed to discriminate between efficient units as in the radial DEA model. To differentiate between efficient DMUs under the SBM model, other DEA models are suggested in the DEA literature as described below.

4.5.4.2 Discrimination between Efficient Countries

4.5.4.2.1 Slack-Based Super Efficiency Model

As observed in Table (4.24), SBM divided developing countries into efficient and non-efficient ones and could not discriminate between efficient countries, giving an efficiency score of one to all efficient DMUs. Thus, it cannot go further to discriminate between efficient counties (Du et al., 2010). Therefore, Tone (2001) allows efficient DMUs to be ranked by developing a non- radial super-efficiency approach as an extension to the traditional super-efficiency model introduced by Andersen and Petersen (1993) to differentiate between efficient DMUs known as the super SBM model. This Super-SBM model takes the slacks into consideration as well. Recall that, under the radial DEA models, the super-efficiency DEA models function by removing the DMU under evaluation from the reference set. However, this procedure cannot be done directly in the Super-SBM models to get super-efficiency scores. Thus, Tone (2001) clarifies that the researchers need to firstly identify the efficient DMUs and then proceed to modify the DEA model to have a full ranking for all DMUs.

Thus, this Super-SBM model could discriminate between efficient DMUs but failed to discriminate between inefficient ones (Lee, 2021). Furthermore, Tone (2001) indicates that, unlike the radial super-efficiency DEA models, the Super-SBM model or the Slacks-based super-efficiency models are always feasible under both returns, namely the constant or variable returns to scale assumption. Only occasional infeasibility issues could happen in both models (Wei et al., 2019).

It is important to mention here that the main difference between the two super-efficiency models is that the Andersen and Petersen super-efficiency model gives inefficient countries the same radial efficiency scores thus evaluation of efficiency scores and ranking for all countries can be done in one step if the traditional the super-efficiency model is employed. On the other hand, the Super-SBM failed to give scores to inefficient countries. Thus, the researcher must apply two complementary steps if the SBM approach is the chosen approach to follow. The first step is to adopt the SBM model to provide a non-radial efficiency score for all countries whereas the second step is to apply the super SBM to calculate efficiency scores for efficient countries. Thus, for evaluation and ranking purposes using the non-radial approach two models, namely SBM and Super-SBM should be employed sequentially.

As observed in Tables (4.24) and (4.25), the Kyrgyz Republic then China are the top leaders for developing countries in 2020 by employing the CRS Super-SBM model. This result is consistent with the results of the traditional radial Super efficiency DEA model in which China is the top leader and the Kyrgyz Republic is linear programming infeasible.

Additionally, Iran is the top leader for developing countries in 2020 under the VRS Super-SBM model as in Tables (4.30) and (4.31). This country was linear programming infeasible under the traditional radial Super efficiency DEA model.

To this end, it could conclude that the traditional super efficiency and the Super-SBM have provided the same top leaders for developing countries in 2020 but with different scores with only some exceptions if the DMU/country is linear programming infeasible.

Furthermore, the Super-SBM has superiority over the traditional super-efficiency model in terms of feasibility as only two countries are infeasible in the Super-SBM under both returns the CRS and VRS compared to 3 and 12 infeasible countries under both returns in the traditional super-efficiency model respectively.

4.5.4.2.2 Frequency of the Reference Set Approach

Another approach for discrimination between efficient countries is to calculate how many times an efficient DMU can be used as a benchmark for other inefficient DMUs. Tables (4.28) and (4.29) present how many times each efficient country can be considered as a role model for other inefficient countries. China is the country with the highest frequency under both returns and thus can be emulated by other inefficient countries as in Tables (4.28) and (4.29).

Additionally, the reference set approach could provide a set of countries called a peer group by which the decision-maker could pay attention only to a subgroup of efficient countries referred to as the efficiency reference set countries as in Tables (4.30) and (4.31). This efficiency reference set includes the group of peer units against which each inefficient country was found to be directly inefficient.

Recall that, the value in parentheses in both tables is called Lambda which refers to the relative weight assigned to each efficiency reference set country. Lambda for efficient countries is equal to one because it is a benchmarking for itself, while the weights assigned to other inefficient countries are in parentheses.

Table (4.20): Overall Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency for Developing Countries under Output- Oriented SBM Model.

DMU	OTE Score	PTE Score	Scale Effect Score	RTS	DMU	OTE Score	PTE Score	Scale Effect Score	RTS
Albania	0.007	0.012	0.558	Increasing	**Lao PDR**	1.000	1.000	1.000	Constant
Algeria	0.035	0.074	0.471	Increasing	**Lesotho**	0.008	0.009	0.855	Increasing
Angola	1.000	1.000	1.000	Constant	**Madagascar**	0.231	1.000	0.231	Increasing
Argentina	0.368	1.000	0.368	Increasing	**Malaysia**	1.000	1.000	1.000	Constant
Armenia	1.000	1.000	1.000	Constant	**Mali**	0.005	0.005	0.908	Increasing
Azerbaijan	0.110	0.110	0.998	Decreasing	**Mauritania**	1.000	1.000	1.000	Constant
Botswana	0.010	0.010	0.997	Increasing	**Mexico**	0.558	0.561	0.994	Increasing
Brazil	1.000	1.000	1.000	Constant	**Mongolia**	0.107	1.000	0.107	Increasing
Bulgaria	0.099	1.000	0.099	Increasing	**Morocco**	0.129	0.136	0.951	Increasing
Burkina Faso	1.000	1.000	1.000	Constant	**Mozambique**	0.009	1.000	0.009	Increasing
Burundi	0.002	1.000	0.002	Increasing	**Namibia**	0.009	0.009	0.991	Increasing
Cambodia	0.018	0.019	0.951	Increasing	**Nepal**	0.030	0.036	0.844	Increasing
China	1.000	1.000	1.000	Constant	**Nicaragua**	0.009	0.011	0.749	Increasing
Colombia	0.376	0.382	0.983	Increasing	**Nigeria**	0.048	1.000	0.048	Increasing
Costa Rica	0.037	0.038	0.981	Decreasing	**North Macedonia**	0.089	1.000	0.089	Increasing
Côte d'Ivoire	1.000	1.000	1.000	Constant	**Pakistan**	0.114	1.000	0.114	Increasing
Ecuador	0.067	0.082	0.817	Increasing	**Paraguay**	0.028	1.000	0.028	Increasing
Egypt, Arab Rep.	1.000	1.000	1.000	Constant	**Peru**	0.229	0.233	0.982	Increasing
El Salvador	0.006	0.006	0.957	Increasing	**Philippines**	1.000	1.000	1.000	Constant
Ethiopia	1.000	1.000	1.000	Constant	**Russian Federation**	0.635	0.647	0.982	Decreasing
Gambia, the	1.000	1.000	1.000	Constant	**Rwanda**	0.005	1.000	0.005	Increasing
Georgia	1.000	1.000	1.000	Constant	**Senegal**	0.009	0.012	0.787	Increasing
Ghana	0.024	0.025	0.977	Increasing	**Serbia**	0.129	0.133	0.969	Decreasing
Guatemala	1.000	1.000	1.000	Constant	**South Africa**	1.000	1.000	1.000	Constant
Honduras	0.037	0.043	0.867	Increasing	**Sri Lanka**	0.143	0.172	0.830	Increasing
India	0.447	0.470	0.952	Increasing	**Thailand**	0.157	0.164	0.958	Increasing
Indonesia	0.154	0.160	0.964	Increasing	**Tunisia**	0.120	0.134	0.895	Increasing
Iran, Islamic Rep	1.000	1.000	1.000	Constant	**Turkey**	0.314	0.314	0.999	Decreasing
Jamaica	1.000	1.000	1.000	Constant	**Uganda**	0.091	1.000	0.091	Increasing
Jordan	0.068	0.073	0.927	Increasing	**Ukraine**	0.443	1.000	0.443	Increasing
Kazakhstan	1.000	1.000	1.000	Constant	**Vietnam**	1.000	1.000	1.000	Constant
Kenya	0.025	0.028	0.894	Increasing	**Zambia**	0.012	0.014	0.865	Increasing
Kyrgyz Republic	1.000	1.000	1.000	Constant					

Table (4.21): Descriptive Statistics for Overall Technical Efficiency Scores Based on SBM-CRS.

Statistics	All countries	Efficient Countries	Inefficient Countries
Number of DMUs	65	21 (Around 32% of the total DMUs)	44 (Around 68% of the total DMUs)
Average Overall Technical Efficiency	0.41	1	0.13
Minimum	0.002	1	0.002
Maximum	1	1	0.635

Note: Calculations are based on the Table (4.20).

Table (4.22): Descriptive Statistics for Pure Technical Efficiency Scores Based on SBM-VRS.

Statistics	All countries	Efficient Countries	Inefficient Countries
Number of DMUs	65	34 (About 52% of the total DMUs)	31 (About 48% of the total DMUs)
Average pure technical efficiency	0.59	1	0.11
Minimum	0.005	1	0.005
Maximum	1	1	0.647

Note: See Table (4.21).

Table (4.23): Descriptive Statistics for the Scale Efficiency Scores based on SBM.

Statistics	All countries	Efficient Countries	Inefficient Countries
Number of DMUs	65	21(32%)	44(68%)
Average scale efficiency	0.76	1	0.65
Minimum	0.002	1	0.002
Maximum	1	1	0.99

Note: See Table (4.21).

Table (4.24): Super-SBM for Efficient Countries under CRS.

No.	DMU	Super-SBM score		No.	DMU	Super-SBM score
1	Kyrgyz Republic	1.98		**12**	Angola	1.11
2	China	1.93		**13**	Malaysia	1.07
3	Armenia	1.50		**14**	Egypt, Arab Rep.	1.06
4	Lao PDR	1.28		**15**	Jamaica	1.05
5	Iran, Islamic Rep	1.28		**16**	The Gambia	1.05
6	Côte d'Ivoire	1.24		**17**	Guatemala	1.04
7	Kazakhstan	1.21		**18**	South Africa	1.03
8	Vietnam	1.19		**19**	Georgia	1.01
9	Ethiopia	1.18		**20**	Brazil	LP infeasible
10	Burkina Faso	1.15		**21**	Mauritania	LP infeasible
11	Philippines	1.14				

Table (4.25): Complete Efficiency Evaluation and Ranking for all Countries Using SBM and Super-SBM Under CRS.

No.	DMU	Score		No.	DMU	Score
1	Kyrgyz Republic	1.98		**34**	Tunisia	0.12
2	China	1.93		**35**	Pakistan	0.11
3	Armenia	1.50		**36**	Azerbaijan	0.11
4	Lao PDR	1.28		**37**	Mongolia	0.11
5	Iran, Islamic Rep	1.28		**38**	Bulgaria	0.10
6	Côte d'Ivoire	1.24		**39**	Uganda	0.09
7	Kazakhstan	1.21		**40**	North Macedonia	0.09
8	Vietnam	1.19		**41**	Jordan	0.07
9	Ethiopia	1.18		**42**	Ecuador	0.07
10	Burkina Faso	1.15		**43**	Nigeria	0.05
11	Philippines	1.14		**44**	Costa Rica	0.04

No.	DMU	Score		No.	DMU	Score
12	Angola	1.11		45	Honduras	0.04
13	Malaysia	1.07		46	Algeria	0.03
14	Egypt, Arab Rep.	1.06		47	Nepal	0.03
15	Jamaica	1.05		48	Paraguay	0.03
16	The Gambia	1.05		49	Kenya	0.02
17	Guatemala	1.04		50	Ghana	0.02
18	South Africa	1.03		51	Cambodia	0.02
19	Georgia	1.01		52	Zambia	0.01
20	Russian Federation	0.64		53	Botswana	0.01
21	Mexico	0.56		54	Senegal	0.01
22	India	0.45		55	Mozambique	0.01
23	Ukraine	0.44		56	Namibia	0.01
24	Colombia	0.38		57	Nicaragua	0.01
25	Argentina	0.37		58	Lesotho	0.01
26	Turkey	0.31		59	Albania	0.01
27	Madagascar	0.23		60	El Salvador	0.01
28	Peru	0.23		61	Mali	0.00499
29	Thailand	0.16		62	Rwanda	0.00491
30	Indonesia	0.15		63	Burundi	0.002
31	Sri Lanka	0.14		64	Brazil	LP infeasible
32	Morocco	0.13		65	Mauritania	LP infeasible
33	Serbia	0.13				

Table (4.26): Super-SBM for Efficient Countries Under VRS.

No.	DMU	Super-SBM score		No.	DMU	Super-SBM score
1	Iran, Islamic Rep	5.220053867		18	Philippines	1.135718406
2	Burundi	4.580657383		19	Mongolia	1.132770376
3	The Gambia	4.53009816		20	Malaysia	1.109519155
4	Brazil	2.698332992		21	Egypt, Arab Rep.	1.104607331
5	Ethiopia	2.151638382		22	Guatemala	1.081389952
6	China	1.963502644		23	Mozambique	1.065112107
7	Armenia	1.924303821		24	Jamaica	1.057360893
8	Kyrgyz Republic	1.717753856		25	Rwanda	1.056318597
9	Burkina Faso	1.641354209		26	Paraguay	1.053484097
10	Nigeria	1.637455929		27	South Africa	1.028711083
11	Angola	1.578743023		28	Bulgaria	1.007720923
12	Mauritania	1.360125132		29	Georgia	1.006798941
13	Côte d'Ivoire	1.349062746		30	Argentina	1.006374605
14	Pakistan	1.302533114		31	Ukraine	1.00482905
15	Madagascar	1.25041892		32	North Macedonia	1.000375105
16	Kazakhstan	1.225219536		33	Lao PDR	LP infeasible
17	Vietnam	1.192736691		34	Uganda	LP infeasible

Table (4.27): Complete Efficiency Evaluation and Ranking for all Countries Using SBM and Super-SBM Under VRS.

No.	DMU	Score		No.	DMU	Score
1	Iran, Islamic Rep	5.22		**34**	Mexico	0.56
2	Burundi	4.58		**35**	India	0.47
3	Gambia, the	4.53		**36**	Colombia	0.38
4	Brazil	2.70		**37**	Turkey	0.31
5	Ethiopia	2.15		**38**	Peru	0.23
6	China	1.96		**39**	Sri Lanka	0.17
7	Armenia	1.92		**40**	Thailand	0.16
8	Kyrgyz Republic	1.72		**41**	Indonesia	0.16
9	Burkina Faso	1.64		**42**	Morocco	0.14
10	Nigeria	1.64		**43**	Tunisia	0.13
11	Angola	1.58		**44**	Serbia	0.13
12	Mauritania	1.36		**45**	Azerbaijan	0.11
13	Côte d'Ivoire	1.35		**46**	Ecuador	0.08
14	Pakistan	1.30		**47**	Algeria	0.07
15	Madagascar	1.25		**48**	Jordan	0.07
16	Kazakhstan	1.23		**49**	Honduras	0.04
17	Vietnam	1.19		**50**	Costa Rica	0.04
18	Philippines	1.14		**51**	Nepal	0.04
19	Mongolia	1.13		**52**	Kenya	0.03
20	Malaysia	1.11		**53**	Ghana	0.02
21	Egypt, Arab Rep.	1.10		**54**	Cambodia	0.02
22	Guatemala	1.08		**55**	Zambia	0.01
23	Mozambique	1.07		**56**	Albania	0.01
24	Jamaica	1.06		**57**	Senegal	0.01
25	Rwanda	1.06		**58**	Nicaragua	0.01
26	Paraguay	1.05		**59**	Botswana	0.01
27	South Africa	1.03		**60**	Lesotho	0.01
28	Bulgaria	1.01		**61**	Namibia	0.01
29	Georgia	1.01		**62**	El Salvador	0.006
30	Argentina	1.01		**63**	Mali	0.005
31	Ukraine	1.00		**64**	Lao PDR	LP infeasible
32	North Macedonia	1.00		**65**	Uganda	LP infeasible
33	Russian Federation	0.65				

Table (4.28): Frequency Count for Efficient Countries with Categorization Based on SBM-CRS.

Highly Robust Countries	Marginally Robust Countries	Efficient Countries by default
China (44)	Kyrgyz Republic (7)	Burkina Faso (0)
Kazakhstan (22)	Brazil (5)	Egypt, Arab Rep. (0)
Armenia (17)	Mauritania (5)	Georgia (0)
Lao PDR (14)	Côte d'Ivoire (4)	Malaysia (0)
Iran, Islamic Rep. (12)	Philippines (4)	South Africa (0)
Angola (10)	Vietnam (2)	
	Ethiopia (1)	
	Gambia (1)	
	Guatemala (1)	
	Jamaica (1)	

Table (4.29): Frequency Count for Efficient Countries with Categorization Based on SBM-VRS.

Highly Robust Countries	Marginally Robust Countries	Efficient Countries by default
China (30)	Ethiopia (6)	Argentina (0)
Angola (20)	Brazil (4)	Bulgaria (0)
Mauritania (16)	Burundi (4)	Egypt, Arab Rep. (0)
Lao PDR (13)	Vietnam (4)	Gambia (0)
Kazakhstan (9)	Côte d'Ivoire (3)	Georgia (0)
Armenia (8)	Kyrgyz Republic (3)	Guatemala (0)
Iran, Islamic Rep (8)	Madagascar (3)	Malaysia (0)
	Philippines (3)	Mozambique (0)
	Mongolia (2)	North Macedonia (0)
	Nigeria (2)	Pakistan (0)
	Burkina Faso (1)	Paraguay (0)
	Jamaica (1)	Rwanda (0)
	Uganda (1)	South Africa (0)
		Ukraine (0)

Table (4.30): Reference Sets for Inefficient Developing Countries Based on SBM-CRS.

DMU	Benchmark (Lambda)
Albania	China (0.04); Kazakhstan (0.08); Kyrgyz Republic (0.04); Lao PDR (0.30); Philippines (0.28)
Algeria	Armenia (0.37); China (0.17); Iran, Islamic Rep (0.14); Kazakhstan (0.00)
Argentina	Armenia (0.10); China (0.08); Iran, Islamic Rep (0.31); Kazakhstan (0.34)
Azerbaijan	Angola (0.53); China (0.05); Kazakhstan (0.54)
Botswana	Angola (0.28); China (0.24); Lao PDR (0.39); Mauritania (0.02); Philippines (0.02)
Bulgaria	Armenia (0.21); China (0.27); Iran, Islamic Rep (0.13); Kazakhstan (0.30)
Burundi	China (0.10); Kyrgyz Republic (0.08); Mauritania (0.03)
Cambodia	China (0.05); Jamaica (0.14)
Colombia	China (0.08); Kazakhstan (0.30); Lao PDR (0.56)
Costa Rica	Armenia (0.53); Brazil (0.00); China (0.12); Kazakhstan (0.06); Lao PDR (0.27); Philippines (0.02)
Ecuador	Armenia (0.59); China (0.15); Kazakhstan (0.02)
El Salvador	Angola (0.36); China (0.07); Lao PDR (0.11)
Ghana	China (0.17); Côte d'Ivoire (0.09); Lao PDR (0.41)
Honduras	Angola (0.51); China (0.01)
India	China (0.29); Kazakhstan (0.26)
Indonesia	Armenia (0.36); China (0.07); Côte d'Ivoire (0.22)
Jordan	Armenia (0.30); Brazil (0.02); China (0.26); Iran, Islamic Rep (0.08); Lao PDR (0.28); Mauritania (0.00)
Kenya	China (0.36); Kyrgyz Republic (0.10)
Lesotho	Angola (0.12); China (0.02)
Madagascar	Angola (0.16); China (0.00)
Mali	China (0.14)
Mexico	China (0.11); Kazakhstan (0.47); Lao PDR (0.32)
Mongolia	Armenia (0.17); China (0.01); Kazakhstan (0.16); Kyrgyz Republic (0.03); Lao PDR (0.21); Philippines (0.12)
Morocco	China (0.13); Iran, Islamic Rep (0.50); Kazakhstan (0.19)
Mozambique	China (0.15); Lao PDR (0.06)

DMU	Benchmark (Lambda)
Namibia	Angola (0.39); China (0.16)
Nepal	Armenia (0.27); China (0.11); Kyrgyz Republic (0.04)
Nicaragua	Angola (0.34); China (0.05)
Nigeria	Armenia (0.23); Brazil (0.04); China (0.02)
North Macedonia	China (0.01); Iran, Islamic Rep (0.34); Kazakhstan (0.48)
Pakistan	Armenia (0.10); Brazil (0.04); China (0.07); Côte d'Ivoire (0.15); Lao PDR (0.06)
Paraguay	Armenia (0.04); China (0.03); Gambia, The (0.27); Guatemala (0.01); Iran, Islamic Rep (0.05); Kazakhstan (0.17); Lao PDR (0.03)
Peru	China (0.04); Kazakhstan (0.37)
Russian Federation	Armenia (0.06); China (0.24); Iran, Islamic Rep (0.42); Kazakhstan (0.19); Vietnam (0.15)
Rwanda	Brazil (0.08); China (0.25); Kyrgyz Republic (0.14); Lao PDR (0.04)
Senegal	China (0.25); Côte d'Ivoire (0.46)
Serbia	Armenia (0.19); China (0.22); Iran, Islamic Rep (0.47); Kazakhstan (0.14)
Sri Lanka	Angola (0.24); Armenia (0.06); China (0.04); Kazakhstan (0.05); Lao PDR (0.43)
Thailand	China (0.45); Kazakhstan (0.38); Mauritania (0.03)
Tunisia	Armenia (0.59); China (0.21); Iran, Islamic Rep (0.04); Kazakhstan (0.04)
Turkey	China (0.29); Ethiopia (0.02); Iran, Islamic Rep (0.23); Kazakhstan (0.12); Mauritania (0.10); Vietnam (0.25)
Uganda	China (0.06); Kyrgyz Republic (0.07)
Ukraine	Armenia (0.26); China (0.07); Iran, Islamic Rep (0.28); Kazakhstan (0.28)
Zambia	Angola (0.03); China (0.13)

Table (4.31): Reference Sets for Inefficient Developing Countries Based on SBM-VRS.

DMU	Benchmark (Lambda)
Albania	Angola (0.32); Ethiopia (0.05); Lao PDR (0.05); Mongolia (0.43); Vietnam (0.15)
Algeria	Angola (0.67); Brazil (0.10); China (0.08); Iran, Islamic Rep (0.15)
Azerbaijan	Angola (0.34); China (0.05); Kazakhstan (0.61)
Botswana	Angola (0.28); China (0.24); Lao PDR (0.38); Mauritania (0.10)
Cambodia	China (0.05); Jamaica (0.01); Mauritania (0.94)
Colombia	Angola (0.18); China (0.08); Kazakhstan (0.24); Lao PDR (0.50)
Costa Rica	Armenia (0.54); China (0.12); Kazakhstan (0.06); Lao PDR (0.25); Philippines (0.02); Vietnam (0.01)
Ecuador	Angola (0.48); Armenia (0.31); Brazil (0.08); China (0.12); Iran, Islamic Rep (0.01)
El Salvador	Angola (0.42); China (0.07); Lao PDR (0.09); Madagascar (0.35); Mauritania (0.08)
Ghana	China (0.16); Côte d'Ivoire (0.24); Lao PDR (0.46); Mauritania (0.14)
Honduras	Angola (0.42); China (0.01); Mauritania (0.57)
India	Angola (0.66); China (0.29); Philippines (0.05)
Indonesia	Armenia (0.26); China (0.07); Lao PDR (0.60); Mauritania (0.08)
Jordan	Armenia (0.27); Brazil (0.03); China (0.24); Iran, Islamic Rep (0.12); Lao PDR (0.13); Mauritania (0.21)
Kenya	Brazil (0.01); Burundi (0.05); China (0.33); Kyrgyz Republic (0.05); Mauritania (0.08); Uganda (0.49)
Lesotho	China (0.02); Mauritania (0.98)
Mali	Angola (0.10); Burundi (0.03); China (0.12); Ethiopia (0.04); Madagascar (0.06); Mauritania (0.65)
Mexico	Angola (0.08); China (0.12); Kazakhstan (0.40); Lao PDR (0.40)
Morocco	Angola (0.30); China (0.12); Iran, Islamic Rep (0.52); Kazakhstan (0.05)
Namibia	Angola (0.17); China (0.15); Lao PDR (0.45); Mauritania (0.23)
Nepal	Angola (0.00); China (0.11); Kyrgyz Republic (0.12); Lao PDR (0.07); Mauritania (0.38); Nigeria (0.32)
Nicaragua	Angola (0.24); China (0.03); Côte d'Ivoire (0.02); Ethiopia (0.05); Mauritania (0.60);

DMU	Benchmark (Lambda)
	Nigeria (0.05)
Peru	Angola (0.62); China (0.04); Kazakhstan (0.09); Lao PDR (0.25)
Russian Federation	Armenia (0.12); China (0.29); Iran, Islamic Rep (0.39); Kazakhstan (0.20)
Senegal	Burkina Faso (0.08); Burundi (0.27); China (0.20); Côte d'Ivoire (0.38); Ethiopia (0.07)
Serbia	Armenia (0.13); China (0.20); Iran, Islamic Rep (0.53); Kazakhstan (0.14)
Sri Lanka	Angola (0.37); Armenia (0.09); China (0.04); Lao PDR (0.12); Mauritania (0.38)
Thailand	Angola (0.38); China (0.45); Mongolia (0.06); Philippines (0.09); Vietnam (0.02)
Tunisia	Angola (0.23); Armenia (0.40); China (0.19); Iran, Islamic Rep (0.13); Kyrgyz Republic (0.05)
Turkey	China (0.29); Ethiopia (0.02); Iran, Islamic Rep (0.23); Kazakhstan (0.12); Mauritania (0.10); Vietnam (0.25)
Zambia	Angola (0.11); Burundi (0.05); China (0.11); Ethiopia (0.07); Madagascar (0.43); Mauritania (0.24)

4.5.4.3 Areas for Efficiency Improvement: Targets Setting Analysis

After identifying the inefficient DMUs, it is reasonable now to set targets in an output-oriented sense. The SBM is in principle a non-radial approach, so it projects the DMU to the furthest point on the efficiency frontier. Therefore, the objective function in the linear programming is minimized to find out the maximum values of the slacks (Luo & Yip, 2017).

Thus, for SBM models, projection values are calculated as the sum of original values and the slack Movement as presented in Tables (4.32), (4.33) for SBM under CRS and SBM under VRS respectively. Recall that the SBM provides targets for each output individually. For example, for Albania, under SBM CRS, the original value of the scientific and technical publications is 180.36 and the slack movement is 20459.09, so the projected value is the addition of the original value and the slack movement and thus equal to 20639.45.

Furthermore, Table (4.34) provides the required different percentage increases in each output for each inefficient country under SBM CRS whereas Table (4.35) presents the same results under SBM VRS. These percentage changes should be attained by every inefficient country to become efficient. In this table, the percentage addition in each output is calculated as the difference between the projected value of the variable and the actual value of this variable (observed data) divided by the actual value and then multiplied by 100. For instance, the percentage addition in scientific and technical publications for Albania is calculated as follows 11343.48% = ((20639.45- 180.36)/ (180.36) *100). In this case, the original value of the scientific and technical publications is 180.36 and the slack movement is 20459.09, so the projected value is the addition of the original value and the slack movement and thus equal to 20639.45.

Thus, for Albania to become an efficient country, then, it should keep its GDP growth (Y1) and the percentage of households with a computer (Y5) unchanged and pay attention to the high-tech exports (Y5) as it must be increased by 61412.73%, and its scientific and technical publications (Y2) must be increased by 11342.48%, and finally, its patents (Y3) must be increased by 217.66% respectively. In other words, Albania should focus on the knowledge utilization dimension, which is peroxided by the percentage of high-tech exports, then the knowledge production dimension and leave aside the other knowledge dimensions, namely knowledge distribution and knowledge acquisition.

Table (4.32): Inputs and Outputs Slacks for Developing Countries by Employing the SBM Under CRS.

DMUs	AV (Y1)	SM (Y1)	Pro. (Y1)	AV (Y2)	SM (Y2)	Pro. (Y2)	AV (Y3)	SM (Y3)	Pro. (Y3)	AV (Y4)	SM (Y4)	Pro. (Y4)	AV (Y5)	SM (Y5)	Pro. (Y5)
Albania	-3.30	0.00	-3.30	180.36	20459.09	20639.45	0.22	0.48	0.70	20.2	0.00	20.20	0.04	27.45	27.50
Algeria	-4.90	3.06	-1.84	5231.44	89736.17	94967.61	0.03	3.37	3.40	42.2	0.00	42.20	0.96	7.91	8.87
Argentina	-9.90	9.50	-0.40	8811.13	51357.59	60168.72	1.44	0.22	1.66	64.3	0.00	64.30	5.21	8.68	13.90
Azerbaijan	-4.30	0.14	-4.16	761.43	26186.90	26948.33	0.28	0.63	0.91	65	0.00	65.00	4.35	16.29	20.64
Botswana	-8.50	7.18	-1.32	280.57	125536.16	125816.73	0.00	3.48	3.48	27.8	0.00	27.80	0.39	17.82	18.20
Bulgaria	-4.20	2.88	-1.32	3311.27	145475.12	148786.39	4.40	0.19	4.59	63	0.00	63.00	10.85	8.61	19.46
Burundi	-1.00	0.46	-0.54	21.12	50454.57	50475.69	0.03	1.35	1.38	1	5.43	6.43	1.53	1.97	3.50
Cambodia	-3.10	1.86	-1.24	145.74	27038.63	27184.37	0.01	0.82	0.83	8	0.00	8.00	1.19	0.81	2.00
Colombia	-6.80	5.99	-0.81	7195.02	37305.12	44500.14	0.79	0.57	1.36	37.2	0.00	37.20	9.12	13.88	23.00
Costa Rica	-4.10	0.00	-4.10	507.41	64130.40	64637.81	0.87	2.36	3.23	47	0.00	47.00	17.56	0.00	17.56
Ecuador	-7.80	3.76	-4.04	2142.19	79601.82	81744.01	0.12	3.69	3.81	43.9	0.00	43.90	5.53	5.47	11.00
El Salvador	-7.90	6.10	-1.80	45.44	36740.16	36785.60	0.05	0.96	1.01	16.7	0.00	16.70	6.39	0.00	6.39
Ghana	0.40	0.00	0.40	1275.99	86943.83	88219.82	0.02	2.43	2.45	15.8	0.00	15.80	1.14	13.47	14.61
Honduras	-9.00	6.26	-2.74	45.10	5743.87	5788.97	0.06	0.10	0.16	17.1	0.00	17.10	1.97	1.33	3.30
India	-7.30	7.29	-0.01	135787.79	18384.99	154172.78	1.50	2.81	4.31	10.7	27.24	37.94	10.30	6.45	16.75
Indonesia	-2.10	0.00	-2.10	26947.57	8335.30	35282.87	0.07	1.87	1.94	18.8	8.60	27.40	8.10	0.00	8.10
Jordan	-1.60	0.00	-1.60	2627.29	137589.45	140216.74	0.82	3.76	4.58	42.9	0.00	42.90	1.37	15.66	17.03
Kenya	-0.30	0.30	0.00	1246.76	191296.15	192542.91	0.13	5.14	5.27	8.8	12.45	21.25	4.59	7.29	11.88
Lesotho	-5.40	4.80	-0.60	18.54	11542.65	11561.19	0.00	0.32	0.32	5.1	0.00	5.10	0.21	1.16	1.37
Madagascar	-6.10	5.27	-0.83	127.41	1786.09	1913.50	0.00	0.05	0.05	5.2	0.00	5.20	0.37	0.64	1.01
Mali	-1.60	1.91	0.31	90.37	71919.05	72009.42	0.01	1.96	1.97	4.6	2.90	7.50	1.24	2.95	4.20
Mexico	-8.30	7.22	-1.08	16345.64	45362.83	61708.47	1.84	0.03	1.87	44.2	5.70	49.90	20.42	3.60	24.02

DMUs	AV (Y1)	SM (Y1)	Pro. (Y1)	AV (Y2)	SM (Y2)	Pro. (Y2)	AV (Y3)	SM (Y3)	Pro. (Y3)	AV (Y4)	SM (Y4)	Pro. (Y4)	AV (Y5)	SM (Y5)	Pro. (Y5)
Mongolia	-5.30	2.16	-3.14	140.85	5837.67	5978.52	0.72	0.00	0.72	29.7	0.00	29.70	18.94	0.00	18.94
Morocco	-6.30	7.81	1.51	5056.77	87001.66	92058.43	0.13	1.85	1.98	64.2	0.00	64.20	4.90	5.01	9.91
Mozambique	-1.20	1.51	0.31	139.25	76574.77	76714.02	0.00	2.10	2.10	6.7	2.06	8.76	5.65	0.00	5.65
Namibia	-8.00	6.27	-1.73	156.31	83658.72	83815.03	0.13	2.16	2.29	21.2	0.00	21.20	0.48	6.65	7.12
Nepal	-2.10	0.00	-2.10	792.11	59657.63	60449.74	0.03	2.36	2.39	12.7	9.92	22.62	1.18	5.28	6.46
Nicaragua	-2.00	0.25	-1.75	43.67	23748.14	23791.81	0.02	0.63	0.65	13.5	0.00	13.50	1.06	2.30	3.36
Nigeria	-1.80	0.00	-1.80	5602.28	7157.66	12759.94	0.01	0.96	0.97	6.4	9.39	15.79	1.48	1.87	3.35
North Macedonia	-4.50	4.44	-0.06	493.05	23252.58	23745.63	0.32	0.07	0.39	69.5	0.00	69.50	4.18	10.82	15.00
Pakistan	-0.50	0.00	-0.50	12904.31	27533.57	40437.88	0.04	1.36	1.40	14.3	0.00	14.30	1.89	4.87	6.76
Paraguay	-0.60	0.00	-0.60	97.98	16916.73	17014.71	0.00	0.62	0.62	27.7	0.00	27.70	7.18	0.00	7.18
Peru	-11.00	10.13	-0.87	1629.88	19977.41	21607.29	0.27	0.44	0.71	33.1	0.00	33.10	4.08	8.12	12.20
Russian Federation	-3.00	4.47	1.47	81579.36	67832.63	149411.99	3.82	0.00	3.82	72.1	0.00	72.10	13.00	7.12	20.12
Rwanda	-3.40	2.42	-0.98	169.52	138233.63	138403.15	0.02	3.79	3.81	2.5	16.72	19.22	10.55	0.00	10.55
Senegal	1.50	0.00	1.50	388.32	134226.27	134614.59	0.02	3.66	3.68	15.8	3.69	19.49	0.94	12.04	12.97
Serbia	-1.00	1.35	0.35	4523.42	135738.01	140261.43	2.49	1.33	3.82	74.3	0.00	74.30	4.55	8.69	13.23
Sri Lanka	-3.60	1.68	-1.92	1347.54	20072.14	21419.68	0.23	0.56	0.79	23	0.00	23.00	1.02	12.46	13.48
Thailand	-6.10	6.07	-0.03	12513.75	224512.29	237026.04	0.97	5.64	6.61	19.3	37.48	56.78	23.61	1.52	25.14
Tunisia	-8.60	4.78	-3.82	5564.86	108495.11	114059.97	0.28	4.37	4.65	52.1	0.00	52.10	6.89	6.52	13.40
Turkey	1.80	0.00	1.80	33535.80	131381.63	164917.43	3.01	1.29	4.30	52.1	0.00	52.10	3.04	20.06	23.10
Uganda	-0.80	0.31	-0.49	673.07	32993.56	33666.63	0.00	0.92	0.92	3.5	0.92	4.42	2.10	0.36	2.46
Ukraine	-4.00	2.46	-1.54	10379.89	42090.73	52470.62	1.56	0.32	1.88	66.2	0.00	66.20	5.58	7.82	13.39
Zambia	-3.00	3.14	0.14	213.07	68657.56	68870.63	0.02	1.87	1.89	8.1	0.00	8.10	1.37	2.81	4.18

Note: Y (1) = GDP Growth, Y (2) = Scientific and Technical Publications, Y (3)=Patents Granted , Y(4)= Households with a Computer , Y(5)= High-tech Exports; AC= Actual Values, SM=Slack Movement, Pro= Projected Value.

Table (4.33): Inputs and Outputs Slacks for Developing Countries by Employing the SBM Under VRS.

DMUs	AV (Y1)	SM (Y1)	Pro. (Y1)	AV (Y2)	SM (Y2)	Pro. (Y2)	AV (Y3)	SM (Y3)	Pro. (Y3)	AV (Y4)	SM (Y4)	Pro. (Y4)	AV (Y5)	SM (Y5)	Pro. (Y5)
Albania	-3.30	0.00	-3.30	180.36	644.32	824.68	0.22	0.13	0.35	20.2	7.97	28.17	0.04	17.91	17.95
Algeria	-4.90	1.54	-3.36	5231.44	50970.88	56202.32	0.03	1.36	1.39	42.2	0.00	42.20	0.96	6.90	7.86
Azerbaijan	-4.30	0.99	-3.31	761.43	25735.86	26497.29	0.28	0.64	0.92	65	0.00	65.00	4.35	17.37	21.72
Botswana	-8.50	7.22	-1.28	280.57	126088.83	126369.40	0	3.49	3.49	27.8	0.00	27.80	0.39	16.50	16.88
Cambodia	-3.10	1.46	-1.64	145.74	26443.91	26589.65	0.01	0.73	0.74	8	0.00	8.00	1.19	0.39	1.58
Colombia	-6.80	5.20	-1.60	7195.02	38089.66	45284.68	0.79	0.57	1.36	37.2	0.00	37.20	9.12	11.87	20.99
Costa Rica	-4.10	0.00	-4.10	507.41	62855.12	63362.53	0.87	2.34	3.21	47	0.00	47.00	17.56	0.00	17.56
Ecuador	-7.80	2.90	-4.90	2142.19	68968.78	71110.97	0.12	2.67	2.79	43.9	0.00	43.90	5.53	5.20	10.73
El Salvador	-7.90	3.48	-4.42	45.44	35147.51	35192.95	0.05	0.92	0.97	16.7	3.97	20.67	6.39	0.00	6.39
Ghana	0.40	0.00	0.40	1275.99	83571.73	84847.72	0.02	2.34	2.36	15.8	2.84	18.64	1.14	15.96	17.10
Honduras	-9.00	5.72	-3.28	45.1	4960.19	5005.29	0.06	0.08	0.14	17.1	0.00	17.10	1.97	0.77	2.73
India	-7.30	3.92	-3.38	135787.79	18196.33	153984.12	1.5	2.73	4.23	10.7	27.70	38.40	10.30	5.72	16.02
Indonesia	-2.10	0.00	-2.10	26947.57	11103.52	38051.09	0.07	1.70	1.77	18.8	8.39	27.19	8.10	8.92	17.01
Jordan	-1.60	0.00	-1.60	2627.29	131829.19	134456.48	0.82	3.46	4.28	42.9	0.00	42.90	1.37	11.88	13.25
Kenya	-0.30	0.00	-0.30	1246.76	171356.36	172603.12	0.13	4.59	4.72	8.8	12.16	20.96	4.59	6.95	11.54
Lesotho	-5.40	3.68	-1.72	18.54	9905.54	9924.08	0	0.28	0.28	5.1	1.13	6.23	0.21	0.38	0.59
Mali	-1.60	0.00	-1.60	90.37	65173.96	65264.33	0.01	1.78	1.79	4.6	9.39	13.99	1.24	3.73	4.97
Mexico	-8.30	6.91	-1.39	16345.64	45683.31	62028.95	1.84	0.02	1.86	44.2	3.86	48.06	20.42	3.80	24.23
Morocco	-6.30	6.56	0.26	5056.77	85190.87	90247.64	0.13	1.73	1.86	64.2	0.00	64.20	4.90	2.71	7.61
Namibia	-8.00	6.82	-1.18	156.31	80390.48	80546.79	0.13	2.11	2.24	21.2	0.00	21.20	0.48	14.41	14.88
Nepal	-2.10	0.00	-2.10	792.11	60061.70	60853.81	0.03	1.60	1.63	12.7	0.00	12.70	1.18	5.01	6.20
Nicaragua	-2.00	0.00	-2.00	43.67	17719.76	17763.43	0.02	0.46	0.48	13.5	0.00	13.50	1.06	2.40	3.47
Peru	-11.00	7.40	-3.60	1629.88	20018.06	21647.94	0.27	0.37	0.64	33.1	0.00	33.10	4.08	8.54	12.61
Russian Federation	-3.00	3.55	0.55	81579.36	88918.64	170498.00	3.82	0.77	4.59	72.1	0.00	72.10	13.00	3.32	16.32
Senegal	1.50	0.00	1.50	388.32	104456.94	104845.26	0.02	2.85	2.87	15.8	0.69	16.49	0.94	12.89	13.82
Serbia	-1.00	2.00	1.00	4523.42	129353.84	133877.26	2.49	0.91	3.40	74.3	0.00	74.30	4.55	7.45	12.00
Sri Lanka	-3.60	0.32	-3.28	1347.54	20917.67	22265.21	0.23	0.63	0.86	23	0.00	23.00	1.02	5.85	6.87
Thailand	-6.10	3.97	-2.13	12513.75	223901.10	236414.85	0.97	5.58	6.55	19.3	22.07	41.37	23.61	0.00	23.61
Tunisia	-8.60	4.81	-3.79	5564.86	101690.43	107255.29	0.28	3.56	3.84	52.1	0.00	52.10	6.89	4.70	11.58
Turkey	1.80	0.00	1.80	33535.8	131436.47	164972.27	3.01	1.29	4.30	52.1	0.00	52.10	3.04	20.03	23.07
Zambia	-3.00	0.00	-3.00	213.07	59179.97	59393.04	0.02	1.61	1.63	8.1	5.45	13.55	1.37	3.88	5.24

Note: See Table (4.32).

Table (4.34): Percentage Output Addition for Inefficient Countries Under the CRS Output-Oriented SBM.

DMU	% Additive in Y1	% Additive in Y2	% Additive in Y3	% Additive in Y4	% Additive in Y5
Albania	0	11343.48	217.66	0	61412.73
Algeria	62.38	1715.32	11240.93	0	823.41
Argentina	96.01	582.87	15.04	0	166.58
Azerbaijan	3.28	3439.17	225.98	0	374.88
Botswana	84.53	44743.26	0	0	4628.11
Bulgaria	68.64	4393.33	4.24	0	79.33
Burundi	45.85	238894.76	4508.18	543.28	128.4
Cambodia	59.91	18552.65	8178.85	0	67.5
Colombia	88.06	518.49	72.01	0	152.09
Costa Rica	0	12638.77	271.75	0	0
Ecuador	48.27	3715.91	3073.67	0	99.02
El Salvador	77.21	80854.22	1929.76	0	0
Ghana	0	6813.83	12130.27	0	1183.79
Honduras	69.54	12735.85	163.4	0	67.69
India	99.83	13.54	187.02	254.6	62.63
Indonesia	0	30.93	2664.73	45.73	0
Jordan	0	5236.93	458.47	0	1144.14
Kenya	100.06	15343.46	3954.64	141.52	158.67
Lesotho	88.83	62258.08	0	0	558.32
Madagascar	86.39	1401.85	0	0	175.45
Mali	119.6	79582.89	19610.94	62.98	237.26
Mexico	86.95	277.52	1.43	12.9	17.61
Mongolia	40.73	4144.6	0	0	0
Morocco	123.9	1720.5	1419.41	0	102.35
Mozambique	125.93	54990.86	0	30.72	0
Namibia	78.41	53521.03	1664.56	0	1393.13
Nepal	0	7531.48	7850.64	78.14	445.6
Nicaragua	12.74	54380.89	3154.82	0	216.66
Nigeria	0	127.76	9572.25	146.75	125.86
North Macedonia	98.6	4716.07	22.39	0	258.67
Pakistan	0	213.37	3398.01	0	257.88
Paraguay	0	17265.49	0	0	0
Peru	92.09	1225.7	163.53	0	199.21
Russian Federation	149.15	83.15	0	0	54.76
Rwanda	71.28	81544.14	18969.45	668.61	0
Senegal	0	34565.89	18308.31	23.35	1287.07
Serbia	134.81	3000.78	53.33	0	191.09
Sri Lanka	46.74	1489.54	244.59	0	1221.2
Thailand	99.56	1794.12	581.71	194.19	6.46
Tunisia	55.53	1949.65	1561.75	0	94.64
Turkey	0	391.77	42.92	0	658.99
Uganda	39.29	4901.95	0	26.16	16.95
Ukraine	61.44	405.5	20.7	0	140.09
Zambia	104.8	32223.01	9325.76	0	205.9

Note: Y1= output 1 (Real GDP Growth); Y2 = output 2 (scientific and technical publications); Y3= output 3 (Patents Granted); Y4= output 4 (households with a computer), Y5= High-tech exports

Table (4.35): Percentage Output Addition for Inefficient Countries Under the VRS output oriented SBM.

DMU	% Additive in Y (1)	% Additive in Y (2)	% Additive in Y (3)	% Additive in Y (4)	% Additive in Y (5)
Albania	0.00	357.24	58.96	39.48	40058.36
Algeria	31.44	974.32	4534.23	0.00	718.42
Azerbaijan	22.93	3379.94	230.33	0.00	399.72
Botswana	84.93	44940.24	0.00	0.00	4284.29
Cambodia	46.97	18144.58	7305.12	0.00	32.29
Colombia	76.49	529.39	71.61	0.00	130.07
Costa Rica	0.00	12387.44	269.42	0.00	0.00
Ecuador	37.18	3219.55	2223.15	0.00	94.10
El Salvador	43.99	77349.27	1838.27	23.77	0.00
Ghana	0.00	6549.56	11690.33	17.95	1402.79
Honduras	63.58	10998.20	136.73	0.00	38.94
India	53.73	13.40	182.01	258.88	55.58
Indonesia	0.00	41.20	2427.49	44.62	110.11
Jordan	0.00	5017.69	421.64	0.00	867.90
Kenya	0.00	13744.13	3530.73	138.16	151.28
Lesotho	68.09	53427.96	0.00	22.19	182.92
Mali	0.00	72119.02	17818.34	204.04	299.49
Mexico	83.28	279.48	1.05	8.73	18.63
Morocco	104.13	1684.69	1330.78	0.00	55.35
Namibia	85.29	51430.16	1624.15	0.00	3019.79
Nepal	0.00	7582.50	5333.18	0.00	423.22
Nicaragua	0.00	40576.51	2313.44	0.00	226.14
Peru	67.29	1228.19	137.17	0.00	209.32
Russian Federation	118.33	109.00	20.10	0.00	25.53
Senegal	0.00	26899.71	14266.68	4.35	1377.60
Serbia	200.25	2859.65	36.38	0.00	163.95
Sri Lanka	8.93	1552.29	273.07	0.00	573.54
Thailand	65.16	1789.24	574.80	114.37	0.00
Tunisia	55.97	1827.37	1272.05	0.00	68.22
Turkey	0.00	391.93	42.95	0.00	657.97
Zambia	0.00	27774.90	8027.09	67.31	283.57

Note: See Table (4.34).

4.5.4.4 Discussion for Non-Radial DEA Analysis Results

4.5.4.4.1 Classifying KBE Dimensions based on their Degree of Inefficiency using the CRS Output-Oriented SBM Model

Evidently, as presented in the previous Tables (4.34) and (4.35), the knowledge production dimension has the strongest influence on inefficiency among developing countries in 2020 and hence requires greater attention and the highest improvements compared to the other three dimensions of KBE. On the other hand, the knowledge acquisition dimension has the least impact on inefficiency among the sample countries. Based on our empirical results, this is magnified by the upper bound and lower bound required percentage changes (%addition) in each indicator used as a proxy for every knowledge dimension in the study.

For instance, scientific and technical publications as an output variable is used to proxy the knowledge production dimension and call for the largest improvements compared to the other study's proxies. Scientific and technical publications have the maximum percentage change of approximately 238894.8% in Burundi and the least percentage change of 13.54% in India among all selected developing countries. This is followed by the knowledge utilization dimension as represented by the percentage of high-tech exports; with the highest percentage change of 61412.7% in Albania and the lowest percentage addition of approximately 6.46% in Thailand. While it is advisable for Rwanda, El Salvador, Mozambique, Paraguay, Costa Rica, Mongolia, and Indonesia to maintain the percentage of high-tech exports unchanged. Further, the patents granted as a proxy for knowledge production comes next with Mali having the greatest required percentage addition of nearly 19610.9% and the lowest percentage change of approximately 1.43% in Mexico. Additionally, Botswana, Lesotho, Madagascar, Russian Federation, Uganda, Mozambique, Paraguay, and Mongolia should maintain their level of patents granted.

Furthermore, the knowledge distribution dimension has the third effect in terms of inefficiency influence as shown by the highest percentage change of 668.61% in the percentage of households with a computer in Rwanda and the least targeted percentage addition of 12.9% in Mexico. While 31 countries out of the 65 developing countries should maintain their performance in the knowledge distribution dimension unchanged. Finally, the least dimension of inefficiency is the knowledge acquisition dimension as presented by the maximum percentage change of GDP growth with Russian Federation having the upper bound of output addition of 149.2% and Azerbaijan having the lowest targeted percentage of output addition by 3.28%. Additionally, 11 countries should leave the percentage of GDP growth unchanged. These countries are Albania, Costa Rica, Ghana, Indonesia, Jordan, Nepal, Nigeria, Pakistan, Paraguay, Senegal, and Turkey.

To this end, the knowledge dimensions with their share in inefficiency can be ranked in descending order, from the highest to the lowest, as knowledge production, knowledge utilization, knowledge distribution, and knowledge acquisition. Furthermore, with respect to the output proxies used in the study, it can follow a descending order as scientific and technical publications, high-tech exports, the patent granted, households with a computer and real GDP growth.

4.5.4.4.2 Classifying KBE dimensions based on their degree of inefficiency using the VRS output oriented SBM model.

It is obvious that the knowledge production dimension continues to have the strongest influence on inefficiency among developing countries in 2020 under the VRS as well. It has the maximum percentage addition of approximately 77349.3% in El Salvador and the least percentage change of 13.4% in India among all developing countries.

Thus, in terms of the study's proxies, the scientific and technical publications indicator as a proxy for knowledge production is the worst and the high-tech exports as a proxy for knowledge utilization comes next with an upper bound addition of 40058.4 % in Albania and the lowest percentage change of 18.63% in Mexico. This is followed by the patents with required percentage changes of 17818.3% for Mali and 1.05% for Mexico respectively. However, the percentage of households with a computer and GDP growth as proxies for knowledge distribution and knowledge acquisition are the least in terms of inefficiency. To conclude, the knowledge dimensions with their shares in inefficiency can be ranked in descending order, from the highest to the lowest, as knowledge production, knowledge utilization, knowledge distribution, and knowledge acquisition. Furthermore, with respect to the output proxies used in the study, it can follow a descending order as scientific and technical publications, high-tech exports, the patent granted, households with a computer and real GDP growth.

4.5.4.4.3 Country's grouping based on the SBM CRS and SBM VRS Models

After applying the output-oriented non-radial SBM DEA analysis to the developing countries in 2020, we can reach the following conclusion and divide these countries into four groups as follows:

First Group (Cluster A): Countries that attain the best overall comparative technical efficiency and pure technical efficiency under output oriented SBM model for both returns namely, the CRS and VRS. These countries have an efficiency score of one (100%), which means that this group of countries has utilized their inputs/resources effectively to reach the maximum possible outputs. These countries account for 32.3% of the developing countries in the sample (21 out of 65 countries) namely: Angola, Armenia, Brazil, Burkina Faso, China, Côte d'Ivoire, Egypt, Ethiopia, Gambia, Georgia, Guatemala, Iran, Jamaica, Kazakhstan, Kyrgyz Republic, Lao PDR, Malaysia, Mauritania, Philippines, South Africa, and Vietnam. Further, these countries have a scaling efficiency of 100% which means that there are no sources of inefficiency in this group of countries.

Second Group (Cluster B): Countries that achieve pure technical efficiency under the output oriented SBM model under VRS, but do not attain the SBM overall technical efficiency and scale effect efficiency. These countries have an efficiency score of 100% with respect to the SBM model under VRS but have an efficiency score of less than 100% in scale effect and in the overall SBM technical efficiency as well. Thus, the sources of inefficiency in this group are both sides, the pure technical side i.e., managerial side and the scale side. Additionally, all these countries are in the stage of increasing returns to scale which means that these countries could enhance their scale size to be efficient. This group represents 20% of the total sample (13 countries out of 65) and includes North Macedonia, Bulgaria, Argentina, Ukraine, Mongolia, Paraguay, Nigeria, Pakistan, Madagascar, Rwanda, Burundi, Uganda, and Mozambique. These countries have a SBM overall technical efficiency under CRS of North Macedonia (9%), Bulgaria (10%), Argentina (37%), Ukraine (44%), Mongolia (11%), Paraguay (3%), Nigeria (5%), Pakistan (11%), Madagascar (23%), Rwanda (0.4%), Burundi (0.2%), Uganda (9%), and Mozambique (1%). These countries have also the same scale effect scores as the SBM CRS efficiency scores, simply because their SBM VRS efficiency scores are equal to 1. Therefore, these countries have the opportunity to increase their scale size by North Macedonia by 91% (0.91=1- 0.09), Bulgaria by 2% (0.90=1-0.10), Argentina by 63%, Ukraine by 56%, Mongolia by 89% , Paraguay by 97%, Nigeria by 95%, Pakistan by 89%, Madagascar by77%, Rwanda by 96%, Burundi by 98%, Uganda by 91%, and Mozambique by 99% and thus could reach the optimal scale size and hence attain the scale efficiency.

Third Group (Cluster C): This group includes countries that are SBM inefficient under both returns; namely the CRS and VRS. The scale effect for each country in this group is less than 100%. This means that these countries are SBM inefficient under CRS, SBM inefficient under VRS and scale inefficient as well. Thus, the sources of inefficiency for this group of countries are technical inefficiency and scale inefficiency. Therefore, these countries could adjust their scale size to reach the optimal size and could become scale efficient. Further, all these countries have attained increasing returns to scale which is known as economies of scale and means that increasing the inputs size will lead to efficiency gains.

These countries constitute the largest percentage of countries as they account for 40% of the whole sample (26 countries out of 65 developing countries). These countries are Albania, Algeria, Botswana, Cambodia, Colombia, Ecuador, El Salvador, Ghana, Honduras, India, Indonesia, Jordan, Kenya, Lesotho, Mexico, Morocco, Mali, Namibia, Nepal, Nicaragua, Peru, Senegal, Sri Lanka, Thailand, Tunisia, and Zambia. Among this group of countries, Mali has the highest relative inefficiency score of (0.996) according to the SBM CRS model and (0.995) with respect to the SBM VRS model. On the other hand, Mexico has the lowest relative inefficiency score of (0.44) according to the SBM CRS model and the SBM VRS model. Finally, Algeria has the highest relative scale inefficiency score of (0.53) while, Botswana has the lowest relative scale inefficiency scores of (0.003).

Fourth Group (Cluster D): This group includes countries that are inefficient under SBM CRS and SBM VRS models. The scale efficiency for each country is less than 100%. So, these countries are inefficient by employing the SBM CRS, SBM VRS and scale inefficient as in group (3). However, these countries have attained decreasing returns to scale which means that decreasing the inputs size will lead to efficiency gains. These countries represent around 7.7% of the whole sample (5 countries only). Russian Federation, Serbia, Turkey, Azerbaijan, and Costa Rica form this group of countries. Within this group of countries, Russian Federation has the lowest inefficiency score of (0.36) and (0.35) according to the SBM CRS and SBM VRS models respectively, and Costa Rica has the highest inefficiency score of (0.96) according to both models namely the SBM CRS and SBM VRS models. Additionally, within this group of countries, Turkey has the lowest scale inefficiency of (0.001), whereas Serbia has the highest scale inefficiency (0.04).

4.5.4.4.4 Classification by Income

The clustering results presented above can be classified from an economic perspective, as presented in Table (4.36). Countries are classified into low, lower-middle, and upper-middle income groups.

Table (4.36): Countries Clustering by Income Group Under the Non-Radial DEA Models.

	Cluster A	Cluster B	Cluster C	Cluster D
Definition	Countries that achieve overall technical efficiency and pure technical efficiency under SBM model for both returns	Countries that achieve pure technical efficiency under the output oriented SBM model under VRS, but do not attain the SBM overall technical efficiency and scale effect efficiency	Countries that are SBM inefficient under both returns and attained increasing returns to scale	Countries that are SBM inefficient under both returns and attained decreasing returns to scale
Countries Included	21/65	13/65	26/65	5/65
Low-Income ($1,035 or less).	1. Burkina Faso 2. Ethiopia 3. Gambia 4. Georgia	1. Rwanda 2. Burundi 3. Uganda 4. Mozambique	1. Mali	
Lower-Middle Income ($1,036 to $4,045).	1. Angola 2. Côte d'Ivoire 3. Egypt 4. Kyrgyz Republic 5. Lao PDR 6. Vietnam 7. Philippines 8. Mauritania	2. Ukraine 3. Mongolia 4. Nigeria 5. Pakistan 6. Madagascar	1. Algeria 2. Cambodia 3. El Salvador 4. Ghana 5. Honduras 6. India 7. Kenya 8. Lesotho 9. Nicaragua 10. Nepal 11. Senegal 12. Sri Lanka 13. Zambia 14. Morocco	
Upper-Middle Income ($4,046 to $12,535).	1. Armenia 2. Brazil 3. China 4. Guatemala 5. Iran 6. Jamaica 7. Kazakhstan 8. Malaysia 9. South Africa	7. North Macedonia. 8. Bulgaria 9. Paraguay 10. Argentina	1. Albania 2. Botswana 3. Colombia 4. Indonesia 5. Jordan 6. Mexico 7. Namibia 8. Peru 9. Thailand 10. Ecuador 11. Tunisia	1. Russian Federation 2. Serbia 3. Turkey 4. Azerbaijan 5. Costa Rica

4.5.4.5 Summing Up

Most developing countries are inefficient under the applied non-radial DEA models; namely the SBM CRS and SBM VRS models. The SBM CRS model does provide a narrow efficiency area in terms of the total number of efficient countries rather than the SBM VRS model within this case study. Additionally, most developing countries are scale inefficient and are operating with increasing returns to scale as well. Thus, the sources of inefficiency for most developing countries are both sided. That is most developing countries suffer from pure technical inefficiency and scale inefficiency. However, on average, their pure technical inefficiencies are greater than their scale inefficiencies. Thus, policymakers are advised to pay first attention to the managerial efficiency in these countries and then focus on improving the scale efficiency.

4.6 Comparing the Radial and Non-Radial Models

4.6.1 Comparing the Efficiency Scores

To compare the use of radial and non-radial DEA models in assessing KBE efficiency, Table (4.37) presents the efficiency scores for 65 developing countries in 2020 under both returns i.e., CRS and VRS, and for the same orientation i.e., output-orientation.

Table (4.37): Comparing Efficiency Scores for the Radial and Non-Radial Measures.

No.	DMU	Radial-DEA Measures		Non-radial DEA Measures	
		CCR under CRS	BCC under VRS	SBM under CRS	SBM under VRS
1.	Albania	0.51	0.72	0.01	0.01
2.	Algeria	0.68	0.81	0.03	0.07
3.	Angola	1.00	1.00	1.00	1.00
4.	Argentina	0.98	1.00	0.37	1.00
5.	Armenia	1.00	1.00	1.00	1.00
6.	Azerbaijan	0.87	0.88	0.11	0.11
7.	Botswana	0.46	0.46	0.01	0.01
8.	Brazil	1.00	1.00	1.00	1.00
9.	Bulgaria	0.98	1.00	0.10	1.00
10.	Burkina Faso	1.00	1.00	1.00	1.00
11.	Burundi	0.35	1.00	0.00	1.00
12.	Cambodia	0.42	0.60	0.02	0.02
13.	China	1.00	1.00	1.00	1.00
14.	Colombia	0.58	0.61	0.38	0.38
15.	Costa Rica	0.82	0.82	0.04	0.04
16.	Côte d'Ivoire	1.00	1.00	1.00	1.00
17.	Ecuador	0.78	0.79	0.07	0.08
18.	Egypt, Arab Rep.	1.00	1.00	1.00	1.00
19.	El Salvador	0.48	0.56	0.01	0.01
20.	Ethiopia	1.00	1.00	1.00	1.00
21.	Gambia	1.00	1.00	1.00	1.00
22.	Georgia	1.00	1.00	1.00	1.00
23.	Ghana	0.30	0.33	0.02	0.02
24.	Guatemala	1.00	1.00	1.00	1.00
25.	Honduras	0.56	0.59	0.04	0.04
26.	India	0.85	0.86	0.45	0.47
27.	Indonesia	0.58	0.61	0.15	0.16
28.	Iran, Islamic Rep	1.00	1.00	1.00	1.00
29.	Jamaica	1.00	1.00	1.00	1.00
30.	Jordan	0.63	0.67	0.07	0.07
31.	Kazakhstan	1.00	1.00	1.00	1.00
32.	Kenya	0.26	0.28	0.02	0.03
33.	Kyrgyz Republic	1.00	1.00	1.00	1.00

No.	DMU	Radial-DEA Measures		Non-radial DEA Measures	
		CCR under CRS	BCC under VRS	SBM under CRS	SBM under VRS
34.	**Lao PDR**	1.00	1.00	1.00	1.00
35.	**Lesotho**	0.45	0.48	0.01	0.01
36.	**Madagascar**	0.52	1.00	0.23	1.00
37.	**Malaysia**	1.00	1.00	1.00	1.00
38.	**Mali**	0.29	0.46	0.00	0.01
39.	**Mauritania**	1.00	1.00	1.00	1.00
40.	**Mexico**	0.84	0.85	0.56	0.56
41.	**Mongolia**	0.93	1.00	0.11	1.00
42.	**Morocco**	0.87	0.87	0.13	0.14
43.	**Mozambique**	0.33	1.00	0.01	1.00
44.	**Namibia**	0.47	0.48	0.01	0.01
45.	**Nepal**	0.41	0.51	0.03	0.04
46.	**Nicaragua**	0.44	0.68	0.01	0.01
47.	**Nigeria**	0.60	1.00	0.05	1.00
48.	**North Macedonia**	0.99	1.00	0.09	1.00
49.	**Pakistan**	0.56	1.00	0.11	1.00
50.	**Paraguay**	0.84	1.00	0.03	1.00
51.	**Peru**	0.60	0.64	0.23	0.23
52.	**Philippines**	1.00	1.00	1.00	1.00
53.	**Russian Federation**	0.92	0.96	0.64	0.65
54.	**Rwanda**	0.51	1.00	0.00	1.00
55.	**Senegal**	0.52	0.59	0.01	0.01
56.	**Serbia**	0.91	0.96	0.13	0.13
57.	**South Africa**	1.00	1.00	1.00	1.00
58.	**Sri Lanka**	0.66	0.82	0.14	0.17
59.	**Thailand**	0.64	0.71	0.16	0.16
60.	**Tunisia**	0.73	0.74	0.12	0.13
61.	**Turkey**	0.79	0.80	0.31	0.31
62.	**Uganda**	0.35	1.00	0.09	1.00
63.	**Ukraine**	0.97	1.00	0.44	1.00
64.	**Vietnam**	1.00	1.00	1.00	1.00
65.	**Zambia**	0.35	0.48	0.01	0.01

According to the empirical results, both DEA measures yield the same identification for KBE efficient countries with an efficiency score equal to one and inefficient countries with efficiency score less than one under both returns. Based on all applied DEA models, approximately one-third of the developing countries are efficient while two-thirds of the countries are not efficient. However, radial, and non-radial DEA measures are different with respect to the efficiency scores assigned to the inefficient countries with the SBM scores being lower than the radial scores for all inefficient countries. One reason for these lower efficiency scores using SBM could be that SBM deals directly with the slacks which are neglected in radial DEA measures.

For example, the efficiency score for Russian Federation is 0.92, and 0.64 for radial and non-radial measures respectively under CRS. The same overestimation of efficiency scores also existed when we compare the radial and non-radial measures under VRS. For instance, Russian Federation has an efficiency score of 0.96 for radial DEA measures compared to 0.65 for non-radial DEA models under VRS. This final empirical result is consistent with the existing DEA literature as it is argued that traditional radial DEA models introduce an over-estimation of efficiency scores.

It is noteworthy that the least and the worst-performing inefficient countries identified by all DEA models are different with Mali and Zambia being among the worst countries in terms of efficiency scores for all models as in Table (4.38) and Russian Federation and India being the least inefficient country in all models except the CCR model as seen in Table (4.39).

Table (4.38): Worst Inefficient Countries Under Radial and Non-radial DEA Models.

Radial-DEA Measures		Non-Radial-DEA Measures	
CCR-CRS	BCC-VRS	SBM-CRS	SBM-VRS
▪ Kenya (0.26) ▪ **Mali (0.29)** ▪ Ghana (0.30) ▪ Mozambique (0.33) ▪ **Zambia (0.35)**	▪ Kenya (0.28) ▪ Ghana (0.33) ▪ **Mali (0.46)** ▪ Botswana (0.46) ▪ **Zambia (0.48)**	▪ **Mali (0)** ▪ Burundi (0) ▪ Rwanda (0) ▪ Botswana (0.01) ▪ **Zambia (0.01)**	▪ Namibia (0.01) ▪ Lesotho (0.01) ▪ **Zambia (0.01)** ▪ Botswana (0.01) ▪ **Mali (0.01)**

Table (4.39): Least Inefficient Countries Under Radial and Non-radial DEA Models.

Radial-DEA Measures		Non-Radial-DEA Measures	
CCR-CRS	BCC-VRS	SBM-CRS	SBM-VRS
▪ North Macedonia (0.99) ▪ Argentina (0.98) ▪ Bulgaria (0.98) ▪ Ukraine (0.97) ▪ Mongolia (0.93)	▪ **Russian Federation** (0.96) ▪ Serbia (0.96) ▪ Azerbaijan (0.88) ▪ Morocco (0.87) ▪ **India (0.86)**	▪ **Russian Federation** (0.64) ▪ Mexico (0.56) ▪ **India (0.45)** ▪ Ukraine (0.44) ▪ Colombia (0.38)	▪ **Russian Federation** (0.65) ▪ Mexico (0.56) ▪ **India (0.47)** ▪ Colombia (0.38) ▪ Turkey (0.31)

4.6.2 Treatment of the Slacks

Traditional radial DEA models neglect slacks as observed previously in Tables (4.17) and (4.18) which are considered sources of inefficiency beyond the proportionate movement and thus traditional DEA measures provide overestimated and inaccurate efficiency scores. Nonetheless, non-radial DEA models deal directly with slacks and introduce pareto-efficient efficiency scores as shown previously in the Table (4.20).

4.6.3 Country Groupings

In this chapter, developing countries are divided into four groups based on their level of efficiency. The first and the second group continues to be the same in radial and non-radial models and the reason for this is that these countries have zero slacks in inputs and outputs to be dealt with by the non-radial approach. The only differences were found to be in the group (3) and the group (4). Azerbaijan and Costa Rica moved from group 3 in the radial approach to group 4 in the non-radial approach. The same difference occurred when countries are classified by income group.

Furthermore, Morocco, Tunisia, and Ecuador moved from group 4 in the radial approach to group 3 in the non-radial approach. The same difference occurred when countries are classified by income group. Recall that these two groups are inefficient under both returns whatever the applied DEA approach and scale inefficient as well. The only difference between these two groups is related to the returns to scale. Countries in group 3 in both DEA approaches are characterised by increasing returns to scale and therefore the expansion of these countries is suggested i.e., these countries should increase the size of inputs to move to a better efficiency level. However, countries in group 4 are scale inefficient with decreasing returns to scale and thus contraction in these countries will lead to better efficiency levels i.e., downsizing their resources to observe efficiency gains.

4.6.4 Comparing Output Targets under Radial and non-Radial Projections.

For inefficient countries, DEA introduces not only performance measurement scores but also presents the required expected changes on the input/output side depending on the orientation of the model. That is; DEA guidelines set output targets for inefficient countries to be efficient. This is done by enabling these inefficient countries to improve their performance through output augmentation while holding inputs unchanged if the output orientation is utilized and vice versa if the input orientation is employed. However, DEA target-setting analysis varies based on the applied DEA methodology.

To elaborate more, the radial DEA models provide a proportionate increase for all outputs and thus require a change in all outputs by the same proportion as observed in the second column in the Table (4.38), whereas the non-radial DEA models provide varying degrees of output improvement for each output separately because not all outputs behave in the proportional way. In other words, non-radial DEA models consider each output individually and thus provide output adjustments in diversified proportions as in columns from 3 to 7 in the Table (4.40).

It is noteworthy that all output targets derived from the radial DEA measures are totally different from those obtained by using the non-radial measures. For instance, Albania is an inefficient country, if it wants to improve its performance to become an efficient/frontier country, then all its output variables should be increased by the same proportion of 95.8% if the radial approach is employed. However, these improvement targets in outputs are based on the overall performance of the country and neglect the possibility that some outputs might have been produced by utilizing efficient use of resources (inputs). Therefore, non-radial DEA measures focus on each output individually.

Thus, Albania could increase its output variables by different proportions i.e., Albania must increase output (2) which is scientific and technical publications by approximately 11343%, increase its output (3), the patents granted, by nearly 217.7% and finally increase its outputs (5) which is high-tech exports by 61412.7% while leaving other outputs unchanged namely, output (1) and output (4). This indicates that Albania should maintain its efficient use of inputs/resources in generating the outputs Y (1) and Y (4) while paying attention to improving its use of resources in producing outputs 5, 2, and 3 respectively to improve its overall efficiency and become a frontier country.

Paraguay is another example worth pointing out. If we use the radial DEA measures, then Paraguay could be an efficient country by improving all its outputs Y1, Y2, Y3, Y4, and Y5 by 19.2%. Though, Paraguay must pay attention only to scientific and technical publications (Y2) and increase it by nearly 17265.5% while keeping all other outputs unchanged if the non-radial projections are employed. Thus, in terms of knowledge dimensions, Paraguay must concentrate on the knowledge production dimension and maintain its performance in the other dimensions.

To this end, we can conclude that non-radial DEA models offer more reasonable targets for each output individually and maintain effective use of resources at the same time. This is observed from the non-radial projections in which some outputs must increase by a larger proportion, others by a smaller proportion, while some others could be left unchanged to render the inefficient countries to become efficient. This in turn will allow policymakers to focus on specific KBE dimensions (output targets) that need the highest improvements. It also leads to efficient utilization and prioritization of available resources and thus guides the efficiency improvement process in the desired direction and helps in achieving the highest level of efficiency. This is contrary to the radial models in which policymakers are directed to pay the same attention to all outputs when working towards achieving output targets which seems to be unwarranted and unrealistic in practice.

Table (4.40): Comparing CRS Output Targets Under Radial and Non–Radial Projections.

	Radial Projection (% change)	Non-Radial Projection (% Change)				
		% Additive in Y (1)	% Additive in Y (2)	% Additive in Y (3)	% Additive in Y (4)	% Additive in Y (5)
Albania	95.8	0	11343.48	217.66	0	61412.73
Algeria	47.3	62.38	1715.32	11240.93	0	823.41
Argentina	2.0	96.01	582.87	15.04	0	166.58
Azerbaijan	14.7	3.28	3439.17	225.98	0	374.88
Botswana	118.2	84.53	44743.26	0	0	4628.11
Bulgaria	1.6	68.64	4393.33	4.24	0	79.33
Burundi	181.7	45.85	238894.76	4508.18	543.28	128.4
Cambodia	136.8	59.91	18552.65	8178.85	0	67.5
Colombia	72.0	88.06	518.49	72.01	0	152.09
Costa Rica	22.2	0	12638.77	271.75	0	0
Ecuador	27.6	48.27	3715.91	3073.67	0	99.02
El Salvador	109.1	77.21	80854.22	1929.76	0	0
Ghana	232.6	0	6813.83	12130.27	0	1183.79
Honduras	79.2	69.54	12735.85	163.4	0	67.69
India	17.7	99.83	13.54	187.02	254.6	62.63
Indonesia	71.9	0	30.93	2664.73	45.73	0
Jordan	58.9	0	5236.93	458.47	0	1144.14
Kenya	288.1	100.06	15343.46	3954.64	141.52	158.67
Lesotho	122.1	88.83	62258.08	0	0	558.32
Madagascar	90.9	86.39	1401.85	0	0	175.45
Mali	239.2	119.6	79582.89	19610.94	62.98	237.26
Mexico	18.9	86.95	277.52	1.43	12.9	17.61
Mongolia	7.7	40.73	4144.60	0	0	0
Morocco	15.1	123.90	1720.50	1419.41	0	102.35
Mozambique	198.9	125.93	54990.86	0	30.72	0
Namibia	111.1	78.41	53521.03	1664.56	0	1393.13
Nepal	145.8	0	7531.48	7850.64	78.14	445.6
Nicaragua	128.2	12.74	54380.89	3154.82	0	216.66
Nigeria	66.6	0	127.76	9572.25	146.75	125.86
North Macedonia	1.0	98.60	4716.07	22.39	0	258.67
Pakistan	78.7	0	213.37	3398.01	0	257.88
Paraguay	19.2	0	17265.49	0	0	0

	Radial Projection (% change)	Non-Radial Projection (% Change)				
		% Additive in Y (1)	% Additive in Y (2)	% Additive in Y (3)	% Additive in Y (4)	% Additive in Y (5)
Peru	66.8	92.09	1225.70	163.53	0	199.21
Russian Federation	8.7	149.15	83.15	0	0	54.76
Rwanda	95.6	71.28	81544.14	18969.45	668.61	0
Senegal	92.2	0	34565.89	18308.31	23.35	1287.07
Serbia	9.4	134.81	3000.78	53.33	0	191.09
Sri Lanka	51.6	46.74	1489.54	244.59	0	1221.2
Thailand	55.2	99.56	1794.12	581.71	194.19	6.46
Tunisia	37.4	55.53	1949.65	1561.75	0	94.64
Turkey	26.4	0	391.77	42.92	0	658.99
Uganda	187.2	39.29	4901.95	0	26.16	16.95
Ukraine	3.5	61.44	405.5	20.7	0	140.09
Zambia	183.0	104.8	32223.01	9325.76	0	205.9

Note: Y (1) = Output 1 (Real GDP Growth); Y (2) = Output 2 (Scientific and Technical Publications); Y(3) = Output 3 (Patents Granted); Y(4) = Output 4 (Households with a computer), Y(5) = Output 5 (High-tech Exports).

4.6.5 Determining the Worst Knowledge Dimension

With radial, it is impossible to determine the worst knowledge dimension because of the assumption of proportionate movement for all outputs. However, with non-radial DEA models it is possible to determine accurately the knowledge dimension with the worst efficiency and the one with the least efficiency because non-radial DEA models set targets for each output individually and thus the knowledge dimension with the highest required percentage change is the worst in terms of efficiency and vice versa.

In this study, knowledge production is the worst in terms of efficiency while knowledge acquisition is the least dimension. Furthermore, with respect to the output proxies used in the study, it is organized in descending order as scientific and technical publications, high-tech exports, the patent granted, households with a computer, and real GDP growth.

4.7 Summing Up and Policy Recommendations

This chapter presents an experimental study for the most frequently utilised methodology of the frontier analysis. DEA happens to be an appropriate tool for comparative performance analysis of KBE efficiencies in all countries. In this study, we concluded that the KBE efficiency for any country could be measured through the ability of this country to maximize output given a certain level of input. The country's efficiency score could be used as an early warning stage or as a benchmark of its performance relative to other countries. Further, DEA could provide country-specific future improvements in various KBE dimensions.

In this chapter, different DEA models are employed to assess the relative efficiencies of developing countries in their transition to KBEs in 2020. In DEA literature, DEA models could be methodologically divided into two broad measures namely radial and non-radial measures. The basic traditional radial DEA models are the CCR model with a constant return-to-scale assumption and the BCC model with a variable return-to-scale assumption. On the other hand, the SBM is one of the most widely used non-radial DEA models. By critical examination of the existing empirical literature, it is found that DEA is widely applied as a tool for performance evaluation by means of input-output analysis, though it is not widely employed in the area of KBE efficiency assessment and when it comes to the assessment of the KBE in developing countries, it is almost non-existent with only limited DEA-based studies which dealt with KBE efficiency assessment in developed countries, to the best of the researcher's knowledge. Even if this study exists the number of developing countries under investigation is very small compared to developed countries with the general tendency of DEA application on small samples. Further, most of the existing empirical literature uses the radial DEA approach while the non-radial DEA approach has been ignored to a large extent, despite the merits that the latter approach has.

Thus, in this chapter, we have departed from applying the traditional radial DEA models in which the highest attention is paid only to efficiency measurement to focus greater attention not only on efficiency measurement but also on efficiency improvements through presenting more appropriate and reasonable output targets for policymakers in inefficient developing countries.

To this end, we could say that this chapter assesses the performance of developing countries in their transition towards KBE by employing DEA as follows. First, the radial approach is employed through applying an output-oriented radial DEA model namely the CCR and BCC model to assess the efficiencies of KBEs in developing countries in 2020. After that, super efficiency models are employed to discriminate among efficient countries. Second, given the existing limitation in the radial DEA models as these traditional radial DEA models failed to assess the impact of slacks on the efficiency scores and provide overestimated efficiency scores, the output-oriented non-radial DEA model namely the SBM and the super-SBM are also applied to assess the efficiencies of developing countries in their transition towards the KBE in 2020 in an attempt to fill the gap in the literature and to introduce more accurate efficiency scores for developing countries and to provide a full ranking for these countries as well.

Furthermore, the non-radial DEA model provides more in-depth and reasonable efficiency analysis than the radial DEA models. The non-radial and non-proportional improvement targets on the output side help policymakers to work on major tasks, identify key challenges, re-examine their inputs/resources utilization, efficiently use their available resources and sometimes reshuffle their resource pool, which is a matter of great concern, especially in developing countries. Thus, we conclude that, concerning the application of DEA for assessing KBE in developing countries, the non-radial approach is found to be the best approach that could explain the different aspects of KBE.

As for the empirical findings, this study assesses the KBE efficiencies for all developing countries in 2020, though due to data availability and the mandatory rules for DEA modelling, this study has been limited to evaluating KBE efficiencies for only sixty-five developing countries using the two DEA approaches. Recall that DEA is a data-driven efficiency analysis that depends heavily on data accuracy under the assumption of the right choice of inputs and outputs framework for analysing DMUs. In practical situations, scholars use estimation and proxies for inputs/outputs combination because they cannot cover all the appropriate inputs and all outputs in only one study. Therefore, in this study, selected variables are the ones that best reflect KBE performance i.e., have a theoretical base and are constrained by data availability as well.

The CCR DEA results show that most of the countries are inefficient with respect to their overall technical efficiency scores, with around 32% of countries efficient and about 68% (44countries) of the countries being inefficient. Subsequently, with the same original data, based on the production frontier, we do not only estimate over all technical efficiency for each country but also, we employ the BCC DEA model and calculate the pure technical efficiency i.e., managerial efficiency for each country. Scale efficiency and returns to scale have been calculated as well to assess the scale effect of each country and to verify whether the returns-to-scale of each country are decreasing, increasing or constant.

It is also observed that the average overall technical efficiency for all developing countries (OTE, mean=0.74) is decomposed into pure technical efficiency (PTE, mean=0.84) and scale efficiency (SE, mean =0.88) as shown previously in Tables (4.6), (4.7), and (4.8) for the radial approach. Additionally, with respect to the non-radial DEA model, the average overall technical efficiency for all developing countries (OTE, mean=0.41) is decomposed into pure technical efficiency (PTE, mean=0.59) and scale efficiency (SE, mean =0.76) as shown previously in Tables (4.20), (4.21), and (4.22) respectively. This empirical result reveals that the overall technical inefficiencies of KBE in developing countries are on average due to their pure technical inefficiencies (i.e., the managerial inefficiency) rather than the scale inefficiencies. Therefore, this result provides a confirmative guideline to policymakers in developing countries as they must pay attention to their managerial inefficiency firstly, and then proceed to enhance their scale efficiencies. Additionally, the empirical findings pertaining to returns-to-scale in the developing countries show that the predominant form of scale inefficiency is increasing returns-to-scale which means that these countries need to increase the size of their inputs to attain higher efficiency levels. To this end, the DEA results have interesting policy implications for promoting KBE in developing countries. However, it is worth mentioning here that the observed results of the study are critically based on the choice of KBE variables. Thus, the policy implications discussed here should be considered from this perspective.

Up to this stage, the applied DEA models give efficiency scores and divide countries into efficient and inefficient countries but failed to present ranking and to discriminate between efficient countries, i.e., those having efficiency scores of one. Thus, the study used two common approaches to rank the efficient countries, namely the frequency set approach and the super-efficiency model. It is obvious that China, Kazakhstan, and Iran are among the role models for all inefficient developing countries in 2020 for any employed DEA model. Therefore, other inefficient developing countries can learn from their experience. DEA analysis also provides an accurate answer to which frontier countries can inefficient developing countries emulate to be efficient.

On the other hand, by using a different ranking approach to discriminate among efficient countries, China and the Kyrgyz Republic are the global leaders for all developing countries in 2020 if the super efficiency scores under SBM CRS are calculated whereas, Angola and Iran are the global leader for all developing countries in 2020 if the supper efficiency scores under SBM VRS is used.

Additionally, the DEA guidelines introduced target-setting analysis for inefficient countries by determining the required (projected values) improvements for each of the study's KBE outputs. However, due to the limitation of the radial models of which the proportionate movement, in which policymakers are required to pay the same attention to all outputs by the same proportion when working towards achieving output targets and this seems to be unrealistic in practice, thus the non-radial non-proportional projected targets are wiser to be applied by policymakers in developing countries. Because it is reasonable for some outputs to be increased by a larger proportion, others by a smaller proportion, while some others could be maintained unchanged to shift the inefficient countries to become efficient. Finally, with respect to the KBE dimensions it is found that the knowledge production dimension continues to be the worst knowledge dimension and the largest contributor of efficiency.

To conclude, this study provides empirical evidence and practical guidelines to measure the comprehensive efficiency of KBEs. This is done in this chapter by employing the DEA methodology which would allow governments in developing countries to determine areas requiring greater investment to develop the KBE transition. Additionally, the emphasis on efficiency improvement as to how to present the DEA projections for inefficient countries to become efficient allows for resource utilization. It also provides context-based guidelines through providing the most appropriate guidance to policymakers in developing countries on what to manage and how to accomplish the changes.

4.8 Future Research

This study introduces a good starting point for the application of different DEA models to KBE efficiency assessment. Unlike most other empirical studies that employed radial DEA models only, this study tries to deal with radial DEA models' weaknesses by using the SBM non-radial DEA models together with the radial CCR and BCC models to assess the former's merits (SBM) in assessing the relative efficiencies of developing countries in their transition to a KBE.

Furthermore, this study utilizes the traditional super-efficiency model and super-SBM model to provide a full ranking of all countries and presented a target-setting analysis to guide policymakers to specific KBE dimensions for further improvements. However, certain gaps still exist in the empirical literature, calling for more research to deepen the understanding of KBE efficiencies. For instance, in the development of further DEA models, there are areas in which the DEA modelling could be improved by employing more advanced DEA models. Conventional DEA models are built on deterministic, precise, and quantitative data for input and output observations. Nevertheless, a more diagnostic analysis can be provided by using specialized models of DEA such as Fuzzy DEA to deal with the missing data or to forecast the future relative efficiency of DMUs efficiency scores using imprecise data. Other researchers could use another line of research in DEA named network DEA or dynamic DEA with which the researcher could deal with the many sub-processes within the KBE and thus introduce an in-depth and advanced analysis of the KBE.

Another direction of analysis could be adding undesirable outputs related to KBE such as poverty, brain drain, environmental degradation, and inequality. This addition of possible undesirable outputs could enrich the efficiency analysis. Additionally, scholars could calculate the Malmquist productivity index or apply window analysis for the changes in efficiency scores over time. Using cross-sectional data would only give a snapshot of the current situation and what is really going on. However, analysing panel data over time can show the true changes. The DEA's final guidelines in our study refer to only one year. One may argue that a one-year efficiency assessment may not reflect the actual performance of a country. Thus, the panel-data analysis for a period suggests the stability of KBE efficiency throughout the observed period. Additionally, like index numbers, we could add prior knowledge and use factor weight in DEA to assign specific weights before the application of DEA analysis. It is also possible to adopt a two-stage DEA analysis to add the effect of external factors that are uncontrollable by the decision-makers or a three-stage DEA analysis. Finally, the research could be directed towards sensitivity analysis; generally, the researcher could apply sensitivity analysis of changing the DEA model, by adopting different input and output variables and investigating the effect on DMUs efficiency scores. Another area within sensitivity analysis could be assessing the effect of sample (i.e., DMUs) change.

Chapter 5

KBE Assessment in Developing Countries in the Context of KAM and GII

5.1 Introduction

KAM is the most widely used KBE measurement framework, although it stopped in 2012. Therefore, for comparing purposes, KAM is replicated for the year 2020. KAM 2020 is then compared with DEA 2020 and GII 2020 results to opt for the best measure for KBE in developing countries.

5.2 The Knowledge Assessment Methodology (KAM)

5.2.1 KAM Mechanism of Working and Advantages

The World Bank methodology KAM takes the lead for being the most popular and hence the most widely used methodology among all the mainstream measurement frameworks discussed previously in Chapter 2, due to its merits as observed in the coming paragraphs. Numerous studies carried out by Afzal and Lawrey (2012a, b); Chen (2008 a, b); Hvidt (2015); Rezny et al. (2019); Rim et al. (2019) have confirmed its popularity.

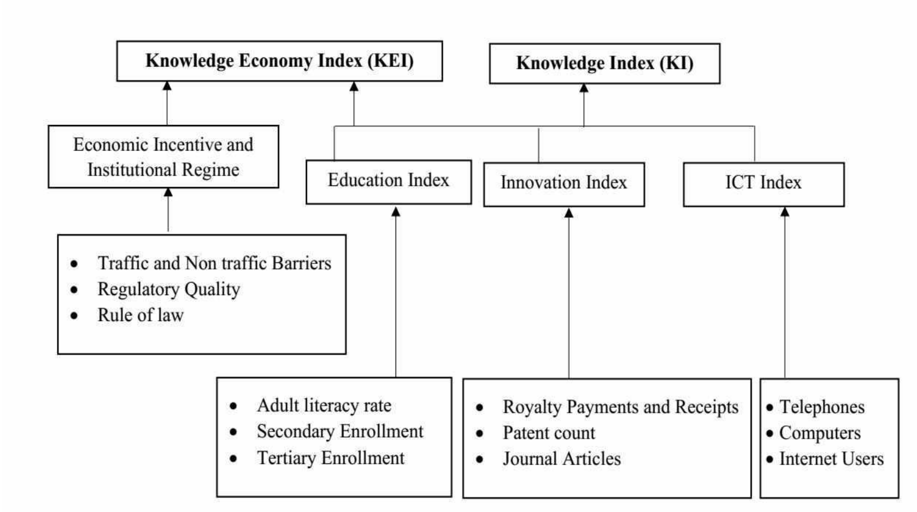
The World Bank Institute, in 1999, introduced the Knowledge for Development (K4D) program. As a part of this program, the KAM was developed to boost the KBE transition in its client countries by presenting diagnostic assessments and identifying the challenges and opportunities they face in making the transition (Chen & Dahlman, 2005).

The distinctive feature of KAM lies in its cross-sectoral analysis that adopts a holistic approach to the wide spectrum of factors that are related to the KBE (Robertson, 2008). KAM involves four pillars of KE, namely the economic incentive and institutional regime, education and human resources, the innovation system, and the information and communications technologies. KAM takes into consideration a set of 83 structural and qualitative variables that serve as proxies for these pillars. Each pillar is evaluated by a sub-index that is basically based on three indicators. Combining these three indicators constitute a proxy for the performance of the pillar (Chen & Dahlman, 2005).

Overall, these variables are organized as follows: economic incentive and institutional regime index (19), ICT index (12), overall economic performance (9), innovation system index (24), and education and human resources index (19). The comparison is undertaken for a group of 146 countries which includes most of the developed OECD economies and about 90 developing economies. Each variable is then normalized on a scale of zero to ten relative to other countries in the comparison group and the higher index reflects the high level of KE as well. The results of this assessment methodology could be presented through six different modes. Within these six modes, the basic scorecard mode and the knowledge economy index are the widely used modes to reflect a country's readiness in the KBE because of the difficulties in involving all available indicators in the analysis (Chen & Dahlman, 2005).

Methodologically, the Knowledge Economy Index (KEI) is defined as the simple average of the normalized values of the four pillar of the knowledge economy that exhibit a country's overall readiness for a knowledge economy. This means that 12 knowledge indicators are used to build the knowledge economy index. Therefore, the KEI is the numerical index for quantifying the KBE. On the other hand, the basic scorecard mode is a graphical (spider chart) and disaggregated representation of the of the KEI and consists of only 14 variables (two performance variables and 12 knowledge variables) with 3 variables representing each of the four pillars as follows in Figure (5.1) (Chen & Dahlman, 2005).

Figure (5.1): The KEI and the KE Calculation.



Source: Chen and Dahlman (2005)

KAM has tremendous merits compared with the other mainstream frameworks such as being user-friendly, internet-based, transparency, simplicity, and versatility. Furthermore, KAM incorporates the core features of the OECD and APEC frameworks. Put differently, each mainstream framework has a specific purpose which is highly related to the needs of the relevant organization's member states. KAM was designed to show a country's preparedness to switch to a KBE. The OECD framework, however, paid the highest attention to innovation performance. Furthermore, the APEC framework focuses only on APEC economies (Marouf & Chaudhry, 2013). It is obvious, after comparing the three frameworks that KAM is the most comprehensive assessment methodology.

Additionally, the wide use of KAM is distinguishable in the numerous empirical studies and reports that employed World Bank methodology for KBE assessment. Moreover, recent empirical studies still utilize this methodology even though its use ceased in 2012 without any further updates. Other more recent studies are grounded on KAM but with different approaches to assess the KBE. Similarly other studies used KAM to introduce a new index for the KBE or may use KAM besides other indices to provide a more holistic analysis of KBE assessment as presented previously in the empirical literature in chapter 3.

5.2.2 Replicating KAM for 2020

In this section, KAM is replicated for the same year as is the DEA approach for consistency and comparing purposes. In KAM 2020, the same methodological considerations, and the same set of countries as in the last released version are analysed, however for 2020 data or the latest available year for the variables.

5.2.2.1 Data Collection for KAM 2020

The objective here is to calculate the knowledge economy index (KEI) for all countries in 2020 using the same data sources and methodological considerations as in the latest update of KAM, namely KAM (2012). In this updated version of i.e., KAM (2020), countries are included in the KAM database only if the 12 variables of the basic scorecard are available.

If at most the data for one variable from each of the four KBE pillars is not available, then this country is not included in KAM (2020) calculations. As an example, if Country X does not have data for the secondary and tertiary gross enrollment rates, thus the education pillar index cannot be computed because it is the simple average of three variables which constitute the data (of which secondary and tertiary gross enrollment rates are required). Consequently, the KI and KEI cannot be calculated because the education index is part of these calculations. Thus, a pillar index is not calculated if more than one variable from the pillar is missing and therefore, country X is excluded from the KAM database.

5.2.2.2 Variables Description, Definitions, and Sources of Data in KAM 2020

Table (5.1) presents a detailed explanation of each sub-index along with the variables included. For each variable, data is collected for 2020 or for the latest available year.

Table (5.1): Decomposition of the KEI.

Indicators	Year	Source of Data	Definition
The Institutional Pillar Index Is calculated as the average of the normalised values of 1-1, 1-2 and 1-3			
1-1Tariff & Nontariff Barriers	2020	Heritage Foundation	- This score is given to each country based on an analysis of its tariff and non-tariff barriers to trade. - Import bans and quotas; strict labelling and licensing requirements are among these barriers. - The Trade freedom score is proxy by tariff and non-tariff barriers and is based on the Heritage Foundation's Trade Freedom; it ranges from (0-100). 0 means restrictive barriers (Repressed) and 100 mean free barriers. - **Available at:** https://www.heritage.org/index/explore
1-2 Regulatory Quality	2019	Governance Indicators, World Bank	- This indicator evaluates the existence of market-unfriendly policies. - Price controls; inadequate bank supervision; perceptions of the burdens imposed by excessive regulation in areas such as foreign trade and business development are among these policies. - Countries are ranked in a score from 0 the lowest to 100 the highest. The higher the score, the best is the regulatory quality situation in a country. - **Available at:** https://info.worldbank.org/governance/wgi/
1-3 Rule of law	2019	Governance Indicators, World Bank	- This indicator includes several measures which assess the extent to which agents have confidence in and adhere to society's rules as well as the extent of crime and violence in a country. - These include perceptions of the incidence of both violent and non-violent crime, the effectiveness and predictability of the judiciary as well as the quality of contract enforcement. - Countries are ranked in a score from 0 the lowest to 100 the highest. The highest score indicates the best situation in a particular country. - **Available at:** https://info.worldbank.org/governance/wgi/
The Education Pillar Index Is calculated as the average of the normalised values of 2-1,2-2 and 2-3			
2-1 Average years of schooling	2010	Barro-Lee Educational Attainment	- This variable is used as an aggregate measure of educational stock in a particular country. - **Available at:**

Indicators	Year	Source of Data	Definition
(Age 15 years old and above)		Dataset	https://databank.worldbank.org/source/education-statistics-%5E-all-indicators#
2-2 Gross secondary enrollment rate (%)	2019	World Bank Data Bank. Original source: UNESCO Institute for Statistics	- This variable is defined as the ratio of total enrolment, regardless of their ages, to the population of the age group that is eligibly officially at the secondary level of education (school-age population) - **Available at:** https://databank.worldbank.org/source/world-development-indicators
2-3 Gross Tertiary enrolment rate School enrolment, tertiary (% gross)	2019	World Bank Data Bank. Original source: UNESCO Institute for Statistics	- This variable is defined as the ratio of total enrolment, regardless of their age, to the population of the age group that is eligible officially for the tertiary level of education (school-age population) - **Available at:** https://databank.worldbank.org/source/world-development-indicators
The Innovation Pillar index Is calculated as the average of the normalised values of 3-1,3-2 and 3-3			
3-1 Royalty and License Fees Payments and Receipts (US$ millions)	2019	World Bank Data Bank. Original source: International Monetary Fund, Balance of Payments Statistics Yearbook, and data files.	- This variable is calculated as the sum of Royalty and License Fees Payments (US$ mil.) it is also called charges for the use of intellectual property payments and the Royalty and License Fees Receipts (US$ mil.) which is also called charges for the use of intellectual property receipts. - **Available at:** https://databank.worldbank.org/source/world-development-indicators
3-2 Scientific and technical journal articles	2018	World Bank Data Bank. Original source: Thomson Reuters, SCI and SSCI; The Patent Board; and National Science Foundation, Division of Science Resources Statistics, special tabulations.	- Scientific and technical journal articles refer to the number of scientific and engineering articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences. - **Available at:** https://databank.worldbank.org/source/world-development-indicators
3-3 Patent Applications Granted by the USPTO	Average 2015 - 2019	World Bank	- This variable presents the number of worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office. - A patent is generally defined as an exclusive right granted for a specified period (generally 20 years) for a new way of doing something or a new technical solution to a problem - an invention. - The invention must be of practical use and

Indicators	Year	Source of Data	Definition
			display a characteristic unknown in the existing body of knowledge in its field. - Most countries have systems to protect patentable inventions. - **Available at:** https://knoema.com/WBWDI2019Jan/world-development-indicators-wdi
The ICT Pillar Index **Is calculated as the average of the normalised values of 4-1,4-2 and 4-3**			
4-1Telephones Per 1000 people	2019	World Bank Data Bank. Original source: International Telecommunication Union (ITU); World Telecommunication/ICT Indicators Database	- This variable consists of the sum of telephone mainlines and mobile phones. - Telephone mainlines are telephone lines connecting a customer's equipment to the public switched telephone network. Mobile telephone subscribers are subscribers to a public mobile telephone service using cellular technology. - The available indicators are per 100 people, so it is multiplied by 10 to be per 1000 people. - **Available at:** http://knoema.com/ITUKIICT2019Apr/global-ict-developments
4-2 Internet users per 1000 people	2015	World Bank Data Bank. Original source: International Telecommunication Union (ITU); World Telecommunication/ICT Indicators Database	- This indicator refers to the reported Internet Service Provider subscriber counts. Generally, this indicator is obtained from nationally reported data, but in some cases, it is based on national surveys. - **Available at:** https://knoema.com/WBMDG2017/millennium-development-goals-discontinued
4-3 Computer per 100 people	2008	World Bank Data Bank. Original source: International Telecommunication Union (ITU); World Telecommunication/ ICT Indicators Database	- This indicator refers to personal computers which are self-contained computers designed to be used by a single individual. - **Available at:** https://knoema.com/WBEDS2017Jun/education-statistics

5.2.2.3 Countries Included in KAM 2020

KAM database includes countries from different regions as presented in Table (5.2). Countries included in the replicated KAM 2020 are the same as those in KAM 2012.

Table (5.2): Countries Included in KAM 2020.

Regions	Countries Included in KAM 2020	Number of Countries Included in Every Region
North America	Canada; United States.	2
Europe and Central Asia	Albania; Armenia; Austria; Azerbaijan; Belarus; Belgium; Bosnia & Herzegovina; Bulgaria; Croatia; Cyprus; Czech Republic; Demark; Estonia; Finland; France; Germany; Greece; Georgia; Hungary; Iceland; Ireland; Italy; Kazakhstan; Kyrgyz Republic; Latvia; Lithuania; Luxemburg; Macedonia, FYR; Moldova; Netherlands; Norway; Poland; Portugal; Romania; Russian Federation; Serbia; Slovak Republic; Slovenia; Spain; Sweden; Switzerland; Tajikistan; Turkey; Ukraine; United Kingdom; Uzbekistan.	46
East Asia and the Pacific	Australia; Cambodia; China; Fiji; Hong Kong, China; Indonesia; Japan; Korea, Rep.; Lao PDR; Malaysia; Mongolia; Myanmar; New Zealand; Philippines; Singapore; Taiwan, China; Thailand; Vietnam.	18
South Asia	Bangladesh; India; Nepal; Pakistan; Sri Lanka.	5
Latin America and the Caribbean	Argentina; Aruba; Barbados; Bolivia; Brazil; Chile; Colombia; Costa Rica; Cuba; Dominica; Dominican Republic; Ecuador; El Salvador; Guatemala; Guyana; Haiti; Honduras; Jamaica; Mexico; Nicaragua; Panama; Paraguay; Peru Trinidad and Tobago; Uruguay; Venezuela, RB.	26
The Middle East and North Africa	Algeria; Bahrain; Djibouti; Egypt, Arab Rep.; Iran, Islamic Rep.; Israel; Jordan; Kuwait; Lebanon; Malta; Morocco; Oman; Qatar; Saudi Arabia; The Syrian Arab Republic; Tunisia; United Arab Emirates; Yemen, Rep.	18
Sub-Saharan Africa	Angola; Benin; Botswana; Burkina Faso; Cameroon; Cape Verde; Cote d'Ivoire; Eritrea; Ethiopia; Ghana; Guinea; Kenya; Lesotho; Madagascar; Malawi; Mali; Mauritania; Mauritius; Mozambique; Namibia; Nigeria; Rwanda; Senegal; Sierra Leone; South Africa; Sudan; Swaziland; Tanzania; Uganda; Zambia; Zimbabwe.	31

Source: Chen and Dahlman (2005)

5.2.2.4 Calculating the sub-indices for each of the Four KBE Pillars

Based on the information provided in Table (5.1), it is possible to collect data for each country and normalize it as follows. The normalization procedure is explained in detail in the appendix (II). For each sub-index, data is collected and normalized as shown in Tables (5.3), (5.4), (5.5), and (5.6) respectively.

5.2.2.4.1 The Institutional Sub-Index

Table (5.3): The Institutional Sub-Index in KAM 2020.

Country	1-The Economic Incentives and Institutional Regime Pillar						
Countries in KAM 2020	1-1Tariff & Nontariff Barriers, 2020		1-2 Regulatory Quality, 2019		1-3 Rule of law, 2019		The institutional index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Albania	82.80	6.92	0.27	5.89	-0.41	3.82	**5.54**
Algeria	57.40	0.77	-1.30	0.55	-0.82	1.81	**1.04**
Angola	70.20	3.92	-0.89	1.03	-1.05	0.97	**1.97**
Argentina	62.60	1.61	-0.49	2.74	-0.43	3.61	**2.65**
Armenia	73.80	4.83	0.25	5.82	-0.13	4.93	**5.19**
Aruba	n/a	n/a	0.86	7.05	1.26	8.40	**7.73**
Australia	89.80	9.72	1.87	9.59	1.73	9.10	**9.47**
Austria	84.00	9.09	1.46	8.70	1.88	9.58	**9.12**
Azerbaijan	68.00	3.08	-0.23	3.63	-0.58	2.78	**3.16**
Bahrain	83.60	7.06	0.49	6.37	0.49	6.74	**6.72**
Bangladesh	63.40	1.68	-0.93	0.89	-0.64	2.50	**1.69**
Barbados	58.40	0.91	0.41	6.23	0.36	6.46	**4.53**
Belarus	76.00	5.59	-0.54	2.60	-0.79	1.88	**3.36**
Belgium	84.00	9.02	1.29	8.29	1.36	8.54	**8.62**
Benin	60.40	1.05	-0.38	3.08	-0.66	2.43	**2.19**
Bolivia	61.60	1.33	-0.99	0.82	-1.12	0.69	**0.95**
Bosnia & Herzegovina	69.20	3.64	-0.19	4.04	-0.23	4.65	**4.11**
Botswana	77.40	6.08	0.37	6.10	0.50	6.81	**6.33**
Brazil	64.60	2.17	-0.18	4.18	-0.18	4.79	**3.71**
Bulgaria	84.00	8.95	0.53	6.64	0.04	5.56	**7.05**
Burkina Faso	61.00	1.12	-0.38	3.01	-0.43	3.54	**2.56**
Cambodia	66.60	2.52	-0.57	2.40	-0.94	1.39	**2.10**
Cameroon	55.20	0.49	-0.83	1.30	-1.12	0.63	**0.81**
Canada	88.80	9.65	1.72	9.25	1.76	9.17	**9.35**
Cape Verde	68.00	3.01	-0.22	3.84	0.52	6.88	**4.57**
Chile	83.00	6.99	1.22	8.08	1.07	8.06	**7.71**
China	71.20	4.41	-0.24	3.56	-0.27	4.58	**4.18**
Colombia	77.00	5.80	0.40	6.16	-0.42	3.75	**5.24**
Costa Rica	75.00	5.24	0.50	6.44	0.54	6.94	**6.21**
Cote d'Ivoire	73.80	4.76	-0.24	3.49	-0.57	2.85	**3.70**
Croatia	84.00	8.88	0.59	6.78	0.37	6.53	**7.40**
Cuba	64.20	1.89	-1.49	0.34	-0.32	4.24	**2.16**
Cyprus	84.00	8.81	1.01	7.67	0.76	7.50	**7.99**
Czech Republic	84.00	8.74	1.25	8.15	1.05	7.99	**8.29**
Denmark	84.00	8.67	1.57	8.77	1.90	9.65	**9.03**
Djibouti	43.20	0.00	-0.77	1.51	-0.91	1.46	**0.99**
Dominican Republic	69.40	3.78	-0.05	4.73	-0.35	4.03	**4.18**
Ecuador	59.80	0.98	-0.82	1.37	-0.58	2.71	**1.69**
Egypt, Arab Rep.	67.00	2.73	-0.83	1.23	-0.42	3.68	**2.55**
El Salvador	70.80	4.20	0.02	5.07	-0.76	2.01	**3.76**
Eritrea	69.20	3.57	-2.27	0.07	-1.60	0.21	**1.28**
Estonia	84.00	8.60	1.59	8.84	1.28	8.47	**8.64**
Ethiopia	61.40	1.26	-0.89	0.96	-0.47	3.19	**1.80**
Fiji	55.00	0.42	-0.22	3.77	-0.03	5.35	**3.18**
Finland	84.00	8.53	1.85	9.45	2.02	9.93	**9.30**

Country	1-The Economic Incentives and Institutional Regime Pillar						
Countries in KAM 2020	1-1Tariff & Nontariff Barriers, 2020		1-2 Regulatory Quality, 2019		1-3 Rule of law, 2019		The institutional index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
France	84.00	8.46	1.44	8.63	1.41	8.68	**8.59**
Georgia	86.00	9.37	1.12	7.88	0.31	6.32	**7.86**
Germany	84.00	8.39	1.72	9.18	1.62	9.03	**8.87**
Ghana	62.40	1.54	-0.11	4.52	0.05	5.63	**3.89**
Greece	84.00	8.32	0.53	6.58	0.20	6.04	**6.98**
Guatemala	75.60	5.31	-0.22	3.70	-1.05	0.90	**3.31**
Guinea	66.40	2.45	-0.77	1.44	-1.21	0.42	**1.43**
Guyana	66.80	2.66	-0.62	2.26	-0.43	3.47	**2.80**
Haiti	65.40	2.31	-1.26	0.62	-0.97	1.25	**1.39**
Honduras	71.80	4.48	-0.49	2.67	-1.01	1.18	**2.78**
Hong Kong, China	95.00	9.93	1.98	9.73	1.60	8.96	**9.54**
Hungary	84.00	8.25	0.60	6.85	0.49	6.67	**7.26**
Iceland	86.80	9.51	1.37	8.49	1.77	9.24	**9.08**
India	69.40	3.71	-0.16	4.25	-0.03	5.28	**4.41**
Indonesia	79.20	6.36	-0.09	4.59	-0.34	4.10	**5.02**
Iran, Islamic Rep.	54.20	0.28	-1.42	0.48	-0.75	2.08	**0.95**
Ireland	84.00	8.18	1.60	8.90	1.39	8.61	**8.57**
Israel	84.20	9.16	1.28	8.22	1.05	7.92	**8.43**
Italy	84.00	8.11	0.95	7.12	0.28	6.18	**7.14**
Jamaica	69.20	3.50	0.17	5.75	-0.31	4.38	**4.54**
Japan	80.40	6.57	1.33	8.36	1.54	8.82	**7.92**
Jordan	71.00	4.27	0.03	5.14	0.14	5.90	**5.10**
Kazakhstan	74.60	5.17	0.14	5.62	-0.43	3.40	**4.73**
Kenya	62.20	1.47	-0.28	3.29	-0.45	3.33	**2.70**
Korea, Rep.	79.00	6.22	1.07	7.81	1.19	8.33	**7.46**
Kuwait	75.80	5.45	0.06	5.21	0.22	6.11	**5.59**
Kyrgyz Republic	72.80	4.62	-0.35	3.22	-0.89	1.60	**3.14**
Lao PDR	67.80	2.94	-0.71	1.85	-0.94	1.32	**2.04**
Latvia	84.00	8.04	1.19	8.01	1.01	7.78	**7.94**
Lebanon	74.40	5.03	-0.43	2.95	-0.86	1.67	**3.22**
Lesotho	62.20	1.40	-0.54	2.53	-0.38	3.89	**2.61**
Lithuania	84.00	7.97	1.16	7.95	1.02	7.85	**7.92**
Luxemburg	84.00	7.90	1.70	9.11	1.79	9.31	**8.77**
Macedonia, FYR	77.40	6.01	n/a	n/a	n/a	n/a	**n/a**
Madagascar	65.40	2.24	-0.73	1.71	-1.01	1.11	**1.69**
Malawi	68.20	3.22	-0.70	1.99	-0.33	4.17	**3.12**
Malaysia	82.40	6.85	0.67	6.92	0.59	7.15	**6.97**
Mali	64.00	1.82	-0.57	2.33	-0.83	1.74	**1.96**
Malta	84.00	7.83	0.96	7.19	0.95	7.64	**7.55**
Mauritania	63.80	1.75	-0.76	1.64	-0.58	2.64	**2.01**
Mauritius	88.00	9.58	1.00	7.40	0.76	7.43	**8.14**
Mexico	81.60	6.78	0.10	5.34	-0.66	2.36	**4.83**
Moldova	76.80	5.73	0.01	5.00	-0.37	3.96	**4.90**
Mongolia	74.60	5.10	-0.01	4.86	-0.27	4.51	**4.83**
Morocco	70.60	3.99	-0.21	3.90	-0.14	4.86	**4.25**
Mozambique	70.80	4.13	-0.72	1.78	-1.02	1.04	**2.32**
Myanmar	n/a	n/a	-0.76	1.58	-1.06	0.76	**1.17**
Namibia	71.20	4.34	-0.11	4.45	0.31	6.25	**5.01**
Nepal	57.60	0.84	-0.70	1.92	-0.54	2.99	**1.91**

Country	1-The Economic Incentives and Institutional Regime Pillar						
Countries in KAM 2020	1-1Tariff & Nontariff Barriers, 2020		1-2 Regulatory Quality, 2019		1-3 Rule of law, 2019		The institutional index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Netherlands	84.00	7.76	1.86	9.52	1.81	9.38	**8.89**
New Zealand	90.20	9.79	1.88	9.66	1.88	9.51	**9.65**
Nicaragua	68.40	3.36	-0.69	2.05	-1.18	0.49	**1.97**
Nigeria	68.40	3.29	-0.86	1.16	-0.90	1.53	**1.99**
Norway	84.00	7.69	1.80	9.38	1.98	9.86	**8.98**
Oman	73.60	4.69	0.29	5.96	0.55	7.01	**5.89**
Pakistan	64.60	2.10	-0.64	2.19	-0.67	2.29	**2.19**
Panama	77.20	5.94	0.36	6.03	-0.12	5.14	**5.70**
Paraguay	76.40	5.66	-0.20	3.97	-0.56	2.92	**4.18**
Peru	86.40	9.44	0.56	6.71	-0.49	3.06	**6.40**
Philippines	74.20	4.97	0.01	4.93	-0.48	3.13	**4.34**
Portugal	84.00	7.55	0.97	7.26	1.14	8.26	**7.69**
Qatar	81.40	6.71	0.68	6.99	0.73	7.36	**7.02**
Romania	84.00	7.48	0.46	6.30	0.36	6.39	**6.72**
Russian Federation	74.00	4.90	-0.43	2.88	-0.72	2.15	**3.31**
Rwanda	61.20	1.19	0.08	5.27	0.08	5.76	**4.08**
Saudi Arabia	75.80	5.38	-0.07	4.66	0.17	5.97	**5.34**
Senegal	66.40	2.38	-0.11	4.38	-0.19	4.72	**3.83**
Serbia	77.20	5.87	0.11	5.48	-0.12	5.07	**5.47**
Sierra Leone	64.60	2.03	-0.88	1.10	-0.77	1.94	**1.69**
Singapore	95.00	9.86	2.16	9.79	1.88	9.44	**9.70**
Slovak Republic	84.00	7.41	1.01	7.53	0.56	7.08	**7.34**
Slovenia	84.00	7.34	1.01	7.47	1.12	8.13	**7.64**
South Africa	72.60	4.55	0.16	5.68	-0.08	5.21	**5.15**
Spain	84.00	7.27	1.05	7.74	0.98	7.71	**7.57**
Sri Lanka	47.00	0.21	-0.18	4.11	-0.01	5.49	**3.27**
Sudan	45.00	0.07	-1.67	0.21	-1.14	0.56	**0.28**
Swaziland	n/a	n/a	n/a	n/a	n/a	n/a	**n/a**
Sweden	84.00	7.20	1.80	9.32	1.91	9.79	**8.77**
Switzerland	86.00	9.30	1.66	9.04	1.91	9.72	**9.35**
Syrian Arab Republic	47.00	0.14	-1.76	0.14	-2.08	0.07	**0.12**
Taiwan, China	86.00	9.23	1.40	8.56	1.14	8.19	**8.66**
Tajikistan	69.60	3.85	-1.01	0.68	-1.23	0.35	**1.63**
Tanzania	64.40	1.96	-0.64	2.12	-0.58	2.57	**2.22**
Thailand	80.00	6.43	0.12	5.55	0.10	5.83	**5.94**
Trinidad and Tobago	68.80	3.43	-0.15	4.32	-0.12	5.00	**4.25**
Tunisia	66.80	2.59	-0.44	2.81	0.06	5.69	**3.70**
Turkey	76.00	5.52	-0.01	4.79	-0.28	4.44	**4.92**
Uganda	67.40	2.87	-0.37	3.15	-0.31	4.31	**3.44**
Ukraine	79.20	6.29	-0.26	3.42	-0.70	2.22	**3.98**
United Arab Emirates	81.40	6.64	0.98	7.33	0.84	7.57	**7.18**
United Kingdom	84.00	7.13	1.63	8.97	1.60	8.89	**8.33**
United States	80.40	6.50	1.35	8.42	1.46	8.75	**7.89**
Uruguay	70.80	4.06	0.51	6.51	0.62	7.22	**5.93**

Country	1-The Economic Incentives and Institutional Regime Pillar						
Countries in KAM 2020	1-1Tariff & Nontariff Barriers, 2020		1-2 Regulatory Quality, 2019		1-3 Rule of law, 2019		The institutional index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Venezuela, RB	54.80	0.35	-2.36	0.00	-2.32	0.00	**0.12**
Vietnam	79.00	6.15	-0.26	3.36	-0.02	5.42	**4.98**
Yemen, Rep.	67.40	2.80	-1.66	0.27	-1.77	0.14	**1.07**
Zambia	68.20	3.15	-0.55	2.47	-0.46	3.26	**2.96**
Zimbabwe	56.00	0.70	-1.46	0.41	-1.26	0.28	**0.46**

5.2.2.4.2 The Education Sub-Index

Table (5.4): The Education Sub-Index in KAM 2020.

Country	2-The Education Pillar						
Countries in KAM 2020	2-1Average Years of Schooling, (15 years old and above) 2010		2-2 Gross secondary enrollment rate, 2019		2-3 Gross Tertiary enrollment rate, 2019		The Education Index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Albania	9.93	5.98	95.09	4.82	59.78	6.12	**5.64**
Algeria	6.68	2.52	99.61	5.84	51.37	5.52	**4.63**
Angola	n/a	n/a	50.67	1.31	9.34	1.04	**0.52**
Argentina	9.51	5.35	108.73	8.10	89.96	9.33	**7.59**
Armenia	10.73	7.24	86.47	3.72	51.49	5.60	**5.52**
Aruba	n/a	n/a	111.16	8.32	15.60	2.24	**5.28**
Australia	11.54	8.58	132.77	9.49	107.81	9.78	**9.28**
Austria	9.60	5.59	99.96	5.91	86.69	8.96	**6.82**
Azerbaijan	n/a	n/a	94.78	4.74	31.54	3.73	**4.24**
Bahrain	7.06	2.83	97.11	5.18	55.63	5.90	**4.64**
Bangladesh	5.91	1.89	72.56	2.48	24.02	3.13	**2.50**
Barbados	9.45	5.28	102.71	6.86	65.43	6.94	**6.36**
Belarus	n/a	n/a	102.44	6.72	87.43	9.10	**7.91**
Belgium	10.69	7.09	155.96	9.93	78.90	8.28	**8.43**
Benin	4.43	0.71	59.04	1.82	12.52	1.72	**1.42**
Bolivia	8.25	4.17	89.72	4.31	n/a	n/a	**4.24**
Bosnia & Herzegovina	n/a	n/a	n/a	n/a	40.19	4.48	**n/a**
Botswana	9.55	5.43	79.92	2.99	25.08	3.21	**3.88**
Brazil	7.89	3.86	95.26	4.89	43.46	5.00	**4.58**
Bulgaria	11.24	7.95	96.82	5.11	71.52	7.84	**6.97**
Burkina Faso	n/a	n/a	41.31	0.66	7.10	0.75	**0.70**
Cambodia	4.72	1.02	45.22	1.02	14.74	2.16	**1.40**
Canada	12.32	9.53	114.12	8.61	70.11	7.46	**8.53**
Cape Verde	n/a	n/a	88.16	3.94	23.62	2.99	**3.46**
Chile	9.78	5.83	102.37	6.64	90.90	9.48	**7.32**
China	7.51	3.23	88.17	4.01	53.76	5.67	**4.30**
Colombia	8.95	4.96	97.51	5.40	55.33	5.82	**5.39**
Costa Rica	7.97	3.94	141.36	9.64	57.67	5.97	**6.51**
Cote d'Ivoire	4.65	0.94	54.61	1.68	9.34	1.12	**1.25**
Croatia	11.30	8.11	100.08	5.99	67.65	7.24	**7.11**
Cuba	10.16	6.22	100.34	6.20	41.38	4.70	**5.71**
Cyprus	11.07	7.80	100.25	6.06	81.34	8.58	**7.48**
Czech Republic	12.80	9.69	102.30	6.57	63.77	6.72	**7.66**
Denmark	11.30	8.03	129.75	9.42	81.18	8.51	**8.65**

Country	2-The Education Pillar						
Countries in KAM 2020	2-1Average Years of Schooling, (15 years old and above) 2010		2-2 Gross secondary enrollment rate, 2019		2-3 Gross Tertiary enrollment rate, 2019		The Education Index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Djibouti	n/a	n/a	51.97	1.61	5.35	0.37	**0.99**
Dominica	n/a	n/a	101.06	6.35	n/a	n/a	**n/a**
Dominican Republic	7.85	3.78	81.59	3.28	59.92	6.19	**4.42**
Ecuador	7.60	3.46	101.44	6.50	44.89	5.07	**5.01**
Egypt, Arab Rep.	7.15	2.99	89.48	4.23	35.16	4.03	**3.75**
El Salvador	7.77	3.70	71.66	2.41	29.37	3.58	**3.23**
Eritrea	n/a	n/a	47.70	1.24	3.36	0.15	**0.70**
Estonia	12.11	9.29	116.65	8.91	70.37	7.61	**8.60**
Ethiopia	n/a	n/a	34.94	0.22	8.22	0.90	**0.56**
Fiji	9.96	6.06	89.88	4.38	16.14	2.31	**4.25**
Finland	11.62	8.82	154.82	9.78	90.26	9.40	**9.33**
France	10.68	7.01	104.14	7.08	67.62	7.16	**7.08**
Georgia	n/a	n/a	106.30	7.74	63.92	6.79	**7.26**
Germany	12.37	9.61	97.59	5.47	70.34	7.54	**7.54**
Ghana	7.00	2.68	74.68	2.70	17.23	2.46	**2.61**
Greece	10.30	6.46	104.88	7.30	142.85	9.93	**7.89**
Guatemala	4.57	0.87	51.15	1.39	21.78	2.84	**1.70**
Guinea	4.26	0.55	39.33	0.44	10.52	1.49	**0.83**
Guyana	8.79	4.65	97.73	5.55	11.62	1.64	**3.94**
Haiti	5.11	1.57	n/a	n/a	n/a	n/a	**N/A**
Honduras	6.19	2.20	66.24	2.26	26.16	3.28	**2.58**
Hungary	11.85	8.98	103.92	7.01	50.31	5.37	**7.12**
Iceland	11.05	7.72	117.98	9.05	73.10	7.99	**8.25**
India	6.24	2.28	73.79	2.63	28.57	3.43	**2.78**
Indonesia	7.61	3.62	88.91	4.09	36.31	4.18	**3.96**
Iran, Islamic Rep.	8.88	4.88	86.31	3.58	62.79	6.57	**5.01**
Ireland	12.03	9.13	154.91	9.85	77.28	8.21	**9.07**
Israel	12.32	9.45	105.56	7.59	61.48	6.42	**7.82**
Italy	9.63	5.67	101.35	6.42	64.29	6.87	**6.32**
Jamaica	9.87	5.91	85.35	3.50	27.13	3.36	**4.26**
Japan	11.60	8.74	n/a	n/a	n/a	n/a	**N/A**
Jordan	9.59	5.51	65.19	2.04	34.42	3.88	**3.81**
Kazakhstan	11.33	8.27	113.23	8.54	61.75	6.49	**7.77**
Kenya	6.14	1.97	56.76	1.75	11.46	1.57	**1.76**
Korea, Rep.	12.05	9.21	98.51	5.69	95.86	9.70	**8.20**
Kuwait	6.34	2.36	97.83	5.62	55.31	5.75	**4.58**
Kyrgyz Republic	10.71	7.17	96.37	4.96	42.32	4.85	**5.66**
Lao PDR	5.02	1.42	65.77	2.12	14.45	2.09	**1.87**
Latvia	10.65	6.85	109.16	8.25	93.02	9.63	**8.24**
Lebanon	n/a	n/a	n/a	n/a	n/a	n/a	**n/a**
Lesotho	5.85	1.81	62.01	1.97	10.20	1.42	**1.73**
Lithuania	10.89	7.48	108.24	8.03	73.73	8.06	**7.86**
Luxemburg	10.99	7.64	104.30	7.15	18.59	2.54	**5.78**
Macedonia, FYR	n/a	n/a	79.99	3.07	n/a	n/a	**n/a**
Madagascar	n/a	n/a	34.60	0.15	5.35	0.45	**0.30**
Malawi	4.81	1.10	37.08	0.36	0.82	0.00	**0.49**
Malaysia	10.44	6.61	83.75	3.36	43.06	4.93	**4.97**
Mali	1.97	0.08	41.03	0.58	5.50	0.52	**0.40**

Country	2-The Education Pillar						
Countries in KAM 2020	2-1Average Years of Schooling, (15 years old and above) 2010		2-2 Gross secondary enrollment rate, 2019		2-3 Gross Tertiary enrollment rate, 2019		The Education Index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Malta	10.52	6.69	107.27	7.88	59.25	6.04	**6.87**
Mauritania	4.53	0.79	39.41	0.51	5.76	0.60	**0.63**
Mauritius	8.86	4.72	97.12	5.26	40.60	4.63	**4.87**
Mexico	8.79	4.57	105.10	7.45	41.52	4.78	**5.60**
Moldova	10.40	6.54	86.36	3.65	39.21	4.33	**4.84**
Mongolia	9.20	5.12	91.52	4.53	65.60	7.01	**5.55**
Morocco	4.96	1.26	81.19	3.21	38.55	4.25	**2.91**
Myanmar	4.85	1.18	68.44	2.34	18.82	2.61	**2.04**
Namibia	6.17	2.13	65.78	2.19	22.89	2.91	**2.41**
Nepal	4.23	0.47	80.18	3.14	13.33	1.94	**1.85**
Netherlands	11.39	8.43	134.28	9.56	87.10	9.03	**9.01**
New Zealand	10.98	7.56	114.64	8.76	82.98	8.73	**8.35**
Nicaragua	6.61	2.44	73.43	2.55	n/a	n/a	**2.50**
Nigeria	n/a	n/a	42.00	0.80	10.17	1.34	**1.07**
Norway	11.59	8.66	117.45	8.98	83.02	8.81	**8.82**
Oman	n/a	n/a	107.09	7.81	40.45	4.55	**6.18**
Pakistan	5.02	1.34	43.82	0.88	8.96	0.97	**1.06**
Panama	9.27	5.20	76.14	2.85	47.80	5.22	**4.42**
Paraguay	7.57	3.39	75.91	2.77	34.63	3.96	**3.37**
Peru	8.88	4.80	108.83	8.18	70.74	7.69	**6.89**
Philippines	8.43	4.41	84.05	3.43	35.48	4.10	**3.98**
Poland	11.32	8.19	111.97	8.47	68.62	7.39	**8.01**
Portugal	7.52	3.31	120.83	9.20	65.66	7.09	**6.53**
Qatar	8.43	4.33	105.47	7.52	18.95	2.69	**4.85**
Romania	10.67	6.93	89.07	4.16	51.01	5.45	**5.51**
Russian Federation	11.53	8.50	103.76	6.93	84.58	8.88	**8.11**
Rwanda	4.36	0.63	44.32	0.95	6.24	0.67	**0.75**
Saudi Arabia	8.53	4.49	111.79	8.39	70.90	7.76	**6.88**
Senegal	2.74	0.16	46.24	1.09	13.14	1.87	**1.04**
Serbia	10.85	7.40	94.47	4.67	67.79	7.31	**6.46**
Sierra Leone	4.23	0.39	41.80	0.73	n/a	n/a	**0.56**
Singapore	10.81	7.32	105.84	7.66	88.89	9.25	**8.08**
Slovak Republic	12.82	9.76	91.36	4.45	45.37	5.15	**6.46**
Slovenia	11.89	9.06	114.49	8.69	77.11	8.13	**8.63**
South Africa	9.69	5.75	100.51	6.28	23.80	3.06	**5.03**
Spain	10.27	6.30	126.18	9.34	91.11	9.55	**8.40**
Sri Lanka	10.06	6.14	100.34	6.13	21.13	2.76	**5.01**
Sudan	3.21	0.24	46.62	1.17	16.92	2.39	**1.26**
Swaziland	5.06	1.50	n/a	n/a	n/a	n/a	**n/a**
Sweden	11.64	8.90	151.70	9.71	72.46	7.91	**8.84**
Switzerland	13.02	9.84	102.57	6.79	61.38	6.27	**7.63**
Taiwan, China	n/a	n/a	n/a	n/a	n/a	n/a	**n/a**
Tajikistan	10.30	6.38	87.05	3.80	31.26	3.66	**4.61**
Tanzania	5.81	1.73	32.04	0.07	3.09	0.07	**0.63**
Thailand	7.99	4.02	115.15	8.83	49.29	5.30	**6.05**
Trinidad and Tobago	10.63	6.77	n/a	n/a	n/a	n/a	**n/a**
Tunisia	7.48	3.15	92.87	4.60	31.85	3.81	**3.85**
Turkey	7.05	2.76	104.48	7.23	113.22	9.85	**6.61**

Country	2-The Education Pillar						
Countries in KAM 2020	2-1Average Years of Schooling, (15 years old and above) 2010		2-2 Gross secondary enrollment rate, 2019		2-3 Gross Tertiary enrollment rate, 2019		The Education Index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Uganda	5.70	1.65	24.64	0.00	3.91	0.22	**0.63**
Ukraine	11.15	7.87	96.44	5.04	81.71	8.66	**7.19**
United Arab Emirates	9.07	5.04	104.95	7.37	n/a	n/a	**6.21**
United Kingdom	12.24	9.37	120.78	9.12	61.38	6.34	**8.28**
United States	13.18	9.92	99.28	5.77	88.30	9.18	**8.29**
Uruguay	8.17	4.09	121.18	9.27	63.13	6.64	**6.67**
Uzbekistan	n/a	n/a	97.42	5.33	12.58	1.79	**3.56**
Venezuela, RB	8.41	4.25	88.08	3.87	79.30	8.36	**5.49**
Vietnam	7.15	2.91	n/a	n/a	28.64	3.51	**3.21**
Yemen, Rep.	3.68	0.31	51.58	1.53	10.15	1.27	**1.04**
Zambia	7.32	3.07	n/a	n/a	4.12	0.30	**1.68**
Zimbabwe	7.61	3.54	51.55	1.46	10.01	1.19	**2.07**

5.2.2.4.3 The Innovation Sub-Index

Table (5.5): The Innovation Sub-Index in KAM 2020.

Country	3-The Innovation Pillar						
Countries in KAM 2020	3-1 Royalty Payments and receipts (US$), 2019		3-2 S&E Journal Articles, 2018		3-3 Patent Applications Granted by the USPTO, average for 2015-09 (USPTO)		The innovation index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Albania	51933262.32	3.59	180.36	2.39	13.80	2.19	**2.73**
Algeria	143276580.76	4.61	5231.44	6.48	121.80	5.09	**5.39**
Angola	127684961.47	4.38	30.12	0.63	4.00	0.70	**1.90**
Argentina	1986402715.02	7.42	8811.13	7.11	538.00	6.75	**7.10**
Armenia	0.00	0.55	521.33	3.73	111.60	5.00	**3.09**
Aruba	18598837.80	2.27	n/a	n/a	n/a	n/a	**n/a**
Austria	3512069315.99	7.97	12362.28	7.75	2092.20	8.33	**8.02**
Azerbaijan	28208000.00	2.58	761.43	4.23	166.80	5.44	**4.08**
Bahrain	N/A	N/A	321.51	3.17	7.40	1.58	**2.37**
Bangladesh	54702399.65	3.67	3135.08	5.92	63.20	3.95	**4.51**
Barbados	27491265.00	2.42	37.97	0.70	16.00	2.63	**1.92**
Belarus	288300000.00	5.55	1179.81	4.79	436.60	6.40	**5.58**
Belgium	7245596035.2	8.52	15688.13	8.31	954.40	7.19	**8.01**
Benin	17885.46	0.63	227.74	2.68	n/a	n/a	**1.65**
Bolivia	83776754.58	3.98	102.80	1.48	35.50	3.51	**2.99**
Bosnia & Herzegovina	36841367.78	2.89	703.79	4.15	69.00	4.12	**3.72**
Botswana	106081156.64	4.30	280.57	3.10	2.25	0.26	**2.55**
Brazil	5887333181.9	8.44	60147.96	9.23	5153.0	8.95	**8.87**
Bulgaria	380830000.00	5.94	3311.27	6.13	215.60	5.96	**6.01**
Burkina Faso	1285178.10	0.94	251.99	2.96	n/a	n/a	**1.95**
Cambodia	38471607.58	2.97	145.74	2.04	2.50	0.44	**1.82**
Cameroon	4355320.90	1.33	875.62	4.58	n/a	n/a	**2.95**
Canada	18098896538	9.14	59967.79	9.15	4199.0	8.86	**9.05**
Cape Verde	10069591.84	1.80	8.69	0.07	2.33	0.35	**0.74**

Country	3-The Innovation Pillar						
Countries in KAM 2020	3-1 Royalty Payments and receipts (US$), 2019		3-2 S&E Journal Articles, 2018		3-3 Patent Applications Granted by the USPTO, average for 2015-09 (USPTO)		The innovation index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Chile	1767785119.9	7.19	7121.74	6.83	419.60	6.32	**6.78**
China	40975172430	9.38	528263.3	9.93	1211265.	9.91	**9.74**
Colombia	1452263398.4	6.95	7195.02	6.97	459.60	6.49	**6.81**
Costa Rica	599627134.83	6.41	507.41	3.66	13.80	2.11	**4.06**
Cote d'Ivoire	12148619.57	1.88	248.14	2.89	n/a	n/a	**2.38**
Croatia	409987310.39	6.17	4276.90	6.20	161.60	5.35	**5.91**
Cuba	N/A	N/A	968.74	4.65	29.25	3.33	**3.99**
Cyprus	418435173.06	6.25	1245.42	4.86	5.00	1.05	**4.05**
Czech Republic	2199221110.89	7.50	15576.60	8.24	781.80	6.93	**7.56**
Denmark	5381457205.40	8.28	13978.80	8.10	1423.40	8.07	**8.15**
Djibouti	N/A	N/A	6.16	0.00	N/A	N/A	**N/A**
Dominica	661690.49	0.86	12.60	0.14	N/A	N/A	**0.50**
Dominican Republic	41500000.00	3.05	49.26	1.06	22.60	2.72	**2.27**
Ecuador	141086830.00	4.45	2142.19	5.56	28.80	3.25	**4.42**
El Salvador	100566363.56	4.22	45.44	0.99	3.80	0.61	**1.94**
Eritrea	N/A	N/A	21.37	0.42	N/A	N/A	**N/A**
Estonia	82620272.81	3.91	1414.72	5.14	30.20	3.42	**4.16**
Ethiopia	34534546.07	2.73	1994.44	5.49	13.75	2.02	**3.41**
Fiji	7130559.83	1.72	139.78	1.90	N/A	N/A	**1.81**
Finland	4586913732.3	8.20	10598.94	7.32	1329.40	7.72	**7.75**
France	28942649238	9.30	66352.18	9.30	14266.60	9.30	**9.30**
Georgia	41580689.73	3.13	550.41	3.80	91.60	4.39	**3.77**
Germany	52625712505	9.61	104396.12	9.72	47379.60	9.56	**9.63**
Ghana	264732618.68	5.47	1275.99	5.00	14.00	2.46	**4.31**
Greece	397362435.84	6.09	10906.99	7.46	488.00	6.58	**6.71**
Guatemala	258398100.00	5.39	99.89	1.41	5.20	1.14	**2.65**
Guinea	-830000.00	0.00	27.84	0.49	n/a	n/a	**0.25**
Guyana	4726380.00	1.48	13.70	0.21	1.50	0.09	**0.59**
Haiti	25267316.33	2.34	29.18	0.56	n/a	n/a	**1.45**
Honduras	N/A	N/A	45.10	0.92	6.50	1.32	**1.12**
Hong Kong, China	2735823621.7	7.73	n/a	n/a	291.20	6.14	**6.94**
Hungary	3036908388.9	7.81	6700.92	6.76	503.00	6.67	**7.08**
Iceland	385738461.56	6.02	680.89	4.08	42.80	3.60	**4.57**
India	8761290566.6	8.75	135787.79	9.79	15296.40	9.39	**9.31**
Indonesia	1863637536.1	7.34	26947.57	8.66	1786.00	8.16	**8.05**
Iran, Islamic Rep.	N/A	N/A	48305.64	8.94	13417.75	9.21	**9.08**
Ireland	106130533082	9.84	7174.11	6.90	68.75	4.04	**6.93**
Israel	3099400000.00	7.89	12234.69	7.68	1379.00	7.89	**7.82**
Italy	9449575321.70	8.83	71240.28	9.44	8910.25	9.04	**9.10**
Jamaica	58838985.63	3.75	163.85	2.18	15.40	2.54	**2.83**
Japan	73923960351.1	9.69	98792.50	9.65	255675.4	9.74	**9.69**
Jordan	36112676.06	2.81	2627.29	5.85	26.80	3.16	**3.94**
Kazakhstan	144112610.00	4.69	2367.46	5.77	1027.00	7.46	**5.97**
Kenya	184696463.96	5.00	1246.76	4.93	190.80	5.61	**5.18**
Korea, Rep.	17661400000.0	9.06	66376.17	9.37	164789.40	9.65	**9.36**
Kuwait	N/A	N/A	1003.84	4.72	7.00	1.49	**3.10**
Lao PDR	0.00	0.47	86.91	1.20	1.67	0.18	**0.61**

Country	3-The Innovation Pillar						
Countries in KAM 2020	3-1 Royalty Payments and receipts (US$), 2019		3-2 S&E Journal Articles, 2018		3-3 Patent Applications Granted by the USPTO, average for 2015-09 (USPTO)		The innovation index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Latvia	69392327.90	3.83	1417.73	5.21	97.80	4.56	**4.53**
Lebanon	47753585.43	3.28	1776.31	5.42	110.00	4.91	**4.54**
Lesotho	3171115.10	1.17	18.54	0.28	N/A	N/A	**0.73**
Lithuania	141655603.48	4.53	2267.30	5.70	89.60	4.30	**4.84**
Luxemburg	8758408984.78	8.67	869.10	4.51	139.20	5.26	**6.15**
Macedonia, FYR	171303922.00	4.92	493.05	3.59	N/A	N/A	**4.26**
Madagascar	18595718.89	2.19	127.41	1.62	6.75	1.40	**1.74**
Malawi	N/A	N/A	231.21	2.82	4.50	0.88	**1.85**
Malaysia	2439023047.82	7.66	23661.33	8.59	1146.80	7.63	**7.96**
Mali	0.00	0.39	90.37	1.27	N/A	N/A	**0.83**
Malta	1860130287.87	7.27	422.02	3.52	5.67	1.23	**4.00**
Mauritania	2137462.30	1.02	20.32	0.35	N/A	N/A	**0.68**
Mauritius	14166129.20	1.95	126.94	1.55	4.80	0.96	**1.49**
Mexico	320742844.00	5.70	16345.64	8.38	1373.60	7.81	**7.30**
Moldova	33100000.00	2.66	210.37	2.46	81.00	4.21	**3.11**
Mongolia	27648893.47	2.50	140.85	1.97	102.20	4.74	**3.07**
Morocco	159911115.52	4.77	5056.77	6.41	209.00	5.79	**5.65**
Mozambique	0.00	0.31	139.25	1.83	24.00	2.89	**1.68**
Myanmar	49416077.88	3.44	230.65	2.75	N/A	N/A	**3.09**
Namibia	3128782.68	1.09	156.31	2.11	14.00	2.37	**1.86**
Nepal	N/A	N/A	792.11	4.30	14.00	2.28	**3.29**
Netherlands	85045139928.76	9.77	30457.33	8.73	2215.40	8.60	**9.03**
New Zealand	1756903509.00	7.03	7888.75	7.04	922.80	7.02	**7.03**
Nicaragua	N/A	N/A	43.67	0.85	N/A	N/A	**N/A**
Nigeria	252840000.00	5.23	5602.28	6.69	101.67	4.65	**5.52**
Norway	966322298.32	6.72	11802.78	7.61	1114.20	7.54	**7.29**
Oman	N/A	N/A	856.43	4.44	11.60	1.75	**3.10**
Pakistan	192000000.00	5.08	12904.31	7.89	245.00	6.05	**6.34**
Panama	83921600.00	4.06	172.88	2.32	56.80	3.77	**3.39**
Paraguay	N/A	N/A	97.98	1.34	N/A	N/A	**N/A**
Peru	446502791.77	6.33	1629.88	5.35	93.00	4.47	**5.38**
Philippines	860599737.68	6.64	2237.34	5.63	411.00	6.23	**6.17**
Poland	4379000000.00	8.13	35662.6	8.87	4191.00	8.77	**8.59**
Portugal	1011896209.09	6.80	14294.6	8.17	731.40	6.84	**7.27**
Romania	1044996880.02	6.88	10345.01	7.18	1011.80	7.37	**7.14**
Russian Federation	7879830000.00	8.59	81579.36	9.51	25420.80	9.47	**9.19**
Rwanda	391089.91	0.78	169.52	2.25	4.50	0.79	**1.27**
Saudi Arabia	N/A	N/A	10897.88	7.39	N/A	N/A	**N/A**
Senegal	14195607.66	2.03	388.32	3.38	992.00	7.28	**4.23**
Serbia	358377242.01	5.86	4523.42	6.34	N/A	N/A	**6.10**
Sierra Leone	4582975.44	1.41	40.72	0.77	174.40	5.53	**2.57**
Singapore	25703761171.4	9.22	11458.63	7.54	N/A	N/A	**8.38**
Slovak Republic	791138901.93	6.56	5321.60	6.55	N/A	N/A	**6.56**
Slovenia	333509535.64	5.78	3206.15	6.06	210.80	5.88	**5.90**
South Africa	1757615341.78	7.11	13008.74	7.96	N/A	N/A	**7.53**
Spain	10256973392.53	8.91	54536.59	9.08	N/A	N/A	**9.00**
Sri Lanka	0.00	0.16	1347.54	5.07	2104.80	8.42	**4.55**
Sudan	0.00	0.08	397.77	3.45	N/A	N/A	**1.76**

Country	3-The Innovation Pillar						
Countries in KAM 2020	3-1 Royalty Payments and receipts (US$), 2019		3-2 S&E Journal Articles, 2018		3-3 Patent Applications Granted by the USPTO, average for 2015-09 (USPTO)		The innovation index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Swaziland	N/A	N/A	N/A	N/A	N/A	N/A	**N/A**
Sweden	15620323087.97	8.98	20420.56	8.45	n/a	n/a	**8.72**
Switzerland	47027312077.7	9.53	21378.56	8.52	1940.40	8.25	**8.77**
Syrian Arab Republic	N/A	N/A	274.65	3.03	1385.60	7.98	**5.51**
Taiwan, China	N/A	N/A	N/A	N/A	N/A	N/A	**N/A**
Tajikistan	83390.00	0.70	62.40	1.13	135.50	5.18	**2.34**
Tanzania	5767551.75	1.56	602.71	3.87	1.00	0.00	**1.81**
Thailand	5509385696.62	8.36	12513.8	7.82	13.00	1.93	**6.04**
Romania	1044996880.02	6.88	10345.01	7.18	1011.80	7.37	**7.14**
Russian Federation	7879830000.00	8.59	81579.36	9.51	25420.80	9.47	**9.19**
Rwanda	391089.91	0.78	169.52	2.25	4.50	0.79	**1.27**
Saudi Arabia	N/A	N/A	10897.88	7.39	N/A	N/A	**N/A**
Senegal	14195607.66	2.03	388.32	3.38	992.00	7.28	**4.23**
Serbia	358377242.01	5.86	4523.42	6.34	N/A	N/A	**6.10**
Sierra Leone	4582975.44	1.41	40.72	0.77	174.40	5.53	**2.57**
Singapore	25703761171.42	9.22	11458.63	7.54	N/A	N/A	**8.38**
Slovak Republic	791138901.93	6.56	5321.60	6.55	N/A	N/A	**6.56**
Slovenia	333509535.64	5.78	3206.15	6.06	210.80	5.88	**5.90**
South Africa	1757615341.78	7.11	13008.74	7.96	N/A	N/A	**7.53**
Spain	10256973392.5	8.91	54536.59	9.08	N/A	N/A	**9.00**
Sri Lanka	0.00	0.16	1347.54	5.07	2104.80	8.42	**4.55**
Sudan	0.00	0.08	397.77	3.45	N/A	N/A	**1.76**
Swaziland	N/A	N/A	N/A	N/A	N/A	N/A	**N/A**
Sweden	15620323087.97	8.98	20420.56	8.45	n/a	n/a	**8.72**
Switzerland	47027312077.7	9.53	21378.56	8.52	1940.40	8.25	**8.77**
Syrian Arab Republic	N/A	N/A	274.65	3.03	1385.60	7.98	**5.51**
Taiwan, China	N/A	N/A	N/A	N/A	N/A	N/A	**N/A**
Tajikistan	83390.00	0.70	62.40	1.13	135.50	5.18	**2.34**
Tanzania	5767551.75	1.56	602.71	3.87	1.00	0.00	**1.81**
Thailand	5509385696.62	8.36	12513.75	7.82	13.00	1.93	**6.04**
Trinidad and Tobago	50974358.33	3.52	211.21	2.54	N/A	N/A	**3.03**
Tunisia	43040677.93	3.20	5564.86	6.62	2.75	0.53	**3.45**
Turkey	2274000000.00	7.58	33535.80	8.80	191.75	5.70	**7.36**
Uganda	48906917.52	3.36	673.07	4.01	n/a	n/a	**3.69**
Ukraine	688000000.00	6.48	10379.89	7.25	10.33	1.67	**5.13**
United Arab Emirates	N/A	N/A	3144.89	5.99	2198.20	8.51	**7.25**
United Kingdom	41951996769.3	9.45	97680.90	9.58	45.25	3.68	**7.57**
United States	160133000000.0	9.92	422807.71	9.86	13394.00	9.12	**9.63**
Uruguay	161318826.59	4.84	852.23	4.37	289554.80	9.82	**6.34**
Venezuela, RB	258000000.00	5.31	639.03	3.94	N/A	N/A	**4.63**
Vietnam	N/A	N/A	4286.48	6.27	59.33	3.86	**5.06**

Country	3-The Innovation Pillar						
Countries in KAM 2020	3-1 Royalty Payments and receipts (US$), 2019		3-2 S&E Journal Articles, 2018		3-3 Patent Applications Granted by the USPTO, average for 2015-09 (USPTO)		The innovation index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Yemen, Rep.	207445510.00	5.16	137.44	1.76	N/A	N/A	**3.46**
Zambia	16903078.70	2.11	213.07	2.61	24.00	2.81	**2.51**
Zimbabwe	4322232.37	1.25	359.33	3.31	12.00	1.84	**2.13**

5.2.2.4.4 The Information and Communication Technology Sub-Index

Table (5.6): The Information and Communication Technology Sub-Index in KAM 2020.

Countries in KAM 2020	4-The Information and Communication Technology Pillar						
	4-1Telephones Per 1,000 People, 2019		4-2Internet Users Per 1,000 people, 2015		4-3 Computers Per 1,000 Persons, 2008		The ICT Index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Albania	997.23	2.05	632.53	5.90	46.13	2.42	**3.46**
Algeria	1201.22	3.90	382.00	3.54	n/a	n/a	**3.72**
Angola	469.91	0.27	124.00	0.83	6.47	0.33	**0.48**
Argentina	1481.53	6.58	680.43	6.39	n/a	n/a	**6.48**
Armenia	1376.16	5.41	591.02	5.63	n/a	n/a	**5.52**
Aruba	1686.78	8.29	886.61	9.17	97.37	4.29	**7.25**
Australia	1416.49	5.89	845.61	8.54	n/a	n/a	**7.22**
Austria	1616.85	7.81	839.40	8.47	n/a	n/a	**8.14**
Azerbaijan	1236.45	4.04	770.00	7.85	80.46	3.74	**5.21**
Bahrain	1325.21	4.66	934.78	9.72	745.76	9.23	**7.87**
Bangladesh	1024.38	2.33	144.00	1.04	22.51	1.32	**1.56**
Barbados	1567.97	7.19	761.10	7.71	n/a	n/a	**7.45**
Belarus	1704.13	8.42	673.00	6.25	n/a	n/a	**7.34**
Belgium	1338.03	4.86	850.53	8.68	n/a	n/a	**6.77**
Benin	880.06	1.58	112.55	0.56	7.14	0.55	**0.89**
Bolivia	1070.87	2.67	355.62	3.26	n/a	n/a	**2.97**
Bosnia & Herzegovina	1358.58	5.14	526.00	4.86	63.99	3.29	**4.43**
Botswana	1799.35	9.11	373.12	3.40	62.46	3.19	**5.23**
Brazil	1148.12	3.22	583.28	5.56	n/a	n/a	**4.39**
Bulgaria	1300.95	4.38	566.56	5.28	109.62	4.73	**4.80**
Burkina Faso	1005.83	2.19	113.88	0.63	6.32	0.22	**1.01**
Cambodia	1302.59	4.52	223.27	2.08	3.63	0.11	**2.24**
Canada	1279.89	4.25	884.70	9.10	943.37	9.78	**7.71**
Cape Verde	1187.76	3.84	426.80	3.96	142.65	5.38	**4.39**
Chile	1466.96	6.37	766.30	7.78	n/a	n/a	**7.07**
China	1336.83	4.79	503.00	4.65	56.52	2.75	**4.07**
Colombia	1456.02	6.23	559.05	5.21	112.48	4.84	**5.43**
Costa Rica	1743.82	8.70	597.63	5.69	n/a	n/a	**7.20**
Cote d'Ivoire	1463.97	6.30	384.40	3.61	n/a	n/a	**4.96**
Croatia	1389.32	5.55	698.03	6.74	n/a	n/a	**6.14**
Cuba	666.23	0.68	373.05	3.33	56.22	2.64	**2.22**

Countries in KAM 2020	4-The Information and Communication Technology Pillar						
	4-1Telephones Per 1,000 People, 2019		4-2Internet Users Per 1,000 people, 2015		4-3 Computers Per 1,000 Persons, 2008		The ICT Index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Cyprus	1813.31	9.18	717.16	7.15	383.42	7.47	**7.93**
Czech Republic	1373.16	5.27	756.69	7.57	n/a	n/a	**6.42**
Denmark	1429.07	6.03	963.31	9.79	549.31	8.02	**7.95**
Djibouti	450.39	0.21	119.22	0.69	37.68	1.98	**0.96**
Dominica	1095.02	2.74	650.00	6.04	n/a	n/a	**4.39**
Dominican Republic	945.91	1.85	542.16	5.07	n/a	n/a	**3.46**
Ecuador	1038.87	2.47	489.40	4.44	129.52	5.05	**3.99**
Egypt, Arab Rep.	1036.98	2.40	378.19	3.47	39.21	2.09	**2.65**
El Salvador	1612.98	7.67	268.03	2.71	n/a	n/a	**5.19**
Eritrea	223.03	0.00	10.84	0.07	9.29	0.88	**0.32**
Estonia	1716.47	8.49	884.12	9.03	261.50	6.92	**8.15**
Ethiopia	383.28	0.07	138.55	0.90	6.76	0.44	**0.47**
Fiji	1264.92	4.18	425.00	3.89	n/a	n/a	**4.03**
Finland	1341.07	4.93	864.22	8.75	n/a	n/a	**6.84**
France	1686.48	8.22	780.10	8.13	651.97	8.57	**8.30**
Georgia	1476.71	6.44	475.70	4.31	271.65	7.03	**5.92**
Germany	1767.30	8.77	875.90	8.89	655.53	8.68	**8.78**
Ghana	1352.68	5.07	314.48	3.13	10.71	0.99	**3.06**
Greece	1612.04	7.60	668.35	6.18	93.73	3.96	**5.91**
Guatemala	1299.56	4.32	288.06	2.85	n/a	n/a	**3.58**
Guinea	1007.97	2.26	82.00	0.28	n/a	n/a	**1.27**
Guyana	1004.88	2.12	340.00	3.19	n/a	n/a	**2.66**
Haiti	575.82	0.48	121.98	0.76	52.56	2.53	**1.26**
Honduras	777.72	1.10	276.20	2.78	24.85	1.43	**1.77**
Hong Kong, China	3430.44	9.93	849.48	8.61	692.96	8.90	**9.15**
Hungary	1375.52	5.34	728.35	7.22	255.74	6.59	**6.38**
India	858.07	1.44	260.00	2.57	32.90	1.76	**1.92**
Indonesia	1309.94	4.59	219.76	2.01	20.31	1.21	**2.60**
Iran, Islamic Rep.	1773.12	8.84	453.35	4.17	105.86	4.51	**5.84**
Ireland	1415.82	5.82	834.95	8.40	582.05	8.24	**7.49**
Israel	1624.53	7.88	773.52	7.92	n/a	n/a	**7.90**
Italy	1654.86	8.01	581.42	5.49	n/a	n/a	**6.75**
Jamaica	1160.65	3.42	422.21	3.82	n/a	n/a	**3.62**
Japan	1913.48	9.73	910.58	9.44	n/a	n/a	**9.59**
Jordan	805.29	1.16	601.14	5.76	74.77	3.52	**3.48**
Kazakhstan	1558.88	7.05	708.30	6.94	n/a	n/a	**7.00**
Kenya	1039.03	2.53	166.00	1.18	n/a	n/a	**1.86**
Korea, Rep.	1827.61	9.32	899.00	9.24	586.19	8.35	**8.97**
Kuwait	1866.20	9.52	775.23	7.99	n/a	n/a	**8.75**
Kyrgyz Republic	1390.53	5.62	302.47	3.06	n/a	n/a	**4.34**
Lao PDR	816.38	1.23	182.00	1.53	n/a	n/a	**1.38**
Latvia	1205.95	3.97	792.01	8.33	326.93	7.14	**6.48**
Lebanon	746.84	0.75	740.00	7.43	101.80	4.39	**4.19**
Lesotho	1142.26	3.15	250.00	2.43	n/a	n/a	**2.79**

Countries in KAM 2020	4-The Information and Communication Technology Pillar						
	4-1Telephones Per 1,000 People, 2019		4-2Internet Users Per 1,000 people, 2015		4-3 Computers Per 1,000 Persons, 2008		The ICT Index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Lithuania	1821.64	9.25	713.78	7.08	258.45	6.70	**7.68**
Luxemburg	1791.86	8.97	0.00	0.00	672.82	8.79	**5.92**
Macedonia, FYR	1175.96	3.63	703.80	6.88	357.60	7.36	**5.96**
Madagascar	408.33	0.14	41.74	0.14	n/a	n/a	**0.14**
Malawi	478.51	0.34	92.98	0.35	n/a	n/a	**0.34**
Malaysia	1598.63	7.47	710.64	7.01	231.46	6.26	**6.91**
Mali	1162.80	3.49	103.30	0.49	7.86	0.66	**1.55**
Malta	2025.06	9.79	759.60	7.64	n/a	n/a	**8.72**
Mauritania	1054.57	2.60	151.99	1.11	45.39	2.31	**2.01**
Mauritius	1856.32	9.45	501.39	4.58	175.58	5.82	**6.62**
Mexico	1127.85	3.08	574.31	5.42	143.92	5.49	**4.66**
Moldova	1158.81	3.36	690.00	6.53	114.31	4.95	**4.94**
Mongolia	1492.90	6.64	225.00	2.15	246.88	6.48	**5.09**
Morocco	1335.86	4.73	570.80	5.35	58.15	2.86	**4.31**
Mozambique	479.29	0.41	169.34	1.25	n/a	n/a	**0.83**
Myanmar	1148.14	3.29	217.26	1.94	9.24	0.77	**2.00**
Namibia	1187.65	3.77	256.88	2.50	240.30	6.37	**4.21**
Netherlands	1598.05	7.40	917.24	9.51	911.53	9.67	**8.86**
New Zealand	1720.38	8.63	882.23	8.96	525.74	7.80	**8.46**
Nicaragua	919.29	1.78	197.04	1.67	n/a	n/a	**1.72**
Nigeria	882.56	1.64	245.00	2.36	n/a	n/a	**2.00**
Norway	1176.82	3.70	968.10	9.86	628.88	8.46	**7.34**
Oman	1510.56	6.78	735.30	7.36	179.11	5.90	**6.68**
Pakistan	775.14	1.03	140.00	0.97	n/a	n/a	**1.00**
Panama	1493.08	6.71	512.05	4.72	60.50	2.97	**4.80**
Paraguay	1113.05	2.95	497.20	4.51	n/a	n/a	**3.73**
Peru	1403.08	5.68	409.00	3.75	n/a	n/a	**4.72**
Philippines	1586.14	7.26	537.00	4.93	72.33	3.41	**5.20**
Poland	1559.69	7.12	679.97	6.32	169.27	5.71	**6.38**
Portugal	1666.16	8.15	686.33	6.46	183.39	6.04	**6.88**
Qatar	1546.17	6.92	928.85	9.65	156.91	5.60	**7.39**
Romania	1345.29	5.00	557.63	5.14	188.23	6.15	**5.43**
Russian Federation	1850.47	9.38	701.00	6.81	133.33	5.16	**7.12**
Rwanda	765.82	0.82	180.00	1.46	3.04	0.00	**0.76**
Saudi Arabia	1362.08	5.21	696.16	6.67	697.89	9.01	**6.96**
Senegal	1109.95	2.88	216.90	1.88	n/a	n/a	**2.38**
Serbia	1256.12	4.11	653.17	6.11	258.50	6.81	**5.68**
Sierra Leone	861.78	1.51	63.44	0.21	n/a	n/a	**0.86**
Singapore	1892.12	9.59	790.13	8.26	720.62	9.12	**8.99**
Slovak Republic	1479.72	6.51	776.35	8.06	579.82	8.13	**7.56**
Slovenia	1548.62	6.99	730.99	7.29	424.72	7.69	**7.32**
South Africa	1690.58	8.36	519.19	4.79	n/a	n/a	**6.57**
Spain	1606.54	7.53	786.90	8.19	394.95	7.58	**7.77**
Sri Lanka	1543.04	6.85	299.89	2.99	n/a	n/a	**4.92**
Sudan	774.34	0.96	266.10	2.64	107.15	4.62	**2.74**
Swaziland	971.72	1.99	n/a	n/a	36.94	1.87	**1.93**

Countries in KAM 2020	4-The Information and Communication Technology Pillar						
	4-1Telephones Per 1,000 People, 2019		4-2Internet Users Per 1,000 people, 2015		4-3 Computers Per 1,000 Persons, 2008		The ICT Index
	Actual	Normalized	Actual	Normalized	Actual	Normalized	
Sweden	1455.04	6.16	906.10	9.38	881.01	9.56	**8.37**
Switzerland	1632.72	7.95	874.79	8.82	962.38	9.89	**8.88**
Syrian Arab Republic	1302.32	4.45	299.80	2.92	92.02	3.85	**3.74**
Taiwan, China	1777.72	8.90	n/a	n/a	n/a	n/a	**N/A**
Tajikistan	1169.22	3.56	189.80	1.60	n/a	n/a	**2.58**
Tanzania	823.40	1.30	100.00	0.42	n/a	n/a	**0.86**
Trinidad and Tobago	1797.25	9.04	691.98	6.60	133.97	5.27	**6.97**
Tunisia	1387.40	5.48	465.00	4.24	95.96	4.07	**4.60**
Turkey	1106.61	2.81	537.45	5.00	61.04	3.08	**3.63**
Uganda	577.10	0.55	178.35	1.39	16.86	1.09	**1.01**
Ukraine	1405.93	5.75	488.85	4.38	45.33	2.20	**4.11**
United Arab Emirates	2248.13	9.86	905.00	9.31	330.77	7.25	**8.81**
United Kingdom	1659.06	8.08	920.00	9.58	801.92	9.34	**9.00**
United States	1616.16	7.74	745.54	7.50	806.07	9.45	**8.23**
Uruguay	1717.39	8.56	646.00	5.97	n/a	n/a	**7.27**
Uzbekistan	1119.81	3.01	428.00	4.03	31.34	1.65	**2.90**
Venezuela, RB	772.40	0.89	618.69	5.83	n/a	n/a	**3.36**
Vietnam	1450.19	6.10	435.00	4.10	96.49	4.18	**4.79**
Yemen, Rep.	579.54	0.62	240.85	2.29	27.73	1.54	**1.48**
Zambia	969.56	1.92	210.00	1.81	n/a	n/a	**1.86**
Zimbabwe	919.17	1.71	227.43	2.22	76.23	3.63	**2.52**

5.2.3 Calculation of the Knowledge Index (KI) and Knowledge Economy Index (KEI)

After calculating the four sub-indices of the knowledge economy. It is possible now to calculate the KEI and the KI as in Table (5.7).

Table (5.7): Calculating the KEI and the KI for 2020.

Countries in KAM 2020	The Institutional Sub-Index (1)	The Education Sub-Index (2)	The Innovation Sub-Index (3)	The ICT Sub-Index (4)	Knowledge Index (KI) (Simple average of 2,3,4)	Knowledge-Economy Index (KEI) (Simple average of 1,2,3,4)
Albania	5.54	5.64	2.73	3.46	3.94	4.34
Algeria	1.04	4.63	5.39	3.72	4.58	3.70
Angola	1.97	0.52	1.90	0.48	0.97	1.22
Argentina	2.65	7.59	7.10	6.48	7.06	5.96
Armenia	5.19	5.52	3.09	5.52	4.71	4.83
Aruba	7.73	5.28	n/a	7.25	6.26	6.75
Australia	9.47	9.28	8.58	7.22	8.36	8.64

Countries in KAM 2020	The Institutional Sub-Index (1)	The Education Sub-Index (2)	The Innovation Sub-Index (3)	The ICT Sub-Index (4)	Knowledge Index (KI) (Simple average of 2,3,4)	Knowledge-Economy Index (KEI) (Simple average of 1,2,3,4)
Austria	9.12	6.82	8.02	8.14	7.66	8.03
Azerbaijan	3.16	4.24	4.08	5.21	4.51	4.17
Bahrain	6.72	4.64	2.37	7.87	4.96	5.40
Bangladesh	1.69	2.50	4.51	1.56	2.86	2.57
Barbados	4.53	6.36	1.92	7.45	5.24	5.07
Belarus	3.36	7.91	5.58	7.34	6.94	6.05
Belgium	8.62	8.43	8.01	6.77	7.74	7.96
Benin	2.19	1.42	1.65	0.89	1.32	1.54
Bolivia	0.95	4.24	2.99	2.97	3.40	2.79
Bosnia & Herzegovina	4.11	n/a	3.72	4.43	4.08	4.09
Botswana	6.33	3.88	2.55	5.23	3.89	4.50
Brazil	3.71	4.58	8.87	4.39	5.95	5.39
Bulgaria	7.05	6.97	6.01	4.80	5.92	6.21
Burkina Faso	2.56	0.70	1.95	1.01	1.22	1.55
Cambodia	2.10	1.40	1.82	2.24	1.82	1.89
Cameroon	0.81	1.99	2.95	1.55	2.16	1.82
Canada	9.35	8.53	9.05	7.71	8.43	8.66
Cape Verde	4.57	3.46	0.74	4.39	2.86	3.29
Chile	7.71	7.32	6.78	7.07	7.06	7.22
China	4.18	4.30	9.74	4.07	6.04	5.57
Colombia	5.24	5.39	6.81	5.43	5.88	5.72
Costa Rica	6.21	6.51	4.06	7.20	5.92	5.99
Cote d'Ivoire	3.70	1.25	2.38	4.96	2.86	3.07
Croatia	7.40	7.11	5.91	6.14	6.39	6.64
Cuba	2.16	5.71	3.99	2.22	3.97	3.52
Cyprus	7.99	7.48	4.05	7.93	6.49	6.87
Czech Republic	8.29	7.66	7.56	6.42	7.21	7.48
Denmark	9.03	8.65	8.15	7.95	8.25	8.44
Djibouti	0.99	0.99	N/A	0.96	0.65	0.98
Dominica	4.44	n/a	0.50	4.39	2.45	3.11
Dominican Republic	4.18	4.42	2.27	3.46	3.38	3.58
Ecuador	1.69	5.01	4.42	3.99	4.47	3.78
Egypt, Arab Rep.	2.55	3.75	6.92	2.65	4.44	3.97
El Salvador	3.76	3.23	1.94	5.19	3.45	3.53
Eritrea	1.28	0.70	N/A	0.32	0.51	0.76
Estonia	8.64	8.60	4.16	8.15	6.97	7.39
Ethiopia	1.80	0.56	3.41	0.47	1.48	1.56
Fiji	3.18	4.25	1.81	4.03	3.37	3.32
Finland	9.30	9.33	7.75	6.84	7.97	8.31
France	8.59	7.08	9.30	8.30	8.23	8.32
Georgia	7.86	7.26	3.77	5.92	5.65	6.20
Germany	8.87	7.54	9.63	8.78	8.65	8.70
Ghana	3.89	2.61	4.31	3.06	3.33	3.47
Greece	6.98	7.89	6.71	5.91	6.84	6.88
Guatemala	3.31	1.70	2.65	3.58	2.64	2.81
Guinea	1.43	0.83	0.25	1.27	0.78	0.94
Guyana	2.80	3.94	0.59	2.66	2.40	2.50

Countries in KAM 2020	The Institutional Sub-Index (1)	The Education Sub-Index (2)	The Innovation Sub-Index (3)	The ICT Sub-Index (4)	Knowledge Index (KI) (Simple average of 2,3,4)	Knowledge-Economy Index (KEI) (Simple average of 1,2,3,4)
Haiti	1.39	N/A	1.45	1.26	1.36	1.37
Honduras	2.78	2.58	1.12	1.77	1.82	2.06
Hong Kong, China	9.54	8.25	6.94	9.15	8.11	8.47
Hungary	7.26	7.12	7.08	6.38	6.86	6.96
Iceland	9.08	8.25	4.57	8.39	7.07	7.57
India	4.41	2.78	9.31	1.92	4.67	4.61
Indonesia	5.02	3.96	8.05	2.60	4.87	4.91
Iran, Islamic Rep.	0.95	5.01	9.08	5.84	6.64	5.22
Ireland	8.57	9.07	6.93	7.49	7.83	8.01
Israel	8.43	7.82	7.82	7.90	7.85	7.99
Italy	7.14	6.32	9.10	6.75	7.39	7.33
Jamaica	4.54	4.26	2.83	3.62	3.57	3.81
Japan	7.92	N/A	9.69	9.59	9.64	9.06
Jordan	5.10	3.81	3.94	3.48	3.74	4.08
Kazakhstan	4.73	7.77	5.97	7.00	6.91	6.37
Kenya	2.70	1.76	5.18	1.86	2.93	2.87
Korea, Rep.	7.46	8.20	9.36	8.97	8.84	8.50
Kuwait	5.59	4.58	3.10	8.75	5.48	5.51
Kyrgyz Republic	3.14	5.66	2.72	4.34	4.24	3.96
Lao PDR	2.04	1.87	0.61	1.38	1.29	1.48
Latvia	7.94	8.24	4.53	6.48	6.42	6.80
Lebanon	3.22	n/a	4.54	4.19	4.37	3.98
Lesotho	2.61	1.73	0.73	2.79	1.75	1.96
Lithuania	7.92	7.86	4.84	7.68	6.79	7.07
Luxemburg	8.77	5.78	6.15	5.92	5.95	6.65
Macedonia, FYR	n/a	n/a	4.26	5.96	5.11	N/A
Madagascar	1.69	0.30	1.74	0.14	0.72	0.96
Malawi	3.12	0.49	1.85	0.34	0.89	1.45
Malaysia	6.97	4.97	7.96	6.91	6.61	6.70
Mali	1.96	0.40	0.83	1.55	0.92	1.18
Malta	7.55	6.87	4.00	8.72	6.53	6.79
Mauritania	2.01	0.63	0.68	2.01	1.11	1.33
Mauritius	8.14	4.87	1.49	6.62	4.33	5.28
Mexico	4.83	5.60	7.30	4.66	5.85	5.60
Moldova	4.90	4.84	3.11	4.94	4.30	4.45
Mongolia	4.83	5.55	3.07	5.09	4.57	4.64
Morocco	4.25	2.91	5.65	4.31	4.29	4.28
Mozambique	2.32	0.37	1.68	0.83	0.96	1.30
Myanmar	1.17	2.04	3.09	2.00	2.38	2.08
Namibia	5.01	2.41	1.86	4.21	2.83	3.37
Nepal	1.91	1.85	3.29	3.64	2.93	2.67
Netherlands	8.89	9.01	9.03	8.86	8.97	8.95
New Zealand	9.65	8.35	7.03	8.46	7.95	8.37
Nicaragua	1.97	2.50	N/A	1.72	2.11	2.06
Nigeria	1.99	1.07	5.52	2.00	2.87	2.65
Norway	8.98	8.82	7.29	7.34	7.81	8.11
Oman	5.89	6.18	3.10	6.68	5.32	5.46
Pakistan	2.19	1.06	6.34	1.00	2.80	2.65

Countries in KAM 2020	The Institutional Sub-Index (1)	The Education Sub-Index (2)	The Innovation Sub-Index (3)	The ICT Sub-Index (4)	Knowledge Index (KI) (Simple average of 2,3,4)	Knowledge-Economy Index (KEI) (Simple average of 1,2,3,4)
Panama	5.70	4.42	3.39	4.80	4.20	4.58
Paraguay	4.18	3.37	N/A	3.73	3.55	3.76
Peru	6.40	6.89	5.38	4.72	5.66	5.85
Philippines	4.34	3.98	6.17	5.20	5.12	4.92
Poland	7.27	8.01	8.59	6.38	7.66	7.57
Portugal	7.69	6.53	7.27	6.88	6.89	7.09
Qatar	7.02	4.85	2.86	7.39	5.03	5.53
Romania	6.72	5.51	7.14	5.43	6.03	6.20
Russian Federation	3.31	8.11	9.19	7.12	8.14	6.93
Rwanda	4.08	0.75	1.27	0.76	0.93	1.72
Saudi Arabia	5.34	6.88	N/A	6.96	6.92	6.39
Senegal	3.83	1.04	4.23	2.38	2.55	2.87
Serbia	5.47	6.46	6.10	5.68	6.08	5.93
Sierra Leone	1.69	0.56	2.57	0.86	1.33	1.42
Singapore	9.70	8.08	8.38	8.99	8.48	8.79
Slovak Republic	7.34	6.46	6.56	7.56	6.86	6.98
Slovenia	7.64	8.63	5.90	7.32	7.28	7.37
South Africa	5.15	5.03	7.53	6.57	6.38	6.07
Spain	7.57	8.40	9.00	7.77	8.39	8.18
Sri Lanka	3.27	5.01	4.55	4.92	4.83	4.44
Sudan	0.28	1.26	1.76	2.74	1.92	1.51
Swaziland	n/a	n/a	N/A	1.93	N/A	N/A
Sweden	8.77	8.84	8.72	8.37	8.64	8.67
Switzerland	9.35	7.63	8.77	8.88	8.43	8.66
Syrian Arab Republic	0.12	3.31	5.51	3.74	4.18	3.17
Taiwan, China	8.66	n/a	N/A	N/A	N/A	N/A
Tajikistan	1.63	4.61	2.34	2.58	3.17	2.79
Tanzania	2.22	0.63	1.81	0.86	1.10	1.38
Thailand	5.94	6.05	6.04	6.67	6.25	6.17
Trinidad and Tobago	4.25	n/a	3.03	6.97	5.00	4.75
Tunisia	3.70	3.85	3.45	4.60	3.97	3.90
Turkey	4.92	6.61	7.36	3.63	5.87	5.63
Uganda	3.44	0.63	3.69	1.01	1.77	2.19
Ukraine	3.98	7.19	5.13	4.11	5.48	5.10
United Arab Emirates	7.18	6.21	7.25	8.81	7.42	7.36
United Kingdom	8.33	8.28	7.57	9.00	8.28	8.30
United States	7.89	8.29	9.63	8.23	8.72	8.51
Uruguay	5.93	6.67	6.34	7.27	6.76	6.55
Uzbekistan	0.72	3.56	3.45	2.90	3.30	2.66
Venezuela, RB	0.12	5.49	4.63	3.36	4.49	3.40
Vietnam	4.98	3.21	5.06	4.79	4.36	4.51
Yemen, Rep.	1.07	1.04	3.46	1.48	1.99	1.76
Zambia	2.96	1.68	2.51	1.86	2.02	2.25

Countries in KAM 2020	The Institutional Sub-Index (1)	The Education Sub-Index (2)	The Innovation Sub-Index (3)	The ICT Sub-Index (4)	Knowledge Index (KI) (Simple average of 2,3,4)	Knowledge-Economy Index (KEI) (Simple average of 1,2,3,4)
Zimbabwe	0.46	2.07	2.13	2.52	2.24	1.80

5.2.4 The Position of Developing Countries in KAM 2020

After calculating KEI and KI for all counties, it is possible therefore to separate the scores of KEI for 65 developing countries as indicated in Table (5.8).

Table (5.8): Developing Countries in KAM 2020.

NO.	Developing Countries	KEI Score (2020)	NO.	Developing Countries	KEI Score (2020)
1.	Albania	4.34	**34.**	Lao PDR	1.48
2.	Algeria	3.70	**35.**	Lesotho	1.96
3.	Angola	1.22	**36.**	Madagascar	0.96
4.	Argentina	5.96	**37.**	Malaysia	6.70
5.	Armenia	4.83	**38.**	Mali	1.18
6.	Azerbaijan	4.17	**39.**	Mauritania	1.33
7.	Botswana	4.50	**40.**	Mexico	5.60
8.	Brazil	5.39	**41.**	Mongolia	4.64
9.	Bulgaria	6.21	**42.**	Morocco	4.28
10.	Burkina Faso	1.55	**43.**	Mozambique	1.30
11.	Burundi	N/A	**44.**	Namibia	3.37
12.	Cambodia	1.89	**45.**	Nepal	2.67
13.	China	5.57	**46.**	Nicaragua	2.06
14.	Colombia	5.72	**47.**	Nigeria	2.65
15.	Costa Rica	5.99	**48.**	North Macedonia	N/A
16.	Côte d'Ivoire	3.07	**49.**	Pakistan	2.65
17.	Ecuador	3.78	**50.**	Paraguay	3.76
18.	Egypt, Arab Rep.	3.97	**51.**	Peru	5.85
19.	El Salvador	3.53	**52.**	Philippines	4.92
20.	Ethiopia	1.56	**53.**	Russian Federation	6.93
21.	Gambia, the	N/A	**54.**	Rwanda	1.72
22.	Georgia	6.20	**55.**	Senegal	2.87
23.	Ghana	3.47	**56.**	Serbia	5.93
24.	Guatemala	2.81	**57.**	South Africa	6.07
25.	Honduras	2.06	**58.**	Sri Lanka	4.44
26.	India	4.61	**59.**	Thailand	6.17
27.	Indonesia	4.91	**60.**	Tunisia	3.90
28.	Iran, Islamic Rep	5.22	**61.**	Turkey	5.63

NO.	Developing Countries	KEI Score (2020)	NO.	Developing Countries	KEI Score (2020)
29.	Jamaica	3.81	**62.**	Uganda	2.19
30.	Jordan	4.08	**63.**	Ukraine	5.10
31.	Kazakhstan	6.37	**64.**	Vietnam	4.51
32.	Kenya	2.87	**65.**	Zambia	2.25
33.	Kyrgyz Republic	3.96			

5.2.4.1 Least Performing Countries among the Sample of Developing Countries (65 countries)

Based on the above KEI scores in Table (5.8), it is possible to present the least-performing developing countries in the sample as in Table (5.9).

Table (5.9): Least Performing Developing Countries.

Country	KEI Score (2020)
Madagascar	0.96
Mali	1.18
Angola	1.22
Mozambique	1.30
Mauritania	1.33
Lao PDR	1.48
Burkina Faso	1.55
Ethiopia	1.56
Rwanda	1.72
Cambodia	1.89
Lesotho	1.96

5.2.4.2 Top Performing Countries among the Sample of Developing Countries (65 countries)

Based on the above KEI scores in Table (5.8), it is also possible to present the top-performance developing countries in the sample.

Table (5.10): Top Performing Developing Countries.

Country	KEI Score (2020)
Russian Federation	6.93
Malaysia	6.70
Kazakhstan	6.37
Bulgaria	6.21
Georgia	6.20

Thailand	6.17
South Africa	6.07
Costa Rica	5.99
Argentina	5.96
Serbia	5.93
Peru	5.85
Colombia	5.72

5.3 Robustness Test for KAM 2012

To validate the results of KAM 2020, a robustness test for the last published year KAM 2012 was performed. A detailed presentation of the replicated KAM 2012 is in Appendix (XIII). The correlation coefficient between the applied KAM and the Published KAM is 99%, indicating a strong relationship between the two results. Based on these results, it is clear that these results for KAM replication are robust and can be utilised until substitutes for KAM from the World Bank is developed.

5.4 Comparing the Position of Developing Countries in The Context of KAM 2020 And DEA 2020

Comparing KAM and DEA reveals that KAM and DEA share a nearly equivalent main objective. Both methodologies are used to evaluate the performance of a nation, business, or organization. However, the DEA approach is unique in that it generates a single relative efficiency ratio for each DMU (for example, a single country) without requiring any prior knowledge of any functional form by comparing total weighted outputs to total weighted inputs for each unit.

With KAM, there are several issues that arise when applying this methodology to member nations. For instance, if a follower country wants to develop the performance of its knowledge economy, then choosing which neighbouring country to emulate initially presents problems, especially when two or more neighbouring countries are ranked similarly. However, calculating the Most Productive Scale Size (MPSS) for the ineffective DMU is another crucial component of DEA. In contrast to KAM, this unique feature of DEA is intended to identify which nations are the ineffective or low-ranking nations should be imitated.

Due to data limitations, it is not possible to calculate the KEI while applying KAM. However, with DEA whatever the available data it is possible to provide relative efficiency measures for every country. In the applied sample of countries, countries such as Burundi, Gambia, and North Macedonia are not included in the KAM calculation but are included in DEA calculations.

In applying KAM, the WB definition of KBE did not explicitly outline the KBE definition in relation to how a country can acquire, produce, disseminate, and use its knowledge by employing the different WB variables. This means that it is difficult to segregate the KBE variables under the four KBE dimensions. However, with DEA it is possible to apply the segregation of variables under the four KBE dimensions and thus build a policy-focused KBE framework.

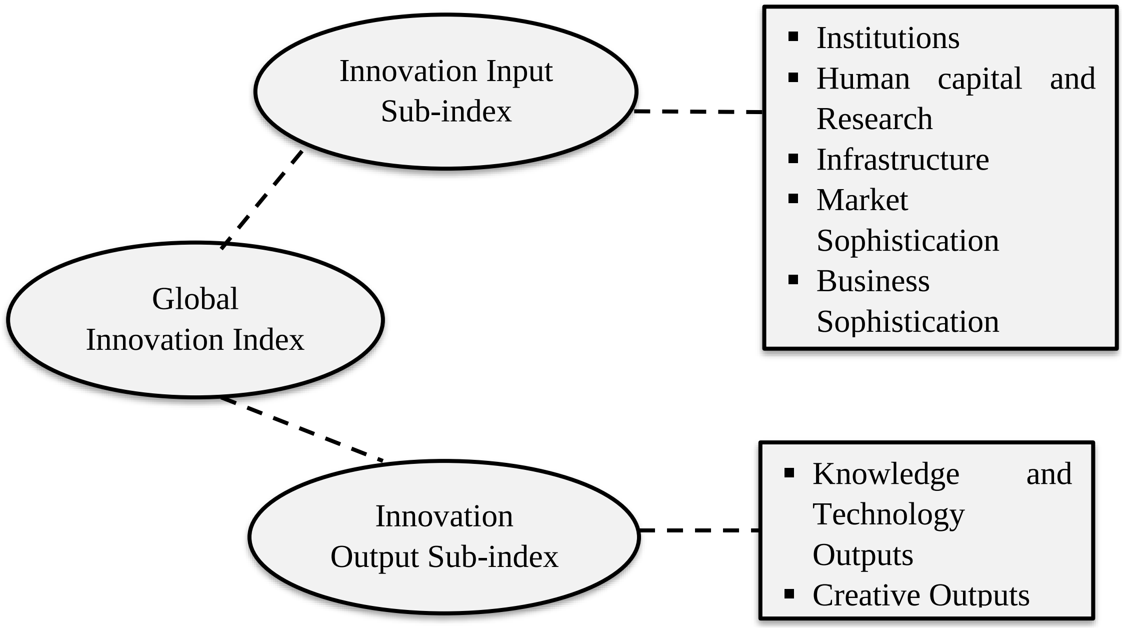
5.5 Global Innovation Index

5.5.1 Methodology of GII

The Global Innovation Index (GII) aims to capture the multi-dimensional factors of innovation since its first publication in 2007. It was developed by a collaboration between Cornell University, INSEAD-European Institute of Business Administration), the World Intellectual Property Organization (WIPO), and other institutions to assess a country's position in relation to its innovation. This index could provide an annual ranking of the world's countries based on their innovation capabilities and their success in innovation (Dutta et al., 2016).

In 2020, the GII index included 131 countries of the world and 80 indicators with 7 innovation pillars, which were divided into 21 sub-pillars, 2 sub-indices, namely the innovation input sub-index and the innovation output sub-index and, finally, an overall GII. On the one hand, the innovation input sub-index consists of the enablers of innovative activities in an economy and is computed as the average of the first five pillar scores, namely institutions, human capital and research, infrastructure, market sophistication, and business sophistication. On the other hand, the innovation output sub-index is the resulting innovation outputs and is calculated as the average of the last two output pillars scores, namely knowledge and technology outputs, and creative outputs. Figure (5.2) presents a detailed description of the GII.

Figure (5.2): Decomposition of the Global Innovation Index.



Source: Soumitra et al. (2020)

The GII is computed as the simple average of the innovation input and innovation output sub-indices within an interval score between 0 (the worst performer) and 100 (the highest performance). The above Figure (5.2) portrays the dimensions (sub-pillars) of the GII. The results of the GII are used by many decision-makers and they design policy responses to enhance their performance as evidenced by Ahmed and Alfaki (2013); Aldulaimi et al. (2020); Fernández et al. (2021).

Additionally, the GII is considered a measure of innovation by many governments, for instance, the Philippine Innovation Act uses the GII as a methodology for assessing the measure of innovation. Furthermore, the GII is used by many studies as a proxy to assess the performance of a KBE, because the considered studies argue that innovation is core to any knowledge development and all the GII dimensions are directly associated with the KBE dimensions, namely the knowledge creation, utilization, distribution, and production as in the study by Al-Sudairi and Haj Bakry (2014).

5.5.2 The Position of Developing Countries in GII 2020

Table (5.11) depicts the scores and ranking of the 65 developing countries in the GII 2020 as follows.

Table (5.11): GII Scores and Ranking for the 65 Developing Countries in 2020.

NO.	Classification for the fiscal year 2020	GII Score (0-100)	GII Global ranking		NO.	Classification for the fiscal year 2020	GII Score (0-100)	GII Global ranking
1	**China**	53.28	14		**35**	El Salvador	24.85	92
2	Malaysia	42.42	33		**36**	Kyrgyz Republic	24.51	94
3	Bulgaria	39.98	37		**37**	Nepal	24.35	95
4	Vietnam	37.12	42		**38**	Egypt, Arab Rep.	24.23	96
5	Thailand	36.68	44		**39**	Paraguay	24.14	97
6	Ukraine	36.32	45		**40**	Ecuador	24.11	99
7	Russian Federation	35.63	47		**41**	Sri Lanka	23.78	101
8	India	35.59	48		**42**	Senegal	23.75	102
9	Philippines	35.19	50		**43**	Honduras	22.95	103
10	Turkey	34.9	51		**44**	Namibia	22.51	104
11	Serbia	34.33	53		**45**	Guatemala	22.35	106
12	Mexico	33.6	55		**46**	Pakistan	22.31	107
13	Costa Rica	33.51	56		**47**	Ghana	22.28	108
14	North Macedonia	33.43	57		**48**	Cambodia	21.46	110
15	Mongolia	33.41	58		**49**	Côte d'Ivoire	21.24	112
16	South Africa	32.67	60		**50**	Lao PDR	20.65	113
17	Armenia	32.64	61		**51**	Uganda	20.54	114
18	Brazil	31.94	62		**52**	Madagascar	20.4	115
19	Georgia	31.78	63		**53**	Nigeria	20.13	117
20	Tunisia	31.21	65		**54**	Burkina Faso	20	118
21	Iran, Islamic Rep	30.89	67		**55**	Algeria	19.48	121
22	Colombia	30.84	68		**56**	Zambia	19.39	122
23	Jamaica	29.1	72		**57**	Mali	19.15	123
24	Morocco	28.97	75		**58**	Mozambique	18.7	124
25	Peru	28.79	76		**59**	Ethiopia	18.06	127
26	Kazakhstan	28.56	77		**60**	Angola	N/A	N/A
27	Argentina	28.33	80		**61**	Burundi	N/A	N/A
28	Jordan	27.79	81		**62**	The Gambia	N/A	N/A
29	Azerbaijan	27.23	82		**63**	Lesotho	N/A	N/A
30	Albania	27.12	83		**64**	Mauritania	N/A	N/A
31	Indonesia	26.49	85		**65**	Nicaragua	N/A	N/A
32	Kenya	26.13	86					
33	Botswana	25.43	89					
34	Rwanda	25.06	91					

Source: GII 2020 Database.

5.5.3 Comparing the Position of Developing Countries in the context of GII 2020 and DEA 2020

Based on the GII results, China is considered the top performer among developing countries in 2020; while Mozambique and Mali are considered the least performing. This result is almost consistent with the applied DEA models whether by employing the radial DEA or the non-radial DEA models as in the previous chapter (4). However, the DEA results should be treated with caution because it is affected by the choice of inputs and outputs variables and the number of DMUs under investigation. It is observed that most of the indicators included in the DEA analysis in chapter four, are used in the GII as well.

Nonetheless, developing countries such as Angola, Burundi, The Gambia, Lesotho, Mauritania, and Nicaragua are not included in the GII report while being included in our DEA analysis and we could assess the position and the KBE performance of these countries using DEA methodology. Furthermore, analyzing the key findings of our DEA approach reveals some interesting conclusions as observed in Table (5.12) and this supports the robustness of the DEA's approach in one way or another.

5.5.3.1 Comparing Leading Developing Countries in the Context of the DEA Approach and GII Approach.

Table (5.12): Comparing Leading Developing Countries in the Context of the DEA Approach and GII Approach.

Developing Country	GII Findings	DEA Findings
China	Among the top 3 innovation economies (the top 1) by income group (upper-middle-income group).	CCR Efficient/ SBM CRS Efficient. BCC Efficient/ SBM VRS Efficient. Scale Efficient/Scale Effect Efficient. Among the Highly Robust Countries under CCR and BCC models (Top 3 and 2 for CCR and BBC respectively). Top 1 among the Highly Robust Countries under SBM CRS and SBM VRS Models. Top 1 under CRS super-efficiency Model. Top 2 under CRS SBM super-efficiency Model. Top 3 under VRS super efficiency Model. Top 6 under VRS SBM super efficiency Model.
Iran	Among the top 3 innovation economies (the	CCR Efficient/ SBM CRS Efficient. BCC Efficient/ SBM VRS Efficient. Scale Efficient/Scale Effect Efficient.

Developing Country	GII Findings	DEA Findings
	top 2) by region (Central and Southern Asia).	Among the Highly Robust Countries under CCR and BCC models (Top 2 and 4 for CCR and BBC respectively). Top 5 and 7 among the Highly Robust Countries under SBM CRS and SBM VRS Models. Top 8 under CRS super-efficiency Model. Top 5 under CRS SBM super-efficiency Model. LP infeasible under VRS super efficiency Model. Top 1 under VRS SBM super efficiency Model.
Vietnam	Among the top 3 innovation economies (the top 1) by income group (Lower-middle-income group).	CCR Efficient/ SBM CRS Efficient. BCC Efficient/ SBM VRS Efficient. Scale Efficient/Scale Effect Efficient. Among the Marginally Robust Countries under CCR and BCC models and SBM CRS and SBM VRS Models. Top 9 under CRS super-efficiency Model. Top 8 under CRS SBM super-efficiency Model. Top 7 under VRS super efficiency Model. Top 17 under VRS SBM super efficiency Model.
Rwanda	Among the top 3 innovation economies (the top 1) by income group (Low-income group).	CCR Inefficient/ SBM CRS Inefficient BCC Efficient/ SBM VRS Efficient. Scale Inefficient/Scale Effect inefficient; with increasing returns to scale Efficient country by default under BCC DEA and SBM VRS models
Malaysia	Among the top 3 innovation economies (the top 2) by income group (upper-middle-income group).	CCR Efficient/ SBM CRS Efficient. BCC Efficient/ SBM VRS Efficient. Scale Efficient/Scale Effect Efficient. Among the Marginally Robust Countries under CCR and BCC models and efficient country by default under the SBM CRS and SBM VRS Models Top 13 under CRS super-efficiency Model, VRS super efficiency Model, CRS SBM super-efficiency Model, and VRS SBM super efficiency Model.
Kazakhstan	Among the top 3 innovation economies (the top 3) by region (Central and Southern Asia).	CCR Efficient/ SBM CRS Efficient. BCC Efficient/ SBM VRS Efficient. Scale Efficient/Scale Effect Efficient. Among the Highly Robust Countries under CCR and BCC models (Top 1 and 3 for CCR and BBC respectively). Top 2 and 5 among the Highly Robust Countries under SBM CRS and SBM VRS Models. Top 7 under CRS super-efficiency Model. Top 7 under CRS SBM super-efficiency Model. Top 8 under VRS super efficiency Model. Top 8 under VRS SBM super efficiency Model.
South Africa	Among the top 3 innovation economies (the top 1) by region (Sub-Saharan Africa).	CCR Efficient/ SBM CRS Efficient. BCC Efficient/ SBM VRS Efficient. Scale Efficient/Scale Effect Efficient. Efficient country by default under the CCR, BCC, SBM CRS, and SBM VRS Models Top 16 under CRS super-efficiency Model. Top 18 under CRS SBM super-efficiency Model. Top 15 under VRS super efficiency Model. Top 27 under VRS SBM super efficiency Model.

5.5.3.2 Comparing Least Developing Countries in the Context of the DEA Approach and GII Approach.

Table (5.13): Comparing Least Developing Countries in the Context of the DEA Approach and GII Approach.

Developing Country	GII Findings	DEA Findings
Mali	**GII Score**: 19.15/100 **Global Ranking**: 123/131 **Ranking within the study's sample of developing countries included in the GII report in 2020:** (57/59)	Ranked among the worst countries in the CCR model (64/65). Ranked among the worst countries in the BCC model (63/65). Ranked among the worst scale inefficient countries (65/65). Ranked among the worst countries in the SBM CRS model (63/65). Ranked among the worst countries in the SBM VRS model (65/65).
Mozambique	**GII Score**: 18.7/100 **Global Ranking**: 124/131 **Ranking within the study's sample of developing countries included in the GII report in 2020**: (58/59)	Ranked among the worst countries in the CCR model (62/65). Ranked among the worst scale inefficient countries (65/65). Ranked among the worst countries in the SBM CRS model (57/65). Ranked among the worst countries in the scale effect (63/65).
Kenya	**GII Score**: 26.13/100 **Global Ranking**: 86/131 **Ranking within the study's sample of developing countries included in the GII report in 2020**: (32/59)	Ranked among the worst countries in the CCR model (65/65). Ranked among the worst countries in the BCC model (65/65). Ranked among the worst countries in the SBM CRS model (51/65). Ranked among the worst countries in the SBM VRS model (54/65).
Cambodia	**GII Score**: 21.46/100 **Global Ranking**: 110/131 **Ranking within the study's sample of developing countries included in the GII report in 2020**: (48/59)	Ranked among the worst countries in the CCR model (57/65). Ranked among the worst countries in the BCC model (52/65). Ranked among the worst countries in the SBM CRS model (53/65). Ranked among the worst countries in the SBM VRS model (56/65). Ranked among the worst scale-inefficient countries (56/65).

Note: These results are based on the observed DEA Results in chapter (4) and the GII in 2020.

5.5.4 Limitations of GII in Comparison to DEA

The GII index has been criticized on several grounds. Of these limitations, ratio analysis requires a priori set of weights to transform all indicators into a common measure for performance assessment and these subjective weights schemes may be criticized on the grounds that these prior weights may not be fair to a particular country (Soumitra et al., 2020). Thus, to sort this defect, in the GII report in 2020, an efficiency frontier analysis is performed using DEA to test the robustness of the GII results and they found that the empirical results are to a large extent consistent with the DEA results.

Furthermore, ratio analysis cannot operate within multidimensional situations characterized by multiple inputs and outputs, although, ratio analysis is considered one of the simplest techniques for measuring technical efficiency by using different indicators as ratios; therefore, scholars must evaluate different ratios simultaneously to get an estimate of the overall efficiency. Otherwise, calculating only partial indicators for efficiency will lead to misleading results (Nyhan & Martin, 1999; Thanassoulis et al., 1996).

Additionally, GII is criticized for including factors that are not essential to the innovation process in an economy. Including in these factors are electricity output and venture capital deals (Dašić et al., 2020). Furthermore, the GII was calculated based on many indicators (80 indicators), however, investing in those indicators, could be financially unrealizable, unsustainable, and unfocussed for some countries, especially in developing countries as observed in the studies by Afzal and Lawrey (2012 a, b, c, d).

Finally, developing countries such as Angola, Burundi, The Gambia, Lesotho, Mauritania, and Nicaragua are not included in the GII report while, it is possible to analysis the KBE performance of these countries by employing the DEA approach, and then it is possible to present policy recommendations to foster the transformation of such countries to KBE.

5.6 How DEA Could Solve the Weakness in KAM and GII?

The objective of this section is to summarise the main differences between the DEA approach and the previously applied ones, namely KAM and GII and to address how this approach contributes to filling the current research gap in KBE measurement and thus has superiority over other approaches even if the results are quite similar.

As a starting point, it is essential to highlight that the substantial aim of all these methodologies namely KAM, GII, and DEA is almost the same. On the one hand, all techniques are used mainly to assess the performance in any country as observed in many studies such as Ahmed and Krishnasamy (2013); Ramanathan (2006); Staníčková and Skokan (2011); Wu et al. (2014).

Despite the fact that KAM is the most widely used technique in the existing empirical literature, tremendous questions and issues arise while employing this technique for KBE assessment; although, the World Bank clearly defines the KBE concept and its related issues. Yet, the relationship between how a specific country can acquire, produce, distribute, and utilize its knowledge by using the KAM variables is not explicitly stated. Over and above that, if a country intends to transit to a KBE or wants to achieve KBE development, then this country must, besides other things, learn from other countries' experiences in this regard. To this end, a question arises as to how the follower country (inefficient country in the DEA context) can select which neighbouring country they can emulate. More specifically if there are two or more neighbouring countries with the same ranking.

A distinctive characteristic of DEA, unlike KAM and GII, is the ability of DEA to set a target analysis for required improvements for inefficient countries. Hence, the previous challenge of which high-ranking (efficient) countries should be imitated by the low-ranking (inefficient) countries could be settled. Viewed in other words, with DEA, it is possible to find out exactly which neighbouring country (benchmark country) should be emulated by the inefficient countries by calculating the required improvements for inputs and outputs depending on the model's orientation and the DEA methodological approach applied whether it is the radial or the non-radial approach. However, with KAM and GII, in contrast to DEA, inefficient countries should follow and imitate the efficient ones, but in the case of equal rankings, finding a benchmarking country is far from being straightforward.

Furthermore, with DEA, it could be possible to calculate the relative efficiency ratio through comparing total weighted outputs to total weighted inputs for each country without requiring the proposition of any specific functional form for the relationship between multiple inputs and multiple outputs. Therefore, with DEA, finding the benchmark countries in each knowledge dimension for the sample of countries is not far from being achieved. Moreover, this way of calculating efficiency is more advantageous than other traditional efficiency measures used in KAM and GII as both methodologies uses ratio analysis, which has its limitation as mentioned in-depth previously.

Over and above, unlike the normalization procedure used in KAM and GII, the DEA efficiency value has an upper bound of one and a lower bound of zero. To clarify, in KAM and GII, indicators are expressed in different units or measurement techniques. Therefore, it is worth applying the process of normalization, which means making the indicators expressed in different units comparable on a common basis. During this process of normalization, measurement errors can be made, and the indicator may lose its quality. Moreover, different normalization techniques can yield different values and thus, create significant differences in the results of the final index (Guaita Martínez et al., 2020).

Moreover, still DEA has superiority over other methodologies as it could be possible to include more than one dependent variable. Also, it is possible to carry out a DEA analysis with multiple inputs and outputs measured at different units.

Furthermore, with KAM and GII, countries are ranked using raw data of the variables, whereas, with DEA, it ranks the best-performing countries by calculating the efficiency score using weights. These weights are objectively determined from the date not subjectively determined as in KAM and GII.

In DEA, KBE variables are segregated under input-output indicators and then distributed between the four knowledge dimensions, namely acquisition, production, distribution, and utilization. Input indicators show investment or capacity-building efforts for each dimension toward KBE transformation. On the other hand, output indicators determine what degree of knowledge economy a country has. Thus, output indicators illustrate the impact of input indicators or the performance of a country toward the knowledge economy. This approach allows for setting up causal connections among the indicators used, which in turn will enable us to analyse the dynamic of the new economy in a more effective manner. Indeed, this segregation of the variables under different knowledge dimensions, although provides a more effective picture from the analytical point of view, is missing in KAM. However, with GII, this division of variables as inputs and outputs exists but with many indicators under each dimension. Table (5.15) summarizes the key distinctive features of DEA in KBE assessment.

Table (5.14): How DEA Has Superiority Over Existing KBE Measurement Frameworks?

Problem	How to Solve Problem?
Not explicitly divide the KBE under the four KBE pillars. No clear functional relationship. Bias (for instance; OECD and GII are biased towards knowledge production) Presentation frameworks. Conventional classification of indicators is organized and grouped according to different aspects.	By using the "input" and "output" approach. Classifying the KBE dimension under relevant statistics of "input" and "output" indicators. By using this approach, setting up a "causal connection" among the indicators is possible, which in turn will enable us to analyse the dynamic of the new economy in a more effective manner. Data-driven frameworks. Input indicators show investment or capacity-building efforts for each dimension towards KBE transformation. On the other hand, output indicators determine what degree of knowledge economy a country has. Thus, output indicators illustrate the impact of input indicators or the performance of a country towards a knowledge economy.
No logical structure/no systematic approach for transition.	Set policies towards KBE much more.
None of them tried to measure the efficiency with which the knowledge inputs are transformed into knowledge outputs.	DEA could measure different types of efficiency.
High-ranking (efficient) countries should be imitated by the low-ranking (inefficient) countries.	The most productive scale size (MPSS) for the inefficient countries.
Rating methodologies.	DEA efficiency value has an upper bound of one and a lower bound of zero.
Forecasting future performance.	It is impossible to forecast future performance given the current data.

5.7 Summing-Up and Policy Recommendations

The key findings of chapter five can be summarised as follows. Limitations of GII, weaknesses of KAM, and finally the superiority of DEA.

1- Limitations of GII:

a. Subjectivity and Bias: GII's ratio analysis, requiring a set of weights for performance assessment, faces criticism due to its subjectivity and potential bias.

b. Multidimensional Limitation: Ratio analysis struggles with multiple inputs and outputs situations, which can lead to inaccurate results if not all ratios are evaluated simultaneously.

c. Inclusion of Non-Essential Factors: Factors such as electricity output and venture capital deals are criticized as not essential to the innovation process.

d. Exclusion of Developing Countries: Several developing countries are not included in the GII report, impacting its comprehensiveness and the inclusivity of its findings.

e. Financially Unrealistic: The numerous indicators used by GII can be financially unrealistic and unsustainable, especially for developing countries.

2- Weakness in KAM:

a. Lack of Explicit Relationship Definition: The relationship between acquisition, production, distribution, and utilization of knowledge by a country using KAM variables is not clearly stated.

b. Inability to Determine Benchmarking Countries: KAM does not allow inefficient countries to clearly determine which efficient countries to emulate, especially when there are equal ranks.

3- Superiority of DEA:

a. Target Analysis for Improvements: DEA uniquely offers target analysis to indicate required improvements for inefficient countries, providing clear benchmarking opportunities, unlike KAM and GII.

b. Multidimensionality and Objective Weights: DEA allows consideration of multiple inputs and outputs and calculates efficiency through objective, data-determined weights.

c. Normalization and Measurement Precision: DEA's normalization procedure is superior to those in KAM and GII, minimizing the potential for measurement errors and quality loss.

d. Causal Connections: DEA's segregation of variables into different knowledge dimensions allows for a clearer understanding of causal connections, making it analytically advantageous.

To this end, the findings indicate that the key limitations in the current KBE frameworks include: identifying efficiency scores driven from the data, setting actual targets for inefficient countries, ability to consider multiple inputs and outputs, finding the appropriate peers or best practice countries to emulate, benchmarking countries more systematically, forecasting future performance of countries can be solved by DEA analysis. Thus, DEA has superiority over current KBE frameworks. Therefore, policymakers are advised to utilize the DEA approach in KBE measurement.

Additionally, KBE is now widely accepted as the direction in which all countries are moving. Central to this KBE is innovation which is regarded as the most crucial pillar for transition into this KBE. This recognized importance of innovation among scholars and policymakers for long-run economic growth has raised researchers' interest in the mechanisms explaining national innovation performance. Nonetheless, developing countries are lagging behind developed countries in terms of the four KBE pillars, with the innovation pillar being the worst relative to the other three pillars. Consequently, to improve innovation system performance, this study aims to enhance the innovation system performance for quicker KBE transition through an effective innovation policy and this is the main concern of the next chapter.

Chapter 6

Innovation Policy for Selected Developing MENA Countries

6.1 Introduction

The KBE paradigm is increasingly recognized as the prevailing direction towards which global economies are gravitating. Innovation is seen as the key determinant for transitioning into this KBE paradigm. The significance of innovation in driving KBE transition and fostering long-term economic growth has incited extensive scholarly interest in exploring the mechanisms underpinning national innovation performance, that is, identifying its crucial determinants (Arshed et al., 2022). Despite a vast corpus of theoretical and empirical literature on the antecedents of innovation, a clear, unified definition remains elusive (Bate et al., 2023).

Developing countries generally lag behind developed counterparts in terms of the four integral KBE pillars discussed in previous chapters, with innovation being the least developed relative to the other three KBE pillars (Phale et al., 2021). Moreover, despite the evident importance of innovation in these developing contexts, comprehensive academic investigations into the situation are conspicuously limited (Arshed et al., 2022). Therefore, further studies are warranted to comprehensively delineate the drivers of the innovation process in such developing economies.

In the domain of innovation theory, the field is persistently evolving, with different conceptual and methodological strands gradually transitioning from a linear process of innovation towards a paradigm that accentuates a dynamic, nonlinear process of innovation involving a range of interacting stakeholders. Concurrent with this systemic dynamic approach to innovation theory, the term "innovation policy" is commonly used to denote any policy intervention aimed at augmenting innovation processes from the inception of novel ideas or solutions to their implementation and diffusion (Edler & Fagerberg, 2017).

Furthermore, it is posited that bolstering innovation development in any country can be achieved by formulating an effective innovation policy, founded on a country-specific set of innovation policy instruments among other criteria. Such instruments are essentially strategies designed to address challenges within the innovation system. Evaluating innovation system indicators is regarded as the most effective means of gathering data pertinent to these challenges. Furthermore, within the innovation literature, these policy instruments are bifurcated into supply-side (technology-push) and demand-side (demand-pull) categories, the relevance of each remains a point of ongoing scholarly debate. Moreover, for these policy instruments to be effective, they should be context specific (inter alia Borrás & Edquist, 2013).

The central question posited in this chapter is how innovation performance can be enhanced to expedite the KBE transition in selected developing MENA countries through an effective innovation policy predicated upon country-specific innovation policy instruments. These countries were chosen due to their potential for KBE transition (Ibrahim, 2021; Morrar, 2018), despite their current lagging behind other regions (Boussetta et al., 2022). However, providing a context-based analysis for every developing nation falls beyond the scope of this chapter.

The primary objective of this chapter is achieved by conducting an econometric analysis using the System Generalized Method of Moments is conducted. The primary aim of this analysis is to empirically identify the fundamental innovation factors that contribute most significantly to improved innovation performance within the context of the selected MENA countries. Thus, the focus is to empirically explore whether the demand-pull or technology-push policy instruments have a greater impact on innovation performance in these countries.

To this end, the empirical analysis will yield significant policy implications for promoting innovation performance in these countries. As such, this chapter is divided into two main parts. The first part offers a review of the academic literature on innovation and innovation policy, identifying their theoretical foundations. The second part introduces the econometric analysis for the selected developing MENA countries.

The chapter's structure is organized as follows: Section 6.2 provides definitions of innovation, its classifications, and reviews the theoretical and empirical justifications of why innovation is important for policymakers at any development phase. Section 6.3 reviews the theoretical and empirical literature on innovation policy. Section 6.4 outlines the econometric analysis. Section 6.5 reports and discusses the chapter's findings using different model specifications. Finally, Section 6.6 summarizes the chapter and lays out the salient policy implications which emerge from the empirical analysis.

6.2 Innovation: Definition and Peculiarities

6.2.1 The Nature of Innovation: An Exploration of Definitions

Articulating a precise definition of innovation is a multifaceted endeavour, given the lack of consensus across various studies (Carvalho et al., 2015; Gault, 2016; Pansera and Martinez, 2017). In the domain of innovation literature, Erika and Watu (2010) have posited that there is neither a universal definition of innovation nor a standard policy for its implementation. These studies illuminate that the path to innovation for development is not unified; rather, innovation is a composite process shaped by factors including education, culture, risk-taking ability, formal institutional environment, and a balanced socio-economic context.

Innovation functions as a central mechanism driving economic change. Joseph Schumpeter, often hailed as the father of innovation theory, described innovation as the act of bringing a new good or service to market as a result of technological advancements or, more broadly, as a consequence of "new combinations" within the existing knowledge base. Schumpeter's theories position evolving institutions, entrepreneurs, and technological change as the cornerstone of both economic growth and fluctuations in output (Schumpeter, 1934). Schumpeter further differentiated between invention and innovation, regarding the former as the conception of a new idea and the latter as the practical application of that idea. This distinction gives rise to two integral facets of innovation: novelty and implementation. Novelty may represent something unprecedented, or merely a new development within a specific sector, ranging from incremental enhancements to radical alterations. The economic and social significance of innovation, as opposed to the mere idea, lies at the heart of Schumpeter's distinction between invention and innovation (Fagerberg, 2003).

This perspective is supported by scholars like Fukugawa (2018), who emphasize that the dissemination of innovation is of greater consequence than its creation, particularly in the context of developing countries. Contemporary researchers further affirm that for innovation to be valuable, its sharing and application are crucial (Kaur, 2019; Manniche & Testa, 2018). Though myriad definitions of innovation permeate the literature, commonalities exist in the underlying principles(1). Regardless of terminological variation, the essence of innovation remains the introduction of a novel idea to the market, rendering it accessible to prospective users. This reflects the Schumpeterian notion of novelty and dissemination.

Gault (2016) has emphasized that any claims regarding the impact of innovation must be underpinned by a measurable conceptual framework for innovation. Consequently, economists often rely on the OECD definition of innovation as delineated in the Oslo Manual (Blind, 2009; Ortigueira-Sánchez et al., 2022). The Oslo Manual, devised by OECD since 1992, furnishes international guidelines for collecting and interpreting data on innovation. The manual's fourth latest iteration in 2018 includes a comprehensive definition that encompasses both the activity and outcome of innovation (OECD, 2018)(2). Moreover, the manual carefully differentiates between "innovation activities" (referring to process view) and "innovation" (limited to outcomes), providing a refined formulation primarily applicable to businesses. In this chapter, the expansive definition provided by the fourth edition of the Oslo Manual is adopted, justified by its alignment with the chapter's objectives, its coherence with

(1) Pierce and Delbecq (1977) defined it as "a process including three stages: generation, acceptance, and implementation". Camisón-Zornoza et al. (2004) stated that innovation refers to the uniqueness of a concept that strives to improve organisational performance. Others characterise innovation as the organization's acceptance and adoption of a concept or behaviour relating to a new good, service, device, system, policy, or programme (Damanpour & Gopalakrishnan, 2001). A recent study by Obunike and Udu (2021) defined it as developing novel products or new services either to a firm or to the market, new or improved processes, opening new markets, and using new resources to create value in the market.

(2) This manual has introduced a general definition of innovation as "a new or improved product or process (or combination thereof) that differs significantly from the previous products or processes and that has been made available to potential users (product) or brought into use by the unit (process)" (OECD/Eurostat, 2018, P.20).

mainstream innovation studies (Vukoszavlyev, 2019), and its consistency with the GII methodology, which also relies on the Oslo definition (Dutta & Lanvin, 2012).

6.2.2 Classifications of Innovation

Schumpeter's pioneering work in innovation theory led to the identification of five distinct categories of innovation, specifically: the introduction of a novel product or enhancement of an existing one; the development of new industrial processes; the inauguration of a new market; the creation of novel sources for raw materials or other inputs; and finally, structural alterations to industrial organization (OECD, 2018). Subsequently, classifications have evolved, with the third edition of the Oslo Manual presenting a typology that has been widely adopted across various studies (Diaconu, 2011; Evangelista & Sirilli, 1995; Guillard & Salazar, 2017).

In its latest iteration, the fourth edition of the Oslo Manual (2018) introduced a more streamlined typology, intended to mitigate the complexity and ambiguity inherent in previous classifications. This revised approach differentiates between only two primary types of innovation, namely product innovation and business process innovation. This distinction serves to clarify the conundrum that was prevalent in the third edition, particularly with respect to discerning significant changes from mere improvements. Accordingly, the manual defines product innovation as "a new or improved good or service that differs significantly from the firm's previous goods or services and that has been introduced on the market," and business process innovation (firm-level innovation) as "a new or improved business process for one or more business functions that differ significantly from the firm's previous business processes and that has been brought into use by the firm" (OECD, 2018, p. 21).

Within the context of this chapter, the focus is directed towards the national-level transition to a KBE. Consequently, the discussion emphasizes product innovation, aligning with a macroeconomic perspective, rather than the microeconomic, firm-level lens.

6.2.3 Why Innovation? Effects of Innovation

6.2.3.1 Innovation and Long-Term Economic Growth

In the academic discourse and among policymakers, a consensus has emerged recognizing innovation as an essential driver of economic growth and social advancement. The pivotal role of innovation in shaping long-term economic growth has gained traction in scholarly literature since the seminal work of Schumpeter (1934). A substantial and convergent body of empirical research has subsequently affirmed that innovation serves as the catalyst and foundation for sustained economic expansion (Gocer, 2013; Pece et al., 2015; Pradhan et al., 2018; Sarangi et al., 2022; Sener & Tunali, 2017). This has established innovation as a central pillar of any growth strategy (Dutta et al., 2016).

The underpinnings for innovation being a paramount determinant for long-term economic growth are multifaceted. Firstly, innovation fosters the discovery of novel technologies and processes, enabling the generation of increased output from identical levels of inputs. This enhances productivity and efficiency, and potentially facilitates convergence with industrialized economies (Chaminade et al., 2009). Secondly, innovation plays a vital role in the development of new value-added products and services (OECD, 2015; Rosenberg, 2006; Sarangi et al., 2022).

Several studies have endorsed the proposition that innovation accelerates economic growth, such as Fan (2011); Guloglu and Tekin (2012); Maradana et al. (2019); Pradhan et al. (2020) and Yang (2006). According to this perspective, the "supply-leading" hypothesis operates, with innovation contributing to innovative products, services, and processes, thereby stimulating economic growth. Contrarily, other studies have furnished evidence that economic growth induces innovation, aligning with the "demand-following" hypothesis. This argument posits that as economies grow, investments in innovation and R&D increase to meet global competition (Howells, 2005; Pradhan et al., 2016; Sinha, 2008). Indirect effects may also be observed, such as through trade openness, which facilitates specialization in competitive sectors, thereby enhancing innovation within the country (Burange et al., 2019; Sarangi et al., 2022). Others concur on a reciprocal causality between innovation and economic growth (Çetin, 2013;

Guloglu & Tekin, 2012; Pradhan et al., 2017). This symbiotic relationship between innovation and growth is observable across both developed and developing countries (Barrichello et al., 2020).

Research on this subject has been conducted at both macro and micro levels. At the macro-level, numerous studies have emphasized innovation's preeminent role in national economic growth and global trade patterns (Pradhan et al., 2018; Sarangi et al., 2022). Conversely, at the firm level (micro level), R&D enhances the ability to assimilate and utilize various knowledge forms, with studies underscoring the firm's role in disseminating innovation and technology (Collins & Troilo, 2015; Mairesse & Robin, 2009; Parisi et al., 2006; Wakelin, 2001).

Additionally, in the context of a KBE, R&D serves dual strategic functions: the execution of internal innovation strategies and the bolstering of capacity to assimilate external technology (Feldman & Link, 2001). Numerous studies have evaluated R&D's significant contribution to economic growth (Griliches, 1979; Tellis et al., 2008).

For MENA countries, empirical evidence reveals a positive and substantial relationship between innovation (proxied by R&D expenditure) and economic performance (Omar, 2019). Similarly, EU countries emphasize fostering innovation as a key strategy (Zabala-Iturriagagoitia et al., 2021), and innovation also aligns with sustainable development goals (Choi & Zo, 2019).

6.2.3.2 Innovation and Other Macro Economic Objectives

Beyond its influence on economic growth, innovation is intertwined with several macro-economic objectives, such as competitiveness, productivity, and employment (Erika & Watu, 2010; Gust-Bardon, 2014; Markatou, 2013; Barrichello et al., 2020; Nelson & Winter, 2002; Porter, 2011; Schumpeter, 1934). Hausman and Johnston (2014) contended that innovation also leads to job creation and income generation, fortifying long-term economic growth. Other works have pointed to innovation's role in addressing broader social challenges (Gault, 2016; Fukugawa, 2018). Empirically, Doğan (2016) identified significant positive effects of innovation determinants on competitiveness in European Union countries. Furthermore, innovation policy is recognized as a tool for mitigating socio-economic challenges, including public health crises (Kadakia et al., 2020).

6.2.3.3 Innovation for Transition to a KBE

The transition to a KBE has become a universally recognized objective, pursued with fervour and urgency by nations across the globe. This ambition is substantiated by extensive research, including seminal works by Joumard and Boughédaoui (2010) and Bach and Matt (2005). Within the multifaceted structure of a KBE, innovation stands as the pivotal pillar, orchestrating the transition and shaping its trajectory (Kontolaimou et al., 2016). Central to this economy are the creation and adaptation of new technologies and processes, energized by the synthesis of local, indigenous, and formally created knowledge through R&D (Diyamett, 2009; Erika & Watu, 2010; Lundvall et al., 2009)

During the ongoing Fourth Industrial Revolution, the transition to a KBE has been underscored by innovation, serving as the primary engine powering this metamorphosis (Omar, 2019). Parallel arguments by Rose and Winter (2015) emphasize innovation's role as both the cornerstone and a preeminent pillar in the structural development of a KBE. Recently, Phale et al. (2021) further accentuated the paramount importance of innovation, rating it as the most influential factor in this transition, overshadowing even ICT infrastructure.

The empirical evidence reinforcing the centrality of innovation in the transition to a KBE is both broad and convergent. A study by Ibrahim (2021) illuminated the significant trajectory of the BRICS nations towards a KBE, positioning innovation activities as the bedrock of economic dynamics and value generation. In this evolving economic landscape, the cultivation and nurturing of a national system of innovation are not only beneficial but essential. It stands as the lifeblood of the transition, fostering growth, enhancing adaptability, and driving sustained development in this new economic epoch.

By framing innovation as a complex interplay of creativity, technology, and knowledge, this body of work offers profound insights into the nature of modern economic transformation. It underscores the importance of innovation in not only shaping the economic landscape but also in contributing to the broader societal goals of sustainability, inclusiveness, and resilience. Thus, the research on innovation and its role in transitioning to a KBE provides an essential roadmap for policymakers, academics, and industry leaders.

6.2.4 Determinants of Innovation

Given the recognized importance of innovation as delineated in previous sections, the question naturally arises: what drives innovation? More specifically, what elements or factors exert an influence on innovation? An understanding of these determinants enables governmental entities to prioritize efforts and allocate resources in a strategic and effective manner (Arshed et al., 2022). The identification of factors that facilitate or hinder innovation development is vital for constructing targeted policy measures (Fukugawa, 2018; Seidel et al., 2013).

6.2.4.1 Theoretical Literature on Innovation Determinants

Theoretically, innovation determinants can be elucidated by tracing the evolution of innovation theory. This chapter endeavours to delineate this evolution, identifying the determinants that have been applied as policy guidelines and for diagnostic analysis of innovation performance in developing MENA countries.

Greenacre et al. (2012) elucidated that innovation theory does not adhere to a specific discipline or theoretical paradigm. Rather, it draws upon various academic fields and research domains. Martin (2012) emphasized that understanding innovation requires an interdisciplinary approach involving economics, management, policy studies, economic history, and sociology, among other disciplines.

Historical analysis reveals that the early 20th-century, pre-1950, discourse on the role of innovation in societal evolution is anchored in the works of Marx and Schumpeter. Marx asserted that scientific and technological advancements facilitate the expansion of capital (Wang & Li, 2021), while Schumpeter articulated a three-stage one directional innovation process: invention, innovation, and diffusion (Schumpeter, 1934). He emphasized that maximizing the contribution of innovation to economic progress requires not only the genesis of a novel idea but its practical implementation (Kline & Rosenberg, 1986). This process, characterized by initial slow adoption followed by accelerated diffusion and eventual saturation, is often referred to as the linear model of innovation (Greenacre et al., 2012). This relatively simple innovation model is a continuous flow starting from basic research through applied research and reaching technology diffusion. Further insights into this linear model of innovation highlight that the trajectory of innovation is driven by scientific knowledge enhancements. Strategies to boost technological advancements are thus centred on allocating additional resources to R&D, following a technology push process (Nemet, 2007). Schumpeter's notion of creative destruction "incessantly revolutionizes the economic structure from within, incessantly destroying the old one, incessantly creating a new one" is a catalyst for economic growth (Schumpeter, 1942).

Modern interpretations of the innovation process have been strongly influenced by Schumpeter's ideas, but some critics have argued that his work focuses more on the effects of innovation rather than its causes (Ruttan et al., 2000). From the 1950s to the 1960s, the technology-push approach was increasingly critiqued. Critics argued that it neglects economic factors that might influence innovation profitability and adheres to a unidirectional progression incompatible with complex feedback and network interactions. Contrarily, the demand-pull approach emphasized consumer demand as the primary driver for a firm's innovative activities rather than improvements in the level of technology (Nemet, 2007). Thus, changes in the market demand control the rate and direction of innovation. Although criticized for its limited applicability to disruptive changes, it provided an important counterpoint to the technology-push perspective.

Recognizing the complexity of the innovation process, scholars began to advocate for a more nuanced understanding that integrates both demand and supply approaches (Greenacre et al., 2012; Mestre-Ferrandiz et al., 2022). Concurrently, national-level studies started to investigate macro-economic aspects of innovation, with Solow's neo-classical growth model attributing growth to a residual component referred to as technical change (Solow, 1956). The latter half of the 20th century saw the continued evolution of innovation theory with the emergence of induced innovation approach, evolutionary approaches, and path-dependent models. Induced innovation emphasizes market-driven changes, while evolutionary and path dependency perspectives underscore the constraints of historical decisions on contemporary innovation. Additionally, these two approaches are linked to concepts, namely bounded rationality and uncertainty lead to mindsets that generally favour small, incremental changes to existing products or processes in place of large radical and disruptive ones (Arrow, 1962; Arthur, 1994; Greenacre et al., 2012).

Attempts to develop comprehensive theories of innovation continued into the 1970s and 1980s, with scholars such as Nelson and Winter emphasizing uncertainty and institutional frameworks. For instance, the institutional framework plays a key role in simulating innovation or preventing it. Due to this, R&D is seen as a process of looking for solutions that is influenced by both technology capabilities (supply-push) and user demands (demand-pull), leading to a wide range of possibilities (Nelson & Winter, 1977, 1982). The limitations of these approaches led to a shift towards a systems theory of innovation, characterized by related approaches like the NIS, National Innovative Capacity (NIC), and Technological Innovations Systems (TIS). This emerging systems perspective has been characterised by a variety of related approaches, but each has tended to consider the significance of knowledge flows among actors, expectations about future technology, market, policy developments, political and regulatory risk, and institutional structures that influence incentives and barriers. Of the related approaches to the systems perspective, Kline and Rosenberg (1986) made an early attempt to depict the systems feedback within the innovation process using the ”chain linked” concept, acknowledges that there exist feedback loops between each innovation stage. Yet, it has a limited definition of system and, in contrast to later theories introduced in the next paragraphs; it ignores the broader economic, political, social, and cultural as determinants of innovation (Foxon, 2005).

Another attempt towards a system-based approach of innovation was presented by Freeman and Perez (1988), providing four taxonomy of the innovation process, namely incremental innovations, radical innovations, changes in the technology system and changes in “techno-economic paradigm” which also known as “technological revolutions”.

One of the most widely cited, developed innovation approaches that is based on the system perspective is the so-called NIS approach with a focus on individual and comparative evaluations of the innovation systems across different technologies in various countries. This approach justified the implementation of innovation policy as explained in the next section. Furthermore, related to the system perspective of innovation is a concept named NIC.

NIC is made up of the NIS theory by Nelson (1993a), the earliest description of this concept was made by Furman and co-authors who defined it as "the ability of a country to produce and commercialize a flow of innovative technology over the long term" (Furman et al., 2002). In this NIC framework, three drivers are introduced, namely common innovation infrastructure: (2) cluster-specific environment for innovation, and (3) quality of linkages between the common innovation infrastructure and industrial clusters. Furthermore, the NIC's approach to data collection suggests a focus on the firm level. However, scholars investigating NIC at the macro level by suggesting more factors that could have a significant effect on national innovative performance (Dincer, 2019). More recently, Andrijauskiene et al. (2021) updated Furman's framework by adding more dimensions and variables to the existing framework. Another recent attempt under the system perspective of innovation is the TIS approach. This approach highlights how crucial it is to recognise not only the structural elements of a system, such as the overall framework conditions and the various entities involved, but also the dynamic interactions between them and with the knowledge flows (Hekkert et al., 2007; Winskel & Moran, 2008).

In conclusion, the evolution of innovation theory is marked by a rich and diverse theoretical landscape. It has progressively shifted from a linear understanding towards a complex systems-oriented perspective that acknowledges the multifaceted interactions among various actors. This theoretical evolution coincides with a growing policy interest in what is termed "innovation policy" which will be explored in the subsequent section.

6.2.4.2 Empirical Literature on Innovation Determinants

Investigating the considerable body of empirical literature spanning over a century, it is evident that the driving forces behind innovation remain elusive, despite the extensive research and rich theoretical literature on the subject. This conclusion is drawn from various innovation studies (Fagerberg, 2015;

Kowalski, 2021; Tebaldi & Elmslie, 2013). The debate persists across different levels of analysis, including micro and macro perspectives. Additionally, a recent study by Bate et al. (2023) argued that the key determinants influencing innovation performance at the country level remain ambiguous, and comparative studies on innovation among countries with different income levels are scant.

The literature on innovation determinants can be categorized into three major groups depending on the focus: 1) economic determinants (including knowledge spillovers, income, FDI, and international trade); 2) institutional dimensions (focusing on the rule of law and the protection of property rights); 3) financial determinants (such as bank finance) (Wang et al., 2021). The literature can also be classified based on the scope of determinants: 1) micro-level determinants (identifying innovation determinants at the firm or sectoral level (Abderrezzak et al., 2016; Abdu and Jibir, 2018; Bettencourt et al., 2013; Hadhri et al., 2016; Malerba, 2004). For instance, firm-level determinants include corporate governance systems (Belloc, 2012), ownership structure (Choi et al., 2012), and stock liquidity (Fang et al., 2014). 2) macro-level determinants which identify innovation determinants at the country level, encompassing various conceptual frameworks.

Appendix (XIV) provides a summary of representative empirical studies. The macro-level studies can be further divided into three groups depending on the conceptual framework adopted and the methodological framework used. Furthermore, within these studies, there are various types of innovation, and it may stem from diverse sources. Yet, the formal technological and economic aspects of innovation have been considered in a far greater amount of scientific research.

Differentiating the existing literature based on the conceptual framework employed, some studies have focused on 1) building a National Innovation System (NIS) (Ibrahim, 2021), while others concentrated on 2) the National Innovation Capability (NIC) (Andrijauskiene et al., 2021; Furman et al., 2002); Additionally, 3) the system perspective approach of innovation and they constitute most of prior studies. In such studies, although scholars argue with the system perspective, they rely on indicators-based analysis. That is, they used specific innovation-related variables that are theoretically justified and then try to empirically test the effect of these variables on innovation performance at country level.

Of these studies, a recent study by Barrichello et al. (2020) aimed at identifying the countries' innovation determinants and articulated that the seven determinant of innovation performance are the one's introduced in the global competitiveness report. These seven factors of innovation determinants are capacity for innovation; quality of scientific research institutions; availability of scientists and engineers; company spending on R&D; university-industry collaboration in R&D; government procurement of advanced technology products; and patent applications. Additionally, a recent study by Qureshi et al. (2021) highlighted a continuous debate on what drives innovative activities at nation's level. Qureshi et al. (2021) analysed the innovation performance in two regions, namely Asia-Pacific and Latin America and the Caribbean. They concluded that investment in R&D, human capital measured by secondary school enrolment, infrastructure access and financial development all have positive effects on innovation. Other studies under this category are (Malik, 2023; Seidel et al., 2013).

Within these three groups of macro-level innovation studies, they differ in the selection of the indicators used. Dziallas and Blind (2019) performed an extensive literature on innovation indicators used to assess the performance of innovation process that could reflect the innovation performance in the form of inputs and outputs. The main-stream studies used GII as their conceptual and measurement framework in classifying innovation inputs and outputs and proceed to investigate the relevance of the innovation determinants within this methodology (Bate et al., 2023; Menna et al., 2019; Naqvi, 2016). Other rare studies used the methodology proposed by WEF in the global competitiveness report to verify the relevance of the determinants introduced by it (Barrichello et al., 2020; Jackson et al., 2014).

Additionally, with respect to innovation inputs, expenditures on innovative processes are one of the extensively used input indicators with substantial agreement on its effects (Ege & Ege, 2019; Filippetti & Guy, 2020; Filippetti et al., 2017; Zang et al., 2019). Another crucial variable numerously investigated in the literature is the private R&D investment. Many scholars highlighted that private R&D investment acts as an engine of innovation performance. It does so by the exploitation of scientific and technological opportunities that result in the introduction of new products and processes (Rodríguez-Pose & Wilkie, 2019). However, R&D only accounts for roughly one-third of innovation expenditures (Lhuillery et al., 2017). Therefore, other non-R&D innovation investment is also crucial input for innovation. The purchase of sophisticated equipment, computer hardware and software, market research, and training related to the introduction of new goods or processes are possible examples of non-R&D innovation investments (Onea, 2020).

With respect to innovation output, 74 percent of the scientific papers in the period from 1980 to 2015 employed technological innovation indicators of innovation (Dziallas & Blind, 2019). Patents is the commonly used indicator to describe technological innovation (Ang & Madsen, 2013). Patents could be measured in absolute number, the rate per million people, or in citation rate (Baesu et al., 2015; Malik, 2023; Santana et al., 2015; Schneider, 2005; Varga & Sebestyén, 2017; Wu et al., 2017). Schmookler (1966) and Griliches (1979) were the first to use the number of patents as a proxy of innovation (Tebaldi & Elmslie, 2013).

However, patents as a measure suffers from some deficiencies that cast doubts on their relevance as a measure of innovation outputs. Janger et al. (2017) demonstrated that patents could capture patents in product innovation i.e., in the manufacturing sector not in services. Additionally, Wu et al. (2017) argued that every novel idea does not grant the benefits of a patent. Thus, it is essential to add non-technologically innovative output to the pervasive focus on technological ones. The non-technologically innovative outputs could include trademark applications (Baesu et al., 2015; van den Besselaar et al., 2018), design applications as used in Baesu et al. (2015) and criticised by Sunley et al. (2008), and marketing and organizational innovations introduced by small and medium enterprises (SMEs) (Stojčić et al., 2020). Other studies include the commercialization of innovation as a proxy for innovation output. In this case, indicators of sales of new-to-market innovations, new-to-firm innovations, exports of high technology products and exports of knowledge-intensive services are used to capture this commercialization of innovation proxy (Carvalho et al., 2015; Napiorkowski, 2018).

From a methodological perspective, these macro-level innovation studies differ in the methodology adopted. For instance, Kleszcz et al. (2021) utilised a PCA to select the main principal components of innovation within the European Innovation Scoreboard (EIS) dimensions. Similarly, relying on EIS dimensions in 2020 and by using exploratory factor and correlation analysis, Onea (2020) analysed the impact of certain innovation indicators on the overall innovation process. Other studies used system GMM such as Malik (2023).

Several scholars have investigated the reasons behind the ongoing debate surrounding innovation determinants. The complexity of the phenomenon, difficulty in defining variables, and challenges in estimation techniques are key issues (Kleszcz et al., 2021; Tebaldi & Elmslie, 2013). A consensus in the literature is that innovation perspectives and determinants are multifaceted and not well-constructed. The literature also emphasizes innovation inputs and outputs. Innovation inputs include expenditures on innovative processes, private R&D investment, and non-R&D innovation investments (Onea, 2020). Outputs can be measured using technological indicators, such as patents, or non-technologically innovative outputs, including trademark applications and commercialization of innovation (Baesu et al., 2015; Dziallas & Blind, 2019).

To address this debate, Edquist (2011) defined a general determinant of innovation development as “Activities” within the innovation systems. These activities can be classified into those performed by private and public organizations, including R&D, financing for commercialization of new knowledge, and formulating new standards for product quality (Edquist & Zabala-Iturriagagoitia, 2012).

To conclude, despite the wealth of published studies on innovation, the mechanisms that drive innovation remain little understood, but it can be sub-divided into micro (firm-level) or macro (country-level) innovation determinants. It could be subdivided into three groups based on the type of innovation determinants namely economic, financial, and institutional determinants. The macro-level innovation studies, our concern, differ in the selection of the indicators used that could reflect the innovation performance in the form of inputs and outputs. As a general guideline to policymakers “Activities” within the innovation systems constitute its inputs (determinants) while results of these activities constitute its outputs.

6.3 Innovation Policy

This section provides an in-depth examination of innovation policy, addressing the underlying questions of what constitutes innovation policy, why it is significant, and how it is implemented. It elucidates the various definitions, typologies, theoretical underpinnings, and empirical justifications of innovation policy, along with its execution strategies. The comprehensive discussion includes an exploration of both demand and supply-side innovation policy instruments, their integration, and a methodical linkage to the overarching goals of innovation policy. A subsequent component of this section is dedicated to assessing the impacts of innovation policy instruments, post-implementation.

6.3.1 Definitions of Innovation Policy

The literature surrounding innovation policy is vast, as indicated by many studies such as Edquist (2011) and Lundvall (2007). Erika and Watu (2010) underlines the principal utility of the innovation systems framework in crafting context-specific innovation policies. This framework assists in formulating policy choices to alleviate social and economic dilemmas. An increase in interest in these two terms, emerging around 1990, is graphically demonstrated by Fagerberg (2014) using Google search data. Historically, Fagerberg (2017) traces the origin of this term to innovation studies at the Science Policy Research Unit (SPRU) at the University of Sussex during the late 1960s and 1980s. The real momentum began in the 1990s when OECD, other international organizations, and national governments turned their attention to this phenomenon.

Though the term “innovation policy” is of recent origin and has evolved under different nomenclatures, it may be interpreted in varied ways depending on the interpretation of innovation itself. This will be elucidated in the subsequent paragraphs.

Policymakers’ growing concern with innovation’s role in economic growth and environmental challenges such as climate change is a prominent theme. While the term “innovation policy” is recent, policies influencing innovation have existed for centuries. An illustrative example includes policies fostering military technological advancements and innovation. The labelling of these policies as "innovation policy" is a more contemporary phenomenon that gained traction from the mid-1990s, underlining the substantial role of innovation policy in cultivating innovation (Edler & Fagerberg, 2017).

Furthermore, policies affecting innovation have been identified by diverse terms, titles, and theories while being implemented, depending on the policy's focus. This evolution of terminology is explored further in Boekholt (2010). Fagerberg (2017) argues that these shifting terminologies have added complexity for researchers trying to understand the interactions between various institutions and policy instruments.

The term "innovation policy" may be employed in assorted ways, reflecting different understandings of the innovation definition. Early conceptions of innovation were tied to highly specialized roles, where the Schumpeterian view prevailed. From this prescriptive, innovation has a narrow definition and is only limited to the first occurrence of a new product or process i.e. invention stage only (Fagerberg, 2014). Modern innovation studies have adopted a more inclusive perspective adhering to the innovation cycle from creation to implementation and dissemination, recognizing innovation as new solutions to address societal problems, challenges, or opportunities (Edler & Fagerberg, 2017; Lundvall et al., 2009). This perspective incorporates not only science and technology but also processes like commercialization, marketing, and management, leading to the diffusion of new knowledge (Foray, 2004; Rose, 2009). Thus, innovation becomes a nonlinear, evolutionary process involving various stakeholders (Choi & Zo, 2019).

The diverse perspectives on innovation are reflected in policy formulation as well. The choice between a broad or narrow definition may mirror the analytical purpose. The comprehensive broad definition is more appropriate if concerned with significant consequences on various systems like economic, environmental, social, defence, security, and health.

These macro-economic objectives are pre-established in complex political processes, involving multiple stakeholders (Borrás & Edquist, 2013). The growing momentum of innovation policy in various countries, especially in the EU and OECD-developed nations, emphasizes the importance of a comprehensive understanding of both innovation and innovation policy.

In the context of the KBE, innovation policy must be concerned with the creation, distribution, and utilization of knowledge and technology, and address deficiencies in the innovation system (Feldman & Link, 2001). Empirically, he four KBE constructs, as argued by Robertson et al. (2021), act as drivers of innovation performance in developed and developing countries.

Lastly, as for the scope and adoption of the innovation policy, Fagerberg (2017) asserts that innovation policy can be applied at various levels and its adoption ranges from simple analyses to complex models based on foresight exercises and systematic data collection (Tsipouri, 2013).

6.3.2 Types of Innovation Policy

In the context of innovation policy, Edler and Fagerberg (2017) have identified three distinct types that can be delineated based on their core objectives and approaches. A synopsis of these types is presented below:

1. **Mission-Oriented Policies**: These policies are preoccupied with devising novel solutions to pressing challenges that are at the forefront of the political agenda (Ergas, 1986). The solutions must be pragmatic, encompassing all phases of the innovation cycle, from ideation to implementation. Hekkert et al. (2020) conceptualized "mission-oriented innovation policy" as comprising "networks of agents and sets of institutions that contribute to the development and diffusion of innovative solutions with the aim to define, pursue and complete a societal mission" (p.77). Such policies have been used to direct innovation to attain sustainable development goals or to address grand societal challenges like global warming (Fagerberg et al., 2016; Mowery, 2011) and are considered comprehensive but complex to analyse (Fagerberg, 2017).
2. **Invention-Oriented Policies**: These policies are confined to the initial stage of innovation, specifically the genesis of new ideas. Unlike the broad scope of mission-oriented policies, invention-oriented policies are more focused and predominantly pertain to R&D. Emerging in the post-World War II era, these policies have been instrumental in leveraging the potential benefits of science and technology for societal welfare (Edler & Fagerberg, 2017).

3. **System-Oriented Policies**: A more recent addition, system-oriented policies centre on the structural features of the innovation system. They stem from the NIS approach initiated in the 1990s and are concerned with the interactions and integrations among the diverse actors in the innovation ecosystem. These policies also aim to enhance the essential components and capabilities of the system (Edler & Fagerberg, 2017).

In the ensuing discussion of this chapter, the focus will be on adopting the double broad definitions of innovation and innovation policy, as they are particularly congruent with the chapter's objective of examining the ramifications of innovations within the economic system. Specifically, the mission-oriented type of innovation policies will be utilized, considering all aspects of the innovation process, from the emergence of ideas to their adaptation and distribution, in addressing the challenge of transitioning to a KBE. Furthermore, the analysis will be oriented toward national-level innovation policy in the selected developing countries of the MENA region.

6.3.3 Theoretical and Empirical Rationales for Innovation Policy

The theoretical underpinnings of innovation policy are often traced to two key concepts: the market failure approach and the emergence of the NIS. The market failure approach provides the rationale for what is sometimes termed the first-generation innovation policy, designed to rectify inefficiencies and failures within the market system. In contrast, the second-generation innovation policy targets the deficiencies and failures associated with the NIS, striving to foster a more coherent and effective innovation ecosystem (Hekkert et al., 2020).

In addition to the theoretical justification, empirical support for the need for innovation policy intervention and formulation can be gleaned from recent innovation surveys. As an illustrative example, the UK Innovation Survey (2021) has revealed a series of stylized facts that underscore the significance of tailored policy measures in advancing the innovation landscape. These empirical findings offer tangible evidence, reinforcing the argument for the thoughtful design and implementation of innovation policies (Department for Business, Energy & Industrial Strategy, 2021).

6.3.3.1 The Market Failure Approach to Innovation Policy

The concept of innovation policy has long been a core component of governmental policy missions, often without explicitly bearing the label “innovation policy” The underpinning of these innovation-supporting policies predates even the emergence of social sciences, including economics. Consequently, the theoretical justification for such policies can be viewed as an ex-post rationalization of practices adopted during the decades following the Second World War. During this period, significant investments in innovation by the UK and US governments resulted in substantial societal payoffs. Further, natural science scholars largely concur that increased public investments contribute to societal success. Conversely, economists of the time, influenced by the dominant neo-classical perspective, maintained that free-regulating markets would yield optimal societal progress (Edler & Fagerberg, 2017).

The paradox arises when considering why private firms would abstain from engaging in such lucrative investments. Research in the economics of innovation, conducted by a U.S. team after the Second World War, found that the creation of new knowledge—a main source of innovation—is a public good that can be freely exploited. Consequently, the financial rewards for creating new knowledge are not fully conferred to the originating entities, thereby reducing incentives for investment. This misalignment between public and private returns leads to under-investment in new knowledge creation, even when potential societal benefits are high (Fartash et al., 2021). This “market failure” has justified policy interventions to elevate investment levels in new knowledge creation to those desired by society (Arrow, 1962).

Edler and Fagerberg (2017) identified three policy instruments to address this market failure: (1) enhancing the protection of newly created knowledge through strengthening Intellectual Property Rights (IPR); (2) subsidizing R&D for private firms to foster investment in new knowledge creation; and (3) promoting investment in basic research, characterized by uncertainty and future commercialization opportunities, through government engagement in public knowledge production via universities and public research institutions.

Nevertheless, the market failure approach has faced criticisms for being theoretically inconsistent and incongruent with many empirical results from innovation process studies. Its influence, simplicity, and wide applicability notwithstanding, it has shown some limitations. One such limitation, referred to as "policy failure" arises from the government's inability to discern the optimal level of new knowledge creation required by society, leading to potential policy inadequacies (Mazzucato & Semieniuk, 2017).

A further criticism of the market failure approach is the conflation between information and knowledge by market-failure theorists (Metcalfe, 2005). While information may be easily accessible, knowledge—with its various types and applications—is more elusive. For instance, having a manual containing some information is totally different from understanding how things work and how to use this information in practical applications. Obviously, having knowledge is much more demanding for the creation of new knowledge. Further, the notion of "perfect knowledge" where any actor (firm, person, or government) possesses comprehensive insight relevant to solving any practical problem, is debunked as an impossibility, leading firms to allocate substantial resources in search of relevant, often elusive, knowledge (Cohen & Levinthal, 1990; Hayek, 2009; Nelson & Winter, 1982). In light of these criticisms, Mazzucato and Semieniuk (2017) concluded that the market failure argument alone is insufficient to effectively guide the design of innovation policy.

6.3.3.2 The National Innovation Systems

The early 1970s were marked by an era of high productivity growth, impressive income levels, and near full employment across the Western world. However, subsequent decades brought about challenges, necessitating new perspectives for policy formulation. Scholars such as Freeman (1987) observed distinctions between countries in economic performance and in patterns concerning the creation and diffusion of innovation, as well as variances in innovation-supporting institutional frameworks at the national level. As a result, the role of innovation in sustained economic growth attracted considerable attention from scholars, policymakers, and international organizations (Dosi et al., 1988; OECD, 1992; Romer, 1990). The result of this attention is that policymakers became aware of how and if the policy could help in raising innovation and, hence flourishing the economy.

In response to this attention, different scholars, including Freeman (Freeman, 1987), Lundvall (Lundvall, 1992), Nelson (Nelson, 1993b), and Edquist (Edquist, 1997), contributed early insights to the NIS concept. These scholars concurred on the notion of systematic interdependence and interaction between organizations within a specific country, shaping that nation's innovation landscape. However, they diverged in defining the organizations and institutions constituting the NIS (Chaminade et al., 2018). A substantial body of research subsequently adopted this innovation approach (Alexander, 2021; Balzat & Hanusch, 2004; Fagerberg & Sapprasert, 2011; Lundvall, 2007; Patel & Pavitt, 1994).

The NIS framework has been widely embraced and quickly popularized through the OECD (OECD, 2018), influencing advice to governments and innovation policy evaluation. Historical publications related to NIS since 1960 have been documented by many studies and underscored the widespread application of the NIS framework by international organizations and policymakers to assess national innovation system performance (inter alia Choi & Zo, 2019; Godin, 2009).

Lundvall (2007) provided an in-depth analysis of NIS, discussing its classification as a theory, a framework for innovation, and an approach to innovation. Lundvall developed the NIS theory, a theoretical framework that emphasises the dynamics and interconnections of innovation at the national level. the theory's main assumptions are the systemic approach, according to the NIS theory, innovation is a multifaceted, interactive process that involves a range of individuals, organisations, and connections inside a country. From a holistic perspective, innovation is seen as the outcome of interactions between many entities, such as businesses, academic institutions, governmental bodies, and other organisations. Additionally, of its methods is the incorporation of the institutional analysis to fully understand how a nation's institutions, such as its industrial structures, educational programmes, and government regulations, shape its innovation system. Further, the theory places a strong emphasis on interactive learning processes, in which knowledge is gained by organisations both internally and through interactions and cooperation with other stakeholders in the innovation system. Furthermore, realising that many industries may have distinctive innovation dynamics and characteristics, Lundvall expanded the theory to investigate sector-specific innovation systems.

The idea of NIS resulted in improved policy insights as it allows for understanding how institutions and policies affect a nation's capacity for innovation. It draws attention to the necessity of laws that encourage cooperation and information exchange between different players. The NIS theory also has implications on country's global competitiveness, by highlighting how crucial an effective innovation system is to raise economic growth and productivity. It also has effective empirical applications, as scholars have studied and compared the innovation systems of many nations using the NIS framework, offering insights into elements that promote or hinder innovation at the national level.

To conclude, the NIS theory developed by Lundvall has influenced thinking about how institutions, laws, and relationships might promote innovation in a nation. Policymakers and scholars interested in understanding and strengthening national innovation capacities have benefited greatly from its implementation.

Edler and Fagerberg (2017) posited that, based on Lundvall's exposition, NIS can be conceptualized as a policy-related synthesis that encompasses various research domains relevant to innovation, such as Schumpeter's work, empirical studies on innovation determinants, and the contributions of evolutionary economists during the late 1980s.

The NIS paradigm inherently challenges the concept of an optimal state, necessitating a holistic perspective on policy. Given that responsibilities for different NIS components are distributed across various governmental authorities (e.g., separate ministries for knowledge creation and finance), a systematic comprehension of innovation policy and effective collaboration among involved parties are imperative. This underscores the NIS's requirement for a coordinated and synergistic approach to understanding and implementing innovation policy.

6.3.3.3 Empirical Evidence: A Synthesis of Stylized Facts

Fagerberg (2017) posited that the relevance of theory is hinged on its coherence with empirical evidence. A historical review of scholarly endeavours reveals a concentration since the 1960s on probing the multifarious determinants that shape firms' innovative activities, which are in turn influenced by policy. Milestones in this investigative trajectory include the SAPPHO project at SPRU (refer to Rothwell et al. (1974) for comprehensive details), the Yale survey in the United States as documented in Levin et al. (1987), the Community Innovation Survey (CIS) initiated by the European Union in 1991, and the UK innovation survey spearheaded by the Department for Business, Energy & Industrial Strategy. Collectively, these empirical undertakings provide insight into the innovation landscape, thereby furnishing policymakers with foundational knowledge to refine innovation policies.

The consistency of the findings emanating from these diverse efforts was affirmed by Fagerberg (2014). This consistency extends across different methodologies and temporal dimensions. To further elucidate this point, recent empirical insights from the UK Innovation Survey Report in 2021 have been marshalled to probe some stylized statistics and information pertaining to innovation at the firm level within UK businesses. These selected facts possess salience for the discourse on innovation policy.

Sources of Information for Innovation: An analysis of UK firms from 2014 to 2020 revealed that the most vital wellspring of information for broader innovator businesses emanates from within the firms themselves or their enterprise groups. Among the external vectors, private sector customers and suppliers were paramount. Competitors and higher education institutions figured less prominently. This pattern undermines the support for the "linear model" in this specific (Department for Business, Energy & Industrial Strategy, 2021).

Innovation Cooperation Dynamics: The 2021 UK innovation survey indicated a discernible augmentation in innovation collaboration between two compared periods. Specifically, 58% of broader innovator businesses engaged in cooperation arrangements in 2018-2020, compared to 49% in 2016-2018. This cooperation implies a shared responsibility for tasks and information sharing. Predominantly, the data revealed an alignment with suppliers and customers, followed by other firms in the same enterprise group. Public sector cooperation was less frequent, with only 22% working with government or public research institutes, and 23% with universities or other higher education institutions (Department for Business, Energy & Industrial Strategy, 2021). These patterns reaffirm the conceptualization of innovation as an interactive, multifaceted process between diversified actors, organisations, and institutions.

Drivers of Innovation in UK Firms: Factors that stimulate innovation were ascertained through the expression of importance ratings by broader innovators from 2014-2016 to 2018-2020. According to the 2021 UK innovation survey, 39% of businesses in 2018-2020 rated the enhancement of goods or services quality as highly influential. The coronavirus pandemic emerged as the second most impactful factor, followed closely by regulatory compliance, with respective ratings of 35% and 34%. These empirical observations reinforce the notion that innovation is propelled by a spectrum of drivers, underscoring the salient role of the institutional environment (Department for Business, Energy & Industrial Strategy, 2021).

6.3.4 Innovation Policy: Addressing the "How" Question

Policy implementation is often characterized by the utilization of specific policy instruments, necessitating a comprehensive understanding of the historical context, classification, integration, and alignment of these instruments with the objectives of innovation policy. This section provides a systematic exploration of the subject.

6.3.4.1 Definition and Objectives of Innovation Policy Instruments

Public policy instruments may be defined as a collection of techniques through which governmental authorities wield their power to either facilitate or impede societal change (Bemelmans-Videc., 2017). Within the domain of innovation, these instruments function as specific interventions that modulate the innovation process, thereby potentially inducing or inhibiting innovation (Howlett, 2019; Mestre-Ferrandiz et al., 2022). This can also be framed as methodologies devised to articulate policy objectives (Martin, 2016).

Mestre-Ferrandiz et al. (2022) delineated three overarching goals that historically guide innovation policy instruments. The first goal emphasizes fostering invention by addressing market challenges associated with the R&D phase. The second goal centers on the systemic development and sustenance of innovation, while the third, more recently emphasized goal, is mission-driven, targeting distinct societal issues prominent in political discourse.

Empirical literature reveals that many innovation policy instruments prioritize invention promotion over nurturing innovation systems or addressing specific societal challenges (Mestre-Ferrandiz et al., 2022). Additionally, Wang and Li (2021) highlighted that, in innovation context, policy makers implement an innovation policy by means of innovation policy instruments which are applied to attain the innovation policy objectives. The innovation policy goals could be directed towards innovation generation, innovation diffusion, and innovation adoption.

6.3.4.2 Nature, Design, and Impact of Innovation Policy Instruments

Innovation policy instruments possess an intentional nature, targeting direct innovation policy objectives, thereby potentially achieving broader socio-economic-political ends (Edler & Fagerberg, 2017). Factors influencing the design of these instruments include theoretical comprehension of the subject matter, lessons gleaned from practice, and stakeholder engagement. These instruments, however, directly affect innovation processes and do not directly influence governmental ultimate objectives (Borrás & Edquist, 2013). Therefore, innovation serves not as an end but as a means to achieve broader objectives, such as fostering the transition to a KBE (Fagerberg, 2017).

6.3.4.3 Identification and Selection of Innovation Policy Instruments

The process of identifying innovation system challenges leverages multiple information sources, such as innovation indicators, comparative studies, benchmarking, and expert assessments. Among these, innovation indicators are deemed most influential (Borrás & Edquist, 2013).

Nevertheless, the mere identification of problems does not suffice as a rationale for public intervention. It is crucial to ascertain the underlying causes behind the identified challenges to tailor appropriate innovation policy instruments. For instance, if low performance in an innovation system stems from inadequate research levels, policy instruments might need to focus on enhancing R&D investment. Conversely, if the issue relates to insufficient demand for specific innovations, demand-side instruments like public procurement for innovation may be employed (Borrás & Edquist, 2013).

The multifaceted nature of innovation policy instruments necessitates a structured selection process. This involves the primary selection of suitable instruments from a broad spectrum, specific design or customization to the context, and the assembly of complementary instrument mixes to address identified problems (Borrás & Edquist, 2013).

Emphasizing the critical nature of this choice, Omidi et al. (2020) contended that the selection of innovation policy instruments constitutes an essential component in innovation policy formulation. Governments are thus advised to prioritize these instruments in line with the specific challenges of their national innovation systems, thereby leading to more systematic and problem-oriented policy instrument designs for innovation.

6.3.4.4 Classification of Innovation Policy Instruments

The classification of innovation policy instruments plays a pivotal role in the literature, guiding national policymakers in the design and deployment of these instruments. Over time, various taxonomies have been developed, reflecting the evolving understanding of the essential function that innovation performs in both social and economic development. Notable scholars and entities such as Bemelmans-Videc et al. (2011); Borrás and Edquist (2013); Edler and Georghiou (2007); Edler et al. (2016a); European Commission (2013); Gok et al. (2016); Meissner and Kergroach (2021); Mestre-Ferrandiz et al. (2022) and Rothwell and Zegveld (1981), have contributed to a diverse range of taxonomies.

One instance of these taxonomies is found in the work of Rothwell and

Zegveld (1981), who distinguished between three types of policy instruments: supply side, environmental side, and demand side instruments. Similarly, Rogge and Reichardt (2016) segmented innovation policy instruments into three categories based on their operational characteristics:

1. Regulatory measures, encompassing rules, regulations, norms, and standards governing social and market interactions.
2. Economic or financial instruments, which offer incentives or disincentives to encourage or discourage specific behaviours.
3. Communications-based instruments, supporting evidence-based and superior decision-making through voluntary and non-coercive informational measures.

Rogge and Reichardt (2016) posited that these governance modes tend to be mutually exclusive, e.g., R&D tax credits are regarded as an economic incentive, not a regulatory instrument. In a similar vein, Borrás and Edquist (2013) contributed to this classification, offering a general typology that includes regulatory instruments, economic and financial instruments, and soft instruments.

Further classifications can be found in Bemelmans-Videc et al. (2017), who provided examples of studies for three categories: regulation (sticks), economic means (carrots, including grants, prizes, subsidies, loans, permits, and capital provisions), and informational campaigns (sermons). Additionally, Mestre-Ferrandiz et al. (2022) introduced a 3 × 3 matrix for classifying instruments based on their aim, governance mode, and target constituencies.

Historical perspectives reveal debates from the sixties and seventies, focusing on technology-push versus demand-pull approaches to technical change (Dawid et al., 2021; Dosi, 1982). By the eighties, a consensus emerged among scholars that both approaches are complementary and that innovation is driven by a symbiosis of intrinsic scientific and technological nature along with market forces that shape the demand in any country (Dawid et al., 2021; Di Stefano et al., 2012; Mowery & Rosenberg, 1979; Pavitt, 2005; Toselli, 2017). Different types of policy instruments supporting innovation policy must, therefore, be precisely tailored (Borrás & Edquist, 2013).

In this chapter, given the extensive array of innovation policy instruments, it is essential to introduce a comprehensive, systematic typology based on the orientation of the innovation policy instruments. Consequently, prior to commencing the diagnostic analysis of innovation systems in selected developing MENA countries in the subsequent section, a systematic classification of innovation policy instruments is presented. Within this context, instruments may be divided according to their orientation into supply and demand side innovation policy instruments.

6.3.4.4.1 Supply-Side Innovation Policy Instruments

Supply-side innovation policies focus intensively on the firms, or originators, providing the innovations, as well as the role of science and technology in the development of innovations. Referred to as technology-push or technology-driven policy instruments, these strategies emphasize driving technological change from the supply side, cantering on the innovators. Examples of such instruments encompass government-sponsored R&D, and fiscal incentives such as tax credits for corporate investment in R&D.

Proponents of the technology-push concept advocate for innovation driven by the supply side, prioritizing scientific and technological opportunities. They contend that effective technological progress necessitates concentrated attention on scientific and technical development (Rosenberg, 1982, 1984). This perspective often aligns with a belief in a linear innovation process from research to development, culminating in the diffusion of knowledge (Bush, 1945). Analytically, supply-side advocates often characterize innovation as an autoregressive process wherein previous knowledge plays an essential role, captured in the cumulative, localized, and persistent nature of technology. Within this framework, particular attention is paid to specific sectoral technological opportunities (Atkinson & Stiglitz, 1969; Dawid et al., 2021).

In recent decades, supply-side innovation policy instruments have garnered greater focus than their demand-side counterparts (European Commission, 2016). Economists such as Romer (1990), Olsson (2000), and Weitzman (1998) have emphasized the importance of supply-side factors in innovation, viewing them as paramount over other potential influences on innovation growth. For example, Weitzman (1998) posited that the genesis of new innovations arises from the recombination of existing ones, while Olsson (2000) asserted that knowledge dissemination from other economies is a crucial source of knowledge expansion. However, some scholars, such as Crisan (2020), have argued that an exclusive focus on supply-side innovation policies has not yielded the anticipated results, leading to calls for the adoption of demand-side innovation policies as well.

6.3.4.4.2 Demand-Side Innovation Policy Instruments

Contrary to the emphasis on supply-side policies, demand-side advocates assert that market conditions, specifically market demand, play an essential role in shaping and driving innovation in novel directions (Myers & Marquis, 1969; Schmookler, 1966).

Edler and Georghiou (2007) characterizes demand-side innovation policies as encompassing all governmental measures that stimulate or accelerate the diffusion of innovations by boosting demand for them, delineating novel functional requirements, or articulating demand more effectively. Similarly, Tsipouri (2013) describes these policies as public measures to induce innovation demand by creating or expanding markets. These markets, in turn, can provide essential feedback to enhance the innovation process, serving as a platform where innovators can connect with users and customers (European Commission, 2016). This signifies that demand-side instruments advocate for a perspective where demand factors broaden the market and strengthen incentives for firms to innovate, viewing demand as a crucial determinant of both the pace and direction of innovation.

The study of influential demand-factors on innovation can be traced back to the work of Schmookler (1966), who argued that the applicability of new innovations is vital for innovation growth. Subsequent studies have built upon this concept, emphasizing the importance of demand-side instruments (Edler, 2016; Godin & Lane, 2013; Guerzoni & Raiteri, 2015; Keely, 2002). This growing emphasis is evident in the incorporation of demand policies within governmental innovation portfolios across OECD and European Commission countries. OECD (2011) and Wang and Li (2021) have underscored the importance of demand-pull instruments, outlining specific policies in various OECD countries, and emphasizing the increasing focus on these policy tools. Furthermore, Dawid et al. (2021) empirically found that demand-pull policies are more effective for product than for process innovation and thus Dawid et al. (2021) suggested that governments should play a role in promoting an economic policy that combine both a Keynesian perspective i.e., focusing on increasing demand with a Schumpeterian perspective i.e., promoting those strands of demand through fostering the diffusion of new products.

Several arguments underscore the merits of demand instruments. These include the direct positive effect of increased sales on innovation financing (Agénor & Canuto, 2017; Giudici & Paleari, 2000; O'Sullivan, 2006) the reduction of uncertainty through optimistic demand forecasts for new innovative products (Fontana & Guerzoni, 2008), and the correlation between market size and the intensity and expected profitability of new innovations (Kamien & Schwartz, 1982; Loury, 1979; Shrieves, 1978).

Primarily implemented at the national level (Kaiser & Kripp, 2010), demand-side instruments are also studied for their relevance regionally (Wintjes, 2015). As tools addressing societal challenges, these instruments are considered rational state interventions, aligned with market and competition rationales, where the state's role manifests in public demand, procurement, standardization, and regulations (Tsipouri, 2013).

Scholarly literature has introduced various typologies for demand-side instruments (Cunningham, 2009; Edler, 2013; Lember et al., 2013; OECD, 2011). Despite the complexity of these classifications, the European Commission (2016) has endorsed the Elder's typology, which is followed in this chapter. This typology identifies four main types: public demand, private demand, regulatory approaches, and systematic approaches that integrate various demand measures. A detailed classification is presented in Appendix (XV).

Empirical literature centers demand-side innovation policy around public procurement (Bento et al., 2022; Demircioglu & Vivona, 2021; Uyarra, 2016). As supply-side innovation policy tools failed to attain expected outcomes, the emphasis on public procurement has increased (Crisan, 2020). Defined as government and state-owned enterprise purchases of goods and services (Demircioglu & Vivona, 2021), public procurement has been associated with addressing grand challenges (Edler & Georghiou, 2007) since its inception in

2004.

Public procurement for innovation describes the process whereby public organizations order non-existent goods or systems, requiring the supplier to innovate before delivery. This demand, whether from private or public organizations, serves as a catalyst for the diffusion and creation of innovation (Edquist & Zabala-Iturriagagoitia, 2012). It has garnered attention as a policy tool with substantial societal impact (Grandia & Meehan, 2017), spurring economic growth (Edquist & Hommen, 2000), fostering innovation development, fulfilling human needs, and addressing societal problems (Edler et al., 2015; Edquist & Zabala-Iturriagagoitia, 2012). Additionally, public procurement enhances innovation development in the private sector and facilitates interactive learning among various parties (Crisan, 2020; Edler et al., 2015).

6.3.4.5 Integrating both Demand and Supply Drivers of Innovation

The interplay between demand and supply in innovation processes is well-established within innovation literature, reflecting a shared consensus that both elements are instrumental in fostering innovation (Di Stefano et al., 2012; Nemet, 2009; Peters et al., 2012). This synergistic integration of demand and supply side policy measures is commonly referred to as a “policy mix” (Borrás & Edquist, 2013).

Borrás and Laatsit (2019) have underscored that the primary aim of this innovation policy mix is to both broaden (by incorporating more diverse actions within the innovation policy) and deepen (through the implementation of more nuanced policy instruments) policymakers’ comprehension of innovation drivers in both developed and developing nations. Additionally, Mestre-Ferrandiz et al. (2022) advanced the notion that these systemic policy tools act as facilitative platforms, harmonizing the advantages of both demand-side and supply-side instruments. By operating at the level of the entire innovation system, they foster cooperation, coordination, and knowledge sharing among market participants, thus aligning the instrument mix with the specific needs of the involved parties.

However, the pragmatic implementation of these theoretical considerations often reveals an imbalance. Typically, there is a bias towards supply-side instruments, with demand-side instruments finding limited application or being applied inconsistently and sparingly (Tsipouri, 2013). At the national level, this trend is apparent with varying adoption rates across countries; while some, including most OECD and EU nations, have embraced demand-side policy instruments, others have shown reluctance. The complexity inherent in demand-side instruments, their multilevel operation within governmental frameworks, and the requirement for sustained engagement may account for this hesitant uptake in comparison to supply-side measures (Lember et al., 2013).

Despite these challenges, it has become increasingly clear that relying solely on supply-side instruments such as R&D subsidies may be inadequate in nurturing innovation and technological advancement (Tsipouri, 2013). As Lember et al. (2013) eloquently expressed, there has been a shift in focus over the past decade towards recognizing the significance of demand-side instruments within the broader discourse of the innovation policy mix.

This paradigm shift has been influenced by the comprehensive empirical studies and policy experiences that highlight the complementary nature of indirect demand-side instruments to direct supply-side measures. The impetus for this incorporation stems from multiple factors. Firstly, there was a realization that relying exclusively on supply-side innovation policy instruments did not yield the anticipated results. Secondly, the constraints imposed by increasing budgetary pressures have nudged policymakers towards seeking more efficacious solutions without incurring additional costs (Flanagan et al., 2011). Consequently, the coordinated application of both demand and supply drivers of innovation has emerged as an essential strategy in contemporary innovation policy, reflecting a nuanced understanding of the complexity of the innovation ecosystem.

6.3.4.6 Connecting Innovation Policy Instruments to Innovation Policy Goals

Mestre-Ferrandiz et al. (2022) elucidated that governments face a veritable "ocean" of innovation policy instruments, presenting a formidable challenge in synthesizing and consolidating this diverse array. Edler et al. (2016a) embarked on the development of an overarching synthesis of existing innovation policy instruments, focusing on their orientation—namely, the supply and/or demand for innovation—and, importantly, connecting these instruments with pivotal innovation policy goals. They provided an insightful analysis of how different demand and supply innovation policy instruments correspond with specific innovation policy objectives, as summarized in Table (6.1).

Table (6.1) illustrates the seven innovation policy goals introduced by Edler et al. (2016a), derived from an in-depth analysis of the principal findings from their reviewed reports. They further identified fifteen essential innovation policy instruments to underpin these goals, with the first eight primarily aligned with the supply side of innovations. Intriguingly, many of these instruments—whether demand or supply-oriented—contribute to the realization of multiple innovation policy goals. Conversely, several goals may be addressed by employing a combination of innovation policy instruments.

Table (6.1): Linking Innovation Policy Instruments to Innovation Policy Goals.

Innovation policy instruments	Overall Orientation		Innovation Policy Goals						
	Supply	Demand	Increase R&D	Skills	Access to expertise	Improve systemic capability, complementarity	Enhance demand for innovation	Improve framework	Improve discourse
1-fiscal incentives for R&D	●●●		●●●	●○○					
2- Direct support to firm R&D and innovation	●●●		●●●						
3-policies for training and skills	●●●			●●●					
4-Entrepreneurship policy	●●●				●●●				
5- Technical services and advice	●●●				●●●				
6- Cluster policy	●●●					●●●			
7- Policies to support collaboration	●●●		●○○		●○○	●●●			
8- innovation network policies	●●●					●●●			
9- Private demand for innovation		●●●					●●●		
10- Public Procurement policies		●● ●	●●○				●●●		
11- pre-commercial	●○○	●●●	●●○				●●●		

Innovation policy instruments	Overall Orientation		Innovation Policy Goals						
	Supply	Demand	Increase R&D	Skills	Access to expertise	Improve systemic capability, complementarity	Enhance demand for innovation	Improve framework	Improve discourse
procurement									
12- innovation inducement prizes	●●○	●●○	●●○				●●○		
13- standards	●●○	●●○					●○○	●●●	
14-Regulations	●●○	●●○					●○○	●●●	
15- Technology foresight	●●○	●●○							●●●

Note: ●●● = major relevance, ●●○ = moderate relevance and ●○○ = minor relevance to the overall orientation and stated innovation policy goals of the listed innovation policy instruments.
Source : Edler et al. (2016a)

Elaborating further, the initial two innovation policy instruments are directed towards the genesis of new knowledge and innovation, potentially achieved through financial backing for R&D and innovation, including fiscal incentives adopted in various countries with diverse designs (Larédo et al., 2016). Instruments three to five primarily focus on bolstering the requisite capabilities and skills to create and commercialize innovation, reflecting the continuous need for learning within innovation systems. The subsequent instruments, six to eight, are crafted to facilitate myriad possible forms of interactions and learning at both national and regional levels (Isaksen & Trippl, 2017), and the impact of cluster support on innovation policy has garnered substantial attention (Uyarra & Ramlogan, 2016).

While the first eight instruments are supply-oriented, instruments nine to twelve are demand-oriented, influencing the demand for innovation in distinct ways. For example, stimulating private demand can be achieved by offering incentives, such as vouchers, to encourage the acquisition of innovative goods and services with demonstrable social and environmental benefits. Public procurement policies target the creation of markets, and pre-commercial procurement fosters markets for innovative products and promotes experimental applications of emerging technologies.

Instrument thirteen (standardization) and instrument fourteen (regulations) exhibit a dual influence on both the supply and demand facets of innovation. Blind (2009) delved into the support standardization can provide for innovation and explored the regulatory effects on innovation in OECD countries (Blind, 2012). Technology foresight, as the fifteenth instrument, is delineated as an approach aiding policymakers and stakeholders in discerning future technological trajectories, facilitating the formulation of policies aligned with emerging trends.

In conclusion, diverse sets of innovation policy instruments have evolved over time, mirroring multifaceted theoretical underpinnings and various policy ambitions, or political priorities. Following the adoption of innovation policy instruments, a logical subsequent step involves the evaluation of their impact. Consequently, the ensuing discussion will pivot towards an examination of the extant literature concerning the effects of these instruments, thereby further illuminating their role and significance within the broader innovation policy landscape.

6.3.5 The Impact of Innovation Policy Instruments

The assessment of innovation policy's effectiveness transcends mere nomenclature, becoming paramount to its intrinsic value (Boni et al., 2019). Literature abounds with endeavours to gauge the impacts of innovation policy interventions through innovation policy instruments, as documented in Boni et al. (2019); Borrás and Laatsit (2019); Edler et al. (2010, 2012); Georghiou (1998); Haddad and Bergek (2020); Molas-Gallart and Davies (2006); Papaconstantinou and Polt (1997). Recently, Collin et al. (2022) posited that the proliferation of innovation policy instruments has been accompanied by a corresponding increase in evaluation methodologies. However, they contend that such evaluations remain markedly limited in their systematic application.

The realm of policy evaluation, encompassing its methodology, actors, and overarching impacts, is fraught with complexity, partially attributable to inherent difficulties encountered in such evaluation endeavours. Edler and Fagerberg (2017) elucidated the feasibility of assessing immediate effects of specific policy instruments on innovation activities but acknowledged the considerable challenge in evaluating broader impacts on social and economic development.

Edler et al. (2016b) reinforced this sentiment, asserting increased uncertainty regarding the extended implications of innovation policy interventions, although immediate effects generally aligned with expectations. Spaapen and Van Drooge (2011) accentuated the societal and economic repercussions of innovation policy, underscoring the absence of robust measurement mechanisms. For example, it might be feasible to determine whether R&D support enhances R&D outputs, but gauging its impact on innovation performance, productivity, or job creation—fundamental objectives at the core of policymaker concerns—proves more elusive.

Two primary challenges underpin this assessment quandary. First, the intrinsic difficulty in quantifying innovation itself, as highlighted by Smits and Kuhlmann (2004), and second, the complexity of calculating the temporal gap between innovation policy interventions and their eventual socio-economic effects—a typically prolonged latency period (Kline & Rosenberg, 2009).

Another intricacy arises from the context-specific nature of innovation policy instrument impacts, heavily reliant on the overarching innovation system within a given country. Edler et al. (2016b) concluded that variations in context—across different countries or even within the same country at disparate times—yield divergent policy impacts, even when utilizing identical instruments with analogous designs. Chaminade et al. (2009) and Erika and Watu (2010) emphasized that no monolithic innovation policy approach is universally applicable, necessitating careful consideration of demographic challenges, local conditions, informal economic activity, and differential management of technological innovation across developed, emerging, and developing countries. Furthermore, Chaminade et al. (2009) and Erika and Watu (2010) claimed that technological innovation in developed and emerging countries needs to be managed quite differently than developing countries. Innovation in developed countries is mainly dependent on R&D i.e., the creation of new knowledge whereas in developing countries non technological innovation and the use of existing knowledge to create market value is what usually found in these countries.

Echoing these sentiments, Flanagan and Uyarra (2016) suggested that the effectiveness of innovation policy is inextricably tied to its contextual introduction. This leads to the assertion that mechanical policy transfers between NIS may be misleading and problematic unless contextual factors are prioritized. A constellation of variables, including local and national capabilities, economic structures, national science bases, financial market statuses, and cultural attitudes, often escapes policymakers' awareness, further complicating evaluations. Given these complexities, many scholars advocate for a more systematic and holistic evaluation approach over individualized assessments (Flanagan et al., 2011; Smits & Kuhlmann, 2004). While OECD has made strides in this direction, the majority of existing frameworks persist in focusing on singular evaluations.

Complications also arise from policy mixes; wherein diverse innovation policy instruments may interact synergistically or antagonistically. Edler and Fagerberg (2017) noted the challenges in discerning the individual impacts of each policy instrument in such interconnected scenarios. Empirical literature emphasizes the necessity of a systematic and holistic perspective in policy formulation (Fagerberg, 2017). Edler et al. (2016a) have collated substantial academic and policy evaluation reports to present robust evidence of innovation policy instruments' impacts, identifying those most prevalently employed and attentively regarded. Edler et al. (2016a) argued that R&D support, training, supporting skills and regulations are the commonly used instruments and have gained the highest attention.

Lastly, the potential failure of innovation policy instruments can be attributed to various reasons. Hudson et al. (2019) delineated four broad categories linked to public policy failures: inadequate collaborative policymaking, fragmented governance implementation, overly optimistic expectations, and political cycle whims. In such intricate landscapes, the production of positive outcomes through innovation policy instruments becomes an intricate undertaking.

To conclude, assessing the impacts of innovation policy intervention is done through innovation policy instruments. However, in practical situations, researchers and policymakers face challenges while attempting to evaluate the individual impact and overall impact of these innovation policy instruments. As a practical guideline, researchers and policymakers must take into consideration the context in which these policies are going to be applied. Additionally, policymakers should be aware of the common policy failure factors such as inadequate collaborative policymaking, implementation in dispersed governance, too optimistic expectations, and the whims of the political cycle.

6.4 Empirical Analysis

6.4.1 Objectives of this Empirical Analysis

The evolutionary theories of innovation systems have been highlighted as a beneficial theoretical framework for developing countries (Erika & Watu, 2010). However, it is imperative to complement these theoretical insights with empirical analysis. This integration not only ensures adaptability to the specific context of developing countries but also facilitates the design of country-specific innovation policies.

As elucidated earlier, the extensive literature on innovation policy has predominantly focused on three distinct approaches to policy instruments. These approaches can act either on the supply side, pushed by technological and scientific advancements; on the demand side, pulled by market needs; or as a balanced integration of both sides. Works such as Barrichello et al. (2020) and Omidi et al. (2020) emphasize that governmental prioritization of efforts and resources in these domains is pivotal for promoting innovation.

Consequently, the empirical section of this study seeks to discern the relative importance of these different innovation policy instrument approaches. Specifically, it aims to empirically identify and assess the factors that most substantially influence innovation output in developing MENA countries.

6.4.2 Literature Gaps to be Addressed in this Empirical Analysis

This empirical analysis contributes to the existing literature by addressing several notable gaps.

First, it aims to undertake a comprehensive and systematic examination of innovation drivers, focusing on middle-income developing countries across various stages of development. Conducting an econometric analysis exclusively with seven developing MENA countries (as included in the prior diagnostic analysis) is unfeasible due to the limited sample size. This study, therefore, employs the World Bank's classification by income group, focusing on middle-income developing countries. This approach circumvents the challenges posed by data scarcity for low-income countries while maintaining relevance to the previously diagnosed developing

MENA countries within this income group.

Second, the analysis facilitates the identification of key factors that hold substantial relevance for innovation development. This refined understanding assists policymakers in focusing their efforts on innovation policy development. Unlike numerous innovation-related studies that empirically assess the impact of various macroeconomic factors without a systematic categorization into supply or demand-side factors (Canh et al., 2019; Malik, 2023), this study systematically segregates these drivers for a nuanced investigation into the most critical determinants of innovation in developing MENA countries.

Third, this study diverges from conventional analyses, such as Edler et al. (2016a), by treating entrepreneurship as a demand-side innovation factor. This unique categorization is substantiated with robust theoretical and empirical justifications, acknowledging the essential role of entrepreneurship within the innovation process.

Fourth, this analysis introduces a non-linear model to explore the intricate relationship between institutional quality and innovation, an area marked by conflicting findings in previous empirical studies. The nuanced interplay between institutional quality and innovation development is thoroughly examined, elucidating the potential channels through which institutions might influence innovation output.

Fifth, the study incorporates cross-country analysis to investigate national innovative output in developing countries, offering insights at the broader national level. This perspective is often overlooked in existing scholarly research.

Lastly, the analysis addresses the often-neglected issue of endogeneity-related difficulties in the study of innovation-influencing factors. Of the limited welcome evidence that addresses the endogeneity issue, Arshed et al. (2022) employed a two-step robust system GMM estimation, this empirical analysis aims to identify determinants that influence a country’s innovation within developing MENA countries, thereby contributing to the closure of these research gaps.

6.4.3 Methodological Approach

6.4.3.1 Data Description and Sample Construction

The analysis utilizes annual data for middle-income countries as per the WB classification by income group. This classification bifurcates middle-income countries into two strata: lower middle-income economies, characterized by a Gross National Income (GNI) per capita ranging from $1,046 to $4,095, and upper middle-income economies, identified by a GNI per capita between $4,096 and $12,695 for the fiscal year 2021. Consequently, the total enumeration of middle-income countries amounts to 108. The focus on middle-income countries is intentional, reflecting the classification of developing MENA countries in the preceding diagnostic analysis. Additionally, the dearth of available data for low-income countries posed constraints on expanding the sample to encompass all developing nations.

Nevertheless, some middle-income countries have been necessarily excluded due to considerations of data accessibility and consistency at the country level. Exclusions pertain to countries lacking innovation data (the dependent variable) or for those without available innovation data spanning at least five years within the research time frame. Countries deficient in data regarding other pertinent indicators (independent variables) are also omitted. Moreover, extreme outliers from the sample are identified and excluded. These outliers are defined as data points that deviate substantially from the interquartile range (IQR), specifically those exceeding Q1 (25th percentile) - 3 * IQR or Q3 (75th percentile) + 3 * IQR (Boukerche et al., 2020; Vinutha et al., 2018).

As a result of these methodological considerations, the final sample was narrowed down to 56 countries, as delineated in Table (6.2). This table further illustrates the distribution of the available time-points for the dependent variable across countries, thereby highlighting that the dataset constitutes an unbalanced panel. Within this context, the temporal frame extends from 2011 to 2021. The inception of the timeframe in 2011 is not arbitrary but is dictated by the availability of data pertinent to the dependent variable (innovation output), thereby constraining the analysis to this specific period.

Table (6.2): Middle Income Countries and Their Respective Number of Years for Dependent Variable.

Country	Number of years with data availability	Country	Number of years with data availability
1. Albania	11	**29.** Malaysia	11
2. Algeria	11	**30.** Mauritius	11
3. Argentina	11	**31.** Mexico	11
4. Armenia	11	**32.** Moldova	11
5. Azerbaijan	11	**33.** Mongolia	11
6. Belarus	10	**34.** Montenegro	10
7. Benin	10	**35.** Morocco	11
8. Bosnia and Herzegovina	11	**36.** Namibia	11
9. Botswana	11	**37.** Nepal	10
10. Brazil	11	**38.** Nigeria	11
11. Bulgaria	11	**39.** North Macedonia	11
12. Cambodia	11	**40.** Pakistan	11
13. China	11	**41.** Peru	11
14. Colombia	11	**42.** Philippines	11
15. Costa Rica	11	**43.** Russian Federation	11
16. Côte d'Ivoire	11	**44.** Senegal	11
17. Dominican Republic	10	**45.** Serbia	11
18. Egypt, Arab Rep.	11	**46.** South Africa	11
19. El Salvador	11	**47.** Sri Lanka	11
20. Georgia	11	**48.** Tajikistan	11
21. Guatemala	11	**49.** Tanzania	11
22. Guyana	5	**50.** Thailand	11
23. India	11	**51.** Tunisia	11
24. Indonesia	11	**52.** Turkey	11
25. Jamaica	11	**53.** Ukraine	11
26. Jordan	11	**54.** Uzbekistan	6
27. Kazakhstan	11	**55.** Vietnam	11
28. Kyrgyz Republic	11	**56.** Zimbabwe	10

Source: GII database in different years.

6.4.3.2 Variables Justification and Hypotheses

Innovation drivers are manifold, and identifying the determinants of innovation growth necessitates a methodological categorization. Thus, this analysis divides these drivers into demand side factors, represented by the entrepreneurial effect, and supply side factors, encapsulated by FDI and previous knowledge within the country. Additionally, the analysis considers the influence of institutional quality on innovation. The objective is to methodically examine the impact of entrepreneurship, FDI, and institutional quality on innovation output across selected middle-income developing countries. By utilizing cross-country panel data, the importance of each of these contributing factors is assessed.

6.4.3.2.1 The Dependent Variable

The innovation output subindex of the GII is employed as a surrogate for innovation output within a given country. This subindex is bifurcated into two pillars: the knowledge and technology outputs pillar, encapsulating the facets of knowledge creation, impact, and diffusion; and the creative outputs pillar, encompassing intangible assets, creative goods, services, and online creativity within a nation. Data pertaining to these pillars are extracted from the GII database, with availability commencing from 2011.

In the related literature, diverse measures have been invoked to capture innovation, ranging from R&D expenditures (Hasan & Tucci, 2010), patents (Canh et al., 2019; Kaasa et al., 2007), to growth of total factor productivity (Naceur et al., 2017). Despite the prevalence of patents as an innovation proxy in mainstream studies, its limitations as an all-encompassing measure of innovation output in a country have guided this analysis towards the adoption of the innovation output measure. This approach is aligned with studies such as Ortega and Serna (2020), advocating that research into innovation performance should extend beyond the mere quantification of patents to an examination of their impacts. Similarly, Canh et al. (2019) contended that patents, as a proxy for innovation, only furnish a partial depiction of innovation's functional role.

Although seldom employed in prior research, the output innovation proxy is justified in studies such as Bate et al. (2023); Boudreaux (2017); Kawabata and Camargo Junior (2020); and Omidi et al. (2020). Given the drawbacks associated with utilizing patents as a surrogate for innovation output, a rationale for selecting this measure is provided, contrasting it with the overall GII, thereby sidestepping the potential overlap with some independent variables employed in this empirical inquiry, such as government effectiveness, regulation quality, and human capital.

Consequently, to render a holistic assessment of innovation performance, this empirical investigation employs an array of criteria, extending from knowledge genesis to diffusion. The innovation output subindex is thus favoured, given its enhanced precision in mirroring the innovation outcomes and overall performance across countries.

6.4.3.2.2 The Independent Variables

Although extant empirical research on factors influencing innovation has elucidated a wide array of potential explanatory variables, the inclusion of all these factors remains impractical due to constraints related to resources and the occasional absence of pertinent data. The selection and measurement of the variables in the present empirical analysis are unmistakably shaped by prior empirical studies and the availability of relevant data.

Consequently, the explanatory variables in this chapter represent proxies for both supply-side and demand-side innovation determinants. In subsequent stages of the model, institutions are incorporated to furnish a more nuanced analysis, potentially guiding context-sensitive policy implications. Additional explanatory variables, such as growth rates of GDP and human capital, are integrated as controlled variables to augment the reliability of the estimation results. The dataset encompasses the following variables:

A. Supply-side Innovation Factors

As delineated previously, innovation policy instruments can actuate technological change from the supply side, impelled by technology and science, particularly through knowledge generation. In this empirical exploration, FDI and lagged value of prior innovation or knowledge constitute the supply-side factors under examination.

Based on scholarly discourse by Olsson (2000); Omidi et al. (2020); Proksch et al. (2017); Romer (1990); and Weitzman (1998), countries that leverage existing knowledge to engender new knowledge tend to yield greater innovative output. Given the cumulative nature of knowledge, extant knowledge becomes an indispensable prerequisite for the genesis of novel knowledge, rendering the lagged value a vital determinant of contemporary knowledge creation within any nation (Foray, 2004).

Regarding FDI, its influence on innovation development in host countries manifests through diverse channels. Loukil (2016) illustrated the multifaceted impact of FDI on technological innovation in host countries, including backward and forward linkages, competitive and demonstration effects, effects on human capital formation, and knowledge dissemination through brain (Berger & Diez, 2008). Prior empirical findings present an incongruous picture, with some scholars asserting the fundamental role of FDI in knowledge and technology transfer in developing nations such as Canh et al. (2019); De Mello Jr (1997); Erdal and Göçer (2015); Loukil (2016); Sivalogathasan and Wu (2014).

For instance, studies such as Erdal and Göçer (2015) and Paul and Feliciano-Cestero (2021) have detected a positive impact of FDI on innovation in selected developing nations, and others have empirically verified the positive and significant relationship between FDI and innovation (Fu & Yang, 2009; Omidi et al., 2020; Papageorgiadis & Sharma, 2016; Wang & Kafouros, 2009).

In contrast, some studies, such as Malik (2023), have demonstrated a negative impact of FDI on innovation in certain Asian countries during 2008–2017. Other research has concluded that FDI inward flows stimulate innovation in developing nations only when an adequate level of absorptive capacity exists (Mohamad & Bani, 2017; Haq, 2023). Furthermore, some scholars have disclosed no substantial impact of FDI on innovation (Connolly, 2003; Schneider, 2005).

In summation, despite burgeoning literature on this relationship, empirical consensus remains elusive. Therefore, to empirically gauge the effect of inward FDI on middle-income developing nations, net inflows of FDI, measured in U.S. dollars, are utilized, with data extracted from the World Development Indicators Database (WDI). The natural logarithm of this variable is considered. While some studies commonly employ inward FDI as a percentage of GDP as a proxy, others use the U.S. dollar measure (Erdal & Göçer, 2015) This analysis opts for FDI measured in U.S. dollars, given its superior data availability within the sample of countries. Finally, due to potential endogenous issues stemming from reverse causality, the lagged value is treated as an endogenous variable, whereas FDI is considered exogenous, consistent with most related research literature (Javorcik, 2004; Yue, 2022). Thus, the hypothesis is formulated as follows:

- H1: Supply-side innovation determinants are positively related to innovation output within the country.

B. Demand-side Innovation Factors

In the context of the myriad demand factors that drive innovation, entrepreneurial activity has emerged as a pivotal contributor to innovation, competitiveness, and economic development (Fernandes & Ferreira, 2022). The term “entrepreneur” traces its origin to the early 18th century, introduced by the French economist Richard Cantillon (Brown & Thornton, 2013). Since then, scholars across various disciplines within the social sciences have proposed diverse interpretations and definitions of entrepreneurship (Burnett, 2000). Among these, perhaps the most widely recognized definition dates back to Schumpeter’s work in 1934, where he identifies entrepreneurs as individuals who implement new combinations (innovations) (Schumpeter, 1934). In elucidating the innovation process, Schumpeter delineates four distinct roles: the inventor, the entrepreneur, the capitalist, and the manager (Stam, 2008).

Various other definitions articulate the entrepreneurial role within economic change. For example, the entrepreneur has been characterized as one who confronts and absorbs uncertainty (Knight, 1921), an innovator, an industrial leader, a decision maker (Schumpeter, 1934; Casson, 2003), an organizer and a coordinator of economic resources (Marshall and Marshall, 1920), an allocator of resources among alternative uses (Schultz, 1980), an arbitrageur alert to opportunities (Kirzner, 2015). Hébert and Link (1989) provides a conclusive definition to entrepreneur after presenting the contributions made by many scholars in the related literature such as Cantillon, Schumpeter, Schultz, and Kirzner as “someone who specializes in taking responsibility for and making judgmental decisions that affect the location, the form, and the use of goods, resources, or institutions” (P. 39).

The OECD, as cited in Ahmad and Hoffmann (2008), provides a more nuanced definition that encompasses three aspects: entrepreneurs, entrepreneurial activity, and entrepreneurship. Here, entrepreneurs are identified as individuals striving to generate value by discovering and capitalizing on new products, processes, or markets; entrepreneurial activity represents the human endeavour aimed at value creation through economic expansion; and entrepreneurship signifies the overarching phenomenon tied to entrepreneurial activity.

There has been a growing scholarly interest in exploring the relationship between entrepreneurship and various economic factors, such as job creation, competitiveness, economic growth, climate change reduction, and sustainable development (Acs et al., 2016; Shepherd & Patzelt, 2011; Wennekers & Thurik, 1999; Youssef et al., 2018).

Historically, the connection between innovation and entrepreneurial activity was first established by Schumpeter (1942). Building on Schumpeter's foundational insights, subsequent research has argued that innovation and entrepreneurship are intertwined, continuous, and complementary processes (Braunerhjelm et al., 2010; Landström et al., 2015; Zhao, 2005).

In terms of innovation development, Stam (2008) portrays entrepreneurship as a micro-driver for innovation growth, essential for translating knowledge spillovers into innovation and expansion (Ejdemo & Örtqvist, 2021). Across different stages of economic development, entrepreneurship is posited as an indispensable instrument for innovation (Acs et al., 2008).

Further, entrepreneurship can be seen as a demand-side factor in the innovation process. This perspective asserts that entrepreneurs, motivated by profit, drive innovation by demanding valuable innovative outcomes and allocating resources accordingly (Mises, 1998; Kontolaimou et al., 2016; among others). Omidi et al. (2020) explained that entrepreneurship activity is an essential factor that can create demand for innovation. The study differentiated between useful and useless innovation as a character of available innovation and in this sense, the entrepreneur is a representative of the economy (an economic actor) who makes decisions about which innovations are valuable and which ones are not at a given time and place. Thus, the entrepreneur first creates demand for innovation and after that re-allocates resources towards the useful innovations. Therefore, based on the above discussion, entrepreneurship is a demanding factor of the innovation process. This theoretical stance contrasts with the views of studies like Edler et al. (2016a), who classified entrepreneurship policy as supply-side oriented.

In the context of developing countries, empirical studies examining the link between entrepreneurship and innovation are scarce. Among the limited studies that do focus on this area, recognizing the significant positive effects of entrepreneurship in developing nations are Hamilton (2000); Parker (2004); Witt (2002); Youssef et al. (2018).

While most previous research has examined the relationship between entrepreneurship and innovation at the firm level (Pham et al., 2021), a handful of studies at the country level have also reported that entrepreneurship can significantly enhance economic growth and innovation (Kontolaimou et al., 2016; Breitenecker et al., 2017).

In literature, the measurement of entrepreneurship brings many conceptual and practical difficulties, chief amongst them being data availability and how it is measured (Urbano et al., 2019). Ahmad and Hoffmann (2008) highlighted that it is challenging to conceptualize and measure entrepreneurship especially in the context of developing countries. Relatedly, previous literature has outlined different divisions to entrepreneurship. Of these divisions, the difference between formal and informal entrepreneurship; and this is related to the registration status of the firm. Legal and illegal entrepreneurship that is related to entrepreneurship activities. The necessity/opportunity entrepreneurship, that is determined by the motivation for entrepreneurship activities either to avoid unemployment or to seek a profit (Desai, 2011). Finally, social and business entrepreneurship which is challenging to conceptualize and measure specifically in developing countries (Ahmad & Hoffmann, 2008).

However, despite the challenges in conceptualization and measurement, limited databases are designed to measure entrepreneurship. The OECD framework (Ahmad & Hoffmann, 2008); self-employment as a measure of entrepreneurship (Storey, 1991; Thurik et al., 2008); the Global Entrepreneurship Monitor (GEM) dataset (Reynolds et al., 2005) and the WB group entrepreneurship survey dataset (Klapper et al., 2010).

In the current chapter, although the importance of measuring the informal sector in the context of developing countries, due to data limitations, only formal entrepreneurship will be measured using the World Bank database. Within this database, entrepreneurship activities are captured through two main indicators: the entry rate and business density. The first indicator is the entry rate, and it is defined as new firms registered in the current year as a percentage of total registered firms. The second indicator is the business density which is determined by the number of registered firms per 1,000 working-age people, namely those ages 15–64. This measure provides well-established measures of formal entrepreneurship and thus is used as a proxy of formal entrepreneurship in this chapter. Furthermore, formal entrepreneurship is considered an endogenous variable to mitigate the risk of reverse causality (Omidi et al., 2020).

Based on the preceding discussion, we can hypothesize:

- H2: Formal entrepreneurship activity at the national level positively impacts innovation output.

A. Institutional Quality

Institutions are defined as “humanly devised constraints that structure political, economic, and social interaction” (North, 1991). North divides the institutional environment into formal and informal rules, emphasizing their importance as critical components of the external environment influencing firms. These institutions significantly impact firms’ decisions to innovate and, more broadly, a country’s economic development (Du, 2018).

In practical applications, Levchenko (2007) illustrated that a well-structured regulatory framework—comprising both official and informal rules and restrictions—clearly delineates property rights, ensures an equitable legal system, and reduces social and economic uncertainty. These features ultimately confer comparative advantages to both the firm and the country. In contrast, a weak institutional environment is characterized by issues such as information asymmetry, an inadequately trained workforce, trade restrictions, numerous administrative barriers, weakened property and judicial rights, and an unstable rule of law. These aspects have been extensively explored in theoretical and empirical studies on the institutional environment and innovation development (Pellegrino & Savona, 2017).

Theoretically, Lundvall (1992) posited that the effectiveness of a national system of innovation is determined by factors including institutional collaborative patterns. Observations from Freeman (1987) and others suggest that the institutional environment can either support or hinder innovative processes and knowledge spillovers. An advantageous institutional environment positively impacts firms' willingness to invest in R&D and the efficacy of public policies for innovation development (Rodríguez-Pose & Di Cataldo, 2015; Olsson, 2000).

The ongoing literature also incorporates intangible components of the institutional environment, such as culture, trust, shared values, and codes of conduct, and their effects on innovation performance (Capello, 1999; Capello and Faggian, 2005; Capello and Lenzi, 2018; Srholec, 2010).

Given the general consensus on the significance of institutions for innovation performance, attention has shifted towards examining institutional quality in terms of structure and effectiveness (Rodríguez-Pose, 2013). However, measuring the effects of institutional quality on innovation has proven challenging in prior studies (Tebaldi & Elmslie, 2013). Various proxies have been used to measure institutional quality, with some studies focusing solely on corruption as a univariate proxy, while others employ multivariate approaches (Efendic et al., 2009; Tebaldi & Elmslie, 2013).

The institutional theory highlights the role of exogenous institutional factors in shaping innovation (Arshed et al., 2022; Karri & Goel, 2006). Several empirical studies have underscored the strong influence of institutional quality on innovation growth and broader economic and social development

On the other hand, some studies found no direct positive impact of democracy on innovation performance (Gao et al., 2017) or argued that more stringent intellectual property rights schemes can hinder innovation development (Sweet & Maggio, 2015). The power of politicians to resist technological change has also been theoretically examined (Acemoglu & Robinson, 2000).

These conflicting findings highlight the empirical ambiguity of the institutional variable. Some researchers have identified this gap in the literature, calling for a more comprehensive empirical analysis of the relationship between institutional quality and innovation (Arshed et al., 2022).

Several research gaps emerge from the current literature:

First, the relationship between institutional quality and innovation may not be linear. A Kuznets curve may better represent the relationship, with innovation outputs initially increasing with institutional development, then declining due to tighter legal requirements and regulatory restrictions (Cole, 2004; Kuznets, 1955; among others). Leys (1965) articulated that with the development of institutions, after a certain point, the hypothesis of money speed is applied, in which bribes and favours may serve as fuel/greasing to the bureaucracy engine i.e., expedite the bureaucratic procedures. This positive association between corruption and investment is explained by many studies such as Campos et al. (1999); Moustafa (2021); Rock and Bonnett (2004).

Amore clarified explanation could be introduced by the theory behind the Pollution Haven Hypothesis (PHH). According to this hypothesis, businesses migrate to poor developing nations to take the advantages of weaker institutions and reduced compliance costs. Additionally, more developed nations with strong institutions may be able to foster better businesses, however, if these restrictions and regulations are overly rigid, they may ultimately result in less innovation (Arshed et al., 2022). This interpret why businesses and firms migrate to nations whose institutions are less developed (Cole, 2004). Therefore, in this chapter, it is argued that institutional quality could have a non-linear relationship with innovation analysed over a time period and with a country's degree of development.

Second, the direction of the relationship between institutions and innovation development is still debated. While mainstream studies often find a significant positive relationship, others report negative or no relationships (Canh et al., 2019; Kawabata & Camargo Junior, 2020; Koçak, 2017; Bariş et al., 2019; Barra & Ruggiero, 2022; Gabsi et al., 2008). Additionally, most empirical investigations focus on developed countries, leaving room for further exploration in developing countries (D'Ingiullo & Evangelista, 2020; Koçak, 2017).

Third, only a limited number of scholars argue for an inverted U-shaped relationship between institutions and innovation. Mainstream studies neglecting the Kuznets curve may lead to unjustified results. Only limited welcome exceptions found in the previous empirical studies highlighted the U-shaped relation between institutions and economic performance (Lehne et al., 2014) and between institutions and innovation (Arshed et al., 2022; Lerner, 2009; Qian, 2007). These studies demonstrated that mature institutions gradually increase businesses compliance costs. To elaborate more, Lerner (2009) demonstrated that innovation activities decrease in situations where IPR regulations are already tight by improved IPR protocols. This relationship is initially positive for IPR protection, but it quickly turned to negative relationship for long-term innovation activities.

In conclusion, the literature reveals a complex and multifaceted relationship between institutional quality and innovation. Understanding this relationship requires nuanced analysis, taking into consideration potential non-linearity, different developmental contexts, and the intricate dynamics of institutional factors. This study aims to contribute to this understanding by exploring the following hypotheses:

- **H3**: Upgrading institutional quality has a positive effect on innovation, whether a linear or non-linear relationship exists.
- **H4**: Institutional quality exhibits an inverted U-shaped relationship with innovation output.

Fourth, a gap in the literature exists in understanding the mechanisms through which institutions influence innovation development. Specifically, the channels through which the institutional environment may affect innovation performance remain ambiguous. This lack of clarity might be attributed to the diversified measures adopted in related literature. Previous research has primarily focused on one or two proxy characteristics, neglecting the comprehensive relationship between all institutional dimensions and innovation (Ahmad & Hall, 2023; Lehne et al., 2014). Moreover, these studies have often overlooked the subdivision of institutions into political and economic categories, as illuminated in a few specific works.

For example, D'Ingiullo and Evangelista (2020) empirically demonstrated a positive effect of the institutional environment on innovation performance, proxied by only three channels: voice and accountability, regulatory quality, and government effectiveness. Additionally, other investigations have revealed diversified effects depending on the specific institutional dimension being analysed. Bariş (2019) found that innovation is positively correlated with voice and accountability, political stability, and the absence of violence and rule of law. Conversely, it is negatively related to control of corruption, and there is no relationship between government effectiveness, regulatory quality, and innovation in a sample of OECD countries from 2002 to 2016. A detailed explanation is presented in Appendix (XVII). Furthermore, De Waldemar (2012); Goedhuys et al. (2016); Mahagaonkar (2008) posited that corruption negatively affects innovation activities, while, Huntington (2006) argued that the relationship between corruption and innovation is positive.

In the empirical analysis undertaken in this chapter, the quality of institutions is assessed using the Worldwide Governance Indicators (WGI), conceptualized by Kaufmann et al. (2005). This database encompasses a full spectrum of institutional dimensions and is considered the most accurate, reliable, and widely applied measure of institutional quality in innovation literature (Dollar & Kraay, 2003; Rodríguez-Pose and Di Cataldo, 2015), despite some criticisms (Thomas, 2010).

The WGI database identifies and evaluates six dimensions of institutional quality: control of corruption, governance effectiveness, regulatory quality, rule of law, voice and accountability, and political stability and absence of terrorism, as detailed in Table (6.26). These dimensions enable an assessment of the impact of each institutional quality aspect on innovation output. These aggregate dimensions consist of several hundred sub-indices compiled from various databases. Moreover, the WGI database draws from interviews reflecting diverse viewpoints from public, private, and non-governmental organization experts on governance.

Table (6.3): Dimensions of World Bank Governance Indicators.

Dimension	Definition	Related Literature	Expected Sign	Abbreviation
Control of corruption	Measures the extent to which public power is used to derive private gain, by considering both small (petty) and large forms of corruption. It also accounts for the management of the State by elites and for deriving private interests. Additionally, the precautions taken against corruptions is	(Anokhin & Schulze, 2009; Lee et al., 2020; Paunov, 2016; Veracierto, 2008)	+	Coru.

Dimension	Definition	Related Literature	Expected Sign	Abbreviation
	also considered.			
Government effectiveness	Measures the quality of the bureaucracy and the quality of public service delivery. Issues such as the capacity of the public function; its independence from political pressures; and the quality of policy formulation are taken into consideration.	(Jiao et al., 2015; Sivak et al., 2011; Wen et al., 2021)	+	Goveff.
Political stability and absence of violence/terrorism	Measures the probability that the government will be damaged by violent affairs, changes in government that is unconstitutional including terrorism.	(Allard et al., 2012; Leydesdorff & Meyer, 2006; Varsakelis, 2006; Waguespack et al., 2005)	+	Political.
Regulatory quality	Measures the extent of market-unfriendly policies i.e., the ability of the government in providing strong policies and regulations that promote the development of the private sector. Issues such as measurement of heavy loads; high level of price controls are considered.	(Boschma, 2005; Hansen, 1992; Rantisi, 2002)	+	Regul.
Rule of law	Measures the extent to which agents trust and accept the rules of society. This includes contract enforcement and property rights, the police, the courts, as well as the likelihood of crime and violence.	(Daniele & Marani, 2011; Rodríguez-Pose & Di Cataldo, 2015)	+	Law.
Voice and accountability	Measures the extent to which citizens participate political elections. It also includes measures of freedom of expression, freedom of association and freedom of the press.	(Crivits et al., 2014; Daniele & Marani, 2011; Edwards et al., 2018; Nadeem et al., 2020)	+	Voice.

Source: Kaufmann et al. (2005) and other related literature collected in column 3.

In the WGI dataset, estimates range from -2.5 (indicating weak governance) to +2.5 (indicating strong governance), providing an aggregate indicator score for each country. The percentile rank, ranging from 0 to 100, signifies a country's relative standing, where 0 implies the lowest rank and 100 the highest (Kaufmann et al., 2009). Both measures have been employed in previous empirical research, with some studies using the estimate (Bakhsh et al., 2021; Bariş, 2019; Canh et al., 2019) and others the percentile ranking (Tran-Nguyen, 2015; Meressa, 2022). In this analysis, the percentile ranking is preferred, as it facilitates comparisons among countries.

Thus, in this chapter, the simple average of these six institutional dimensions is considered as a proxy for institutional quality. A potential strategy (to prevent endogeneity while building the institutional quality index for the global innovation index) is to employ external or objective variables which are unaffected by the innovation results they are intended to measure i.e. an instrumental variables approach. Finding variables that are connected with the institutional quality index but unrelated to innovation outcomes is the first step in employing instrumental variables to adjust for endogeneity. The exogenous variance in institutional quality is then separated out using instrumental variables. Other methods that have been employed include the construction of composite indicators, expert surveys, historical data, using objective indicators. All these methods create an institutional quality index that may characterise the institutional environment regardless of the innovation performance being measured, thus the risk of endogeneity is decreased (Dutta et al., 2016). To this end, it is concluded that given the method of constructing this proxy, potential endogeneity and reverse causality are mitigated. Consequently, this institutional proxy is treated as an exogenous variable (Efendic et al., 2009).

The study leads to the following hypothesis:

- H5: Institutional channels exert an asymmetric effect on innovation output.

B. Controlled Variables

To rigorously assess the dynamic relationship between selected independent variables and innovation, this empirical analysis incorporates additional variables. These are variables that have been theoretically and empirically demonstrated to influence innovation, either directly or indirectly. They have been integrated into the analysis to control their potential effects on innovation. Among the main controlled variables employed in prior studies to minimize estimation bias are

GDP growth and human capital, both of which are utilized in this analysis.

GDP Growth: GDP growth is incorporated into the econometric model to signify the level of economic expansion within a country. This is quantified by the annual percentage growth rate of GDP. Research has posited that countries experiencing sufficient growth levels are more likely to encourage R&D activities by providing necessary resources such as funds, databases, software, expertise, and international collaboration, all of which enhance innovation (Inglesi-Lotz et al., 2018; Omidi et al., 2020). GDP growth is treated as an endogenous variable, recognizing the possible reverse causality between GDP growth and innovation (Çetin, 2013; Pradhan et al., 2017).

Human Capital: Human capital is also included in the analysis as a controlled variable. A country's human capital can be gauged by its populace's level of education, a critical factor in the development and dissemination of innovation. The significance of human capital in fostering innovation has been thoroughly discussed in previous studies (Fu & Yang, 2009; Lenihan et al., 2019; Qureshi et al., 2021; among others). For example, Arshed et al. (2021) revealed that greater capacities for knowledge synthesis and collaborative formation signify robust human capital, thereby enhancing the environment conducive to innovation. Krammer (2009) highlighted that skilled labour contributes to the creation of innovative products and efficient production techniques. Moreover, D'Este et al. (2014) argued that human capital mitigates barriers to innovation, particularly those related to knowledge deficits.

Inclusion of human capital as a variable is also substantiated by other related empirical studies, such as Canh et al. (2019) and Omidi et al. (2020). These works collectively contend that an increase in human capital augments the potential for innovation. In this empirical analysis, human capital is conceptualized as the mean of education and tertiary education scores, with data extracted from the GII. A comprehensive summary of the rationale for including all variables in this empirical analysis is provided in Appendix (XVIII).

6.4.3.3 Descriptive Analysis and Correlation

Table (6.4) provides a summary of the descriptive statistics for the variables employed in this empirical analysis over the period from 2011 to 2021. The table enumerates the mean, standard deviation, and the maximum and minimum values for each variable.

Table (6.4): Descriptive Statistics.

Variable	Obs	Mean	Std. Dev.	Min	Max
INN	599	25.111	7.677	5.6	52.8
Ln_FDI	589	21.418	1.753	15.856	26.534
GDPg	599	3.391	4.007	-9.71	17.278
HC	599	36.073	11.173	5.805	64.445
ENT	517	2.224	2.938	.031	20.091
IQI	599	41.251	14.648	6.384	77.961

- **Innovation Output:** The average number of innovation outputs for the developing middle-income countries stands at 25.11, with a standard deviation of 7.67, a minimum value of 5.6, and a maximum value of 52.8.
- **Foreign Direct Investment (Ln FDI):** This variable exhibits a mean of 21.41 and a standard deviation of 1.75, with a minimum value of 15.86 and a maximum value of 26.53.
- **Entrepreneurship:** On average, entrepreneurship has a value of 2.22, a standard deviation of 2.93, and spans a range from a minimum of 0.03 to a maximum of 20.09.
- **Human Capital:** Incorporated as a proxy to control for human capital and level of development in a country, this variable has a mean value of 36.07, a standard deviation of 11.17, and ranges from 5.80 to 64.44.
- **GDP Growth Rate:** These variable records an average value of 3.39% and a standard deviation of 4.007%, extending from a minimum growth rate of −9.71% to a maximum of 17.27%.
- **Institutional Quality Index (IQI):** The index averages at 41.25, with a standard deviation of 14.64, and ranges from 6.38 to 77.96.

Table (6.5) elucidates the correlation matrix between all variables used in this empirical analysis. It reveals that the correlation between variables is generally weak. A notable exception is the association between IQI and Entrepreneurship (ENT), which exhibits a correlation level of 54.5%.

Additionally, due to the panel structure of this dataset, it is vital to delineate the variations within time and between countries, as emphasized by Taylor (1980), and as presented in Table (6.6). Except for GDP growth, where most variation occurs within time, most of the dataset's variations are observed between countries.

Table (6.5): Pairwise Correlations.

Variables	INN	Ln_FDI	GDPg	HC	ENT	IQI
INN	1.000					
Ln_FDI	0.422	1.000				
	(0.000)					
GDPg	0.095	0.080	1.000			
	(0.020)	(0.053)				
HC	0.310	0.063	-0.144	1.000		
	(0.000)	(0.126)	(0.000)			
ENT	0.163	-0.083	-0.069	0.293	1.000	
	(0.000)	(0.063)	(0.116)	(0.000)		
IQI	0.280	-0.003	-0.097	0.234	0.545	1.000
	(0.000)	(0.939)	(0.018)	(0.000)	(0.000)	

Table (6.6): Between and Within Variations in the Dataset.

Variable		Mean	Std. dev.	Min.	Max.	Observations
INN	**overall**	25.111	7.677	5.6	52.800	N = 599
	between		6.617	13.465	49.006	n = 56
	within		4.007	14.728	41.398	T-bar= 10.696
Ln FDI	**overall**	21.418	1.753	15.856	26.534	N = 589
	between		1.680	18.386	26.195	n = 56
	within		0.527	17.864	23.596	T-bar= 10.518
GDPg	**overall**	3.391	4.007	-9.710	17.278	N = 599
	between		1.807	-0.240	7.056	n= 56
	within		3.584	-10.938	16.425	T-bar= 10.696
HC	**overall**	36.073	11.173	5.805	64.445	N = 599
	between		10.068	12.567	56.358	n= 56
	within		5.025	2.993	59.205	T-bar=10.696
ENT	**overall**	2.224	2.938	0.031	20.091	N = 517
	between		2.784	0.069	14.794	n = 56
	within		0.753	-2.635	7.520	T-bar = 9.232
IQI	**overall**	41.251	14.648	6.384	77.961	N = 599
	between		14.531	9.756	75.597	n = 56
	within		2.943	28.122	53.066	T-bar = 10.696

Multicollinearity among explanatory independent variables is meticulously diagnosed using two tests: the correlation coefficient and variance inflation factors (VIFs) (Weisberg, 2005). Firstly, none of the correlation values between independent variables exceed 0.90, as per Table (6.28), thus affirming the absence of multicollinearity. Secondly, all VIF values remain below the prescribed maximum limit of 10, as seen in Table (6.7), corroborating the non-occurrence of multicollinearity (Neter et al., 1989).

Table (6.7): Variance Inflation Factor

	VIF	1/VIF
ENT	1.495	.669
IQI	1.472	.679
HC	1.154	.867
GDPg	1.055	.948
Ln FDI	1.024	.976
Mean VIF	1.24	.

6.4.3.4 Estimation Method: System GMM

This section of the analysis leverages longitudinal models, also known as panel models, to investigate the temporal dynamics of innovation within middle-income countries included in the sample. Unlike cross-sectional methods, which aggregate time-series, longitudinal models allow for a nuanced examination of the heterogeneity that exists between different countries.

Since the empirical analysis is founded on a panel dataset, the initial procedure is to perform regression using ordinary least squares (OLS), fixed effects (FE) models, and random effects (RE) models. Both the FE and RE models take into consideration the variability and time-related biases among countries. Specifically, the FE model addresses unobserved individual characteristics (unobserved heterogeneity), while the RE model formulation assumes that group effects are normally distributed across all groups (Varsakelis, 2006). The FE model builds upon the assumption of systematic differences across countries and assumes correlations between the observed explanatory variables and the constant terms. In contrast, the RE model presumes no such correlation (Gujarati, 2022). The choice between these two models is often guided by the Hausman test, with its null hypothesis favouring the RE over the FE model (Hausman, 1978).

Research focused on empirically exploring innovation drivers has found statistically significant effects for past values of the variables (Bate et al., 2023; Canh et al., 2019; Omidi et al., 2020). Therefore, the lagged value of innovation is included in the current analysis to reflect the accumulative nature of the innovation process. However, the introduction of the lagged dependent variable as an independent variable creates a dynamic dataset, leading to potential endogeneity through the feedback mechanism (Chesher, 1979).

OLS has limitations in this context , notably its inability to effectively manage endogeneity among the variables, leading to biased and inconsistent estimations (Arellano & Bover, 1995). Endogeneity arises because of the inclusion of the lagged dependent variable is included as an independent variable. Another possible source causes endogeneity is the possible endogeneity that exists among the explanatory independent variables (more specifically due to the possible effect of institutional quality on both FDI and innovation output level).Furthermore, the static nature of the OLS, RE, and FE models and the specific time structure of the data (11 years, less than the number of cross-sectional units) make them inappropriate for accurate parameter estimation (Baltagi, 2008; Lee, 2007).

The presence of endogeneity is a persistent issue, with potential sources including possible endogeneity among the explanatory independent variables and dependencies between transformed lagged dependent variables of innovation and error terms (Nickell, 1981; Hsiao & Tahmiscioglu, 2008). Consequently, static estimators like OLS, RE, and FE models are inconsistent (Cameron & Trivedi, 2005). In this scenario, it is prudent to consider dynamic longitudinal models.

While the instrumental variable estimator is a possible solution for endogeneity, finding valid instruments suitable for panel analyses and validating them conceptually and theoretically remains a significant challenge (Bound et al., 1995). Moreover, the strongly unbalanced character of the data necessitates a model capable of handling the longitudinal dynamics of the innovation values.

The Generalized Method of Moments (GMM) technique, introduced by Arellano–Bond (Arellano & Bond, 1991) and Arellano–Bover/Blundell–Bond (Arellano & Bover, 1995; Blundell & Bond, 1998), is adopted for this analysis. The GMM method is a generic technique that offers a sophisticated approach to parameter estimation, controlling for potential endogeneity and unobserved heterogeneity. It is particularly suitable for samples with a small-time dimension and large panels (Mileva, 2007).

Roodman (2009a) highlighted that difference and system generalized method of moments are extensively used and are appropriate for situations, first, with few time periods (i.e., small T) and many individuals (i.e., large N panels). Second, a linear functional relationship. Third, the dependent variable is dynamic and is depending on its own past realizations. Fourth, independent explanatory variables are not strictly exogenous. This means that these independent explanatory variables are correlated with past and may be correlated with the current realizations of the error. Fifth, situation in which fixed individual effects exists. Finally, situations in which heteroskedasticity and autocorrelation within individuals exists but not across them.

The mechanism of this technique is to account for the impact of previous values of the dependent variable, this method uses lags of the dependent variable as explanatory variables. Thus, lagged dependent variable values are employed as internal instruments to control for this endogeneity. This means that endogeneity is removed by the GMM estimator through transforming the data internally. This transformation is a statistical process. It is done by subtracting the variable's past value from its current value. This internal transformation lowers the number of observations, which boosts the effectiveness of the GMM model (Wooldridge, 2015). This is called difference GMM estimator and is proposed by Arellano and Bond (1991). Though, difference GMM estimator is biased and imprecise (Blundell & Bond, 1998)

To eliminate this imprecision and bias, the second order transformation, as advised by Arellano and Bover (1995) and Blundell and Bond (1998) was taken into consideration to avoid any potential loss of data as we are dealing with strongly unbalanced data. This is an extension of Arellano–Bond estimator. Instead of just deducting the current value from the previous value, this transformation applies orthogonal deviations. In this transformation the average of all future observations of a variable is subtracted from its current value instead of only subtracting from the previous observation (Roodman, 2009a).

In this extension, an extra assumption is applied that is the first differences of the instrument variables have no correlation with the fixed effects (Baltagi, 2008). This estimator is known as system GMM, and it introduces a system of equations that includes the original equation (at levels) and the transformed equation (in first differences). Roodman (2009b) highlighted that in the system GMM the lagged first differences of the regressors are treated as instruments for the original equation'. Roodman (2009b) demonstrated that the lagged levels of the regressors are used as instruments in the transformed equation. This method is the most powerful dynamic panel data estimator.

Additionally, the two-step system GMM introduces more efficient estimators than the one step (Valenta et al., 2021) and thus is applied in this empirical section. Therefore, in this empirical investigation, only the two-step System GMM estimates that yield theoretically robust estimations will be reported, and the robust Hansen-j test could be obtained as well (Roodman, 2009b). Additionally, in the two step system GMM procedure, a sample of small panel may yield "downward bias of the estimated asymptotic standard error" (Baltagi , 2008, p.154). As a solution to this, the Stata command small is added to estimate corrected results through implementing the Windmeijer correction (Baltagi, 2008).

Consequently, based on the theoretical framework we can parameterize the GMM model under consideration as follows:

$$INN_{it} = \varphi \; INN_{it-1} + \beta X_{it} + (\; \eta_i + \varepsilon_{it}) \tag{6.1}$$

Where subscript $_{it}$ refers to the panel structure in which $_i$ refers to the cross-section unit and $_t$ refers to the time period. INN_{it} is the innovation as a dependent variable, X_{it} is a vector of the independent variables, φ is the autoregressive parameter, η_i is the unobserved fixed effect and ε_{it} is the idiosyncratic shocks normally distributed with zero mean and constant variance. Additionally, the error term consists of two error component structures, in which E (η_i) = 0; E (ε_{it}) = 0; E ($\eta_i \varepsilon_{it}$) = 0 and E (ε_{it} ε_{its})= 0

Year dummies variables are added in all specifications to control the time-specific effects and thus reducing the influence of cross-sectional error dependence in the dynamic panel model. Kripfganz and Schwarz (2019) highlighted that time dummies are strictly exogenous and uncorrelated with the country-specific effect. Therefore, time dummies can be used as instruments by themselves. The same study argued that time dummies should be included by default unless there is no clear exception against their use. Further, GDP growth rates and human capital are used as controlled variables to capture the overall economic and social context.

System GMM has the advantages of using moment conditions, which are functions of the model parameters and the data. These moment conditions have an expectation of zero at the true values of the parameters. System GMM accounts for measurement errors, omitted variable bias, unobserved heterogeneity, and endogeneity of the lagged dependent variable in a dynamic panel model, which occurs when there is a correlation between the explanatory variable and the error term in a model. Thus, in this approach a system of two equations is evaluated. The first equation is the original one and is expressed in levels' using with first differences as instruments. Thus, it transforms all aggressors through subtraction. Therefore, fixed effects that do not vary over time are removed. The second equation is a transformed equation with levels as instruments and is expressed in a first-difference form.

To elaborate more: the equation in differences is $\Delta INN_t = INN_{t-2} - INN_{t-1}$ and equation in levels is $INN_t = INN_{t-1}$; $INN_{t-(n-1)} = INN_{t-n}$. In this case the instrument of $INN_{t-(n-1)}$ is INN_{t-n}. In addition, we used one or two lags rather than all the available lags for instruments in system-GMM estimators, as explained in Roodman's approach, to reduce the issue of instrument proliferation (Roodman, 2009a).

To test the accuracy of GMM result the rule of thumb is that the number of instruments must be less than or equal to the number of groups (i.e., countries) (Mileva, 2007; Roodman, 2009b). Additionally, two post estimation tests must be conducted for consistent results, that is the validity of over identifying restrictions and the serially uncorrelated error. To clarify, the first test is the Arellano–Bond test for serial correlation. According to the null hypothesis of this Arellano–Bond test, the residuals are serially uncorrelated. If the null hypothesis is accepted, it means that there is no second-order serial correlation, proving the accuracy of the GMM results.

The second post estimation test is Hansen J-test by Hansen (1982). This test is used to evaluate the validity of the additional moment restriction needed for system GMM as well as the null hypothesis of instrument validity. Accepting the null hypothesis gives reliability to the instruments. In a similar context, Bond

(2002) provides further evidence for the consistency of system GMM estimators by high- lighting that system GMM results frequently fall within the upper and lower bounds provided by the OLS and fixed effects values.

Additionally, another test introduced in the literature for instrument validity is the Sargan test (Sargan, 1958). In prior studies either Sargan test or Hansen J-test are usually used. Despite Sargan test appropriateness, it is less reported in the empirical studies (Iqbal & Daly, 2014). Hakimi and Inglesi-Lotz (2020) is of the limited study founded used Sargan test.

The proposed model used is implemented using STATA software, more specifically the user written command namely xtabond2 for executing the system GMM estimator (Roodman, 2020). In this model, collapsing option is used to reduce the number of instruments. Further, the small option is employed, to inform Stata to apply the small-sample correction, report t-statistics rather than z-statistics, and use the F test rather than the Wald chi-squared test. Furthermore, the robust extension is used to provide that the resulting standard errors in one-step estimation are consistent with panel-specific autocorrelation and heteroskedasticity.

Additionally, the two steps option is used to inform Stata to employ the two-step estimator rather than the one-step estimator. The standard covariance matrix in two-step estimation is robust to panel-specific autocorrelation and heteroskedasticity, but the standard errors are downward biased (Yaffee, 2003). Thus, to obtain the finite-sample adjusted two-step covariance matrix, twostep robust is employed.

6.5 Estimation Results

6.5.1 Testing the First and Second Hypotheses

In this subsection, two principal hypotheses are examined and subjected to empirical testing:

- **H1**: Supply-side determinants of innovation are positively related to innovation output within the country.
- **H2**: Formal entrepreneurship activity at the national level positively influences innovation output.

To assess these hypotheses, the specified econometric model to be estimated is given by the following equation:

$$INN_{it} = \varphi INN_{it-1} + \beta_1 GDP_g + \beta_2 HC + \beta_3 ENT + \beta_4 \text{ Ln\_(FDI)} + (\eta_i + \varepsilon_{it}) \quad (6.2)$$

In Equation (6.2), INN represents innovation as the dependent variable, with INN_{it-1} denoting the one-year lag of the dependent variable. The variable GDP_g symbolizes the growth rate of GDP, HC is indicative of human capital, ENT represents entrepreneurship activity, and Ln_(FDI) is the natural logarithm of FDI. Furthermore, η_i is the country-specific effect, and ε_{it} is the error term. The coefficients β_1, β_2, β_3, and β_4 are the parameters to be estimated.

The expectation is that φ, β_1, and β_2 will be positive, reflecting the understanding that lagged values of innovation, growth rate of GDP, and human capital serve as promoters of innovation activity. However, based on previous related studies, the coefficients β_3 and β_4 may assume either positive or negative values, reflecting the complexity and multifaceted nature of their relationships with innovation output.

The following sub-sections present the estimation results, interpreting the findings in light of the proposed hypotheses and contextualizing them within the broader theoretical framework of innovation economics.

Table (6.8) presents the results of the initial model. The F-statistics emerge as statistically significant, thereby substantiating that the model can explain the innovation process in a substantial manner. Notably, the one-year lagged variable of innovation (denoted as L.INN) exhibits a positive correlation with the dependent variable (INN) and is statistically significant at the 1% level. This variable also exerts the largest influence among the explanatory variables, with a coefficient of 0.502. Such an observation underscores that current innovation is positively contingent on the innovation of the preceding year.

Regarding the impact of FDI on innovation, the analysis reveals a positive and statistically significant influence from inward FDI on innovations, significant at the 5% level. However, the results indicate an insignificant relationship between entrepreneurship and innovation, mirroring the same insignificant result for the correlation between growth rates and innovation output. In contrast, human capital emerges as statistically significant at the 5% level, exhibiting a positive effect on innovation. This finding suggests that greater educational attainment within a country's human capital pool enhances the level of innovation therein. Consequently, a substantial proportion of innovation can be attributed to the lagged value of innovation, FDI, and human capital. These positive coefficients align with a priori expectations drawn from the theoretical framework of innovation drivers, corroborating the empirical findings of Canh et al. (2019) and Omidi et al. (2020).

Table (6.8): Dynamic Panel-Data Estimation, Two-Step System GMM (Model 1).

Independent Variables	Coef.	St.Err.	t-value	p-value	Sig.
L.INN	.502	.179	2.80	.007	***
GDPg	.188	.201	0.94	.352	
HC	.075	.031	2.43	.019	**
ENT	.345	.24	1.44	.157	
Ln_FDI	.941	.394	2.39	.02	**
year	-.49	.203	-2.41	.019	**
y3	1.604	.862	1.86	.068	*
y4	-.026	.941	-0.03	.978	
y5	.529	.817	0.65	.52	
y6	-1.406	.833	-1.69	.097	*
y7	-.127	.955	-0.13	.895	
y8	-.052	1.13	-0.05	.964	
y9	.329	1.226	0.27	.789	
Constant	976.078	407.882	2.39	.02	**
Number of observations	457				
Number of instruments	34				
Number of groups (i.e., countries)	56				
F-test **Prob > F=**	59.39 (0.000)				
Arellano-Bond AR (1) test: (P-value)	-2.93 (0.003)				
Arellano-Bond AR (2) test: (P-value)	1.12 (0.261)				
Hansen test of over identification restrictions (P value)	23.69 (0.256)				

Notes: *** p< .01, ** p< .05, * p< .1; L.INN means lagged value of the dependent variable (innovation); Four instrument(s) y1, y2, y10, y11 are dropped because of collinearity; The command xtabond2 is used using STATA 17 software; Twostep robust small nomata options are employed.

As previously emphasized, the reliability of these GMM estimators' results is corroborated by two widely employed tests: the Hansen J test, and the Arellano–Bond test for second-order autocorrelation. The latter provides no evidence of second-order autocorrelation in the system GMM estimators (Prob > z = 0.261), though the first order in the difference GMM (Prob > z = 0.003) does confirm the expected presence of serial correlation. Furthermore, the result of the Hansen test attests to the validity of the instruments. Therefore, in light of valid instruments and the absence of autocorrelation, the system GMM dynamic estimators are deemed efficient. As a robustness check, FDI as a percentage of GDP, as a proxy for inward FDI, was also employed; this metric yielded consistent results. But the selected FDI measure (FDI in U.S. dollar) is chosen due to its superior data availability across the sample of countries analysed.

In conclusion, the first hypothesis—pertaining to the positive effect of supply-side determinants—is accepted, while the second hypothesis—related to the positive effect of demand-side determinants—is rejected. This outcome signifies that supply-side innovation factors (e.g., L.INN, FDI) exerted the most significant influence on innovation during the study period. Moreover, it affirms that demand-side factors (such as ENT) had no discernible effect on innovation performance, a conclusion consistent with numerous studies advocating a supply-side approach, such as Robertson et al. (2021).

6.5.2 Testing the Third and the Fourth Hypothesis

In this model specification, the following two hypotheses are tested:

- $H3$: Upgrading institutional quality has a positive effect on innovation, and either a linear or nonlinear relationship exists.
- $H4$: Institutional quality constitutes an inverted U-shaped relationship with innovation output.

Firstly, the non-linear relationship between institutions and innovation is introduced and tested. Then, the institutions are incorporated into the original model (equation (6.1)) to assess their effect on innovation output.

The investigation begins by questioning whether the relationship between institutional quality and innovation output is nonlinear. A nonlinear institutional quality-innovation framework is constructed to explore the ongoing debate regarding this relationship. Mathematically, a standard quadratic relationship between institutional quality and innovation is considered, as seen in Table (6.9). Graphically, Figure (6.1) illustrates the nonlinear relationship between innovation and institutional quality, represented by the quadratic fit between INN and IQI. It is noticed that the relationship between IQI and INN is nonlinear. Further, the nonlinear U-shaped relationship is validated using the U-test by Lind and Mehlum (2010).

The U-test jointly examines if the relationship between the dependent and threshold variable increases at low values and decreases at high values within samples. This method mitigates erroneous inferences when the calculated extremum point lies close to the data range's endpoint, unlike the conventional method for verifying nonlinear regression, which may falsely imply a nonlinear relationship if the true relationship is convex but monotonic. Therefore, it is essential to take into consideration the specific characteristics of the data and the underlying relationship to opt for the suitable modelling techniques that convey the true nature of the relationship (Law et al., 2018)

If the U-test indicates significant test statistics, then the relationship is confirmed as nonlinear. If β_1 is negative and β_2 is positive, a U-shaped nonlinear relationship exists between institutional quality and innovation output. Conversely, if β_1 is positive and β_2 is negative, an inverted U-shaped relationship occurs. In this dataset, an inverted U-shape characterizes the nonlinear relationship between institutional quality and innovation, as depicted in Table (6.9) and Figure (6.1).

Figure (6.1): Curve Estimation Between INN and IQI.

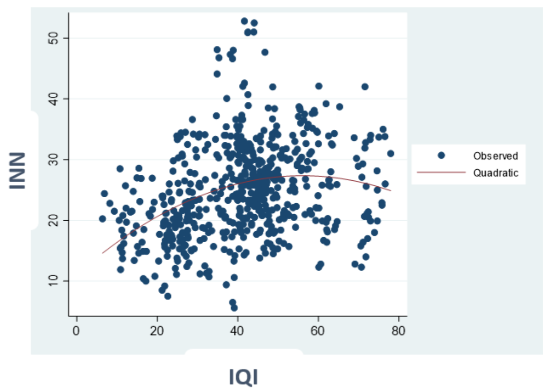


Table (6.9): Parameters of the Curve Fit Estimation Between INN and IQI.

Variable	Quadratic
b_0 _cons 	11.119 6.140 0.000
b_1 _cons 	0.579 6.540 0.000
b_2 _cons 	-0.005 -5.010 0.000
Statistics N r^2_a	 599 0.113

Notes: In the above figure (6.1), the behaviour of the relationship between INN as a dependent variable and IQI as an independent variable is presented. In table (6.9), b_0 is the constant term; b_1 is the slope of the linear relationship between the two variables; b_2 is the coefficient of the quadratic relationship between the two variables; N is the number of observations and the r^2_a is the adjusted r squared.

Based on these results, the relationship between institutional quality and innovation can be expressed as a standard quadratic form, extending equation (6.2):

$$INN_{it} = \varphi INN_{(it-1)} + \beta_1 GDP_g + \beta_2 HC + \beta_3 ENT + \beta_4 \ln(FDI) + \beta_5 IQI_{it} + \beta_6 IQI_{it}^2 + (\eta_i + \varepsilon_{it}) \tag{6.3}$$

Here, IQI is the institutional quality index in linear form, and IQI^2 is the institutional quality index in quadratic form. β_1, β_2, β_3, β_4, β_5, β_6 are the coefficients to be estimated. The expected signs of the coefficients and the country-specific effect are consistent with the previous models. From this equation, the institutional quality turning point can be estimated as

$$\frac{\partial A}{\partial IQI} = \frac{-\beta_5}{2\beta_6} \tag{6.4}$$

Table (6.10): Dynamic Panel-Data Estimation After Adding Institutions, Two-Step System GMM (Model 2).

Independent Variables	Coef.	St.Err.	t-value	p-value	Sig
L.INN	.442	.18	2.45	.014	**
IQI	.317	.168	1.89	.059	*
IQI^2	-.003	.002	-1.70	.089	*
GDPg	.146	.199	0.73	.463	
HC	.065	.027	2.44	.015	**
ENT	.35	.256	1.37	.171	
Ln_FDI	.969	.399	2.43	.015	**
year	-.571	.201	-2.84	.005	***
y3	1.798	.817	2.20	.028	**
y4	.329	.994	0.33	.741	
y5	.774	.821	0.94	.346	
y6	-1.121	.868	-1.29	.197	
y7	.048	.957	0.05	.96	
y8	.215	1.126	0.19	.848	
y9	.57	1.227	0.47	.642	
Constant	1132.426	402.024	2.82	.005	***
Number of observations	457				
Number of instruments	36				
Number of groups	56				
F-test **Prob > F=**	80.88 (0.000)				
Arellano-Bond AR (1) test: (P-value)	-2.68 (0.007)				
Arellano-Bond AR (2) test: (P-value)	1.05 (0.293)				
Hansen test of over identification restrictions **(P value)**	23.49 (0.265)				

Notes: see Table (6.31).

Table (6.10) presents the results of the second model, including institutional quality as an independent variable. Both the baseline (IQI) and curvilinear effects

(IQI^2) of institutional quality on innovation output are statistically significant at the 10% level. Therefore, the third hypothesis is accepted.

Furthermore, the level variable of institutional quality has a positive coefficient 0.317, and the squared variable has a negative coefficient −0.003, thus confirming the fourth hypothesis. The institutional quality turning point, calculated as 48.29 via equation (6.4), implies that institutional quality enhances innovation output only up to this level; beyond 48.29, further improvements in institutional quality negatively affect innovation output.

Lastly, the lagged value of innovation, human capital, and FDI remain statistically significant at the 5% level, all positively affecting innovation output. Meanwhile, entrepreneurship activities persist in their statistical insignificance.

6.5.3 Testing the Fifth Hypothesis: The Asymmetric Effect of Institutional Channels on Innovation Output

The primary aim of this model specification is to meticulously explore the avenues through which institutional factors may influence innovation output. This entails an empirical investigation of the following hypothesis:

H5: Institutional channels exert an asymmetric effect on innovation output.

In this context, each dimension of institutional quality is analysed separately. The literature relevant to this study emphasizes that numerous dimensions of institutional quality are strongly correlated with one another. This correlation signifies characteristics of a country's institutional quality that are not only closely related but also complementary. Consequently, due to the significant correlation among these dimensions, they are evaluated separately (Castellacci et al., 2022; Khan et al., 2017).

For each individual dimension, a U-test is performed to delineate the relationship between innovation output and the particular institutional dimension under consideration. The U-test result subsequently informs the formulation and estimation of the model equation.

6.5.3.1 Control of Corruption

The U-test concerning the relationship between innovation output and control of corruption reveals a significant nonlinear association (see Figure 6.2). Furthermore, the model parameters validate that both β_1 and β_2 are significant (refer to Table 6.11), with β_1 being positive and β_2 negative. This combination verifies an inverted U-shaped relationship between innovation and control of corruption.

Figure (6.2): Curve Estimation Between INN and Coru.

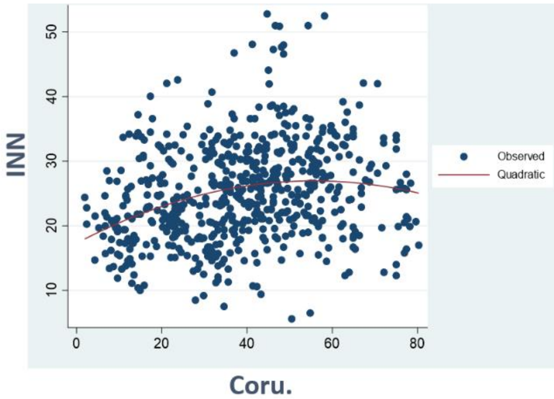


Table (6.11): Parameters of the Curve Fit Estimation Between INN and Coru.

Variable	Quadratic
b_0 _cons	17.312 13.600 0.000
b_1 _cons	0.347 5.120 **0.000**
b_2 _cons	-0.003 -3.770 **0.000**
Statistics N r^2_a	 599 0.072

Notes: See Figure (6.1) and Table (6.9).

In this case, the relationship is mathematically represented by the following equation:

$$INN_{it} = \varphi INN_{it-1} + \beta_1 GDP_g + \beta_2 HC + \beta_3 ENT + \beta_4 \ln FDI + \beta_5 Coru_{it} + \beta_6 \, Coru^2_{it} + (\eta_i + \varepsilon_{it}) \quad (6.5)$$

Here, INN symbolizes the innovation (dependent variable), INN_{it-1} denotes the innovation with a one-year lag, and GDP_g, HC, ENT, and $\ln FDI$ refer to the growth rate of GDP, human capital, entrepreneurship activity, and the natural logarithm of FDI, respectively. $Coru$ and $Coru^2$ denote the linear and quadratic forms of the control of corruption score, and η_i and ε_{it} represent the country-specific effect and error term, respectively.

Further investigation into Table (6.14) (Model 3) reveals that the baseline and the curvilinear effect of control of corruption on innovation output are statistically significant at the 5% level[3]. This corroborates that control of corruption positively

[3] The insignificant results of the different institutional channels are not explained in the main

impacts innovation, either linearly or nonlinearly. With a positive coefficient of 0.245 for the level variable and a negative coefficient of -0.003 for the squared variables, it is affirmed that control of corruption establishes an inverted U-shaped relationship with innovation output. The calculated turning point of 44.350991 implies that control of corruption augments innovation output only up to this level. Beyond this threshold, an increase in control of corruption may inadvertently hinder innovation output.

6.5.3.2 Government Effectiveness

The relationship between innovation output and government effectiveness was examined through a U-test, which revealed a non-significant result, thereby confirming a linear relationship (refer to Figure 6.3). Further inspection of the model parameters indicates that β_1 is significant, while β_2 is not. This lends additional support to the linearity of the relationship, as detailed in Table (6.12).

Figure (6.3): Curve Estimation Between INN and Goveff.

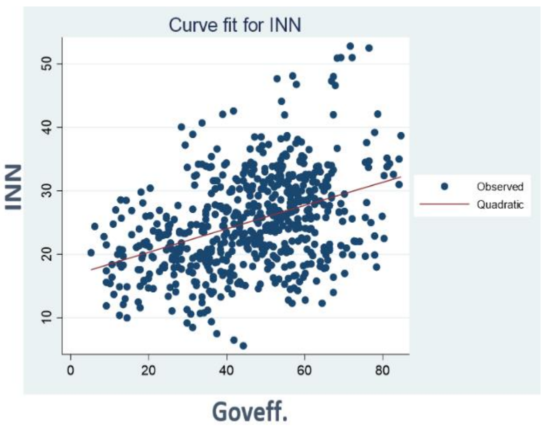


Table (6.12): Parameters of the Curve Fit Estimation Between INN and Goveff.

Variable	Quadratic
b_0 _cons	16.595 10.100 0.000
b_1 _cons	0.187 2.440 **0.015**
b_2 _cons	-0.000 -0.040 **0.966**
Statistics N r^2_a	 599 0.160

Notes: See Figure (6.1) and Table (6.9).

For this analysis, the following equation was estimated:

$$INN_{it} = \varphi INN_{it-1} + \beta_1 GDP_g + \beta_2 HC + \beta_3 ENT + \beta_4 \ln FDI + \beta_5 Goveff_{.it} + (\eta_i + \varepsilon_{it}) \qquad (6.6)$$

In this equation, INN represents innovation as the dependent variable, INN_{it-1} is the innovation with a one-year lag, GDP_g is the growth rate of GDP, HC stands for human capital, ENT denotes entrepreneurship activity, and ln

text, namely models 5,6, and 7.

FDI is the FDI in logarithmic form. *Goveff* signifies the government effectiveness score in linear form, η_i is the country-specific effect, and ε_{it} is the error term. The coefficients $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are to be estimated. Additionally, φ, β_1, and β_2 are anticipated to be positive, as the lagged value of innovation, the growth rate of GDP, and human capital are considered to promote innovation output. According to previous related studies, β_3, β_4, and β_5 could be either positive or negative.

Table (6.14) (Model 4) shows that the baseline linear effect of government effectiveness on innovation output is statistically significant at the 5% level. This finding validates the hypothesis that government effectiveness exerts a positive linear effect on innovation output.

6.5.3.6 Political Stability and Absence of Violence/ Terrorism

The U-test investigating the relationship between innovation output and political stability, as well as the absence of violence/terrorism, is significant. This result confirms the nonlinear relationship as illustrated in Figure (6.4).

The model parameters further demonstrate that both β_1 and β_2 are significant, with β_1 being positive and β_2 negative. These findings corroborate an inverted U-shaped relationship between innovation and political stability, and the absence of violence/terrorism, as detailed in Table (6.13).

Figure (6.4): Curve Estimation Between INN and Political.

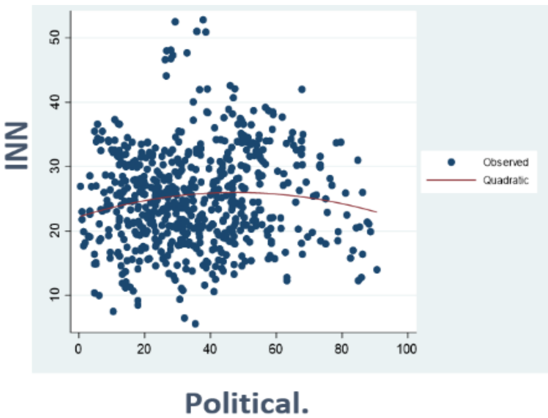


Table (6.13): Parameters of the Curve Fit Estimation Between INN and Political.

Variable	Quadratic
b_0 _cons	22.211 21.140 0.000
b_1 _cons	0.159 2.790 **0.005**
b_2 _cons	-0.002 -2.460 **0.014**
Statistics N r^2_a	 599 0.011

Notes: See Figure (6.1) and Table (6.9).

The estimated equation for this relationship is given by:

$$INN_{it} = \varphi INN_{it-1} + \beta_1 GDP_g + \beta_2 HC + \beta_3 ENT + \beta_4 \ln FDI + \beta_5 Political_{it} + \beta_6 \, Political_{it}^2 + (\eta_i + \varepsilon_{it}) \quad (6.7)$$

In Equation (6.7), INN represents the innovation as a dependent variable, INN_{it-1} denotes the innovation with a one-year lag, GDP_g is the growth rate of GDP, HC stands for human capital, and ENT encapsulates entrepreneurship activity, while ln FDI is the FDI in logarithmic form. The linear and quadratic forms of political stability are represented by $Political$ and $Political^2$, respectively, η_i is the country-specific effect, and ε_{it} is the error term. The coefficients $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ are to be estimated.

Further, φ, β_1, and β_2 are expected to be positive, reflecting that the lagged value of innovation, growth rate of GDP, and human capital generally foster innovation output. Based on existing literature, β_3 through β_6 might be either positive or negative. An extension of this relationship, suggesting a nonlinear connection between political stability and innovation, could lead to a hypothesis of a U-shaped or an inverted U-shaped relationship, contingent upon the signs of β_5 and β_6.

As reflected in Table (6.14) (Model 8), both the baseline and curvilinear effects of political stability on innovation output are statistically significant at the 10% and 5% levels, respectively. Thus, it is inferred that political stability positively influences innovation, either linearly or nonlinearly. The level variable of political stability has a positive coefficient of .134, and the squared variable has a negative coefficient of -.002. This evidence supports an inverted U-shaped relationship between political stability, the absence of violence/terrorism, and innovation output. The turning point of political stability and absence of violence/terrorism, calculated as $(-.1343932)/\ (2 \times (-.0017298))$ = 38.846456, signifies that political stability enhances innovation output only up to a certain threshold (38.85). Beyond this point, political stability negatively impacts innovation output.

In conclusion, as shown in Table (6.14), the U-test results are significant for all dimensions except the government effectiveness dimension. Thus, five of the institutional quality dimensions form a nonlinear relationship with innovation output, while government effectiveness follows a linear relationship. The model specification is adjusted accordingly for each institutional dimension, and empirical estimations from Model 3 to Model 8 reveal that the primary channels affecting innovation output are control of corruption, government effectiveness, and political stability. The AR (2) test yields a non-significant result in all model specifications, indicating that serial correlations of order two do not influence the system-GMM estimators. The non- significant result of the Hansen test further supports the validity of the estimations.

Therefore, the estimators can be logically considered unbiased and consistent. The inverted U-shaped relationship with innovation output for the different institutional dimensions is evident from the signs of the baseline and curvilinear coefficients.

Table (6.14): Dynamic Panel-Data Estimation for Each Institutional Dimension, Two-Step System GMM.

Dependent Variable: INN						
	Model (3)	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
Independent variables	**Coef. (p-value)**	**Coef. (p-value)**	**Coef. (p-value)**	**Coef. (p-value)**	**Coef. (p-value)**	**Coef. (p-value)**
L.INN	.443** (.016)	.488*** (.006)	.448** (.017)	.464*** (.006)	.495 *** (.008)	.448** (.02)
$\boldsymbol{Coru}$.	.245** (.023)					
$\boldsymbol{Coru^2}$	-.003** (.039)					
$\boldsymbol{Goveff}$.		.062** (.021)				
$\boldsymbol{Regul}$.			.126 (.127)			
$\boldsymbol{Regul}^{2}$			-.001 (.357)			
$\boldsymbol{Law}$				.135 (.153)		
$\boldsymbol{Law}^{2}$				-.001 (.353)		
$\boldsymbol{Voice}$					.045 (.514)	
$\boldsymbol{Voice}^{2}$					-.001 (.504)	
$\boldsymbol{Political}$						.134* (.054)
$\boldsymbol{Political}^{2}$						-.002** (.036)
$\boldsymbol{GDPg}$	.18 (.355)	.185 (.301)	.155 .449	.16 (.424)	.183 (.357)	.148 (.494)
$\boldsymbol{HC}$	.064** (.046)	.054* (.059)	.074*** (.009)	.063** (.021)	.079 *** (.01)	.073** (.021)
$\boldsymbol{ENT}$	.486 (.111)	.313 (.186)	.258 (.363)	.292 (.248)	.348 (.168)	.362 (.148)
$\boldsymbol{Ln\_FDI}$	.966** (.022)	.859 ** (.016)	.947** (.016)	.97** (.015)	.967** (.019)	.965** (.03)

Dependent Variable: INN						
	Model (3)	**Model (4)**	**Model (5)**	**Model (6)**	**Model (7)**	**Model (8)**
Independent variables	**Coef. (p-value)**	**Coef. (p-value)**	**Coef. (p-value)**	**Coef. (p-value)**	**Coef. (p-value)**	**Coef. (p-value)**
year	-.556*** (.007)	-.503*** (.007)	-.541** (.015)	-.531*** (.008)	-.497** (.017)	-.574 (.014)
y3	1.657* (.061)	1.584* (.06)	1.798** (.045)	1.73** (.041)	1.645* (.06)	1.752** (.046)
y4	.298 (.763)	-.161 (.85)	.327 (.745)	.083 (.925)	.044 (.963)	.184 (.847)
y5	.75 .359	.423 (.566)	.791 (.367)	.582 (.439)	.598 (.463)	.767 (.381)
y6	-1.206	-1.435* (.075)	-1.181 (.226)	-1.352 (.118)	-1.358 (.107)	-1.067 (.247)
y7	-.094	-.135 (.88)	.047 (.964)	-.051 (.959)	-.104 (.912)	.081 (.937)
y8	.033	-.075 (.942)	.138 (.906)	.048 (.966)	-.02 (.986)	.174 (.886)
y9	.355	0.192 (0.858)	.47 (.702)	.406 (.734)	.36 (.768)	.618 (.65)
Constant	1104.678 *** (.007)	1001.894*** (0.007)	1076.316** (.016)	1055.383*** (.008)	988.189** (.018)	1144.657** (.015)
Number of observations	457	457	457	457	457	457
Number of instruments	36	35	36	36	36	36
Number of groups	56	56	56	56	56	56
F-test Prob > F=	65.09 (0.000)	68.58 (0.000)	78.93 (0.000)	66.77 (0.000)	61.88 (0.000)	65.06 (0.000)
Arellano-Bond AR (1) test: (P-value)	-2.69 (0.007)	-2.90 (0.004)	-2.72 (0.006)	-2.94 (0.003)	-2.91 (0.004)	-2.75 (0.006)
Arellano-Bond AR (2) test: (P-value)	0.88 (0.381)	1.20 (0.232)	1.02 (0.308)	1.02 (0.307)	1.11 (0.268)	0.97 (0.330)
Hansen test of over identification restrictions (P-value)	25.27 (0.191)	24.99 (0.202)	23.26 (0.276)	23.20 (0.279)	23.99 (0.243)	22.64 (0.307)

Notes: see Table (6.8).

6.5.4 Adding Different Model Specifications

6.5.4.1 Interaction Between Institutional Quality and Entrepreneurship Activities

The extant literature presents abundant evidence highlighting the crucial role of institutions in fostering entrepreneurial activities. However, these studies yield mixed results. Some scholars posit that weak institutional quality suppresses entrepreneurial activity and diminishes opportunities for entrepreneurship (Chambers & Munemo, 2019; Crnogaj & Bradač Hojnik, 2016; Omidi et al., 2020; Rodríguez-Pose & Storper, 2006; Samadi, 2019).

Conversely, other studies emphasize that robust institutional quality fosters an environment conducive to job creation, thereby reducing the compulsion for individuals to engage in necessity entrepreneurship (i.e., self-employment driven by high unemployment levels) (El Harbi & Anderson, 2010; Fredström et al., 2021; LêKhang & Thành, 2018). In other words, weak institutions may escalate unemployment, leading individuals to seek self-employment as entrepreneurs. El Harbi and Anderson (2010) utilized investment freedom as a proxy for institutions and discovered that investment freedom positively correlates with self-employment rates, attributable to FDI spillover effects that enhance local skills. Moreover, FDI can stimulate local demand, invigorating entrepreneurial spirit. Additionally, Fredström et al. (2021) noted that in developing countries with extensive informal sectors, efforts to augment institutional quality might adversely affect entrepreneurial productivity.

This divergence in perspectives inspired us to examine the influence of institutional quality on the relationship between entrepreneurship activities and innovation. To this end, we introduced an interaction term comprising institutional quality and entrepreneurship activities into the model. The equation estimated in this context is:

$$INN_{it} = \varphi INN_{it-1} + \beta_1 GDP_g + \beta_2 HC + \beta_3 \text{ENT} + \beta_4 \ln(\text{FDI}) + \beta_5 \text{IQI}_{it} + \beta_6 IQI_{it}^2 + \beta_7 (\text{IQI}_{it} \times \text{ENT}) + \beta_8 (IQI_{it}^2 \times \text{ENT}) + (\eta_i + \varepsilon_{it}) \qquad (6.8)$$

In Equation (6.8), INN represents innovation as the dependent variable, INN_{it-1} denotes innovation with a one-year lag, GDP_g is the growth rate of GDP, HC represents human capital, ENT represents entrepreneurship activity and ln FDI is FDI in logarithmic form. IQI and IQI^2 are the institutional quality index in linear and quadratic form. The linear and quadratic interaction terms between the institutional quality index and entrepreneurship activities are represented by $IQI \times ENT$ and $IQI^2 \times ENT$, respectively, while η_i is the country-specific effect, and ε_{it} is the error term. The coefficients $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5,$ β_6, β_7 *and* β_8 are to be estimated. Furthermore, φ, β_1, and β_2 are expected to be positive, while β_3, β_4, β_5, β_6, β_7 *and* β_8 may be either positive or negative based on related studies.

Interestingly, while the direct effect of entrepreneurship on innovation as a demand-side determinant was found to be insignificant (Tables 8,10 and 14), its interaction with institutional quality is positive and statistically significant at the 1% level, as depicted in Table (6.15). This suggests that institutional quality serves as a mediating channel between entrepreneurship activities and innovation output. The implication is that enhancements in institutional quality can amplify the impact of entrepreneurship activities on innovation.

Therefore, bolstering institutional quality will likely stimulate entrepreneurial activity within middle-income developing countries. This finding also infers that demand-side innovation determinants do not directly influence innovation but do so indirectly through channels like institutional quality. This conclusion resonates with previous research emphasizing the significance of both supply and demand-side determinants in innovation activities, advocating for a holistic policy mix (inter alia Aflaki et al., 2021). The Arellano–Bond test for second-order zero autocorrelation furnished no evidence of second-order autocorrelation in the system GMM estimators (Prob > z = (0.320).

Moreover, the results of the Hansen test confirm the validity of the instruments. Thus, given the absence of autocorrelation and the validity of the instruments, the system GMM dynamic estimators are deemed efficient.

Table (6.15): Dynamic Panel-Data Estimation for the Impact of Institutional Quality on the Association Between Entrepreneurship Activities and Innovation, Two-Step System GMM.

Dependent Variable: INN							
Independent Variables	**Coef.**	**St. Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
L.INN	.537	.159	3.38	.001	.219	.854	***
IQI	.297	.162	1.84	.071	-.026	.621	*
IQI2	-.003	.002	-1.69	.097	-.007	.001	*
ENT	.367	.26	1.41	.164	-.154	.888	
LINS_LENT	**.061**	**.018**	**3.36**	**.001**	**.025**	**.097**	*********
LINS2_LENT	**-.001**	**0**	**-3.34**	**.001**	**-.001**	**0**	*********
GDPg	.115	.17	0.68	.499	-.224	.454	
HC	.062	.038	1.65	.104	-.013	.137	
Ln_FDI	.651	.332	1.96	.055	-.013	1.316	*
year	-.618	.158	-3.91	0	-.934	-.302	***
y3	1.952	.817	2.39	.02	.318	3.585	**
y4	-.045	.83	-0.05	.957	-1.704	1.614	
y5	.697	.711	0.98	.33	-.723	2.118	
y6	-1.092	.732	-1.49	.141	-2.555	.372	
y7	.386	.835	0.46	.646	-1.284	2.055	
y8	.534	1.019	0.52	.602	-1.503	2.571	
y9	.957	1.065	0.90	.372	-1.172	3.085	
Constant	1239.309	318.869	3.89	0	601.898	1876.719	***
Number of observations	457						

Dependent Variable: INN							
Independent Variables	**Coef.**	**St. Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
Number of instruments	46						
Number of groups	56						
Obs per group:	min = 1 avg = 7.49 max = 9						
F-test **Prob > F=**	98.33 (0.000)						
Arellano-Bond AR (1) test: p-value	-3.03 (0.002)						
Arellano-Bond AR (2) test: p-value	0.99 (0.320)						
Hansen test of over identification restrictions (P value)	30.59 (0.288)						
**** p<.01, ** p<.05, * p<.1*							
Notes: Four instrument(s) y1, y2, y10, y11 are dropped because of collinearity. The command xtabond2 is used using STATA 17 software. Twostep robust small nomata options are employed.							

Notes: see Table (6.8).

6.5.4.2 Interaction Between FDI and Entrepreneurship Activities

The objective of this section is to rigorously examine the influence of FDI on the relationship between entrepreneurship activities (ENT) and innovation. To this end, an interaction term comprising FDI and ENT is incorporated into the model.

The equation to be estimated is given as:

$$INN_{it} = \varphi INN_{it-1} + \beta_1 GDP_g + \beta_2 HC + \beta_3 \text{ENT} + \beta_4 \ln(\text{FDI}) + \beta_5 \text{IQI}_{it} + \beta_6 IQI_{it}^2 + \beta_7 (\ln \text{\_FDI} \times \text{ENT}) + (\eta_i + \varepsilon_{it}) \quad (6.9)$$

In Equation (6.9), INN represents innovation as the dependent variable, INN_{it-1} denotes innovation with a one-year lag, GDP_g is the growth rate of GDP, HC represents human capital, ENT represents entrepreneurship activity and ln FDI is FDI in logarithmic form. IQI and IQI^2 are the institutional quality index in linear and quadratic form. The term (ln $FDI \times ENT)$ is the interaction term between FDI and ENT. η_i is the country-specific effect, and ε_{it} is the error term. The coefficients β_1, β_2, β_3, β_4, β_5, β_6, and β_7 are to be estimated. Furthermore, φ, β_1, and β_2 are expected to be positive, while β_3, β_4, β_5,

β_6, and β_7 may be either positive or negative based on related studies.

From Table (6.16), it is apparent that the interaction between FDI and ENT is statistically insignificant, leading to the inference that FDI does not serve as a catalyst for entrepreneurship activities in middle-income developing countries.

Therefore, juxtaposing the results from Tables 15 and 16, it can be deduced that while institutional quality emerges as a viable conduit for promoting entrepreneurship, FDI does not demonstrate a similar effect. These observations are congruent with previous empirical studies such as Albulescu and Tămăşilă (2016); Hong et al. (2021) and also align with the patterns previously discerned in the context of developing nations as observed in Doytch (2012).

Table (6.16): Dynamic Panel-Data Estimation the Impact of FDI on the Association Between Entrepreneurship Activities and Innovation, Two-Step System GMM.

Dependent variable: INN							
Independent variables	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
L.INN	.484	.17	2.84	.006	.143	.824	***
IQI	.297	.162	1.84	.071	-.026	.621	*
IQI2	-.003	.002	-1.69	.097	-.007	.001	*
GDPg	.133	.206	0.65	.52	-.278	.545	
HC	.067	.028	2.40	.019	.011	.124	**
ENT	.367	.26	1.41	.164	-.154	.888	
LFDI_LENT	**-.003**	**.046**	**-0.06**	**.952**	**-.095**	**.089**	
Ln_FDI	.921	.39	2.36	.021	.142	1.7	**
year	-.569	.193	-2.96	.004	-.954	-.184	***
y3	1.779	.833	2.14	.037	.114	3.443	**
y4	.247	.96	0.26	.798	-1.673	2.166	
y5	.713	.764	0.93	.355	-.815	2.24	
y6	-1.17	.817	-1.43	.157	-2.802	.463	
y7	.157	.944	0.17	.868	-1.73	2.045	
y8	.403	1.145	0.35	.726	-1.885	2.691	
y9	.791	1.203	0.66	.513	-1.614	3.195	
Constant	1130.621	385.016	2.94	.005	360.986	1900.257	***
Number of observations			457				
Number of instruments			36				
Number of groups			56				
F-test **Prob > F=**			89.36 (0.000)				
Arellano-Bond AR (1) test: p-value			-2.93 (0.003)				
Arellano-Bond AR (2) test: p-value			1.22 (0.222)				
Sargan test of over identification restrictions (P value)			35.10 (0.020)				
Hansen test of over identification			28.05				

Dependent variable: INN							
Independent variables	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
restrictions (P value)			(0.108)				
**** p<.01, ** p<.05, * p<.1*							

Notes: see Table (6.31).

6.5.4.3 Interaction Between Institutional Quality and FDI

The purpose of this section is to rigorously examine the influence of institutional quality (IQI) on the association between FDI and innovation. An interaction term involving IQI and FDI is introduced into the model to facilitate this analysis. The equation to be estimated is given by:

$$INN_{it} = \varphi INN_{it-1} + \beta_1 GDP_g + \beta_2 HC + \beta_3 \text{ENT} + \beta_4 \ln(\text{FDI}) + \beta_5 \text{IQI}_{it} + \beta_6 IQI_{it}^2 + \beta_7 (\text{IQI}_{it} \times \ln FDI) + \beta_8 (IQI_{it}^2 \times \ln FDI) + (\eta_i + \varepsilon_{it}) \quad (6.10)$$

In Equation 6.10, INN denotes innovation as the dependent variable, while INN_{it-1} represents the innovation with a one-year lag. GDP_g stands for the growth rate of GDP, HC symbolizes human capital, and ENT refers to entrepreneurship activities. The terms ($IQI \times \ln FDI$) and ($IQI^2 \times \ln FDI$) denote the interaction between IQI and FDI in linear and quadratic forms, respectively. η_i represents the country-specific effect, and ε_{it} is the error term. The coefficients β_1, β_2, β_3, β_4, β_5 are to be estimated. Moreover, φ, β_1, and β_2 are expected to be positive, given the proposition that lagged innovation output, GDP growth rate, and human capital are all positive drivers of innovation activity. According to relevant literature, $\beta 4$, $\beta 5$, β_6, β_7 *and* β_8 could be either positive or negative.

From Table (6.17), it can be observed that the interaction between institutional quality and FDI is both positive and statistically significant. This result indicates that institutional quality serves as a critical conduit for FDI, reinforcing its significance.

Therefore, enhancing institutional quality would render developing countries more appealing, thereby stimulating the influx of FDI. This observation aligns well with prior research, such as the study by Bouchoucha and Benammou (2020), reinforcing the empirical link between strong institutional frameworks and increased foreign investment.

Table (6.17): Dynamic Panel-Data Estimation for the Impact of IQI on the Association Between FDI and Innovation, Two-Step System GMM.

Dependent variable: INN							
Independent variables	**Coef.**	**St.Err.**	**t-value**	**p-value**	**[95% Conf**	**Interval]**	**Sig**
L	.484	.171	2.83	.006	.143	.825	***
IQI	1.841	1.543	1.19	.237	-1.243	4.925	
IQI2	-.026	.018	-1.48	.143	-.062	.009	
LINS_LFDI	**.014**	**.007**	**1.83**	**.072**	**-.001**	**.029**	*
LINS2_LFDI	**0**	**0**	**-1.64**	**.106**	**0**	**0**	
GDPg	.135	.209	0.64	.522	-.284	.553	
HC	.067	.028	2.35	.022	.01	.124	**
ENT	.361	.265	1.36	.179	-.169	.891	
Ln_FDI	.63	.351	1.79	.078	-.072	1.333	*
year	-.566	.195	-2.91	.005	-.956	-.177	***
y3	1.78	.834	2.13	.037	.113	3.448	**
y4	.23	.964	0.24	.813	-1.698	2.158	
y5	.7	.766	0.91	.364	-.831	2.231	
y6	-1.177	.827	-1.42	.159	-2.83	.475	
y7	.152	.962	0.16	.875	-1.77	2.074	
y8	.386	1.162	0.33	.741	-1.938	2.709	
y9	.765	1.215	0.63	.531	-1.663	3.193	
Constant	1130.738	390.595	2.89	.005	349.949	1911.527	***
Number of observations			457				
Number of instruments			38				
Number of groups			56				
Obs per group:			min = 1 avg = 7.49 max = 9				
F-test			93.83 (0.000)				
Arellano-Bond AR (1) test: p-value			-3.21 (0.001)				
Arellano-Bond AR (2) test: p-value			1.22 (0.224)				
Sargan test of over identification restrictions (P value)			34.90 (0.021)				
Hansen test of over identification restrictions (P value)			24.28 (0.230)				
**** p<.01, ** p<.05, * p<.1*							
Notes: - L.INN means lagged value of the dependent variable(innovation) - Four instrument(s) y1, y2, y10, y11 are dropped because of collinearity. - The command xtabond2 is used using STATA 17 software. Twostep robust small nomata options are employed.							

Notes: see Table (6.31).

6.6 Summary and Policy Discussion

6.6.1 Summary

The foundational understanding of basic definitions and concepts related to innovation is pivotal, as highlighted throughout this chapter. The works of Borrás and Edquist (2013) and others provide valuable reference for grasping key terminology. It is essential to acknowledge that within the literature of innovation, various definitions have been presented. Despite differences in wording, all these definitions emphasize the characteristics and effects of innovation. A consistent element across these definitions is that for an idea to be considered innovative, it must first enter the market and become available to potential users. Hence, every definition of innovation echoes Schumpeterian notions of novelty and diffusion. Furthermore, understanding the distinctions among classifications of innovation, especially between product and process innovation, is vital.

Innovation is more a means to accomplish broader objectives like job creation, economic growth, sustainable development, and fostering a transition to a KBE, rather than an end in itself. Politicians often prioritize the positive economic impacts of innovation rather than the intricacies of the subject itself.

The innovation process is neither unique nor isolated. It stems from a complex interplay of factors, including education, culture, risk-taking capacity, institutional arrangements, and a stable economic and social environment. The complexity of the innovation phenomenon might explain why there is no universally agreed-upon definition or single approach to innovation policy.

In this context, innovations are conceived as entirely novel creations (processes and products) that bear economic and societal significance. They are mainly generated by firms within the framework of the innovation system, which governs the development, diffusion, and use of innovations. A comprehensive understanding of the innovation system would encompass all factors - economic, social, political, organizational, institutional, etc.- that influence innovation.

Additionally, differentiating between invention and innovation is critical. It is the exploitation of an idea in its economic and social context, rather than the idea itself, that carries weight economically and socially. Thus, the diffusion of innovation requires particular attention, especially in developing nations. The development of innovation, as explored in this chapter, serves as a mechanism to accelerate the national transition to a KBE, emphasizing product innovation at the national level.

The recognized significance of innovation for long-term economic growth, and more recently in tackling environmental challenges like climate change, has sustained interest in its determinants. Accurate identification of these determinants can guide policy development and prioritize governmental actions, hastening the transition to a KBE.

The evolution of innovation theory and its drivers presents challenges, and a consensus on innovation determinants at the country level remains elusive. Investigation of the literature uncovers the ongoing evolution of innovation theory, with diverse conceptual and methodological approaches transitioning from simple linear processes to complex, dynamic innovation systems involving multiple interacting actors.

Along with this systematic approach to innovation theory, the term “innovation policy” commonly refers to collective actions by public organizations that directly or indirectly influence innovation processes. This term has gained traction among policymakers and international organizations like the OECD since the mid-1990s, with full acknowledgment of its significant role in enhancing innovation development.

Developing an innovation policy requires well-defined objectives and strategies. In the domain of a KBE, innovation policy should concentrate on the creation, dissemination, and application of knowledge and technology, and be crafted to address issues within innovation systems. It often includes clearly defined missions aimed at encouraging innovation, known as mission-oriented innovation policy.

Innovation policy may be justified by addressing market inefficiencies, especially private under-investment in R&D, or by adopting a systematic perspective of innovation. From the 1990s, innovation policy began to build national innovation networks and address weaknesses in NIS, emphasizing innovation as a crucial driver of economic growth.

After setting the innovation policy objectives, a crucial question that follows is how to attain those objectives. Given the lack of applicable framework for innovation policy, an attempt has been proposed in the literature is that the innovation policy can be adopted by establishing systematic innovation policy instrument. These instruments attempt to achieve the innovation policy through solving the innovation system problems. Within the possible sources on gathering data on innovation system problems, innovations indicators are regarded as the most influential source for data collection. However, the identification of innovation system problems alone is insufficient as it is essential to understand the fundamental causes of these problems.

A variety of systematic innovation policy instruments can be employed, defined by specific actions to stimulate, or impede the innovation process. These instruments are designed to achieve policy objectives and are vital in addressing innovation system problems.

A systematic typology of innovation policy instruments, based on their orientation, is essential due to the myriad of available instruments. These instruments can focus on supply and demand or create a policy mix, encompassing both technology-push and demand-pull strategies.

Empirical analyses, supplemented by econometric studies using System Generalized Method of Moments, were conducted to pinpoint significant innovation determinants in the context of the chosen MENA nations. This research explored various influences on innovation and systematically divided innovation determinants into demand-side and supply-side factors, using proxies justified by theoretical and empirical rationales.

The impact of institutional quality on innovation was also examined, emphasizing the need for an effective institutional environment to fully leverage innovation incentive policies. GDP growth and human capital were included as controlled variables in this empirical analysis, aiming to provide a holistic understanding of the multifaceted nature of innovation and guide policy formulation in the realm of developing economies.

6.6.2 Policy Recommendations

The empirical analysis led to the acceptance of Hypothesis (1): Supply-side innovation determinants relate positively to innovation output in the country, and rejection of Hypothesis (2): Formal entrepreneurship activity has a positive impact on innovation output.

The empirical analysis also reveals that the lagged value of innovation has the largest estimated coefficient, supporting the proposition that innovation is an auto-regressive process and indicating that policymakers should pay particular attention to initial conditions in a given country when setting innovation policy.

Moreover, the findings support Hypothesis (3): Upgrading institutional quality has a positive linear or nonlinear effect on innovation, and Hypothesis (4): Institutional quality has an inverted U-shaped relationship with innovation output.

This means the institutional development affects innovation development up to a certain level after which adhering to the costs related to the new tight institutional regulations reduces innovation development.

Various channels within the WGI dimensions, such as control of corruption, government effectiveness, and political stability, may influence innovation development in the selected developing MENA countries.

Subsequent testing revealed the mediation of institutional quality in the relationship between entrepreneurship activities and innovation. While the direct effect of entrepreneurship on innovation was found insignificant, its interaction with institutional quality was positively significant. This emphasizes the importance of improving institutional quality to foster entrepreneurship in middle-income developing nations. This finding aligns with research that advocates both supply and demand-side determinants of innovation activities and reveals that demand-side instruments indirectly complement direct supply-side innovation policy instruments.

Furthermore, the study explored the impact of FDI on the association between entrepreneurship activities and innovation, revealing a negligible relationship between FDI and entrepreneurship. This suggests that while institutional quality serves as a beneficial channel for entrepreneurship, FDI does not.

Lastly, the relationship between institutional quality and FDI is statistically significant and favours the former, underscoring that enhancing institutional quality will increase the attractiveness of developing nations and promote FDI inflow.

Chapter 7

Conclusions and Policy Implications

7.1 Introduction

This thesis embarked on a comprehensive investigation into the ongoing transition towards a KBE within developing nations, delving deeply into its varied measurements and ensuing impacts. The overall and overarching objective was to elucidate the existing state of this transition by synthesizing a robust conceptual framework and encapsulating pivotal theoretical contributions that explore KBE dynamics, particularly within the context of developing countries. A thorough review of both theoretical and empirical literature has been conducted, offering insights into the assessment of the transition to a KBE through the perspective of a developing nation and underscoring the constraints of prevailing frameworks.

A fundamental gap that this thesis addresses is the absence of an appropriate measure to gauge the transition to KBE in developing nations. Crucially, current measures often overlook the developmental trajectory and efficiency tiers inherent within a specific developing nation, as they are predominantly calibrated for developed nations. Moreover, these measures are often plagued by data scarcity pertaining to developing countries, thereby limiting their applicability and relevance.

The highlighted limitations necessitate further research and initiatives to formulate novel KBE measures that are contextually tailored to the needs of developing countries. Pursuant to this need, the thesis introduces a novel measure for KBE, utilizing DEA across a broad spectrum of developing countries. This innovative measure is compared against the World Bank's widely recognized KAM, and the GII elucidating the deficiencies inherent in other prevailing measures and underscoring the comparative advantage of the DEA methodology for developing nations.

Following the establishment of a robust KBE measure tailored for developing countries, it is observed that in developing countries context, they are lagging behind developed countries in terms of the four KBE pillars, with the innovation pillar being the worst relative to the other three pillars of KBE. Therefore, to speed up the KBE transition in these countries, the thesis embarks on a profound exploration of the determinants of innovation, delivering comprehensive diagnostic insights into the scenarios unfolding in seven MENA countries. The analysis focuses on strategies to expedite the transition to KBE in the selected developing MENA countries by fostering innovation through finely tuned, country-specific policy instruments.

This concluding chapter seeks to consolidate the principal findings of the thesis and illuminate the key policy recommendations emanating from these insights. It is structured as follows: Section 2 offers a concise recap of the principal findings; Section 3 delves into potential policy ramifications deduced from the findings; and finally, Section 4 delineates prospective directions for subsequent research.

7.2. Key Findings

Chapter Two initiated an exploration into the conceptual and theoretical underpinnings of the KBE, offering a multidimensional perspective on the concept, with knowledge being spotlighted as a fundamental catalyst for worldwide economic advancement and development. It concluded with the affirmation that while a universal definition for KBE remains elusive, the definition proffered by the World Bank is predominantly employed.

Within this chapter, the quadrilateral foundation of KBE as outlined by the WB—comprising the economic and institutional regime, ICT, education, and innovation—was meticulously delineated, emphasizing their transformative impacts on economic growth, productivity, competitiveness, job creation, and poverty alleviation. Driven by compelling theoretical and empirical contributions, these insights are being increasingly integrated into policy dialogues and endeavours to advance the transition to a KBE, representing a paradigmatic shift in economic architectures compared to their traditional counterparts.

Subsequently, the chapter underscored knowledge's integral role in the global economy and the transition towards a KBE, necessitating a reassessment of economic paradigms and doctrines. The discourse pivoted around the incorporation of knowledge within various growth paradigms, accentuating the new and evolutionary growth theories that most distinctly spotlight knowledge's criticality in economic expansion.

Chapter Three engaged in a critical examination of empirical literature to contribute to the proliferating discourse surrounding KBE measurements. In this chapter the first objective of the thesis, namely investigating the strengths and weaknesses of existing measurement frameworks for the KBE has been explored in-depth. Therefore, the first research question: How effectively do the current KBE frameworks explain the KBE in the context of developing countries? has been answered. It is concluded that, despite two decades of extensive studies and scholarly contributions on KBE measurement, a consensus on a universally accepted measurement methodology remains unresolved. The chapter highlighted persistent lacunae in both theoretical expositions and empirical implementations of KBE assessments, particularly in developing countries, advocating for intensified scholarly pursuits to bridge these voids. This necessitates the formulation of a novel measurement paradigm for KBE, particularly attuned to the nuances of developing nations—a theme further unfolded in the succeeding chapter.

This chapter also concluded by emphasizing extant deficiencies in current KBE measurement frameworks, thereby questioning their aptitude for a comprehensive assessment of KBE. Among these, the prevalent frameworks fail to encapsulate the breadth and efficacy of an economy's knowledge base. This quandary is exacerbated in the context of developing nations due to data scarcity. Consequently, the overarching inference drawn from this chapter is the imperative need for a more contextualized and robust KBE transition measure, especially within the context of developing countries, forming the focal point of the subsequent chapter.

Chapter Four discussed how measuring knowledge-based economic performance, particularly in developing countries, poses a significant challenge due to the inconsistency and lack of KBE measures and prevailing data voids.

This chapter aimed to attain the second and the third objectives of the thesis, namely introducing a new measurement framework specifically tailored to the socioeconomic characteristics, challenges, and opportunities of developing countries, with a focus on policy implications and evaluating which dimensions of the KBE require the greatest attention based on the empirical results. Doing this enabled us to answer the following research questions:

- Does the DEA method address the existing gaps in the literature regarding KBE measurement in developing countries?
- Based on the empirical analysis using DEA, what actions can be taken to accelerate the transition process towards the KBE in developing countries?

Therefore, this chapter provides a nuanced contribution by offering a comprehensive analysis using DEA, a non-parametric approach, to assess the relative efficiency of developing countries in their transitions toward KBEs, focusing significantly on developing countries where the existing literature is sparse.

This in-depth analysis employs both radial and non-radial DEA models, including the output-oriented CCR and BCC models and the slack-based models, to present a comparative assessment of KBE efficiency in developing countries. This approach not only distinguishes between efficient countries but also provides insights into potential improvement areas, serving as a guide for policymakers and researchers interested in accelerating the transition to KBEs through improved performance.

The key findings suggest that most developing countries are inefficient under both radial and non-radial models, with predominant issues in pure technical inefficiency and scale inefficiency, the former being more pervasive. The models advise that addressing managerial efficiency should be a priority before focusing on improving scale efficiency for a more expedited and smoother transition to a KBE.

Chapter Five provides an in-depth analytical comparison of knowledge assessment methodology, global innovation index, and data envelopment analysis, focusing on their efficacy in the KBE measurement frameworks. Therefore, this chapter aimed to achieve the fourth and the fifth objectives of the thesis, namely utilizing widely used methodologies to assess the current status of developing countries in their transition to the KBE and compare the results obtained from the existing measurement frameworks with the results derived from the new policy-focused measurement approach, namely DEA to evaluate its merits. Doing this enabled us to answer the following research questions:

- What is the current status of the KBE in developing countries, and which measurement approach provides the most accurate assessment?
- How effectively do the current KBE frameworks explain the KBE in the context of developing countries?

The main conclusion derived from this chapter is that DEA has superiority over current KBE frameworks and thus policymakers should utilize this approach in KBE measurement practically in developing countries context.

Chapter Six examines the innovation performance in selected developing MENA countries intending to propose effective innovation policies to hasten the transition to KBE in these countries to achieve objective six of the thesis. In this chapter, the following research question has been answered: How can policymakers promote effective innovation policies in their respective countries? The key findings from the econometric analysis could be summarised as follows:

a. Supply-side innovation determinants have a positive relationship with innovation output.

b. Formal entrepreneurship activity does not have a direct positive impact on innovation output.

c. Innovation is an auto-regressive process, emphasizing the importance of initial conditions in policy settings.

d. Institutional quality has a positive linear or non-linear effect on innovation, displaying an inverted U-shaped relationship with innovation output, suggesting a threshold beyond which tight regulations reduce innovation development. Furthermore, institutional quality mediates the relationship between entrepreneurship activities and innovation, stressing the importance of improving institutional quality to foster entrepreneurship.

e. The relationship between FDI and entrepreneurship was found negligible, but enhancing institutional quality will increase the attractiveness of developing nations and promote FDI inflow.

7.3. Policy Implications

Chapter Four, which leverages various DEA models to assess the relative efficiencies of developing countries in their transition to a KBE, offers the following policy insights. Target managerial inefficiency: policy reforms should foremost address the prevailing managerial inefficiencies observed in most developing countries. The prioritization of enhancing managerial efficiency is crucial before addressing scale efficiencies. Strategic allocation and scale augmentation; there is a critical need for the strategic allocation of inputs and resources, with countries operating under increasing returns to scale. The countries should look to augment the size of their inputs to realize higher efficiency levels and address scale inefficiencies effectively. Focus on knowledge production; given the identified weakness in the knowledge production dimension, there should be a concentrated effort to bolster capacities in this area, contributing to mitigating the overall inefficiency in developing countries transitioning to a KBE. Benchmarking and learning from leaders; countries like China, Kazakhstan, Iran, the Kyrgyz Republic, and Angola, which have emerged as efficiency leaders in various DEA models, should serve as role models and benchmarks for other developing countries to learn and adapt best practices in transitioning to KBE. Customization and contextualization of policies; the derived insights and resultant policy implications need to be approached with caution, taking into consideration the KBE variables used in this study. It is vital to ensure the careful consideration and contextual adaptation of these findings into actionable policies, tailoring them to the specific needs and contexts of each country. Finally, innovation in assessment models; the use of innovative non-radial DEA models, like slack-based models, should be encouraged for a more detailed and accurate efficiency analysis, addressing the limitations of traditional radial models, and offering a more realistic picture of the efficiency levels.

Overall, the above policy implications emphasize a strategic and focused approach to address prevalent inefficiencies, specifically targeting managerial inefficiencies, and adapting best practices from efficiency leaders. They advocate for tailored policy reforms considering the contextual specificity of each country, and they accentuate the importance of innovative assessment models for a more nuanced understanding of relative efficiencies in transitioning to a KBE.

Chapter Five presents a critical examination of KAM, GII, and DEA, highlighting the limitations and advantages of each, and suggests that DEA, with its multidimensional approach, objective weighting, and clear benchmarking, is superior for assessing KBE transformation. The insights from this analysis could guide more nuanced and effective policy development to foster knowledge-based economies globally. The following policy insights could summarise the key implications that can be drawn from this chapter. Adoption of DEA for KBE assessment; governments and international organizations should consider adopting DEA methodologies for a more precise and inclusive analysis of countries' performances in transforming into a KBE, overcoming the limitations found in GII and KAM. DEA's capability to set actual targets and systematically benchmark countries make it particularly useful for policy formulation in promoting KBE development.

Additionally, inclusivity and comprehensive analysis are mandatory; there is a need for frameworks that include a broader range of developing countries and consider the financial constraints faced by these countries to provide comprehensive and inclusive insights. Furthermore, policymakers should focus on incorporating essential and impactful factors in the innovation process, eliminating non-essential components for a more accurate depiction of innovation capabilities.

Further, future KBE measurement frameworks should emphasize developing methodologies that can effectively handle multidimensional situations and offer objective, data-determined weights, and ratios for fair and accurate assessments. Also, emphasis should be on creating frameworks that help in clearly defining and establishing relationships between different dimensions of knowledge to formulate effective policies for KBE development.

Furthermore, rational resource allocation should be considered. Policymakers in developing countries should consider the financial realism of investing in various indicators and allocate resources rationally to foster sustainable development towards a knowledge-based economy.

Lastly, inefficient or developing countries should leverage DEA analysis to identify the most suitable benchmark countries to learn from and emulate in their pursuit of becoming a KBE.

Chapter Six offers a detailed diagnostic and econometric analysis on innovation in selected developing MENA countries, providing insights into areas of strengths, weaknesses, and the relationships among various factors affecting innovation. The policy implications drawn from this chapter mainly stress on the importance of addressing the identified system barriers, strengthening supply-side innovation determinants, enhancing institutional quality, and tailoring innovation policies according to each country's unique context to promote a quicker transition to a KBE. The following points provide more details on the insights offered by chapter six.

Specific focus on Supply-side Innovation Determinants; given the identified weakness in institutional capacity and business sophistication, there is a need for policies that strengthen these areas to enhance innovation outputs in the MENA region. Furthermore, demand-side innovation policy instruments should also be considered to complement the supply-side instruments, and they should be tailored and customized to the unique context of each country.

Policies should leverage the identified strength in human capital as the prime innovation input pillar and focus on developing it further as it presents a comparative advantage.

As for institutional quality and regulation, policies should aim to upgrade institutional quality as it has a significant positive effect on innovation. Furthermore, regulatory frameworks need a balance; policies should avoid excessive regulations that may hinder innovation development after reaching a certain threshold. Additionally, there is a need to focus on improving different dimensions of institutional quality such as control of corruption, government effectiveness, and political stability to foster innovation development.

Furthermore, policymakers should consider the role of entrepreneurship as a demand-side factor and work on enhancing institutional quality to foster entrepreneurship activities. Additionally, policies to attract FDI should emphasize the enhancement of institutional quality over focusing on the direct relationship between

FDI and entrepreneurship.

Finally, an evaluation framework should be introduced to assess and enhance the design of context-based innovation policies continuously. Further, the customization and contextualization are mandatory. The customization of the selected innovation policy instruments to each country's unique context is essential. Policies must consider various factors affecting the innovation process in different countries.

7.4. Future Research

This study serves as a foundational reference for applying diverse DEA models in assessing KBE efficiency. It addresses the limitations inherent in radial DEA models predominantly used in prior empirical studies by incorporating SBM non-radial DEA models, along with radial CCR and BCC models, to discern the merits of the former (SBM) in gauging the relative efficiencies of developing countries transitioning to a KBE. Additionally, this research employs both the traditional super-efficiency model and the super-SBM model to generate comprehensive rankings for all analysed countries and concludes with a target-setting analysis, aiding policymakers in identifying specific KBE dimensions needing enhancement.

However, despite the advancements, notable gaps persist in the empirical literature, necessitating further in-depth research to elucidate KBE efficiencies. There are opportunities to refine DEA modelling through more advanced models. While conventional DEA models rely on deterministic and quantitative data, deploying specialized DEA models like Fuzzy DEA can furnish more diagnostic analyses to accommodate missing or imprecise data and to project future relative efficiency of DMUs. Moreover, exploring network DEA or dynamic DEA would allow for a meticulous analysis of the multiple sub-processes within KBE.

Future research should also consider incorporating undesirable outputs associated with KBE, such as poverty, brain drain, environmental degradation, and inequality, to render the efficiency analysis more holistic. Scholars could utilize the Malmquist productivity index or implement window analysis to scrutinize changes in efficiency scores over time, and employing panel data analysis can reveal genuine, longitudinal changes, overcoming the limitations of a one-year snapshot provided by cross-sectional data. Extending the analysis to consider factor weights in DEA and assess the impact of uncontrollable external factors through two or three-stage DEA analysis could provide a more nuanced understanding.

Lastly, directing research towards sensitivity analysis could yield valuable insights. Investigating the impact of modifying DEA models by altering input and output variables or assessing the influence of sample changes on DMUs efficiency scores are potential areas within sensitivity analysis that warrant exploration. These further investigations can significantly enhance the breadth and depth of our understanding of KBE efficiencies and provide more tailored guidelines for policymakers.

Appendix (I): Definitions of the KBE.

Author/ Organization	Definition	Source
Brockmann & Roztocki (2017)	Knowledge Economics is a research field that concerns factors and activities aiming to generate knowledge outputs. The knowledge outputs are objects of commercial value and are generated in knowledge-intensive activities or processes by using knowledge creation or modification. Knowledge Economics also deals with the distribution and use of knowledge outputs.	(Brockmann & Roztocki, 2017, p.4445)
Skrodzka (2016)	The knowledge-based economy is an economy where knowledge is created, acquired, transmitted, and used effectively by businesses, organizations, individuals, and communities.	(Skrodzka, 2016, p.281)
Udovič & Bučar (2008)	Knowledge economy/society is defined as a vast growth of services and intangibles, the wide diffusion of information and communication technologies, more intensive use of knowledge and therefore more attention devoted to education and the quality of human resources and last, but definitely not the least important, innovation	(Udovič & Bučar, p.31)
World Bank (2007b)	Is one that uses knowledge as the primary engine of economic growth? Essentially, it is an economy in which knowledge is acquired, created, disseminated, and used effectively to enhance economic development.	(World Bank,2007, P.41)
Brinkley (2006)	"Knowledge economy is what you get when firms bring together powerful computers and well-educated minds to create wealth"	(Brinkley, 2006, p.3)
Economic and Social Research Council (ESRC) (2005)	'Economic success is increasingly based upon the effective utilisation of intangible assets such as knowledge, skills, and innovative potential as the key resource for competitive advantage. The term "knowledge economy" is used to describe this emerging economic structure.	As cited in (Brinkley 2008, p.14)
(Powell & Snellman, (2004)	We define the knowledge economy as production and services based on knowledge-intensive activities that contribute to an accelerated pace of technical and scientific advances, as well as rapid obsolescence.	(Powell & Snellman, 2004, p.199)
Foray (2004)	By economics of knowledge I mean, essentially, economies in which the proportion of knowledge-intensive jobs is high, the economic weight of information sectors is a determining factor, and the share of intangible capital is greater than that of tangible capital in the overall stock of real capital. These developments are reflected in an ever-increasing proliferation of jobs in the production, processing, and transfer of knowledge and information.	(Foray,2004, p.ix)
Godin (2004)	The new economy referred to data that indicated the appearance of new economies in the United States and in a number of smaller OECD countries not very "vibrant" in terms of entrepreneurship. What characterized new economies was the acceleration of trend growth and productivity. Technologies, particularly information and communication technologies (ICT), were believed to be at the heart of the phenomenon, and several researchers, both from universities and governments, developed programs of work to study the phenomenon.	(Godin, 2004, p.679)
World Bank (2003)	A knowledge-based economy relies primarily on the use of ideas rather than physical abilities and on the application of technology rather than the transformation of raw materials or the exploitation of cheap labour.	(World Bank, 2003, p.1)
David & Foray (2003)	'Knowledge-based economy', however, is a recently coined term. As such, its use is meant to signify a change from the economies of earlier periods, more a 'sea change' than a sharp discontinuity	(David and Foray, 2003, p.20)
Foss (2002)	Whatever we think of this journalistic concept, it arguably does capture real tendencies and complementary changes. These include,	(Foss,2002, p.48)

Author/ Organization	Definition	Source
	on the organization side, a shrinking of the corporate boundaries and new ways of structuring these, falling firm sizes and a flattening of internal organization; increased differentiation of tastes on the demand side; acceleration of innovation and technological development on the supply side; and changes in the composition of labour on the input side.	
Quah (2003)	As documented elsewhere in this Handbook (and attested to by journalistic frenzy in the late 1990s' dot-com boom) the New Economy means different things to different observers. Possible dimensions to the New Economy range from e-commerce, e-government, the Internet, the productivity paradox, knowledge-intensive work, social mass-mobilization, and globalization, all the way through auction proliferation, electronic payment systems, venture capital financing saturation, and business restructuring.	(Quah, 2002, p.4)
Coyle &Quah (2002)	Definitions of the 'new economy' tend to cluster into two main types. The first equates the new economy with ICT and its sectoral consequences; either on certain core industry sectors, mainly professional services, or wider economic effects on all economic structures, mainly through cost reduction and networking enabling processes. The second sees the new economy as the post-industrial economy as a whole. Equal emphasis is placed on symbolic analysis and frontline services as areas for employment growth.	(Coyle & Quah, 2002, P.6)
Atkinson & Coduri (2002)	". . . the New Economy is about the transformation of all industries and the overall economy. As such, the New Economy represents a complex array of forces. These include the reorganization of firms, more efficient and dynamic capital markets, more economic "churning" and entrepreneurial dynamism, relentless globalization, continuing economic competition, and increasingly volatile labor markets"	(Atkinson& Coduri,2002 , P.4)
Samuelson & Varian (2001)	Some have asserted that the 1990's witnessed the emergence of a "New Economy." That term dates back to the 1980's when it referred to an economy driven by services rather than manufacturing.	(Samuelson &Varian, 2001, P.362)
Spencer (2001)	The world is currently undergoing a fundamental economic transformation. A combination of technological developments – powerful personal computers, high-speed telecommunications, and the Internet – has created a new market environment variously referred to as the 'information economy', the 'network economy', the 'knowledge economy', or simply the 'New Economy'. This New Economy is anchored primarily in the production, processing, and dissemination of such information goods as software, content, or expertise.	(Spencer 2001,PP.162 7-1628)
Harris (2001)	The KBE is the dominant post-industrial economic development paradigm that emerged in the 1980s, with an emphasis on the role of knowledge creation and distribution as the primary driver in the process of economic growth, the distribution of income, the growing importance of knowledge-based networks among firms, and the interface between government business and citizens in the advanced economies.	(Harris 2001, P.21)
APEC Economic Committee (2000)	The production, distribution and use of knowledge is the main drivers of growth, wealth creation and employment across all industries	(APEC 2000, P.vii)
Thomas & Carl (2001)	Knowledge is created, acquired, transmitted, and used effectively by enterprises, individuals, and communities, it does not narrowly on high-technology industries or on information and communications technologies, but rather presents a framework for analyzing a range of policy options in education, information infrastructure and innovation systems that can help usher in the knowledge economy.	(Thomas & Carl, 2001 p.4)
Houghton & Sheehan (2000)	In an agricultural economy land is the key resource. In industrial economy natural resources, such as coal and iron ore, and labour are the main resources. A knowledge economy is one in which knowledge is the key resource.	(Houghton & Sheehan 2000, p.1)

Author/ Organization	Definition	Source
Quah (1999)	By the weightless economy, I mean that part of the economy comprising the following four categories: 1. Information and communications technology (ICT), including the Internet. 2. Intellectual property, including not only patents and copyrights but more broadly, name brands, trademarks, advertising, financial and consulting services, health care (medical knowledge), and education. 3. Electronic libraries and databases, including new media, video entertainment, and broadcasting4. Biotechnology, which includes carbon-based libraries and databases, as well as pharmaceuticals	(Quah,1999, pp.1-2)
Leadbeater & London (1999)	The knowledge-driven economy is not just a new set of high-tech industries such as software and biotechnology, which have built on a science base. Nor is it just a set of new technologies: information technology and the Internet, for example. The knowledge-driven economy is about a set of new sources of competitive advantage, particularly the ability to innovate, create new products and exploit new markets, which apply to all industries, high-tech and low-tech, manufacturing and services, retailing and agriculture.	(Leadbeater & London, 1999,p.7)
The UK Competitiveness white paper (1998)	A knowledge driven economy is one in which the generation and the exploitation of knowledge has come to play the predominant part in the creation of wealth. It is not simply about pushing back the frontiers of knowledge; it is also about the more effective use and exploitation of all types of knowledge in all manner of economic activity.	(Quoted from Peters 2001, P.7)
OECD (1996)	Knowledge-based economies are economies which are directly based on the production, distribution and use of knowledge and information.	(OECD 1996, P.7)
New Zealand's Ministry of Research, Science and Technology (n.d.)	Those which are directly based on the production, distribution and use of knowledge and information. This is reflected in the trend towards growth in high technology investments, high-technology industries, more highly skilled labour, and associated productivity gains.	(Quoted from Peters 2001, P.7)
Work Foundation initiative in Great Britain (2005)	"Economic success is increasingly based on the effective utilization of intangible assets such as knowledge, skills, and innovative potential as the key resource for competitive advantage. The term knowledge Economy" is used to describe this emerging economic structure"	Quoted from (Amirat and Zaidi, 2020, p.1147)
Kamara et al. (2008)	A knowledge-based economy means that knowledge production, exchange, distribution, and utilization are primarily driven by economic growth, more employment, and the creation of wealth	Murat et al., 2017, p.10
Mohammed bin Rashid Al Maktoum Foundation (MBRF) and the United Nations Development Programme/Regional Bureau for Arab States (UNDP/RBAS), 2015	The United Nations Development Programme (UNDP) defines the knowledge economy as the efficient dissemination, production, and utilisation of knowledge in all areas of societal and economic activity, civil society, politics, and private life including the promotion of human development a phenomenon that necessitates the building and efficient distribution of human potential and capabilities.	Mohammed bin Rashid Al Maktoum Foundation (MBRF) and the United Nations Development Programme/ Regional Bureau for the Arab States ,2015, p.103

Appendix (II): Models of KBE Assessment in the Literature.

1- Models of Comprehensive KBE Assessment

1-1 OECD Framework

Based on their work of producing and publishing science and technology (S&T) indicators, the OECD began researching the KBE and making attempts to assemble statistical indicators on the KBE as early as 1999. The old economic indicators, according to the OECD, "have never been completely satisfactory, primarily because they failed to recognize economic performance beyond the aggregate value of goods and services,". New economic theories and metrics that track phenomena other than standard market transactions are needed to completely comprehend how the KBE functions. In general, the OECD indicated that the following tasks require enhanced KBE indicators (OECD, 1996):

(i) Measuring knowledge inputs.
(ii) Measuring knowledge stocks and flows.
(iii) Measuring knowledge outputs.
(iv) Measuring knowledge networks.
(v) Measuring knowledge and learning.

(i) Measuring Knowledge Inputs
The main measures of knowledge input include the following: international balance of payments, patents, employment of engineers and technical staff, and R&D investment. These are a part of the S&T indicators that the OECD has published.

(ii) Measuring Knowledge Stocks and Flows
Measuring the stock of knowledge capital would seem to be a nearly impossible endeavour given how difficult it is to estimate the stock of physical capital that is available to an economy. Measuring the amount of knowledge stock that enters the economy over time, or the flow of knowledge, is a more challenging task. As a result, the OECD has only recommended a small number of proxy measures.

(iii) Measuring Knowledge Outputs
Only minimal indicators have been created to define and assess the economic performance of nations by converting specific knowledge inputs into knowledge outputs. These metrics frequently categorise different industrial sectors or subsets of the workforce according to how much R&D, knowledge, or information they invest.

(iv) Measuring Knowledge Networks
Indicators of knowledge production and dissemination at the firm level were recommended to be gathered through innovation surveys to assess knowledge networks.

(v) Measuring Knowledge and Learning

A "learning economy" that also reflects efficiency and justice in education and training requires indicators for assessing knowledge and learning. In this regard, the OECD has been working to develop human capital indicators, which are specifically intended to gauge the societal and private rates of return on investments in education and training. The aforementioned methodology was later somewhat adjusted and broadened to cover basically four primary areas as follows rather than approaching the KBE from measurement of knowledge directly as follows: knowledge production and dissemination, the information economy, the integration of economic activity on a global scale, and economic structure and productivity are among the topics covered.

A set of information economy indicators was also established, drawing on the work on indicators for the information society, while indicators on knowledge generation and diffusion built on the work of the S&T indicators.

Later, the OECD Growth Project in 2001 examined the concept of a KBE in greater detail and concluded that several criteria are crucial for a KBE. These findings propose the general components of a KBE framework as follows:

(i) The significance of a macroeconomic environment that is open and stable and has functioning markets.
(ii) ICT adoption
(iii) Encouraging innovation
(iv) Investment in human resources
(v) Promoting business formation.

1-2 The New Economy Index

There is much discussion over the emergence of the so-called New Economy. It has proven difficult to define. What new does it offer? To illustrate the fundamental structural changes in the American economy, to demonstrate the implications of those changes for working Americans, and to assess the nation's advancement in several crucial foundational areas for future economic growth, a new set of economic indicators in the New Economy Index are introduced. These indicators were compiled from already-existing public and private data.

Three kinds of indicators make up The New Economy Index. The transition to the new economy is marked by several fundamental structural changes, which are tracked in the first category. These changes include those in the industrial and occupational sectors, globalization, the nature of competition and economic dynamism, and the development of the information technology revolution. The second group looks at how this change will affect working Americans, including what will happen to wages, economic growth, employment dynamics, and jobs. The third category evaluates the nation's performance in relation to the three key pillars of the new economy's expansion: the rate of the shift to a digital economy, the level of business and governmental investment in technology and innovation, and the advancement of skill and education development.

The 1999 State New Economy Index: Benchmarking the Economic Transformation in the States.

The State New Economy Index continues the work that was started with The New Economy Index, in which a fresh set of economic indicators are employed to highlight the structural underpinnings of what is referred to as the "New Economy." The development of the American economy is followed in the first report along the four primary axes: globalisation, the entrepreneurial dynamism and competition, the IT revolution, and the industrial and occupational mix.

In this report, the same set of metrics for all 50 states is used. This research does not aim to declare "winners" or demonize "losers." Instead, the goal is to draw attention to variations in the structural underpinnings of state economies and to centre the discussion on a progressive policy framework to support economic growth in the New Economy.

The five criteria that best reflect what is novel about the New Economy have been applied to the 17 indicators in this 1999 report:

1. **Knowledge jobs** Separate indicators measure jobs in offices; jobs held by managers, professionals, and technicians; and the educational attainment of the workforce.
2. **Globalization**. Indicators measure the export orientation of manufacturing and foreign direct investment.
3. **Economic dynamism and competition.** Indicators measure the number of jobs in fast-growing “gazelle” companies (companies with sales growth of 20 percent or more for four straight years); the rate of economic “churn” (a product of new business start-ups and existing business failures); and the value of initial public stock offerings (IPOs) by companies.
4. **The transformation to a digital economy.** Indicators measure the percentage of adults online; the number of “.com” domain name registrations; technology in schools; and the degree to which state and local governments use information technologies to deliver services.
5. **Technological innovation capacity.** Indicators measure the number of high-tech jobs; the number of scientists and engineers in the workforce; the number of patents issued; industry investment in research and development; and venture capital activity.

The 2002 State New Economy Index: Benchmarking the Economic Transformation in the States

Most of the indicators used in the 1999 State Index are included in the 2002 State New Economy Index. However, the 2002 Index incorporates several new indicators utilizing recently available data as part of our ongoing attempt to better quantify the new economy, particularly given that it affects all industries and is not simply "high-tech." These metrics evaluate the degree to which non-IT sectors have adopted IT. The study examines the proportion of "traditional" industry IT personnel who use IT, the degree to which farmers utilize computers and the Internet, and the proportion of manufacturing facilities having Internet connectivity. It measures the educational levels of a state's manufacturing workforce to determine the extent to which that sector is adopting high-performance, high-skill work practices. Finally, the infrastructure for high-speed broadband communications in the states is also measured.

Additionally, the study accounts for a state's industry sector mix when controlling for variables that reflect corporate behaviour (R&D, exports, and patents). Since certain industries by their very nature export, patent, or invest more in R&D than others, it is crucial to keep the industry mix consistent for these variables. For instance, because the aviation sector (such as Boeing) is so large and exports account for a sizable portion of the industry's output, Washington State would rank quite well on manufacturing exports without accounting for industry mix. These three variables consider the industrial mix of the state to provide a more precise measurement of the extent to which businesses, regardless of the industry they operate in, export, invest in R&D, or file patents.

The overall scores aren't always comparable because the 1999 and 2002 reports employ different indicators and methodology. Therefore, it should not be assumed that a state's transition from a lower to a higher position between 1999 and 2002 reflects relative changes in the structure of its economy.

The 21 indicators are split into five groups that best reflect the New Economy's innovations:

1) **Knowledge jobs.** Indicators measure the employment of IT professionals; jobs held by managers, professionals, and technicians; the educational attainment of the entire workforce; and the education level of the manufacturing workforce.

2) **Globalization.** Indicators measure the export orientation of manufacturing and foreign direct investment.

3) **Economic dynamism and competition.** Indicators in this category measure the number of fast-growing "gazelle" companies (companies with growth of 20 percent or more for four straight years); the rate of economic "churn" (which is a product of new business start-ups and existing business failures); and the value of initial public stock offerings (IPOs) by companies.

4) **The transformation to a digital economy.** Indicators measure the percentage of the population online; the number of ".com" domain name registrations; technology in schools; the degree to which state and local governments use information technologies to deliver services; Internet and computer use by farmers; Internet use by manufacturers; and access by residents and businesses to broadband telecommunications.

5) **Technological innovation capacity.** Indicators measure the number of jobs in technology-producing industries; the number of scientists and engineers in the workforce; the number of patents issued; industry investment in research and development; and venture capital activity.

The report always uses the most recent numbers that are available, but occasionally older data may be used due to delays in the release of official statistics. Additionally, figures are always given with a denominator such as the number of employees or the gross domestic product to account for the size of the state.

Each indicator's scores are calculated using the formula below: Raw scores are based on standard deviations from the mean to gauge the size of state-to-state variations rather than just their ranking from one to fifty. As a result, on the majority of measures, around half the states start out with low scores (below the national mean), and roughly the same number start out with high scores. To guarantee that all the scores are positive, 10 is added to each of the totals for each of the five indicator categories.

The indicators are weighted in three of the five indicator categories when determining the overall New Economy scores to prevent the results from being skewed by those that are highly associated (such as patents, R&D spending, and high-tech jobs).

The sum of the greatest scores obtained by any state in each category is added to the adjusted scores for each of the five indicator categories, and the total is then divided by five to determine the overall scores. The final score for each state is therefore a percentage of the score it would have received overall if it had won every category.

The following procedure was used to code the maps: Calculated and divided by four, the range between the highest and lowest scores was determined. The range for the 100th to the 76th percentile and for the other three percentile ranges were determined by deducting that product from the highest score. Therefore, rather than necessarily dividing into an equal number of states, the percentiles simply show which state scores lie inside a given range.

The Weighting Methodology

Raw scores were calculated for each state for each indicator. In the composite analyses, the indicators were weighted so that closely correlated ones wouldn't bias the results. In addition, to measure the magnitude of differences between states and not just their ranks, in each indicator, scores were based on the standard deviation of each from the mean score of all the states (Atkinson & Coduri, 2002).

1-3 APEC framework

The APEC Economic Committee launched a project in the middle of 1999, and that project included the creation of the APEC framework. The project, titled Towards Knowledge-based Economies in APEC, was advanced by a specially formed KBE Task Force, which comprised representatives from Australia, Canada, and Korea.

According to the APEC Economic Committee in 2000, the project's goal was to "provide the analytical basis useful for promoting the effective use of knowledge, as well as the creation and dissemination of knowledge among APEC economies."

The study examined empirical data and concluded that economies that are strong in all four of the following dimensions will experience the most sustained economic growth (findings of the OECD Growth study, assessed and cited in the APEC Economic Committee report) (APEC Economic Committee, 2000):

- “Innovation and technological change are pervasive and are supported by an effective national innovation system.”
- “Human resource development is pervasive: education and training are of a high standard, widespread and continue throughout a person’s working life.”

- “An efficient infrastructure operates, particularly in information and communications technology (ICT), which allows citizens and businesses to readily and affordably access pertinent information from around the world.”
- “The business environment is supportive of enterprise and innovation.”

These four dimensions form the basis of the APEC KBE framework:

- Innovation System
- Human Resource Development
- ICT Infrastructure
- Business Environment.

The availability of the chosen indicators for all the case study economies was crucial for the APEC reports. This tended to reduce the number of available indications.

Another study was carried out by APEC in 2001 to look at the underlying principles of the New Economy. The KBE idea and the definition of the New Economy are compatible. They concluded that the New Economy also requires the four KBE success factors (APEC, 2001). The study stretched the analysis beyond the four KBE characteristics to concentrate on achieving high productivity growth in the New Economy and on minimising the escalation of a digital divide that could follow from a discussion of policy that was too reserved.

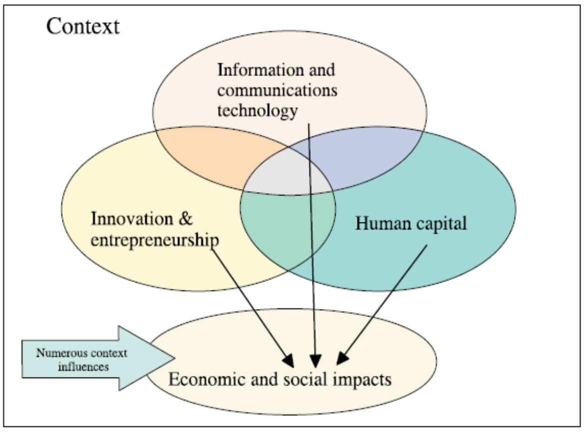
1-4 ABS Model

In 2002, the Australian Bureau of Statistics (ABS) published a report "Measuring a knowledge-based Economy and Society: An Australian Framework" with a detailed framework for measuring a KBE or society. The ABS builds its work mainly based on APEC and OECD frameworks (Trewin, 2002). The ABS framework has five dimensions, with three core dimensions and two supporting dimensions: namely[1] :

- Innovation and entrepreneurship (core dimension and represented by 4 indicators)
- Human capital (core dimension and represented by 4 indicators)
- Information and communications technology (core dimension and represented by 6 indicators)
- Context dimension (supporting dimension and represented by 13 indicators)
- Economic and social impacts (supporting dimension and represented by 2 indicators)

The structure of the ABS can be presented in a diagram as shown:

(1) More details about each dimension are available on Trewin (2002, pp 20-25).



Source: Trewin (2002)

As indicated by the diagrammatic representation, the broader dimension is the context dimension. It combines various background elements and preconditions such as the business environment. The other three core dimensions define the basic characteristics of the KBE. Finally, the economic and social impacts, which shows the effects on the economy and on society because of an increased emphasis on and use of knowledge. Further, the relationships and overlaps between dimensions are numerous. The economic and social impacts component interacts with the other dimensions and has an impact on them. Additionally, the overlapping of the three core dimensions, the pervasiveness of the context dimension, and the economic and social repercussions of the context and core dimensions are all depicted in the above graph. There are more relationships than those seen real situations.

Framework Limitations

- The framework does not try to include all types of knowledge related to the economy and society. Such an endeavour would not only be excessively ambitious, but it would also be deceptive if it suggested that all knowledge could be quantified.

- The framework does not provide a thorough analysis of a knowledge-based society; however, it does cover the social factors that could influence or be affected by economic development.

1-5 Harvard University Assessment Model "Readiness for the Networked World"

What Is the Networked World?

The nature of international interactions, sources of competitive advantage, and possibilities for economic and social growth have all undergone profound change because of the ever evolving and powerful ICTs. The world is now a more interconnected network of people, businesses, schools, and governments talking and interacting with one another through several channels thanks to technologies like the Internet, personal computers, and wireless phones. Because of the rapid growth of this technologically mediated global network, almost everyone now has access to the advantages of being connected to the network (Kirkman et al., 2002).

Examples of the Networked World is:

- A rural village crafts woman selling handmade goods online while utilising a computer at the community centre.
- Healthcare professionals researching latest health alerts by using online databases.
- Students from many nations working together online on a scientific project.
- Programmers use the Internet to create specialised software for far-off clientele.
- personnel in charge of government procurement making purchases and contracts online.
- A farmer looking up market prices on a wireless mobile device.

What Is Readiness?

Is defined as the level of a community's readiness to engage in the Networked World. It can be determined by evaluating a community's relative progress in the areas that are most crucial for ICT adoption and the most significant ICT applications. An evaluation based on these components offers a thorough representation of a community's Readiness when considered collectively in the context of a strategic planning debate.

The importance of measuring a community's readiness resides in identifying its possibilities and challenges. Many towns won't be equally Ready according to all rating criteria. Instead of a straightforward "yes" or "no", the outcome is a complicated map or in-depth picture of a community's possibilities. A community may be in a good position for some uses of ICT in a society, but not for others. The Guide's output is comprehensive and detailed, making it a potent instrument for determining a community's strategic priorities for engaging in the networked world.
A community cannot focus exclusively on one category because the categories are interconnected, and one drives the others. Instead, it must pay attention to each and consider how it might be able to take advantage of the synergies between the categories. Five groups contain the categories as follows:

- **Network Access:** How accessible, expensive, and high-quality are ICT networks, services, and tools?
- **Networked Learning:** Is the use of ICTs in the educational system a part of the community efforts to enhance learning? Are there any local technical training programs that can educate and prepare an ICT workforce?
- **Networked Society**: How much do people use ICTs in their personal and professional lives in the networked society? Do persons with ICT skills have access to numerous opportunities?
- **Networked Economy:** How do corporations and governments connect with the public and with one another by using ICTs?
- **Network Policy:** To what extent does the regulatory climate help or hurt the expansion of the ICT adoption and use?

1-6 UNECE

- The focus of UNECE efforts to reduce the digital divide among its member states has been on transitioning nations, particularly those in Central Asia and the South Caucasus.

- The UNECE organised an evaluation of 14 transitioning nations (Armenia, Azerbaijan, Belarus, Bulgaria, Georgia, Kyrgyzstan, Latvia, Lithuania, Russian Federation, Slovakia, Tajikistan, Yugoslavia, Ukraine, and Uzbekistan) in terms of their readiness for the KBE in 2002 and 2003.

- UNECE also created were a variety of regional studies, such as "Towards a knowledge-based Economy. Regional Assessment Report" (2002), "Information Economy Report - E-Policy Development in Transition Economies 2002-2003," and "Internet Infrastructure Development in Transition Economies" (2000).

- Each report in the regional evaluation report is written by a national expert. It offers a summary and evaluation of the current situation and provides an overview of all the primary areas that make up the KBE's basis, such as policy and policy instruments, institutional regime, information system, innovation system, and human resources, it provides an overview and assessment of the current situation and emerging trends (Ceruti et al., 2019)

1-7 The Arab Knowledge Index - The Global Knowledge Index

- The Arab Knowledge Index

It has been consistently confirmed that there is a serious lack of reliable data and research that can support the decision-making process in the fields of knowledge and development ever since the Arab Knowledge Project was founded and throughout the preparation stages of all three knowledge reports.

As a result, regional monitoring and evaluation techniques are required, as opposed to the current international instruments, which do not account for the contexts, cultures, and needs of the Arab region.

Therefore, the Arab Knowledge Index was created, which accurately captures "knowledge from a development perspective" in the Arab region while also concentrating on the crucial role of Arab youth and the region's unique circumstances, needs, and challenges unique to the Arab region.

Numerous crucial sectors are the focus of the Arab Knowledge Index, namely Education at its Pre-University, Higher and Technical Vocational and Training levels, Research, Development and Innovation, Economy, and ICT. It includes more than 300 variables across these different sectors.

The Arab Knowledge Index stands out from similar attempts by considering areas that are frequently underrepresented, such as technical vocational education and training, the relationship between research and development (R&D) and innovation, and the interaction between various sectors, for the first time.
In addition to regional workshops held around the Arab world, the Index methodology was created in conjunction with renowned local, regional, and international professionals and academics.

In order to become an Index of Knowledge, from the Arab area to the entire world, the Index now expanded its coverage to include 131 from across the world under the term "Global Knowledge Index (GKI)".

It should be noted that in 2015 and 2016, there were published two Arab Knowledge Indexes. The Global Knowledge Index was introduced in 2017.

- The Global Knowledge Index

The Mohammed Bin Rashid Al Maktoum Knowledge Foundation (MBRF) and the United Nations Development Programme (UNDP) collaborated to create the "Global Knowledge Index" (GKI).

The Index seeks to quantify knowledge as a concept with multiple dimensions. The concept is flexible and frequently connected to terms like "knowledge economy" or "knowledge society." It can also be constrained to a certain understanding that concentrates just on technology or education.

The GKI aims to introduce a more systematic understanding of knowledge in two ways, given the variations in its use and meaning.

It divides the idea into its constituent parts, such as pre-university education, technical and vocational education, and training (TVET), higher education, research, development, and innovation (RDI), information and communications technology (ICT), and economy, in addition to the general enabling environment. As a result, it acknowledges that knowledge systems are multidimensional in all contexts and applications that relate to economic and social structures. This makes it possible to explore knowledge policy in connection to many sectors in a more thorough and comprehensive manner.

It also makes it possible to link development and a multifaceted concept of knowledge in a way that is more scientific and based on evidence, in line with both the UNDP's definition of human development and the definition of sustainable development that was adopted by world leaders in 2015 in the form of the 2030 Agenda for Sustainable Development.

Detailed structure, variable selection process, data treatment, normalization, index weighting and index calculation is available in GKI report 2022.

1-8 The Knowledge Assessment Methodology (KAM)

The Knowledge Assessment Methodology (KAM) is an Internet-based tool that provides a basic assessment of countries' and regions' readiness for the knowledge economy. It was created by the World Bank Institute's Knowledge for Development (K4D) Program to aid in this transition process. The KAM is an interactive diagnostic and benchmarking tool that is simple to use and made to help client countries evaluate their strengths and weaknesses by comparing them to competitors, neighbours, or other nations they may like to imitate based on the four KE pillars. To make the transition to the knowledge economy, a country may encounter challenges and opportunities. The KAM can help a country identify these issues and indicate where it should concentrate its policy efforts or future investments. The distinct power of KAM lies in its cross-sectoral approach, which enables a comprehensive assessment of the large range of elements pertinent to the knowledge economy. The KAM uses 109 structural and qualitative factors for 146 nations as a basis for comparisons that act as stand-ins for the four knowledge economy pillars. The comparisons are shown in various graphs and figures that clearly show the similarities and contrasts between the various nations; these will be covered in more detail later. All of the data used to create the KAM have been released by recognized organizations that are at the forefront of collecting and generating trustworthy national statistics that are comparable around the world. The data are regularly updated, and every opportunity is used to broaden the nation coverage.

There are six different display modes for the KAM:

To compare nations based on the aforementioned four KE pillars and determine their total KEI and KI indices, KAM offered six modes: -

- ***Basic Scorecard*** uses 14 essential variables as proxies. Up to three countries can be compared on the scorecard for the years 1995, 2000, and the most recent year that is currently available.
- ***Custom Scorecards***, you can compare up to three nations or regions for 2000 and the most recent year available while using any combination of the 109 factors.
- ***KEI and KI:*** In a sortable table style, KEI and KI Indexes provides performance scores for all nations on the KEI and KI indices as well as on the 4 KE pillars.
- ***Over-time Comparison:*** Country's development on the Knowledge Economy's pillars and indices is shown through time, from 1995 to the most recent year.
- ***Cross-Country Comparison:*** shows the relative contributions of several KE pillars to the countries' total knowledge readiness while allowing bar-chart comparisons of up to 20 countries on their KEI and KI indexes.
- ***World Map:*** A color-coded map of the world's KE preparedness for 1995, 2000, and the most recent year is provided by World Map.

KAM Normalization Procedure

- Variables are scaled from 0 to 10 in comparison to other nations in the comparison group.
- The variables used by the KAM are scaled differently and are measured using various units. So, KAM normalizes all the variables to the same unit of measurement in order to compute aggregate knowledge economy indices and to simplify the graphic portrayal of nations' comparative performance.
- First, based on their actual results for each variable, countries are ranked from "best" to "worst". The results are then standardized against all the other countries in the comparison group on a scale of 0 to 10. The best score is 10 for top performers, and the poorest is 0 for laggards.
- A normalized score between 9 and 10 is given to the top 10% of performers, followed by normalized scores between 8 and 9 for the next 10% of performers, and so on. In other words, the 0–10 scale rates how well each nation performed on each variable in comparison to the other nations in the sample.
- "All countries" (146) is the default comparison group. The nation may also be contrasted with others in the pertinent region or income bracket. In this instance, only the chosen comparison group will be used to rank and normalize

the data. Depending on whatever group a country is compared to, it will receive a different normalized score.

- Utilizing both the actual and the relative (normalized) results together allows for a deeper understanding of what is occurring in a given nation or variable. A chart might, for instance, demonstrate how a nation's relative standing has declined between 1995 and 2000, 2000 and the most recent era, or 1995 and the most recent time. This indicates that the absolute performance of the country on the relevant metric has either actually declined or improved, although not as significantly as in the comparison countries. Knowing whether of these two conditions is present is crucial because they are two very distinct things.
- It is important to note that an economy shouldn't always strive for a perfect score of 10 on every metric and to be at the very edge of the scorecard. Some variables are based on performance, while others are based on trade-offs between various development plans, and yet others are based on the unique structural traits of an economy.
- The following is the KAM's normalization process:

  1. For all the variables and nations, the real data (u) is gathered from World Bank datasets and international literature.

  2. 109 variables are described by absolute values (actual data), which are used to provide ranks to countries (rank u). Countries are given the same rank based on their performance. As a result, the rank is equal to 1 for the nation that performs the best on a given variable among the nations in our sample (i.e., it has the highest score), 2 for the nation that performs second best, and so on.

  3. For each nation, the number of nations having a higher rank (Nh) is determined.

  4. To normalize the scores for each country on each variable in relation to their ranking and the total number of countries in the world, the following formula is used:

  $$\text{Normalized (u)} = 10*(Nh/Nc)$$

  5. Using the aforementioned formula, each nation is given a normalized score between 0 and 10.

The following table summarizes the mainstream KBE models, their pillars and indicators.

Table (3.1): The KBE Pillars and Indicators Developed by OECD, APEC, EU and WBI.

OECD	APEC	EU	WBI (Basic scorecard)
1. Knowledge-Based Economy Knowledge Investment (education, R&D and software) as % of GDP. Education of the adult population as % of the population aged 25-64. R&D expenditure as a percentage of GDP. Basic research expenditure as a percentage of GDP. Expenditure of Business R&D in domestic product of industry. Expenditure of Business R&D in manufacturing. Share of services in R&D expenditure. Expenditure on innovation as a share of total sales. Investment in venture capital as a percentage of GDP.	**1. Business Environment** **1.1** Knowledge based Industries as % of GDP. **1.2** Services Exports as of GDP. **1.3** High-Tech Exports as of GDP. **1.**FDI inward flow as % of GDP. **1.5**Government transparency rating by World Competitiveness Yearbook. **1.6** Financial transparency rating by World Competitiveness Yearbook. **1.7** Competition policy rating by World Competitiveness Yearbook. **1.8** Openness rating by World Competitiveness Yearbook.	**1. Innovation Drivers** **1.1** New S&E graduates per 1000 population aged 20-29. **1.2** Population with tertiary education per 100 population aged 25-64. **1.3** Number of broadband lines per 100 populations. **1.4** Participation in life-long learning per 100 population aged 25-64. **1.5** Percentage population age 20-24 completed secondary education.	**1. Performance** **1.1** Average annual GDP growth (%) **1.2**Human Development Index.
2.Information and Communication Technology **2.1** ICT spending as % of GDP. **2.2** PC penetration in households. **2.3** Number of internet host per 1000 inhabitants. **2.4** Percentage share of ICT industries in GDP. **2.5** Share of ICT in patents granted by USPTO.	**2. ICT Infrastructure** **2.1** Number of mobile telephones in use per 1000 inhabitants **2.2** Number of telephones mainlines in use per 1000 inhabitants. **2.3** Number of computers per 1000 inhabitants **2.4** Number of internet users as % of population **2.5** Internet hosts per 10000 **2.6** Expected e-commerce Revenues, M$US	**2. Knowledge Creation** **2.1** Public R&D expenditures (% of GDP). **2.2** Business R&D expenditures (% of GDP). **2.3** Share of medium high-tech and high-tech R&D. **2.4** Share of enterprises receiving public funding for innovation. **2.5**Share of University R&D expenditures financed by business sector.	**2. Economic Incentive and Institutional Regime** **2.1** Tariff and non-tariff barriers **2.2** Regulatory Quality **2.3** Rule of Law
3. Science and Technology Policies **3.1** Publicly funded R&D as % of GDP. **3.2** Government R&D expenditure on health-defence environment. **3.3** Government R&D expenditure in total R&D expenditure. **3.4** Business R&D expenditure in total R&D expenditure. **3.5** Share of Government Business R&D expenditure financed together. **3.6** Tax subsidies rate for R&D.	**3. Innovation System** **3.1** Scientists Engineers in R&D per million of the population **3.2** Full-time researchers per million of the population **3.3** Gross Expenditure on R&D (% of GDP) **3.4** Business Expenditure on R&D (% of GDP) **3.5** US Patents per annum **3.6** The number of technological cooperation among companies	**3. Innovation and Entrepreneurship** **3.1** SMEs innovating in-house (% of SME) **3.2** Innovative SMEs co-operating with others (% of SMEs) **3.3** Innovative expenditures (% of turnover) 3.4 Early-stage venture capital (% of GDP) **3.5** ICT expenditure (% of GDP) **3.6**	**3. Education and Human Resources** **3.1** Adult Literacy rate (%age 15 and above) **3.2** Secondary Enrolment **3.3** Tertiary Enrolment

OECD	APEC	EU	WBI (Basic scorecard)
	3.7 The number of technological cooperation between company-university	SMEs using non-technological change (% of SMEs)	
4. Globalization **4.1** Share of foreign affiliates in R&D. **4.2** Share of foreign and domestic ownership in total inventions. **4.3** Number of international technological alliances. **4.4** Percentage of scientific publications with a foreign co-author. **4.5** Percentage of patents with a foreign co-investor.	**4. Human Resource Development** **4.1** Secondary enrolment (% of age group) **4.2** Natural Sciences Graduates per annum **4.3** Knowledge Workers (% of Labor force) **4.4** Newspaper (per 1000 inhabitants) **4.5** Human Development Index	**4. Application** **4.1** Employment in high-tech services (% of total workforce) **4.2** Exports of high technology products as share of total exports	**4. Innovation System** **4.1** Researchers in R-D, per million populations **4.2** Patent Applications granted by the USPTO, per million populations. **4.3** Scientific and technical journal articles, per million populations
5. Output and Impact **5.1** Scientific publications per 100 000 population. **5.2** Share of countries in total EPO patent application. **5.3** Share of firm creating any innovative output. **5.4** GDP per employed person. **5.5** Share of knowledge-based industries in total value added. **5.6** Share medium-high technology industries in manufacturing export. **5.7** Technology balance of payments as a percentage of GDP.			**5. Information Infrastructure** **5.1** Telephones per 1000 persons, (telephone mainlines + mobile phones) **5.2** Computers per 1000 persons **5.3** Internet Users per 10000 persons

2 Models of Sectoral KBE Assessment

2-1 Fritz Machlup - Knowledge Industry – 1962

The idea of a knowledge economy was first introduced by Fritz Machlup. The economist, who was born in Austria, published a study in 1962 that examined how knowledge is produced and disseminated in the US. According to the author, the knowledge economy contributed 29% of GNP, or $ 136.4 million, in 1985. The concept of measuring knowledge as it is distributed was initially introduced by Machlup, as prior metrics focused on the production of scientific information, specifically research and development (R&D), rather than its dissemination.

Machlup provided a list of eleven justifications for studying the economics of knowledge, including: -

- Knowledge increased the share of the nation's budget.
- Knowledge has more societal benefits than private ones.
- Increases in production and growth are highly correlated with knowledge.
- Knowledge linkages to new ICTs.
- A shift in the need for brain workers away from physical labourers.

Machlup put up a definition of knowledge that included two features. First, everything that is known by someone can be considered knowledge according to Machlup's definition, including both scientific and ordinary knowledge. Second, knowledge was defined as being both produced and disseminated. In his book, producing knowledge means, not only discovering, designing, and planning, but also disseminating and communicating (Machlup, 1962).

Additionally, Machlup identifies five categories of knowledge:
- Knowledge that is practical
- Knowledge that is intellectual knowledge, that is, general culture and knowledge that satisfies intellectual curiosity.
- Pastime knowledge, that satisfy non-intellectual curiosity or a desire for light entertainment and emotional stimulation.
- Knowledge that is spiritual or religious.
- Knowledge that is unwanted, unintentionally acquired, and aimlessly retained.

2-2 Gifford - Information Society Index (ISI) – 1999

The ISI was developed as the first global indicator of 53 countries' readiness to take part in the information revolution. The ISI is a distinctive study that integrates 15 factors organised into four infrastructures to rank and calculate nations based on one overall index and four sub-indices. The index and sub-indices create a benchmark by which all countries are evaluated on their capacity for gaining access to and utilising information and information technology (Welch, 2000).

Advantages of employing the ISI

The ISI provides the information needed for government planners, multinational IT and telecommunications companies, and asset management companies to analyse current prospects, drivers, and inhibitors and monitor progress within each of the 53 countries. by responding to questions like:

- How do economic variables affect the expansion of IT services and goods?
- Which major IT indicators indicate changes in the market?
- Which international markets have the greatest potential for expansion?

This research assists clients in recognizing and understanding the prospects and financial commitments needed to enter new markets.

2-3 Networked Readiness Index (NRI)

The Networked Readiness Index (NRI) developed by the World Economic Forum assesses a nation's tendency to take advantage of the opportunities presented by information and communications technology. It is released yearly. The NRI aims to understand in greater detail how ICT affects a country's ability to compete internationally (Kirkman et al., 2002).

The NRI is made up of three elements: the ICT environment provided by a particular nation or community, the readiness of the community's major stakeholders (people, companies, and governments), and finally, the adoption of ICT by these stakeholders. The Global Information Technology Report, which uses the index, is published by the World Economic Forum and INSEAD. The Information Technology Group, which operated at the Centre for International Development at Harvard University until 2002, was responsible for creating the index's original version.

2-4 The INTXSK Model

To demonstrate how various combinations of infrastructure, experience, and skills may be promoting knowledge-based development, the INEXSK (INfrastructure, EXperience, Skills, Knowledge) approach can be employed.

The model shows how some of the essential elements of the creation and application of ICT technologies, together with the necessary human skills, combine to create a basis for coordinated policies intended to employ the technologies to enhance social and economic growth (Mansell & Wehn, 1998).

The INEXSK technique uses numerous indicators because there is not an "ideal" indicator or composite indicator for the growth of enhanced knowledge.

The results of the INEXSK approach do not accurately reflect the nuances of the distribution of skills and experience within each country, hence it is not designed to explain how different combinations of experience and abilities connected to information and communication technologies enable knowledge-based development. The strategy highlights the diverse paths that other nations are taking and offers a forum for discussion on future policy decisions and the distribution of investment.

2-5 Science Citation Index (SCI)

Researchers, administrators, instructors, and students have quick and effective access to the bibliographic and citation data they need to locate pertinent, comprehensive data thanks to the Science Citation Index. It overcomes information overload and concentrates on important information from more than 3,700 of the top scientific and technical publications published worldwide over 100 subjects.

The citation index or an index of citations between publications, enables the user to quickly determine which later articles cite which previous works. Legal citators like Shepard's Citations (1873) were among the first citation indices (Carpenter & Narin, 1981). The first citation index for articles published in scholarly journals was created in 1960 by Eugene Garfield's Institute for Scientific Information (ISI), which initially produced the Science Citation Index (SCI) before expanding to create the Social Sciences Citation Index (SSCI) and the Arts and Humanities Citation Index (AHCI). CiteSeer carried out the first automatic citation indexing in 1997. Google Scholar is another source of information of this nature.

Database of the Science Citation Index:

The Science Citation Index (SCI), published by the Institute for Scientific Information (ISI), offers access to recent bibliographic data and cited references.

Over 5,600 of the top scientific and technical publications from around the world are covered by the Web of Science version of SCI, which is available online and covers a wide range of fields. The following URL provides a list of titles: http://www.isinet.com/isi/journals/index.html.

What is a citation index?

Because it is a citation index, SCI is distinctive. A citation index is a list of every reference cited from journal articles that have been indexed in the database. You can search for a published work in a citation index to discover journal publications that have cited it.

Citation Impact and Impact Factors

What is a citation impact?

The number of times a publication has been mentioned is known as the citation impact. Since ISI only indexes articles from a select group of journals, citations from sources like conference proceedings and books might not be included in a paper's total number of citations.

What are the impact factors?

The cited references that ISI gathers are used to create its citation frequency data, sometimes known as impact factors. The association between a discrete unit (like a journal or a university) and the average of a larger group (like similar journals covering a particular discipline) is known as an impact factor. Impact relative to the field is the ratio of the global citation impact for the field to the citation impact for a journal or university in a particular field. For instance, if electrical engineering publications published at Yale have a relative effect of 1.83, they have been referenced 83% more than equivalent papers from universities nationwide.The ISI introduces two tools for measuring impact factors: University Science Indicators (USI), which compares and ranks universities in a variety of ways, including by field or topic discipline, and Journal Citation Reports (JCR), which compares and ranks journals with other journals that cover the same subject discipline. The Yale Science Libraries have copies of these publications. The JCR is available at Kline Science Library, whereas the USI is available on disk from either the Kline Science Library or the Engineering Library.

This computerized tool only indexes key publications; it does not cover conferences, book series, or individual books in-depth. As a result, using it won't guarantee comprehensive coverage. For comprehensive coverage of a specific discipline, other databases could be a better choice.

2-6 The Growth Competitiveness Index (GCI)

The macroeconomic environment's quality, the condition of a nation's public institutions, and a nation's technological readiness—given the growing significance of technology in the development process—are the three pillars that make up the GCI. All these pillars are widely acknowledged as being essential to economic growth (McArthur & Sachs, 2001).

The GCI's main objective is to assess how well-positioned global economies are for sustainable economic growth over the medium to long term.

2-7 The Human Development Index (HDI)

The HDI ranks nations according to their "human development" levels and distinguishes between developed (high development), developing (middle development), and underdeveloped (low development) nations. The statistic is made up of statistics on life expectancy, education, and per-capita GDP (as a measure of standard of living). Additionally, there are HDI offered by regional businesses or organizations for states, cities, villages, etc (Roser, 2014).

Prior to its 2009 report, the HDI combined three dimensions:

- Life expectancy at birth, a measure of population health and longevity
- Information and education, as determined by the adult literacy rate (two-thirds weighted) and the gross enrollment ratio for elementary, secondary, and tertiary education (one-third weighted).
- Living standards, as measured by the natural logarithm of the GDP per person at buying power parity.

The HDI has three dimensions, The HDI combines three dimensions beginning with the 2010 report:

- A long and healthy life: Birth age life expectancy
- Knowledge Access: Average Years in School and Expected Years in School.
- A decent standard of living: GNI per person (PPP US dollars)

2-9 The Regional Economic Architecture (REA)

REA is an effort to develop a uniform, straightforward perspective of the knowledge economy using jobs and qualifications as the "building blocks" of human capital.

By repurposing old data, it is possible to gain fresh insights into the information economy. This is the rationale behind the Economic Architecture model of the knowledge economy, which uses easily accessible employment and labour force statistics to get insights into the knowledge economy and its regional geography in Britain. The Architecture essentially represents the knowledge economy "on one page," offering a summary that generates new ideas, deepens comprehension, and ignites discussion. Having been tried and tested with national, regional, and local policymakers, academics, practitioners, and businesspeople, it has been genuinely successful in these regards. A Regional Perspective in the Knowledge Economy in Great Britain, a paper for the DTI, introduced the Architecture. This study updates the earlier findings and makes use of a newer version of the Architecture. It should be emphasised that because the Architecture is made for tracking structural change rather than yearly changes in the economy and workforce, a longer 3-year or 5-year interval is required to examine economic success.

Appendix (III): Empirical Studies for KBE Assessment.

1-1 Studies used World Bank Methodology (KAM)

1-1-1 Studies Used KAM as Standardized by the WBI at the Country and Regional Levels Assessment.

Author(s)	Objective(s)	Methodology	Key Result(s)
Qamruzzaman and Ferdaous (2014)	To address the main challenges for knowledge-based economic development in Bangladesh.	The World Bank Knowledge Assessment Methodology is used to assess Bangladesh's position among four Asian countries.	Based on the KAM methodology conducted in the study Bangladesh showed the least success among all the four South Asian countries used in the study as benchmarking countries. Additionally, the results of the analysis indicated that the main challenges faced by Bangladesh are economic sectors are reluctant to become IT-based operations rather than a traditional practice. Further, lack of skilled and knowledgeable manpower. Therefore, concerted efforts are required to overcome the previously addressed challenges.

Author(s)	Objective(s)	Methodology	Key Result(s)
Nour (2014b)	To measure the progress of Saudi Arabia in the transition towards a knowledge-based economy.	The paper used mainly the Knowledge Index (KI) and Knowledge Economy Index (KEI) developed by the World Bank. Additionally, the study used other indicators to assess the progress in transition.	Over the studied period (2000-2012), Saudi Arabia has attained significant progress not only in terms of ranking by regional standards but also by international standards. To clarify, the international ranking for Saudi Arabia has climbed 26 places compared to its counterpart in 2000 (It jumped from 76th place in 2000 to 50th in 2012.

Author(s)	Objective(s)	Methodology	Key Result(s)
Rahimić and Kožo (2009)	To measure the current position of Bosnia and Herzegovina on its development towards a knowledge-based economy.	Applying the World Bank assessment methodology and its basic scorecard.	The result of the analysis exhibits a completely unsatisfactory position for the countries as they are ranked in the worst position among countries in the region. Concentrated efforts are required and the priority in advancement must be given to educating, and motivating human potentials, preventing the brain drain and decreasing corruption.

Author(s)	Objective(s)	Methodology	Key Result(s)
Gorij And Alipourian (2011)	To Assess the relative position of Iran in its transformation towards a KBE and compare this position with other countries.	By using the World Bank assessment methodology.	The relative global position of Iran is very weak in many knowledge economy indicators and exhibits the need to develop coherent policies that considers knowledge as a core element in its development strategies. Additionally, more attention must be paid to the economic incentive and institutional regime as they are the weakest pillars in the adopted framework. Additionally, more investments are needed around education and innovation.

Author(s)	Objective(s)	Methodology	Key Result(s)
Asian Development Bank (2007)	-To analyse the ingredients of the global knowledge economy in six Asian countries, namely: Thailand, Singapore, Malaysia, Korea, India, and China. -To highlight each country's initiatives with respect to KBE. -To develop better policies and strategies that help local Asian countries become players in the emerging KBEs.	By adopting the World Bank assessment methodology with its main dimensions.	The main finding is that the past 10 years had seen a wide variety of visions, ambitions, concepts, strategies, policies, and initiatives in Asian countries all aimed at introducing and advancing the KBE.

Author(s)	Objective(s)	Methodology	Key Result(s)
Asian Development Bank **(2014)**	To assess the performance of four Asian economies in their development towards KBE namely, China, Indonesia, India, and Kazakhstan. The study then benchmarked these countries with other advanced countries.	The World Bank Knowledge Assessment Methodology is used throughout the report to assess the challenges and opportunities for each pillar in these four countries.	Depth analysis for the four countries reveals that these countries performed far lower than the average Knowledge economy index for OECD countries.

Author(s)	Objective(s)	Methodology	Key Result(s)
Hvidt (2015)	To analyse the challenges that faced Gulf Cooperation Council (GCC) states in their transformation to Knowledge Economies. To assess the performance of the Gulf Cooperation Council GCC countries in their transformation to a knowledge-based economy.	The World Bank Knowledge Assessment Methodology is used to measure the aggregate index which is called Knowledge Economy Index (KEI). The four pillars included in the Knowledge Economy are: Economic Incentive and Institutional Regime, Innovation, Education and Training, Information and Communication Technologies (ICT).	The GCC countries are ranked between 42 and 64 on the Knowledge Economy Index in 2012. The GCC countries indicated relatively significant weaknesses in two pillars of the knowledge economy namely, Education and Innovation. On the contrary, remarkably high ranking on the ICT pillar.

Author(s)	Objective(s)	Methodology	Key Result(s)
Kaur and Singh (2016)	On the basis of the knowledge economy, the study attempts to investigate inter-country differences among the 42 selected developing economies. To examine the correlation between the knowledge economy index and the level of economic development for the selected developing economies. To investigate the impact of the knowledge economy on the economic growth of 42 selected developing economies.	Regression analysis was applied to investigate the impact of the knowledge economy index on the economic growth of the 42 selected developing economies. The World Bank's KAM is used to assess the development of KE in a particular country. The data used in the study have been taken at four points in time. That is in 1995, 2000, 2005 and 2012, and the selection of this period is constrained by the availability of data.	The inter-country differences in the knowledge economy reveal that the member countries of the European Union have the highest score on the knowledge economy index. Countries of sub-Saharan Africa remained at the lowest value on this index during the four points in time. Additionally, the results of the study reveal that there is high degree of correlation between the knowledge economy index and economic level.

Author(s)	Objective(s)	Methodology	Key Result(s)
Shahabadi et al. (2017)	To examine the effect of KE components on income inequality for 16 selected Islamic countries during the period 1995–2012.	Using the panel data model, the effect of variables of KE components such as education, innovation, information, and communication technology (ICT), and institutional regimes on income inequality was studied. The study follows the KAM in determining the variables that serve as a proxy for KE components. For instance, the Innovation component has been replaced with the number of scientific papers as a proxy.	In the selected Islamic countries, the results reveal that : - For the institutional economic regimes index, there was a significant and positive effect. - For the innovation and creativity index, there was a positive but insignificant effect. - For the education index, there was a negative and significant effect. For the ICT index, there was a negative and insignificant effect. The study concluded that Islamic countries must develop and execute coordinated demand-side policies with the supply-side to build a knowledge-based economy framework.

Author(s)	Objective(s)	Methodology	Key Result(s)
Asongu (2017)	Assess the knowledge economy (KE) development in Africa by comparing its dynamics within African countries to measure the best and worst performers based on fundamental characteristics of the continent's development. So, it is "within assessment" i.e., comparing African countries with each other's.	The World Bank's Knowledge Economy Index (KEI) is used in the study and its four dimensions, notably education, information and communication technology, innovation, economic incentives, and institutional regime. Further, the empirical investigation employed in the study was based on a five-step novel approach with data from 53 African countries for the period 1996–2010. Additionally, the study employed Absolute beta and sigma empirical estimation strategies to measure the dispersions between the determined fundamental characteristics and computed dynamic benchmarks.	The study concluded that landlocked, low-income, conflict-affected, Sub-Saharan African, nonoil-exporting, and French civil law countries are generally more predisposed to lower levels of KE - English common law, openness to sea, absence of conflicts, and North African, and middle-income countries are characteristics that predispose certain nations to higher KE. Additionally, Broad and specific policy implications are discussed in detail.

1-1-2 Recent Studies used KAM as Introduced by the World Bank

Author(s)	Objective(s)	Methodology	Key Result(s)
Zelinska et al. (2020)	To assess the regional development of KE in Ukraine by comparing its regions. Benchmark the Ukrainian economy in comparison with the Polish economy. Depth analysis for each region (22 regions) in Ukraine in the four pillars of the KE and the KEI over the period 2015-2017.	The knowledge assessment methodology developed by the World Bank ("KAM) has been used to attain the objectives of the study. The Knowledge Economy Index as well as the Knowledge Index (The Knowledge Index has been calculated for each country to benchmark the Ukrainian economy worldwide.	Using KAM, The KE index has depicted positive dynamism recently. This is due to continuous growth in the education index as well as the information infrastructure index. However, the destabilizing factors that hinder the development of KE are the institutional regime and economic incentives index as well as the innovation index. The Ukrainian regions classification based on the KAM over the period 2015 to 2017 as indicated in Annex A.1 in the study is as follows: The leading regions as shown in the knowledge economy index were Kyiv, Zaporizhzhia and Lviv regions. The "persecutors" regions are Poltava, Cherkasy, Vinnytsia and Sumy, Regions with relatively slow fluctuations in the knowledge economy index were Kherson, Rivne, Chernigiv, Transcarpathian, and Zhytomyr, The so-called outsiders" or "anti-leaders" are Kirovohrad, Ternopil, Ivano-Frankivsk regions, The "risk group" areas were Volyn, Chernivtsi, and Khmelnytsky. To faster the development of KE in the Ukrainian economy, the following requirements must be considered namely, economic knowledge based on science, modern technologies, high-quality education system and continuous professional training of management staff.

Author(s)	Objective(s)	Methodology	Key Result(s)
Asongu and Andrés (2020)	To assess the KE dynamic ways by which Sub-Saharan African (SSA) and the Middle East and North African (MENA) countries are converging i.e. To investigate whether cross-country differences in SSA and MENA countries in KE are increasing or decreasing. If Sub-Saharan Africa (SSA) and the Middle East and North Africa (MENA) are converging, then; at what rates and what is the required time for the convergence process?	The four components of the World Bank's Knowledge Economy Index (KEI): economic incentives, innovation, education, and information infrastructure are assessed in the study. Variables used in the study are from the World Bank's World Development Indicators. The study estimated a panel for only 21 African and Middle East countries due to data availability constraints over a period of time from the 1996–2010.	The main conclusion from the study was diminishing cross-country disparities in knowledge-based economy dimensions. To clarify, sub-Saharan Africa (SSA), the Middle East and North Africa (MENA) countries that are characterized by a low level of knowledge-economy index dynamics are catching up with their counterparts, where the results of education and ICT dimensions are encouraging. Finally, the estimated time to full convergence is between 4 and 7 years.

Author(s)	Objective(s)	Methodology	Key Result(s)
Asongu and Odhiambo (2019)	To review the literature systematically to determine exactly the policies and strategies with which African countries can faster their transformation towards building KBEs.	The required objective of the study is achieved in terms of three pillars of the World Bank's knowledge economy framework Which is KAM. That is the indices for education, ICT, economic incentives, and institutional regime are investigated and analyzed in depth. A pilot study which has been consolidated within three pillars of the World Bank's framework has been utilized to provide insights into diversified strands of the KBE that were subsequently grouped under the three pillars analyzed in the study. Studies issued between July 2016 and January 2017 were the scope of this systematic review.	The study concluded that African countries are lagging behind other regions of the world in their transformation toward KBEs.

Author(s)	Objective(s)	Methodology	Key Result(s)
Asongu et al. (2020a)	To build a framework for the following objectives: (a) To investigate whether the African business environment hampers or stimulates the knowledge economy (KE). (b) To indicate the KE effects on economic performance. (c)Finally, to determine how economic performance relates to the inequality-adjusted human socioeconomic development (IHDI) of 53 African countries during the 1996-2010 time period	The study used different methodologies to attain its objectives. However, since the scope of this literature is on KE measurement, I will present only the KE framework proposed in the study. The study follows the KAM and set four pillars for the KE. Additionally, the study used World Bank's World Development data as existing data is of limited scope and accuracy. Our methodology has four stylized components to which we turn next: the model, testable hypotheses, variables and data characterization, and the estimation technique.	The results indicate a strong correlation between the dynamics of starting and doing business and the different levels of KE development. Additionally, the results indicate that KE-influenced performance constitutes a major role in socio-economic development than some of the other conventional control variables like foreign direct investment (FDI), foreign aid, and even private investment.

Author(s)	Objective(s)	Methodology	Key Result(s)
Asongu et al. (2020b)	To measure the development of KE in 53 African countries against their frontier counterparts.	The study employed the World Bank methodology and its four dimensions. The empirical analysis has been conducted for the period from 1996 to 2010. Additionally, the study used the principal component analysis to reduce the dimensions of the KE because various components of each dimension of the KE might be highly correlated with one another. The study also used the sigma convergence approach to assess the knowledge economy gaps.	The analysis of the study provided depth analysis of each sub-index of the World's bank knowledge economy dimensions. for instance, it revealed that: I) For the most part of Africa, North African countries are dominant in education. II) Tunisia is the dominant country in 11 of the 15 years, followed by Libya (frontier country in 2 years of the studied period); Cape Verde and Egypt lead only one single year each of the periodicity. Furthermore, Seychelles is mostly the dominant country in ICT over the studied period, but Morocco was the leading in 2009.

Author(s)	Objective(s)	Methodology	Key Result(s)
Cavusoglu (2018)	Benchmark North Cyprus's position with respect to other countries in their development to the KBE. Assess the overall countries' readiness in the KE.	The main methodology used to attain the objectives of the study was the KAM. Government offices and the statistical department of the prime ministry are the main sources for collecting required data. The study calculated the KEI and the sub-indexes for 2012 only.	Based on the KAM and its KEI value, North Cyprus was ranked in 78th place with an index value of 4.61; nonetheless, the value of KI value for North Cyprus ranked it in 59th place out of 147 countries listed in the KAM. Furthermore, benchmarking North Cyprus's position with respect to other countries reveals that its KEI value was less than that of Turkey and South Cyprus. On the other hand, much more than the average index value of all lower-middle income countries. In the same regard, the value of KI is also less than that of Turkey, South Cyprus and Europe. However, its value was more than the lower-middle income, upper-middle income countries and the global average. Additionally, the analysis dedicated to comparison with the global average,

Author(s)	Objective(s)	Methodology	Key Result(s)
Rezny et al. (2019)	The study tried to answer the following question: "Is the knowledge economy delivering on its promise as a proposed means of achieving sustainable economic growth? "Is the KE could solve the problem of resource scarcity and climate disruption?	Through examining the relationship between the knowledge economy index, consecutive economic growth rates and other indicators reflecting resources consumption; namely Material Footprint (MF). Additionally, the knowledge economy index was built based on the knowledge assessment methodology developed by the World Bank.	The comparison of coal, as well as oil consumption with differences in the ranking of the KE from 1995 to 2012, indicated no regular pattern of diminishing reliance on these increasingly scarce and expensive natural resources by successfully developing knowledge economies. The study also indicated that advanced knowledge economies failed to grow after the 2008 period. Furthermore, the study also showed no evidence of higher resource efficiency in advanced knowledge economies when assessing their resource consumption.

1-1-3 Other Studies Grounding on KAM

1-1-3-1 Studies Based on KAM, but with Different Approaches

Author(s)	Objective(s)	Methodology	Key Result(s)
Skrodzka (2016)	To assess the differences in the development level of the knowledge-based economy in the European Union countries (UE-27) in two periods 2000 and 2013. In this study the concept of KBE measurement is based on the KAM methodology and the soft modelling method.	The World Bank methodology and the soft modelling method are used to achieve the objective of the study.	Using the soft modelling method, it is obvious the indicators had a different strength of impact on the KBE latent (unobserved) variable (from very strong to weak) in both estimated models. Additionally, in both estimated models, the impact of the KBE pillars on the KBE development level is positive.

Author(s)	Objective(s)	Methodology	Key Result(s)
Parcero and Ryan (2017)	To measure the development of the Knowledge-based economy in Qatar and the United Arab Emirates (UAE) relative to 17 benchmarked countries.	-The study mainly used the KAM methodology pillars, yet a different set of indicators is utilized. To elaborate, the study is based on the four pillars developed by KAM namely, (1) information and communication technology, (2) education, (3) innovation, and (4) economy and regime. Even though, different set of indicators are used to assess the performance of each pillar compared to KAM as follows: (1) Information and communication technology pillar Total telephones per person, 2009 Computers per person, 2008 Availability of e-government services, 2008 E-government index, 2012 Fixed broadband Internet tariff, 2009 International Internet bandwidth, 2009 Internet users per person, 2009 (2) Education pillar Average years of schooling, 2010 Tertiary School completion, total (% of pop 15+), 2010 Public spending on education as % of GDP, 2009 15-year-olds' science literacy, 2009 15-year-olds' math literacy, 2009 Gross tertiary enrollment rate, 2009 Gross secondary enrollment rate, 2009 (3) Innovation pillar Intellectual property protection 2010 Patents per capita granted by the USPTO, avg. for 2005–2009 University-company research collaboration, 2010 Private sector spending on R&D, 2010	- The analysis reveals that UAE ranks slightly better than the median rank of the 19 benchmarked countries while Qatar ranks somewhat below. -Both countries lag considerably behind knowledge economy leaders. This is obviously evident in the innovation pillar. Developing the two countries' research culture and building solid incentives regime are the main Policy recommendations addressed in the study.

Author(s)	Objective(s)	Methodology	Key Result(s)
		Firm-level technology absorption, 2010 FDI inflows as % of GDP, 2004– 2008 High technology % of manufactured exports, 2011 S&E journal articles per capita, 2007 (4) The economy and regime pillar Regulatory quality, 2009 Tariff & nontariff barriers, 2011 Intensity of local competition, 2010 Days to start a business, 2011 Soundness of banks, 2010 Time required to enforce a contract, 2010 Corruption perceptions index, 2013 Rule of law, 2009 The author clearly defines each indicator, sources for each indicator, the year used as well as the descriptive statistics for each indicator.	

Author(s)	Objective(s)	Methodology	Key result(s)
Vinnychuk et al. (2014)	To investigate the nature of economic growth in the domain of KBE. To determine the required indicators that can describe the key components of knowledge economy and the effect of KE on economic growth is investigated as well.	The study was based on the development of a neural network using selected knowledge economy indicators based on time series data for the years 1996-2011s for four countries namely: Ukraine, Poland, Germany, and Lithuania. The knowledge economy components that are used in the study are as follows: Innovation System Patent applications, residents Patent applications, non-residents Researchers in R&D (per million people) Scientific and technical journal articles Research and development expenditure (% of GDP) GERD in '000 current PPP$ High-technology exports (current US$) High-technology exports (% of manufactured exports) ICT goods exports (% of total goods exports) Education and Human Resources Gross enrolment ratio, ISCED 5 and 6, total Number of students in tertiary education per 100,000 inhabitant's total Public spending on education, total (% of GDP) Information and Communication Technology Mobile cellular subscriptions (per 100 people) Telephone lines (per 100 people) Fixed broadband Internet subscribers (per 100 people) Internet users (per 100 people) Personal computers (per 100 people) Economic and institutional regime Regulatory quality index Control of corruption index Government Effectiveness index Rule of law index Index of economic freedom	Based on the analysis, the idea of a knowledge economy must constitute the theoretical basis for economic growth. The analysis of impacts of knowledge economy components on GDP per capita using neural network reveals that the component with the highest impact on predicted GDP per capita is information and Communication Technology, Innovation System is in the second place, Economic and institutional regime comes next and finally the component of education and human resources.

Author(s)	Objective(s)	Methodology	Key result(s)
Chen (2008b)	To fill the gap in KBE literature through identifying the causal relationship between diversified KBE endowments.	The study tested seven hypotheses, that all the KBE endowments namely, Economic environment, human resources and information technology are positively related to the innovation system as well as to the national competitiveness. This was done through using the path analysis with observed variables (PA-OV) model under the under the structural equation modelling (SEM) by LISREL program. The study used the Knowledge Assessment Scorecards developed by the World Bank in 2005, then applied the linear structural relation model to build the causal model of knowledge-based economy.	The diversified KBE endowments all are positively related to the innovation system and to the KBE competitiveness.

Author(s)	Objective(s)	Methodology	Key Result(s)
Nurunnabi (2017)	To build a knowledge economy framework for Saudi Arabia. To analyse two initiatives implemented in Saudi Arabia to foster transition into a KBE. To plan a policy agenda that supports the previously reported Saudi Arabia's Vision 2030.	Desktop analysis (documentary analysis) based on diversified sources available on 13 November 2016 whether hand collected or collected from the internet from the following sources: • World Bank • United Nations • World Economic Forum • Ministries in Saudi Arabia • Local and international newspapers • International Telecommunication Union • World Telecommunication Indicators database • National Transformation Program 2020 • OECD • Saudi Vision 2030 • US Energy Information Administration • US Patent and Trademark Office.	There are six key aspects which constitute the main components of the knowledge economy framework, namely Human capital, Innovation, information and communications technology (ICT) the economy, education and employment

Author(s)	Objective(s)	Methodology	Key Result(s)
Amirat And Zaidi (2020)	To predict the growth in Saudi Arabia's GDP growth using KBE indicators	Time series Data are used in the study from 1991 to 2017. Data are collected from: the World Bank database, and human development reports issued by Human Nations Development Program. Based on the existing literature, the study selected five pillars for the KBE namely: employment, education, innovation, ICT, and human capital. The study relied on one of the most recent studies (Nurunnabi, 2017) to select indicators (proxies) for each pillar based on	The regression analysis indicated that five out of eight independent variables are significant. This means that GDP growth can be estimated by means of KBE proxies used to describe the KBE pillars like scientific and technical journal articles, mean age of education, mobile telecommunication revenues, unemployment rate, and HD index. An increase or decrease in the previously mentioned

Author(s)	Objective(s)	Methodology	Key Result(s)
		the past studies. The study then used the principal component analysis to determine the most contributing indicators for the KBE. Multiple linear regressions are conducted to estimate GDP.	variables can affect GDP to inflate or deflate.

1-1-3-2 Studies Based on KAM to Develop a New Index

Author(s)	Objective(s)	Methodology	Key Result(s)
Ojanperä et al. (2019)	To construct a Digital Knowledge Economy Index that measures the knowledge economies and empirically applies this index to Sub-Saharan African counties. Compare the result and draw some policy recommendations.	The methodology applied in the study is grounded on the World Bank knowledge economy index. The World Bank methodology is chosen due to its high visibility. The data used are aggregated to the country level. The data also have yearly observations. The index used in the study is based on the four sub-indexes used in the construction of the World Bank knowledge economy index, in addition to a fifth sub-index that includes indicators of participation and digital content creation of knowledge resources. The digital participation index is given the same weight and normalization procedures as the World Bank knowledge economy index. Finally, the digital knowledge economy index for each country is calculated as the simple average of the five sub-indexes. The Digital knowledge economy index goes in in line with the World Bank methodology, except for the year of data collection. That is the data used for digital participation index are measured for the year 2013, but the other indexes are for the year 2012.	For most countries the ranking of the Digital Knowledge Economy Index is to a large extent consistent with the World Bank knowledge economy index. The Digital Knowledge Economy Index rankings for two-thirds of countries fall in comparison with their ranking in the World Bank knowledge economy index. For most of the sub-Saharan countries, the fifth sub-index (digital participation) represents a challenge rather than a prospect.

Author(s)	Objective(s)	Methodology	Key Result(s)
Leung (2004)	To review the existing KBE frameworks introduced by international organizations. To introduce a measurement framework that best suits	The proposed framework introduced in the study for KBE in Hong Kong is based on the OECD, APEC, and World Bank frameworks. Indicators are then organized under four dimensions as follows: Innovation System dimension, which includes indicators that indicate the quantity, quality and rate of knowledge and information production/creation in the economy. Information and Communication Technology (ICT) dimension, which includes indicators that depict the efficiency and effectiveness of knowledge and information distribution in the economy. Human Resource Development dimension, which includes indicators that is related to the quantity and	A KBE framework for Hong Kong. The author confirmed that by mid-2005, the first full set of KBE indicators for Hong Kong could be available. The author contented that the

Author(s)	Objective(s)	Methodology	Key Result(s)
	the situation in Hong Kong, China. To address the issues and challenges in developing KBE indicators.	quality of individuals equipped to access and use of knowledge and information for further production/creation and distribution of knowledge and information in the economy. Business Environment dimension, which includes indicators that is concerned with business environment conducive to the production/creation and distribution of knowledge and information in the economy. The chosen indicators, about 80 indicators listed in Annex (1) in the study, in the proposed framework were selected from the previously listed indicators in the international frameworks. Additionally, the chosen indicators were based on three criteria, including international comparability, availability and relevance.	proposed framework would be revised and reviewed on regular basis with consideration to the latest developments in the international arena.

Author(s)	Objective(s)	Methodology	Key Result(s)
Popov **and Kochetkov** **(2019)**	Ranking of the performance of Russian regions in terms of the knowledge economy development by using the Russian Regional Knowledge Economy Index (Russian RKEI).	The authors selected the data from statistics available in Russia. Grounding on the KAM developed by the World Bank, the study divided the data into three categories: • innovation and technology • science and education • ICT Then three sub-indexes were built, and each category is divided into inputs and outputs except for ICT because the authors stated that they had only usage indicators. The justification for the chosen variables under each sub-index has been mentioned in the study. The trend for each category is calculated by known values according to the linear trend equation $y(x) = a + bx$, then data are normalized to rank countries based on their level of development.	Using the constructed index, the study was able to rank the leading as well as the lagging regions in Russian regions with respect to knowledge economy development. Additionally, Using the constructed index, the authors were able to identify key success factors as well as the hampering factors among Russian regions.

Author(s)	Objective(s)	Methodology	Key Result(s)
Garcia **(2020)**	To introduce the Sustainable Knowledge Economy Index (SKEI); which integrates the knowledge economy variables with agriculture	The study depended on a descriptive approach by using the Principal Components Analysis (PCA) to construct a new knowledge economy index that incorporates the two existing knowledge economy indices (that of the World Bank and the European Bank for Reconstruction and Development (EBRD), these two banks released their own knowledge economy index with varying dimensions) as well as the agricultural production. Integrating the agricultural output in the construction of the index is mandatory to make the newly constructed Knowledge Economy Index sustainable. Secondary data for 26 economic variables was collected online from the World Bank and the European Bank for Reconstruction and Development	The analysis showed that developing or less-developed countries should have at least a 2.50 Sustainable KEI score to achieve long-term economic competitiveness. Moreover, the study indicated that the current Sustainable

Author(s)	Objective(s)	Methodology	Key Result(s)
	output.	(EBRD). Therefore, the new SKEI consists of a set of 26 variables. The sample of countries used in the index is 34 developed countries. KMO and Bartlett's tests were used in the study to analyse the adequacy of the sample and its suitability for principal component analysis. Identification of the correct number of principal components to retain followed through a series of tests such as the Scree test, Kaiser's rule, Parallel Analysis (PA), and Cumulative Percentage of Variance. Once components are identified, the Sustainable Knowledge Economy index was computed for each sample. The Sustainable Knowledge-Economy index was computed for the year 2006 since most of the data are available for that year. In case of missing the value of any variable for the year 2006, the value for the previous year is used.	knowledge economy indices of the developed countries range from 2.50 to 23.70. Additionally, the analysis revealed that the USA was the most competitive and France was the least during the analysed year.

Author(s)	Objective(s)	Methodology	Key Result(s)
Al Shami et al. **(2011)**	To build a unified knowledge economy competitive-ness index (composite index)	Through using fuzzy clustering, the authors combined four of the most well-known and reputable knowledge economy indicators into a unified index that indicates the overall rate of knowledge in an economy. The most well-known indices used in the study are: Knowledge Economy Index (KEI) from World Bank Information and Communication Technologies Development Index (IDI) from United Nations agency for information and communication technology issues (ITU) Global Competitiveness Index (GCI) from the World Economic Forum World Competitiveness Yearbook (WCY) from Institute for Management Development (IMD). Data used in the model are observed data which will be fed into the model to be trained and then tested. A four steps framework is utilized to construct the unified index: The first step used a Correlation analysis, To test if there is a relationship between the four selected indices and how strong it is. Then, the second step is to conduct a Principal Component Analysis (PCA) analysis. - To test the similarity between the four indices and to see whether these indices could be reduced in any form. The third step used an Adaptive Neural Fuzzy Inference Systems (ANFIS) Is used to build rules to create trained sub-	Based on the correlation analysis: High correlation between the ITU & WB = (0.95) Strong correlation resulted between the WEF & IMD = (0.88). High to moderate correlation between the WEF & ITU = (0.74) and (0.75) between WB & WEF. The lowest correlation was moderate which resulted between the ITU & IMD = (0.67) and WB & IMD = (0.67). Concerning the Principal Component Analysis, the results Proved very high similarity between the four selected indices, therefore it is justified now to combine these four indices into a single index. The construction of the model, the sub-models and its equations is depicted in the study. The Unified Knowledge Economy Competitiveness Index (UKPI) developed in

Author(s)	Objective(s)	Methodology	Key Result(s)
		model that could determine which of the input indices make efficient contribution to the new unified knowledge indicator. Finally, the fourth step is to create a unified index based on all existing indices. At this step, the fuzzy c-means clustering technique is utilized to build the newly Unified Knowledge Competitiveness and Progress Indicator (UKPI). The study used MATLAB fuzzy toolbox is employed to implement ANFIS and fuzzy c-means clustering. The newly UKPI combines the four selected aggregate indices into a new single meaningful index to reflect the overall rate of Knowledge competitiveness and progress in a nation.	the study was able to successfully predict aggregate four complex, multi-dimensional composite indices with acceptable error. Finally, the output of the fuzzy clustering model could be used to predict and aggregate scores for any given economy especially for developing economies where the scores usually missing or not reported by one or more of the above indicators.

Author(s)	Objective(s)	Methodology	Key result(s)
Affortunato et al. (2010)	To explain the different ways by which scholars, and researchers could select proper indicators to measure the development of regional contexts towards a knowledge-based society i.e., how KE is measured at the local level?	Taking two international frameworks as a reference point namely the WB and the OECD, the authors identify a framework of variables to reflect the manner and the development of the knowledge economy. It is called Regional Knowledge Economy Indicators (ReKEI). The authors set a process consists of three steps to correctly set up suitable indicators and avoid mismatched indicators. The first step: building the theoretical framework. Based on the principle of fitness for purpose, six selected macro areas have been analysed and selected. The second step: selection of primary indicators and imputation of missing data The selection of the indicators has been based on criteria such as their analytical validity, of their measurability, of their spatial coverage, of their relationship with the other indicators and of their importance for the phenomenon in hand. The third step: how to transform the data and make it comparable. Through standardization of data and construction of a radar chart. Six dimensions have been selected: A - overall performance of the economy B- The economic and institutional regime C - innovation system D - education E-information and communication technology F - Culture and social capital. For each dimension, A sub-set of indicators has been identified and assessed. The total set of variables consists of 54 variables.	The author depicted a simple example for the index.

1-1-3-3 Studies Based on KAM Besides Other Indices

Author(s)	Objective(s)	Methodology	Key result(s)
Nour (2014a)	To assess the position of Arab Gulf countries in transition	Three hypotheses are tested in the study using the OECD definition for the KBE, the Global Innovation Index, and the World Bank Knowledge assessment methodology. The first hypothesis: relative progress in the transition	The empirical analysis supported the three hypotheses. Additionally, the

Author(s)	Objective(s)	Methodology	Key result(s)
	towards knowledge-based economies. To analyse the potential opportunities for these countries in transition to knowledge-based economies.	to knowledge-based economies in Arab Gulf countries. The second hypothesis: transition to knowledge-based economies faces several challenges in Arab Gulf countries and coincides with a substantial knowledge gap compared to other world regions. The third hypothesis: Arab Gulf countries have manifestly lagged far behind other world regions in terms of indicators required for the transition to a knowledge-based economy. Additionally, the progress in tacit and codified sources of knowledge is examined using the broad definition of knowledge that already exists in the new growth literature which highlights both the tacit and codified components of knowledge. On the one hand, tacit knowledge is defined by the share of high skills defined by the share of enrolment in tertiary education. On the other hand, codified knowledge is defined by the embodied knowledge distributed in many indicators including the share of spending on education and R&D as a percentage of GDP.	transformation to the KBE in Arab Gulf countries is Bounded by numerous social, economic, institutional, and organizational constraints. Yet, this does not mean that Arab Gulf countries have potential opportunities that could faster their transformation (explained in detail in the study)

Author(s)	Objective(s)	Methodology	Key Result(s)
Nour (2015)	To Investigate the existence and progress of the Arab region in their transition towards the KBE.	The study used descriptive and comparative approaches to analysis. That is, the study used the literature indicators of tacit and codified knowledge as well as the Knowledge index and knowledge economy index developed by the World Bank Institute to investigate the development of the KE in the Arab region and compared it with other world regions. Tacit knowledge indicators used in the study are Gross enrollment ratios in primary, secondary, and tertiary education; mean years of schooling; and literacy rate. Codified knowledge indicators used in the study are the share of public spending on R&D as a percentage of GDP and the share of public spending on education. Additionally, the percentage of the population accessing the Internet, telephone, and mobile. The number of patents awarded to firms and individuals and the total number of scientific and technical journal articles. The study then tested three hypotheses related to KE in Arab region.	The main result of the study supported the first hypothesis in that, Knowledge economy already exists in the Arab region, yet substantial knowledge gap in comparison with other world regions. As for the second hypothesis, there is variation in knowledge indicators according to the structure of the economy in the Arab region. Concerning the third hypothesis, there is limited progress in knowledge-related indicators in the Arab region. To sum up, the study concluded that, it is crucial for the Arab region to enhance the knowledge economy and its indicators to sustain economic development.

Author(s)	Objective(s)	Methodology	Key Result(s)
Ahmed and Alfaki (2013)	To investigate the role of science, technology, and innovation in the development of KE in the UAE through	The performance of UAE with respect to the rest of the world is assessed using different international KE indicators and indexes. The World Bank knowledge assessment methodology (the knowledge index and	It is obvious that UAE has made significant improvements in the implementation of KE pillars, especially in the ICT pillar.

Author(s)	Objective(s)	Methodology	Key Result(s)
	assessing the country's achievements in implementing the KE pillars. Then, to assess the country's science, technology and innovation capacity and competence in exercising adoption and diffusion of knowledge. Based on the analysis, the study aimed to highlight the weaknesses, strengths, and opportunities	the knowledge economy index) and several other KE indicators are used to achieve the objectives of the study namely: Human Development Index (HDI) the Digital opportunity Index. Gross National Income (GNI) Knowledge-Economy Index (KEI) Global Innovation Index (GII) Global Competitiveness Index (GCI) Environmental Performance Index (EPI) Indicators for Education (for instance: the percentage of adult literacy) Indicators to measure the size and quality of research publications (as proxies for knowledge production, patents granted) are used in the analysis. Then, The UAE position relative to its GCC region is assessed using the KAM methodology together with other two transformation economies namely: Singapore and the Republic of Korea.	One of the most challenges that need to be addressed in UAE is an investment in education and R&D activities; this is observed in the lack position of UAE compared with most transformation economies and some countries in the GCC countries. Finally, Concentrated efforts and rigorous follow up are highly recommended.

Author(s)	Objective(s)	Methodology	Key Result(s)
Ahmed and Al-Roubaie (2012)	To investigate the crucial role played by science, technology, and innovation in building a knowledge-based economy in Muslim countries.	In addition to using the KAM, the study benefit from other major indexes to provide a more holistic approach to the analysis. To assess the level of development for Muslim world, the study used the World Economic Forum stages. Using KAM, to assess the position of the Muslim world in the four pillars of the KBE as well as to calculate the knowledge index and the knowledge economy index. To measure the ability of countries to create new ideas, the study used the INSEAD 2011 published by Dutta (2011) To assess the scientific and technological capacities of the Muslim world, the study used selected indicators from the world economic forum such as University-industry collaboration in R&D, Quality of scientific research institutions, Capacity for innovation, Availability of scientists and engineers and Technological readiness	1- Based on the World Economic Forum classification of stages of development, around 90 percent of Muslims are in either stage 1 or in transition from stage 1 to stage 2 in 2010. 2- Using KAM, most of the Muslim countries lag far from the leading countries (mainly EU members). 3- Except Qatar, all Muslim countries have a disappointing ranking in the INSEAD 2011. 4- The majority of Muslim countries are scoring less than the industrialized countries in all indicators used in the study.

Author(s)	Objective(s)	Methodology	Key result(s)
Bakırcı (2018)	To provide situation analysis to Turkey position	Using KAM and other global Indexes such as the Networked readiness index to evaluate the usage of ICT and the EU, INSEAD, and the Economist Intelligence Unit to assess the innovation	Thanks to reforms that have been implemented by Turkey since the 2000s, it has experienced significant improvement in many

Author(s)	Objective(s)	Methodology	Key result(s)
	in KBE.	performance.	indexes.

Author(s)	Objective(s)	Methodology	Key Result(s)
Krasnokutska (2012)	To introduce and identify the features of existing methods of constructing a system of indicators for the knowledge economy and its applications.	They analysed existing methods of measuring the knowledge economy are: Indicators of Information and Communication Technologies (ICT) ICT Development Index (IDI) Information Society Index (ISI) Networked Readiness Index (NRI) Knowledge Economy Indicators (KEI)) The study also defined the scope of their application.	The most popular frameworks of indicators and composite indexes to assess the development of the knowledge-based potential are using close source information. Moreover, the Correlation analysis of the analysed indexes depicted a high correlation ratio between them.

Author(s)	Objective(s)	Methodology	Key result(s)
Bryl **(2012)**	To elaborate some of the existing KE measuring indices. Then, to empirically investigate these indices to show differences in results. Based on the results, the study ranked countries accordingly.	The measurement indices used in the study are the most popular one's from the point of view of the author, namely: Knowledge Economy Index (KEI), issued by the World Bank Institute since 1995. Network Readiness Index (NRI), issued by the World Economic Forum Since 2002. Global Innovation Index (GII), issued by the Business School of the World and the World Intellectual Property Organization since 2007. ICT Development Index (IDI), issued by the International Telecommunication Union since2008. Two different time periods: 2008 and 2011 for 40 most developed countries.	Major differences in the Chosen countries rank of indices. This means that there is not only one way of new economy measurement at the macro level. High Knowledge Economy Index (KEI) for a country usually means high ranks in other indices as well.

1-1-3-4 Micro-Level Studies Used KAM

Author(s)	Objective(S)	Methodology used	Key Result(s)
Al-Busaidi **(2019)**	To assess the most contributing ICT indicators that faster KE development in	The study used the four KE pillars defined by the World Bank. The study conducted a qualitative analysis and	The majority of the proposed ICT indicators whether at national-level, firm-level or inhabitant-level are input-level ICT indicators. Patents as a percentage of the national

Author(s)	Objective(S)	Methodology used	Key Result(s)
	Oman and its constituting pillars namely: economic and institutional regimes, education, and innovation.	implemented four Delphi. Studies on four groups of experts (23 ICT experts, four educators, three innovation experts and eight economists) in Oman.	total are the only output level for ICT indicators. The commonly ranked ICT indicators by the four groups of experts are: - Total R&D expenditure on ICT. The proportion of businesses using the internet ICT patents as a percentage of the national total Internet subscribers per 100 inhabitants.

1-2 List of Studies which Employ Diversified Methodologies in Measuring the KE Performance.

1-2-1 Studies Based on Existing Frameworks/ Indices (KAM Not Among Them)

Author(s)	Objective(s)	Methodology	Key Result(s)
Almoli and Tok (2020)	To articulate the top-down implementation of the transitions towards a KBE in Qatar. To indicate the public policies related to KBE. To assess the performance trends for Qatar while transforming into a KBE and highlight the strengths, weaknesses, and challenges.	The study was based mainly on the KBE pillars developed by the World Bank institute, yet its methodology is outdated. Therefore, three global indexes are used throughout the study to assess Qatar’s performance in the last ten years, namely: Global Competitiveness Index (GCI) developed by the World Economic Forum. It assesses the overall performance of countries worldwide with respect to economic growth, competitiveness, and knowledge of the economy. Economies’ development stages are organized under three stages: (factor-driven, efficiency-driven, and innovation-driven). Global Innovation Index (GII) which relies on two sub-indices, namely: the innovation input and the innovation output sub-indexes. *Five input pillars* that capture elements of the national economy that enable innovative activities: institutions, human capital and research, infrastructure, market sophistication and business sophistication. *Two output pillars* capture actual	Qatar is located in the innovation-driven economies as indicated by GCI reports from 2013/2014 till the most recent report used in the study 2017/2018. Additionally, a robust competitiveness position has been made by Qatar in the last ten years (2007–2017), along with continuous improvement. This is obvious in its global rank which has improved 13 ranking positions as indicated by GCI reports. Based on the global innovation index, Qatar is ranked 24th globally within the world’s top 25 innovators during GII report 2008–2009, yet it has declined in the ranking compared to previous years, to 43rd in GII report 2013 and to 49th in GII report 2017. However, Qatar is still maintaining an advanced position within the GCC

Author(s)	Objective(s)	Methodology	Key Result(s)
		evidence of innovation outputs: knowledge and technology outputs and creative outputs. Global Entrepreneurship Index (GEI). It is a composite indicator reflecting the health of the entrepreneurship ecosystem in each country. It consists of three sub-indexes, namely: entrepreneurial attitudes, entrepreneurial abilities, and entrepreneurial aspirations.	region, because of its institutions and strong political leadership. Based on the GEI, Qatar has been ranked the first in the GEI 2018 among the GCC countries, second in the Middle East and North Africa region and 22nd out of 137 globally.

Author(s)	Objective(s)	Methodology	Key result(s)
Tadros (2015)	To analyse and review the knowledge-based economy, the information society, innovation ecosystem. Additionally, key Science, Technology, and Innovation (STI) indicators are analysed for selected countries (including the GCC countries and the BRICS countries: Brazil, Russia, India, China, and South Africa. The conducted analyses were in terms of: The Networked Readiness Index 2015 The Global Innovation Index 2014 Key STI Indicators The "Doing Business 2015: Going Beyond Efficiency." Finally, the paper reviewed the GCC's future challenges and opportunities for the development of a KBE.	To measure the performance of an information society, The World Bank's World Development Indicators for 2015 are used. Global Information Technology Report 2015 included ranking for Networked Readiness Index 2015 rankings. The Cornell University, the international business school INSEAD, and the World Intellectual Property Organization (WIPO) have developed a Global Innovation Index (GII) which is used as well. Only two key STI indicators: R&D Expenditures as Percentage of GDP and High-Technology Exports as Percentage of Manufacturing Exports for selected countries.	Based on the indexes used in the study, the author concluding some of the challenges and opportunities facing the GCC countries in their transition towards a knowledge-based economy, among them are the following: Reforming the education sector in such a way that the education outputs could produce more "knowledge workers." High level of interaction between research centers, universities as well as industries.

Author(s)	Objective(s)	Methodology	Key Result(s)
Lagzouli et al. (2020)	To provide a brief conceptual framework for the KE. To assess the level of development for KE in Morocco.	Grounding on the OECD and the European Commission methodologies for measuring the KE, the authors set their own framework for measuring KE based on a set of indicators as follows: Indicators tracing scientific and technological activity: These indicators are categorized under four areas as follows. Research and development activities: Patent tracking, monitoring scientific publications, Measuring the degree of scientific and technological specialization: 2-Indicator measuring the contribution of human resources to the knowledge-based economy. Two data sources are used in the study to assess the contribution of human resources namely, Measuring the contributions of the field of education and measuring the contribution of personal qualifications. Indicators tracing knowledge products.	Despite the multiple assets that Morocco has; the country is lagging its rivals in the development of the knowledge economy, especially in the level of its educational

Author(s)	Objective(s)	Methodology	Key Result(s)
		To measure the innovation, the study used three surveys which had different objectives. • The "YALE 2" survey aims to study the degree of ownership of innovation. • "CIS" surveys of the European community and OECD countries to measure the factors influencing innovation and study the scope and the impact of technological innovation in the enterprise. • The SESSI survey, presents the skills required of companies to innovate. ICT Diffusion Measurement Indicators The study utilized the "Network Readiness Index" which has been developed by the World Economic Forum to rank countries according to their capacity to exploit ICT and the level of digitization of their economies. This framework has been applied to the Moroccan context.	system, its R&D results and in terms of its innovation indicators.

Author(s)	Objective(s)	Methodology	Key Result(s)
Demir et al. (2015)	Ranking Turkey in the Knowledge society Analysis of the reasons for the current position of turkey Investigate the strengths and weaknesses of Turkey	Grounding on the United Nations Public Administration Network (UNPAN)'s Knowledge Society Index, the study built its own Knowledge society index with changes from the previous index in using the latest available data, different set of countries and the methodology of index calculation. The author's new knowledge society index consists of the following three sub-dimensional indices as follows; its indicators, the source of the data and the latest available data used in constructing the index: - **- The "Assets" sub-index** Expected Years of Schooling (UNESCO) (2010), Young Population (World Bank) (2012) , Urban Population (World Bank) (2012) , Newspaper per 1000 (UNPAN) (2005), Internet Diffusion (World Bank) (2012) Telephone Lines (World Bank) (2012) **- The "Advancing" sub-index:** R&D Expenditure (World Bank) (2012) Government Health Expenditure (World Bank) (2012), Government Education Expenditure Advancing (World Bank) (2012) **- The Foresightedness sub-index:** Child Mortality (World Bank) (2011) GINI Coefficient (OECD) (2010) Protected Areas (UNPAN) (2005) CO2 Emissions (World Bank) (2009) After calculating each of the sub-index scores, the Principal Components Analysis (PCA) was applied to determine the final index scores. Finally, countries are ranked accordingly.	Turkey is ranked in the worst group of countries in the overall index because of its performance in the sub-indices and indicators. In a globalized, knowledge-based world Turkey should further improve its infrastructure for communication technologies, invest more in health and education, perform better in the Corruption Perception Index, decrease CO2 emissions per capita, improve its income distribution within the society, and increase its protected areas to improve its position in the world. The index also shows that the developed economies are still dominating the knowledge-driven society and economy

1-2-2 Studies Used Different Approaches for KBE Assessment (KAM Not Among Them).

Author(s)	Objective(s)	Methodology	Key Result(s)
Shen et al. (2016)	- The study defined the knowledge economy as a new economic sector which has specific characteristics compared with traditional sectors. -Technology and capital intensive, as well as the relatively low ratio of fixed capital, are the main characteristics of this sector. -Therefore, the study constructs a new Economy Index to estimate the size of this "new" economic sector in the total economy.	- Through using a big data approach, the study uses relative ratios of labour, capital, and technology innovation as sub-indexes to construct a new economy index and assigns weights to each sub-index. - Data are collected daily from the internet due to the lack of official data to calculate the monthly index for the period from August 2015 up to February 2016.	Nine industries with 111 sub-industries constitute the size of this new economic sector. This sector accounts for about 30 percent of the total economy.

Author(s)	Objective(s)	Methodology	Key Result(s)
Shapira et al. (2006)	To assess Malaysia's progress towards the development of KBE at the micro level (sectoral assessment)	A survey to more than 1800 Malaysian firms in 18 manufacturing and services industries.	Industries classification based on their knowledge content have been identified.

Author(s)	Objective(s)	Methodology	Key result(s)
Chen **(2008 a)**	To build a model for KE indicators	By using exploratory factor analysis and confirmatory factor analysis. The study used exploratory factor analysis to determine some key components of the KBE from the overall KBE indicators. Then, the study used the principal component analysis to choose the most relevant and reliable indicators for each category. After that, confirmatory factor analysis was used to create the required KBE model.	To measure the KBE, researchers can use the KBE index which consists of 5 categories namely. information infrastructure Business environment Human resources Innovation system Performance indicators.

Author(s)	Objective(s)	Methodology	Key Result(s)
Ben Hassen (2020)	To investigate the current situation of the KE in two countries, namely Qatar and Lebanon To present the	The study used five pillars of the knowledge-based economy namely: Information and Communication Technology (ICT), human capital and education; innovation, entrepreneurship, and economic and institutional regime. The research methodology	For Qatar: *Main strength*: The solid determination of Qatar's government to diversify its economy. *Main weakness*: (1) the deficit of human capital qualified enough to cope with the dynamics of the new economy (2) weak performance of

Author(s)	Objective(s)	Methodology	Key Result(s)
	main constraints and drivers in the two countries	consisted of two steps: A literature review based on scholarly literature, written documents, and governmental reports. In-depth interviews and questionnaires with stakeholders.	the innovation system (3) the fear of failure. For Lebanon: *Main strength*: (1) its education system (2) the culture of entrepreneurship culture *Main weaknesses:* (1) weak ICT infrastructure (2) political instability

Author(s)	Objective(s)	Methodology	Key Result(s)
Nachef et al. **(2014)**	To introduce the most suitable and effective model that could help Qatar in its transformation to a knowledge-based economy. This model would be aligned with the Qatar National Vision 2030.	Using a fuzzy approach., the study introduced a model that has been developed in three stages as follows: Factors identification stage, which included the following factors: Education & Learning (Learning System), Contributor Sectors (Future Economy Pillars), Knowledge Investment (Obtaining New Knowledge), Convert Tec Adv into Prod Gains (Knowledge Gains), ICT Infrastructure Knowledge Accumulation Capacity, Knowledge Dissemination Rate, Cost of Knowledge Transmission ICT Flexibility and Adaptability, Entrepreneurship & Leadership Capabilities, Openness to Other Cultures and Nations, Capability in Managing Diversity, and Social System Adaptability The factors are grouped in the model under three sets of factors, the first set factors are related to government policies approach and characteristics (includes factors from 1:4) , the second set factors are related to ICT infrastructure characteristics(includes factors from 5:9), and the third set factors that are associated to society characteristics (includes factors from 10:13)	The outputs of these initial factors through the set of fuzzy rules are labelled as government policies, knowledge infrastructure, and social norms. Additionally, the factor “government policies” is the output of the factors related to government regulations. And the factor “knowledge infrastructure” is the output of factors related to ICT infrastructure characteristics. Whereas the factor “society norms” is the output of factors related to the characteristics of the society. The government policies, ICT infrastructure, and society norms in combination with a set of fuzzy rules create an output to measure the KBE level through two sets, namely: readiness of human capital as well as the readiness of the knowledge economy trading system.

1-2-3 Studies Used Different Approaches for Introducing a new Index (KAM Not Among Them)

Author(s)	Objective(s)	Methodology	Key Result(s)
Donlagic et al. (2015)	To develop a framework for the development of KBE in Bosnia and Herzegovina, considering the specifics of the country.	Questionnaire survey focusing mainly on medium and large enterprises in Bosnia and Herzegovina (sample of 143 medium and large enterprises) has been created to achieve the main objective of the study. The analysis of the Data was performed using factor analysis.	Based on the Factor analysis result, six factors are identified as key drivers of knowledge economy development in Bosnia and Herzegovina namely: • University education and development of the higher education system, • Government regulation and environment, • Utilization of ICT and infrastructure, •Investment in R&D, • Employee education and training, • R&D activities and innovation.

Author(s)	Objective(s)	Methodology	Key Result(s)
Hossain (2015)	To implement a comparative analysis for the KBE indicators of KBE in the Cooperation Council of the Arab States of the Gulf. To create a model for the KBE that combines all indicators of KBE.	The study introduced 26 indicators under five categories. Categories for KBE are: • Education/talent • Economic and institutional regime • innovation • Digital economy • Globalization. Then, the study used an analysis of variance (ANOVA) to calculate the standard deviation, mean, and confidence interval. Additionally, ANOVA is used to compare countries. Data sources: publications, country reports, and existing reports of the international organizations.	The ANOVA showed dramatic differences in most of the indicators used among the countries in the GCC. Taking the advantage of the GCC common market, countries can benefit from each other. That is outperforming countries can help poor-performing ones. The study concludes that micro-dynamics in education, research, and innovation will contribute to formulating macro-dynamics that positively affect the performance of KBE.

Author(s)	Objective(s)	Methodology	Key Result(s)
Dima et al. (2018)	To study the influence of different indicators concerning the knowledge economy on the country's competitiveness in the European Union (EU). Both Bulgaria and	The study was used for the empirical analysis of Pearson coefficients and panel data regression. The study used one dependent variable (the GCI) and 6 independent variables; notably: R&D expenditure as a percentage of the GDP. Tertiary education attainment (percentage of the population with tertiary education (levels 5–8), aged 15 to 64 years). Lifelong learning (the percentage of people aged 18 to 64 who stated that they received education or training in the four weeks preceding the survey). GDP per capita. Energy intensity (gross inland consumption of	It was postulated that the development of EU policies concerning learning opportunities throughout the life of the European workforce as well as concentrating on R&D could significantly enhance and

Author(s)	Objective(s)	Methodology	Key Result(s)
	Luxembourg are excluded from the study as they are considered outliers in the analysis.	energy divided by GDP: kg of oil equivalent per 1000 EUR). Debt to equity (financial sector leverage, %) Source of data: for independent variables: the Eurostat database and for the dependent variable the World Economic Forum.	contribute to the competitiveness of the EU Member States.

Author(s)	Objective(s)	Methodology	Key Result(s)
Chen (2010)	To build short-form Knowledge-based Economy Scorecards (S-KES) to assess KBE competitiveness worldwide. Additionally, to investigate the goodness-of-fit of the KES and S-KES model, to assess the reliability, validation, and cross-validation of this proposed model as well.	Data used in the model: 2003-2006.Source of data: Knowledge-based Economy Scorecard (KES) developed by World Bank. Variables used: a set of seventy-two structural and qualitative variables listed in the study table (1). Countries included in the model: 132 countries (almost all OECD economies and ninety developing countries). finally, the conceptual model and detailed methodology is depicted in the study.	The result of the model reveals that the goodness-of-fit of the KES model is not satisfactory. However, the goodness-of-fit of the S-KES model is not satisfactory. Additionally, the comparison between the two scorecards notably: S-KES and KES model reveals that all measures of the S-KES model are significantly better than the measures of the KES model. Furthermore, preciseness, and efficiency have been achieved in the S-KES model. It is also could be a substitutive scorecard for the KES model.

Author(s)	Objective(s)	Methodology	Key Result(s)
Širá et al. **(2020)**	To identify the factors that are related to KBE and affect the growth of the country's competitiveness, this contributes to its improved sustainability. Therefore, the interconnections and the interactions between KBE, competitiveness, and sustainability in EU countries are the focus of the study. Additionally, to opt for the EU country with the strongest competitive position. Finally, to investigate how the selected indicators of the knowledge economy affect the country's competitiveness in their interaction and whether competitiveness affects the sustainability of the economy.	The study utilized multi-criteria evaluation of countries by the TOPSIS method and a subsequent regression model. Since, the knowledge economy measurement is the scope of my study, the level of the knowledge economy was assessed according to selected indicators: Tertiary education as a percent of the population. R&D expenditure as a percent of GDP. Total amount of patents per million population. Score in the 12th pillar of the GCI.	Sweden—is the leading country among EU countries in the field of knowledge economy, competitiveness, and sustainability.

Author(s)	Objective(s)	Methodology	Key Result(s)
Mêgnigbêto **(2018)**	To study the correlation between the transmission	Six OECD countries are the sample of the study; namely: USA, Canada, France, Germany, Japan,	Japan and South Korea show a positive strong correlation between transmission power and gross domestic expenditure for

Author(s)	Objective(s)	Methodology	Key Result(s)
	power in six OECD countries and some indicators used to assess the development of a KBE.	and South Korea. Six indicators are used as proxies for the KBE; notably: gross domestic expenditure for research and development (GERD), number of researchers, gross domestic product (GDP) growth rate, GDP per capita, Human Development Index (HDI) and total factor productivity (TFP). The analysis was carried out through a time series of the transmission power that covers the period of the 10-year period (2001–2010) and the data used was collected from Web of Science.	research and development (GERD) on one hand and transmission power and number of researchers on the other hand. The study concluded that, at the national level, the transmission power only is not sufficient to assess the degree to which an economy is considered a knowledge based. This is because the transmission power does not consider the synergy contributed at the international level by a nation’s innovation actor.

1-2-4 Studies Used Input-Output Approach

Author(s)	Objective(s)	Methodology	Key Result(s)
Afzal and Lawrey (2012b)	To construct a policy-focused framework for the KBE in five ASEAN countries namely, Indonesia, Malaysia, Singapore, Philippines, and Thailand.	The framework was created based on the OECD definition and ABS assumptions for the KBE. To identify and rank the most contributing elements to the KBE, the study used the Beta coefficient technique. Data sources: The data set are collected from secondary sources namely, The World Bank’s World Development Indicators. The International Institute for Management Development’s World Competitive Yearbook. Data period: 1995-2010	The analysis indicates that the most contributing elements for the five ASEAN countries are: FDI and trade openness in knowledge acquisition R&D expenditure in knowledge production secondary school enrolment in knowledge distribution Knowledge transfer rate in knowledge utilization pillar. After applying the beta coefficient technique, the result indicates that Singapore is the best in three knowledge dimensions while Philippines is the best performer in the knowledge utilization dimension. Additionally, the weak performance countries need to implement pro-KBE policies to improve their efficiency of FDI inflows, get the highest benefits from the use of R&D expenditure, and increase the connections and the interactions between academia and industry, which in turn could facilitate the creation and commercial use of knowledge.

Author(s)	Objective(s)	Methodology	Key Result(s)
Lee (2001)	To provide conceptual background for the KBE. Then, to determine the current position of Korea in transition towards the KBE. To build Indicators for KBE in terms of inputs and outputs. Finally, to provide policies that faster transformation for KBE.	The paper used the OECD indicators for assessing the KBE, but it divided the indicators under knowledge inputs and outputs. The knowledge inputs indicators are: Expenditures on R&D. Number of official researchers per thousand Labor force. Data used are for 1995 and from OECD (Human Capital Investment) and Korea Department of Statistics, Korean Social Indicators. The knowledge outputs indicators are: Number of patents issued per thousand Labor force. shares of gross value added produced by the knowledge-based industries	Combining the results Of Knowledge inputs and knowledge outputs, Korean economy runs inefficiently in the process of transformation towards KBE. Therefore, investing in the knowledge embodied in physical capital are possible strategies for developing countries in their transformation towards a KBE. Moreover, investing in people and institutions to create and use knowledge effectively. For Korea, New organizational forms are needed to increase Korea's productivity.

Author(s)	Objective(s)	Methodology	Key Result(s)
Bashir (2013b)	To provide conceptual and measurement background for the KBE. To measure the current position of Pakistan and other Asian countries in their KBE development.	Through building a policy-focused KBE framework. Eight knowledge input indicators and four knowledge output indicators are used to assess Pakistan's position in the KBE.	Countries are classified according to their efficiency in each knowledge dimension that is: China in the knowledge acquisition. Japan, South Korea, and Singapore in the knowledge production. Taiwan in the knowledge distribution. South Korea and the Philippines in the knowledge utilization. Pakistan's figures show weak performance in almost all the KBE dimensions. That is why, policymakers must increase the efficiency of knowledge production and benefit from its inputs, investing heavily in people and knowledge embodied in physical capital.

Author(s)	Objective(s)	Methodology	Key Result(s)
Afzal And Lawrey (2012e)	To assess the appropriateness of existing KBE frameworks in measuring the KBE for resource-based countries. To develop a measurement framework that	The policy-focused framework proposed by the study consists of eleven Knowledge inputs and eight knowledge outputs distributed under the four KBE dimensions as follows: 1-Knowledge Acquisition *Input Indicators for Knowledge Acquisition* 1. Openness (Exports + imports)/GDP 2. FDI inward flows as % GDP *Output Indicators for Knowledge Acquisition* Competitiveness, HDI, Real GDP growth 2-Knowledge Production *Input Indicators for Knowledge Production*	The analysis of the policy focused framework reveals that: Weak progress in the dimensions of knowledge acquisition and utilization. No available data for knowledge production

Author(s)	Objective(s)	Methodology	Key Result(s)
	divided input-output indicators of KBE under four categories namely: knowledge acquisition, knowledge production, knowledge distribution and knowledge utilization. Given the result of the analysis, the study aimed to build a policy-oriented approach for Brunei Darussalam.	Scientific R & D expenditure as % GDP, Researchers per 1000 population, Intellectual Property Rights (IPR) *Output Indicators for Knowledge production* Scientific publications per 1000 population 3-Knowledge Distribution *Input Indicators for Knowledge Distribution* Education expenditure as % GDP Net enrolment ratio at secondary school ICT spending as % GDP. *Output Indicators for Knowledge Distribution* 1. Tertiary education per 1,000 populations. 2.PC penetration per 1,000 population 3.Internet host per 1,000 population 4-Knowledge Utilization *Input Indicators for Knowledge Utilization* 1. Technological R&D expenditure as % of GDP 2. Business R&D expenditure in total R&D expenditure 3. Knowledge transfer rate 4. FDI inflows %GDP *Output Indicators for Knowledge Utilization* 1. Share of patent applications to EPO total. 2. Exports of ICT products as % of total. 3. Production of High-Tech sector as % of total GDP.	dimension. Brunei exhibit well performance in school enrolment data which is favourable for knowledge distribution. Therefore, pro-knowledge policies should be directed to improving knowledge production, acquisition, and utilization.

Author(s)	Objective(s)	Methodology	Key Result(s)
Karahan (2012)	To present a more effective and comprehensive statistical approach for the KBE in turkey by comparison with OECD countries and the cases of European Union countries.	The study set input-output indicators for the four KBE dimensions based on OECD definition to determine Turkey's position in KBE as follows: Knowledge Acquisition *Input Indicators for Knowledge Acquisition* 1. Export + Import / GDP 2. Foreign Direct Investment inward flow as % of GDP *Output Indicators for Knowledge Acquisition* Competitiveness Rating (World Competitiveness Yearbook) Knowledge Production *Input Indicators for Knowledge Production* Scientific R&D expenditure as a % of GDP Number of Scientists in per 1000 000 population *Output Indicators for Knowledge production* Scientific Publications per 100 000 population Knowledge Distribution *Input Indicators for Knowledge Distribution* Tertiary Education Expenditure as a % of GDP Long life learning Expenditure as a % of GDP ICT spending as % of GDP. *Output Indicators for Knowledge Distribution* Tertiary Education per 1000 population Participation life-long learning per 100 population PC penetration per 1000 Number of internet host per 1000 Knowledge Utilization *Input Indicators for Knowledge Utilization* 1-Technological R&D expenditure as a % of	In terms of knowledge production and knowledge utilization, Turkey has unfavourable position as it is the worst compared with other countries. Therefore, policymaker should pay attention to these two pillars.

Author(s)	Objective(s)	Methodology	Key Result(s)
		GDP 2-Number of Engineers in per 1000 000 population *Output Indicators for Knowledge Utilization* Share of patent application to EPO in total Exports of high-tech products as a % of total Production of high-tech sector as a % of total	

Author(s)	Objective(s)	Methodology	Key Result(s)
Bashir (2013a)	To assess the KBE in 42 Islamic countries in 2012 measured by the Knowledge economy index developed by the World Bank's Knowledge Assessment Methodology (KAM).	The Knowledge Economy Index (KEI) is an aggregate index exhibiting the country's overall readiness for the Knowledge Economy. The Knowledge Economy Index is defined as the simple average of the four pillars for the knowledge economy defined by the World Bank namely: economic incentive and institutional regime, education and human resources, the innovation system and ICT. Each pillar is assessed by a sub- index which is based on three indicators that serve as a proxy for the performance of the pillar. This means that 12 knowledge indicators are used to construct the aggregate Knowledge Economy Index. To illustrate: The Education pillar Indicators are: Average Years of Schooling (15 years old and above), Gross Secondary Enrollment rate, Gross Tertiary Enrollment rate. The Information Communications and Technology pillar Indicators are: Telephones per 1,000 people, Computers per 1,000 people, Internet Users per 1,000 people. The Economic Incentive Regime pillar indicators are: Tariff & Nontariff Barriers, Regulatory Quality, Rule of Law. The innovation pillar Indicators are: Royalty Payments and receipts (US$/pop.), S&E Journal Articles per million populations, Patents Granted by USPTO per million populations.	Pakistan had achieved improvement in all the knowledge economy pillars especially the ICT pillar during the period of study (Pakistan's KEI has increased from 1.89 in 2000 to 2.45 in 2012). In comparison with other countries, Pakistan's Knowledge Economy Index in 2012 was 2.45 compared with 5.12 for the world average and 2.84 for South Asia's average.

Appendix (IV): Mathematical Formulation for the for the basic DEA MODEL (CCR model).

The CCR [CRS] Output-Oriented Model Formulation

Consider a set of n DMU_s: DMU_1, DMU_2,…………., DMU_n . Suppose m input items and s output items are selected. Let the input and output data for: DMU j be (X_{1j}, X_{2j}..., X_{mj}) and (y_{1j}, $y2_{ij}$,……. , Y_{sj}) respectively. In this case, the input data matrix X and the output data matrix Y can be arranged as follows.

$$X = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}$$

$$Y = \begin{pmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ . & . & \cdots & . \\ . & . & \cdots & . \\ y_{s1} & x_{s2} & \cdots & x_{sn} \end{pmatrix}$$

For each DMU, a virtual input and output is formulated by virtual weights (v_i) and {u_r). These weights are not un-known yet. To calculate the weight, using linear programming to maximize the ratio of virtual output/virtual input can be done as follows:

$$\text{Virtual input} = v_i X_{io} + \bullet\bullet\bullet + V_m X_{mo}$$
$$\text{Virtual output} = u_i y_{io} + \bullet\bullet\bullet + y_{io}$$

where:

v_j , j = 1, 2, …, m, are weights assigned to j-th input
u_i , i = 1, 2, …, s, are weights assigned to i-th output.

Each DMU is assigned a best set of weights with values that varies from one DMU to another. Furthermore, the "weights" in DEA are derived from the data instead of being fixed in advance.

So, given the data, we measure the efficiency of each DMU only once and hence need n optimizations, one for each DMU_j to be evaluated. Let the DMU_j to be evaluated on any trial be designated as DMU_o where $_o$ ranges from 1, 2,..., n. In this case, we can solve the following fractional programming problem to obtain values for the input "weights" {vi) {i = l,...,m) and the output "weights" {ur) (r = 1,...,s) as follows:

$$(FP_0) \qquad \max_{v.u} \theta = \frac{u_1 y_{10} + u_2 y_{20} + \cdots + u_s y_{so}}{v_1 x_{10} + v_2 x_{20} + \cdots + v_m x_{mo}}$$

$$Subject\ to \qquad \frac{u_1 y_{1j} + \cdots + u_s y_{sj}}{v_1 x_{1j} + \cdots + v_m x_{mj}} \leq 1 \quad (j = 1, \ldots, n)$$

$$v_1, v_2, \ldots \ldots, v_m \geq 0$$
$$u_1, u_2, \ldots \ldots, u_s \geq 0$$

The above equation is a maximization of an objective function subject to constraints. The first constraint means that the ratio of "virtual output" to "virtual input" should not exceed 1 for every DMU.

From Fractional to Linear Programming

The above fractional program {FP$_o$) should be replaced by a linear program (LPo):

$$(LP_0) \qquad \max_{v.u} \theta = \mu_1 y_{10} + + \cdots + \mu_s y_{so}$$

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$$Subject\ to \qquad v_1 x_{10} + \cdots + v_m x_{mo} = 1$$
$$\mu_1 y_{1j} + \cdots + \mu_s y_{sj} \leq v_1 x_{1j} + \cdots + v_m x_{mj}$$
$$(j = 1, \dots, n)$$
$$v_1, v_2, \dots \dots, v_m \geq 0$$
$$\mu_1, \mu_2, \dots \dots, \mu_s \geq 0$$

The fractional program (FP$_0$) is equivalent to (LP$_0$)

Appendix (V): DEA Softwares.

A. Linear Programming Softwares

These softwares have been introduced to execute linear programming problems. However, it can be customised to run a DEA analysis.

- **General Algebraic Modelling System (GAMS)**
  Web site: https://www.gams.com/products/gams/gams-language/

- **LINDO (L**inear**, In**teractive**, and D**iscrete **O**ptimizer**). This software has a linear programming option. Web Site:** http://www.lindo.com/products.html

- **Microsoft Excel** (It is an Add-In for Microsoft Excel by using the Excel solver tool).

B. Specialised DEA Softwares (Commercial and Non-Commercial)

- **Warwick DEA** — Warwick Business School (UK), http://www.csv.warwick.ac.uk/~bsrlu/dea/deas/deas1.htm. It is currently known as PIM-DEA software developed by Emrouznejad and Thanassoulis.
  Website: http://www.deasoftware.co.uk/ AboutDevelopers.asp

- **FEAR (Frontier Efficiency Analysis in R).** It is developed by Paul W. Wilson, Clemson University, USA. The user guide is available at: www.clemson.edu/economics/faculty/Wilson/software/FEAR.

- **DEA Frontier** by Joe Zhu, available at: http://www.deafrontier.net/.

- **DEAP** – Tim Coelli, **University of New England, Armidale, Australia, available at**: http://www.owlnet.rice.edu/~econ380/DEAP.PDF

- **KonSi Data Envelopment Analysis DEA 5.1, available at:** http://www.dea-analysis.com/.

- **DEA Solver - Pro**, available at: http://www.saitech-inc.com/Products/Prod-DSP.asp

- **Banxia Frontier Analyst Vs. 4**, available at: http://www.banxia.com/frontier/

- **MaxDEA – A Chinese effort**, available at: http://www.maxdea.cn/.

- **Alta-Bering – EPO Software,** available at: http://altabering.com/epo-framework/software/

- **pyDEA**. This is a software package developed in Python for DEA use only, available at: https:// pypi.python.org/pypi/pyDEA**.**

- **EMS** (Efficiency Measurement System), available at: http://www.holger-scheel.de/ems/

- **PIONEER**. This is DEA software developed by Thomas McLoud and Richard Barr. Available at: https://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.466.1472&rep=rep1&type=pdf

C. Specialised DEA Web-based Applications (Commercial and Non-Commercial)

- **DEAOS - D**ata **E**nvelopment **A**nalysis **O**nline **S**oftware. It is a web-based application. For more details: http://www.deaos.com/login.aspx?ReturnUrl¼%2fWelcome.aspx

- **DeaR-shiny**. Available at: deaR: Data Envelopment Analysis in R (shinyapps.io)
- **DEA online**. Available at: http://www.onlineoutput.com/dea-software

- **WebDEA.** Available at: https://sites.google.com/site/dsslabunipi/home

- **DEA Solver Online**. Available at: http://www.dea.fernuni-hagen.de

- **DEAShiny**. Available at: https://deaumh.shinyapps.io/DEASHINY/

Source : Paradi et al. (2017) ; Barr (2004) ; Benítez et al. (2021); Iliyasu et al. (2015)

Appendix (VI): Studies Employed DEA for Evaluating Countries' Efficiencies.

Author(s)	Description (Main objective of the study)
Dehnokhalaji et al. (2022)	Assess efficiency of DMUs with imprecise Data to reflect uncertainty in input and output values.
Melecký et al. (2019)	Use DEA as a mirror for national and regional competitiveness in 28 European Union countries by assessing the technical efficiency using inputs and outputs based on country competitiveness index.
Tasnim and Afzal (2018)	Evaluate the effects of national systems of entrepreneurship on country's efficiency for 59 countries using DEA and Tobit regression.
Chen (2017b)	Assess the overall efficiency, departmental efficiency, and productivity analysis for Taiwan′ s counties/cities by adopting a multi-activity DEA model.
Šegota et al. (2017)	Estimate the competitiveness activities of countries using DEA.
Wu and Pan (2014)	Measure the performance efficiency of 21 OECD countries by utilizing four different DEA models.
Rabar (2013)	Measure the regional efficiency of Croatian economies by observing 63 entities, from 2005-2007.
Staničkova (2013)	Assess the technical efficiency European Union Member State and apply a Malmquist productivity Index to trace changes in efficiency for the period from 2000 and 2011
Malhotra and Malhotra (2009)	Benchmark the relative performance of 15 European Union countries from 1993 to 2006.
Hsu et al. (2008)	Estimate the comparative efficiency between 50 developed and less developed countries.
Christopoulos (2007)	Build an efficiency index for assessing Countries performance.
Mohamad (2007)	To estimate how efficient 25 Asia and the Pacific countries employ their resources.
Ramanathan (2006)	Measure the relative performance of 18 MENA countries in1999 and assess the Malmquist productivity index
Despotis (2005)	Re-assess HDI using DEA for Asia and the Pacific countries.
Deliktas and Balcilar (2005)	Use SFA and DEA to evaluate the macroeconomic performance for 25 transition economies
Halkos and Tzeremes (2005)	Measure the efficiency Greek prefectures in three decades 1980, 1990 and 2000.
Martić and Savić (2001)	Estimate the efficiency of regions in Serbia regarding their resource's utilization.
Breuss and Mahlberg (2000)	Assess the performance of 10 Eastern European countries using economic indicators under three categories namely, the macroeconomic performance, the foreign trade performance, and their ability to participate in the European Monetary Union.
Karkazis and Thanassoulis (1998)	Assess the effectiveness of policies in terms of private investment aimed to reduce regional disparities in Northern Greece.
Golany and Thore (1997)	Modified the standard DEA model formulations to add some constraints such as institutional constraints, considerations of equity and externalities in production to add more flexibility in assessing socio-economic performance.
Lovell (1995)	Measure the macroeconomic performance for ten Asian countries for the period 1970-1988.
Sueyoshi (1992)	Assess the industrial performance for 35 selected Chinese cities in 1985 as well as their returns-to-scale in 1985.
Charnes et al. (1989)	Evaluate efficiency of 28 selected Chinese cities in the economic performance for the years 1983 and 1984.

Appendix (VII): The Empirical Studies that Employed DEA to Assess the KBE Performance.

Author(s)	Siddiqui and Afzal (2022)
Objective	Assess the position of United Arab Emirates in their transition to a KBE.
Dataset	From 2000 to 2020
Inputs and outputs used in DEA Analysis	**Inputs:** Time required to start a business (days), Ease of doing business score, Domestic credit to private sector (% of GDP), cost of business start-up procedures (% of GNI per capita), Technicians in R&D (per million people) ,Labor force with basic education (% of total working-age population with basic education), Labor force with advanced education (% of total working-age population with advanced education), Current education expenditure, primary (% of total expenditure in primary public institutions),Current education expenditure, secondary (% of total expenditure in secondary public institutions ,Researchers in R&D (per million people),Research and development expenditure (% of GDP),Secure Internet servers (per 1 million people),ICT spending (USD). **Outputs:** New business density (new registrations per 1,000 people ages 15– 64), New businesses registered (number), Human capital index (HCI) (scale 0–1), Literacy rate, adult total (% of people aged 15 and above), Scientific and technical journal articles, Individuals using the Internet (% of population), ICT spending (USD) High-technology exports (current US$), ICT goods exports (% of total goods exports).
DEA Model Used	CCR DEA model, among other methodologies to attain the objectives of the study such as Herfindal-Hirschman index to assess the status of economic diversification in UAE.
Key Findings	United Arab Emirates is reasonably diverse until the ended period of the study. Furthermore, the three analysed pillars of the KBE given the availability of data are efficient and productive.

Author(s)	Firsova et al. (2022)
Objective	To assess the efficiency of the knowledge-intensive services in the education, innovation, and ICT sectors in 80 Russian regions.
Dataset	From 2010 to 2020
Inputs and outputs used in DEA Analysis	**Inputs:** the volume of investments in fixed assets in ICT; the share of personnel employed in the ICT; the share of internal expenditures on R&D in GRP; the number of personnel engaged in R&D; the share of innovative-active organizations and registered patents; funding for higher education institutions; and the number of higher education institutions graduated. **Outputs:** the number of used advanced production technologies in the region; share of innovative goods, works, and services in GRP, and use of the intellectual property.

Author(s)	Firsova et al. (2022)
DEA Model Used	Malmquist Productivity Index and its components
Key Findings	There was a positive development in all the knowledge-intensive sectors in Russian regions between 2014–2017 and 2017–2020. Additionally, most of the Russian regions have combined the development of knowledge-intensive economies.

Author(s)	Guaita Martínez et al. (2020)
Objective	To compare the results of three DEA models applied in 36 European countries to assess their effectiveness in the development of KBE.
Dataset	2018
Inputs and outputs used in DEA Analysis	Three DEA models are used throughout the analysis. The main differences between proposed models are determined by 1) the weights assigned to the sub-indicators, 2) the simplicity of use, 3) the discriminatory power and 4) the participatory nature.
DEA Model Used	Three MCA-DEA models from a “Benefit of Doubt” (BoD) approach
Key Findings	Model 1 presented high scores for every country but low discriminating power among analysed DMUs. Model 2 has favoured the most efficient countries in terms of KBE indicators and gives more flexibility to the process. Model 3 allows constructing composite indicators from an optimal balance approach. It also gives the low results overall.

Author(s)	Mutanov et al. (2020)
Objective	Estimate the Malmquist Productivity Index using DEA for 15 regions of the Republic Kazakhstan
Dataset	From 2007 to 2017
Inputs and outputs used in DEA Analysis	**Inputs:** Innovative activity of organizations; the volume of innovative products; Internal expenditures on research and development; Expenses for product and process innovations in the industry; Information technology expenses; Number of organizations engaged in R&D; Number of employees engaged in R&D; The share of workers employed in high-tech industries; Percentage of obtained patents and articles with impact factor per researcher; Share of patents in total research ;Number of information technology specialist; Number of organizations using the Internet ; The proportion of organizations using the Internet; Share of enterprises using new technologies in the total number of enterprises ; Herfindal-Hirschman Index of specialisation gross regional product ;emissions of air pollutants from stationary sources.

Author(s)	Mutanov et al. (2020)
	Outputs: Gross regional product.
DEA Model Used	Malmquist Productivity Index
Key Findings	Urgent need to develop diversified policies aimed at enhancing efficiency of KBE.

Author(s)	Zhuparova et al. (2019)
Objective	Define the most important KBE factors. After that, assess how efficient these KBE components contribute to economic growth for 15 regions of the Republic Kazakhstan.
Dataset	From 2007 to 2017
Inputs and outputs used in DEA Analysis	**Inputs:** Innovative activity of organizations; the volume of innovative products; Internal expenditures on research and development; Expenses for product and process innovations in the industry; Information technology expenses; Number of organizations engaged in R&D; Number of employees engaged in R&D; The share of workers employed in high-tech industries; Percentage of obtained patents and articles with impact factor per researcher; Share of patents in total research ;Number of information technology specialist; Number of organizations using the Internet ; The proportion of organizations using the Internet; Share of enterprises using new technologies in the total number of enterprises **Outputs:** gross regional product.
DEA Model Used	CCR
Key Findings	R&D expenditures are not equally distributed among the regions of Kazakhstan. Further, the efficiency scores for the most influencing KBE components are low.

Author(s)	Yakici Ayan and Pabuçcu (2018)
Objective	To compute the relative efficiency of knowledge economy policy in 22 European Union (EU) countries including Turkey.
Dataset	2016
Inputs and outputs used in DEA Analysis	**Inputs:** Human development index, research, and development expenditure as rate of GDP, growth rate of GDP. **Outputs:** Number of mobile communication subscriptions and penetration per 100 inhabitants, exports of high technology products as a share of total exports, number of internet host per 100 inhabitants, patent applications.
DEA Model Used	context dependent DEA and factor specific DEA

Author(s)	**Yakici Ayan and Pabuçcu (2018)**
Key Findings	Germany is the top among other countries in the sample while Turkey is the least efficient country Further patent applications and high-tech exports constitute the main sources of inefficiency compared to other knowledge economy outputs used in the DEA analysis.

Author(s)	**Prokop et al. (2018)**
Objective	To evaluate the effectiveness of KBE dimension. Then, to determine which dimension provide the intended macroeconomic effects?
Dataset	2011–2015
Inputs and outputs used in DEA Analysis	**Inputs:** Government R&D expenditures, the number of people with tertiary education, Employees in ICT, the number of employees working in the field of science and technology (15–74 years) **Outputs:** Value added (in Euros) (model 1) and patents (model 2)
DEA Model Used	Input oriented BCC models as the study applied two DEA models with different inputs and outputs.
Key Findings	The result of utilizing the DEA approach reveals that the minority of EU countries were efficient

Author(s)	**Tarnawska and Mavroeidis (2015)**
Objective	To estimate the relative efficiency of 25 EU countries with respect to their knowledge triangle policy.
Dataset	2009 and 2012
Inputs and outputs used in DEA Analysis	**Inputs:** Annual expenditure on public and private educational institutions, Research, and development personnel, by sectors of performance, Inter-sectoral mobility of researchers. **Outputs:** High-technology exports, Scientific and technical publications, SME introducing marketing/organisational innovations
DEA Model Used	BCC
Key Findings	Estonia is the role model for less efficient countries. Additionally, the study concluded considerable differences among efficient countries through using the reference share analysis.

Author(s)	**Ahmed and Krishnasamy (2013)**
Objective	To explore the nature and extent of productivity changes of ASEAN5 countries to know whether it is attributed to either technical efficiency change or technological change or both.

Author(s)	Ahmed and Krishnasamy (2013)
Dataset	1993 to 2006
Inputs and outputs used in DEA Analysis	**Inputs:** real gross fixed capital formation (GFCF), total employment and real expenditures in education. **Outputs:** real GDP
DEA Model Used	Malmquist Productivity Index and its components
Key Findings	Malaysia and Singapore reported an increase in TFP and this growth in productivity is derived from both technical efficiency gain and technological progress, in case when human capital is included in the model.

Author(s)	Afzal and Lawrey (2012a)
Objective	To evaluate technical and scale efficiency for each knowledge dimension in 5 countries in the Association of Southeast Asian Nations (ASEAN) and added south Korea to adhere to the rule of thumb regarding the number of DMUs.
Dataset	In 1995 and 2010
Inputs and outputs used in DEA Analysis	**Inputs:** Trade openness, Foreign Direct Investment inward flows, R&D expenditure, intellectual property rights, education expenditure, net enrolment ratio at secondary school, knowledge transfer rate (university to industry), FDI inflows. **Outputs:** Real GDP growth, scientific and technical publications per 1000 population, computer users per 1000 population, high-tech export % of Total exports.
DEA Model Used	CCR and BCC
Key Findings	Indonesia is the efficient country in knowledge acquisition. Singapore, South Korea, and Thailand in knowledge production. Singapore in knowledge distribution. Philippines and South Korea in knowledge utilization. These results are applicable in either one or both years investigated in the study.

Author(s)	Afzal and Lawrey (2012b)
Objective	To measure KBE efficiencies in five ASEAN- countries
Dataset	2005-2010
Inputs and outputs used in DEA Analysis	**Inputs:** Trade openness, Foreign Direct Investment inward flows, legal and regulatory quality, Transparency, R&D expenditure, intellectual property rights, education expenditure, net enrolment ratio at secondary school, knowledge transfer rate (university to industry), FDI inflows. **Outputs:** Real GDP growth, scientific and technical publications per 1000 population, computer users per 1000 population, high-tech export % of Total exports.

Author(s)	Afzal and Lawrey (2012b)
DEA Model Used	DEA/Window Analysis
Key Findings	Indonesia is the efficient country in knowledge acquisition dimension. Thailand and Singapore are the efficient countries in knowledge production and distribution. Philippines is the efficient country in knowledge utilization.

Author(s)	Afzal and Lawrey (2012c)
Objective	Re-evaluate KAM using DEA and applying this on Asian region
Dataset	2010
Inputs and outputs used in DEA Analysis	**Inputs:** Trade openness, Foreign Direct Investment inward flows, R&D expenditure, intellectual property rights, education expenditure, net enrolment ratio at secondary school, knowledge transfer rate (university to industry), FDI inflows. **Outputs:** Real GDP growth, scientific and technical publications per 1000 population, computer users per 1000 population, high-tech export % of Total exports.
DEA Model Used	CCR
Key Findings	KAM can be used more effectively to explain the development of KBE to the client countries

Author(s)	Afzal and Lawrey (2012d)
Objective	To assess the technical efficiencies of KBEs in five countries in the Association of Southeast Asian Nations.
Dataset	1995 and 2010
Inputs and outputs used in DEA Analysis	**Inputs:** Trade Openness, FDI inward flows as % GDP, R & D expenditure as % GDP, Intellectual Property Rights, Education expenditure as % GDP, Net enrolment ratio at secondary school, Knowledge Transfer rate (university to industry), and FDI inflows % of GDP. **Outputs:** Real GDP growth; Scientific & Technical publications per 1000 population; Computer users per 1000 population; High-tech export % of Total exports.
DEA Model Used	CCR, BCC and the Additive Model
Key Findings	Indonesia in the knowledge acquisition dimension. Singapore, South Korea and Thailand in the knowledge production dimension. Singapore in the knowledge distribution dimension. Philippines and South Korea in the knowledge utilization dimension.

Author(s)	Tan et al. (2008)
Objective	To assess the KBEs relative efficiencies in 12 selected Asia Pacific countries. Countries included are Australia, China, India, Japan, USA, Hong Kong, Korea, Singapore, Indonesia, Philippines, Malaysia, and Thailand.
Dataset	Most indicators are collected for 2006 unless otherwise mentioned in the study.
Inputs and outputs used in DEA Analysis	**Inputs:** Gross FDI, Expenditure on R&D, pupil-teacher ratio, and tertiary enrolment. **Outputs:** mobile phones, newspapers, internet hosts number and international telecom.
DEA Model Used	Basic DEA models
Key Findings	India, Indonesia, Thailand, and China are the relatively inefficient in the sample. The other eight countries involved in the study are efficient. Another key finding is that the outflow of human capital to the other developed countries constitutes the main source for this inefficiency.

Author(s)	Tan and Hooy (2007)
Objective	To measure the development of KBE in nine developing as well as emerging countries, namely USA, Finland, Japan, Korea, Singapore China, Malaysia, the Philippines, and Thailand.
Dataset	Most indicators are collected for 2001 unless otherwise mentioned.
Inputs and outputs used in DEA Analysis	**Inputs:** Labor force, Gross domestic product, Gross capital formation, Total expenditure on ICT, Value-added services in GDP. **Outputs:** High-technology export, Scientists & engineers in R&D, Number of personal computers, Number of Internet Host, Telephone main Lines, Mobile telephones, Labor productivity, international telecommunications
DEA Model Used	Radar diagrams and basic DEA models
Key Findings	Finland, Malaysia, Singapore, and South Korea are more efficient with respect to Knowledge outputs when compared with the other relatively large countries namely US and Japan. By using the radar chart, it is obvious that developed countries have sorted more knowledge stock compared with other countries in the study.

Author(s)	**Liping and Shudong (2007)**
Objective	Assessing the KBE for each city in China
Dataset	2004
Inputs and outputs used in DEA Analysis	**Inputs:** capital, Labor, and information resource. **Outputs:** gross regional product.
DEA Model Used	CCR and BCC
Key Findings	All Chinese cities are in the stage of increasing returns to scale. Additionally, they have higher scale efficiency, but lower pure technical efficiency.

Appendix (VIII): The Empirical Studies that Employed DEA for Measuring the Efficiency of the National; Regional and Sectoral Innovation Systems.

Author(s)	Klevenhusen et al. (2021)
Objective	Assessing the participation of international trade to efficiency in innovation for members of the OECD.
Dataset	OECD countries for the period from 2008 to 2017.
Inputs and outputs used in DEA Analysis	Two input measures: researchers in R&D per million people and research and development expenditure per capita. Four output measures: high-technology exports (per capita), patent applications (per 100,000 residents), scientific and technical journal articles (100,000 residents), and charges for the use of intellectual property (receipts per capita).
DEA Model Used	CCR, BCC and Tobit regression.
Key Findings	The findings reveal that being a country in the Asia-Pacific Economic Cooperation is highly correlated to efficiency gains. Further, being a member of the European Union does not necessarily correlate with the same benefits.

Author(s)	Alnafrah (2021)
Objective	Assessing the efficiency of NISs in BRICS economies.
Dataset	Time lag between inputs and outputs is 2 years.
Inputs and outputs used in DEA Analysis	The overall national innovation process into two sub-processes: knowledge production process (KPP) and knowledge commercialization process (KCP).
DEA Model Used	Network DEA
Key Findings	The results showed that national innovation systems in BRICS countries characterised by low performance in commercializing their outputs while their performance in creating scientific and technical knowledge is relatively good compared to other countries in the sample.

Author(s)	Juřičková et al. (2019)
Objective	Assess the technical efficiency of National Innovation System in 28 European Union countries.
Dataset	From 2005 to 2016
Inputs and outputs used in DEA Analysis	**Inputs:** the number of researchers; the expenditures on (R&D). **Outputs:** published scientific journal articles and applied patents.

Author(s)	**Juřičková et al. (2019)**
DEA Model Used	Constant returns to scale model. The out-put orientation is used throughout the study.
Key Findings	Only four countries namely, Cyprus, Luxembourg, Malta, and Romania are founded to be efficient in 2016.

Author(s)	**Kontolaimou et al. (2016)**
Objective	Assess the efficiency of NIS 28 European countries based on efficiency scores.
Dataset	28 European countries
Inputs and outputs used in DEA Analysis	**Inputs:** business expenditures on R&D, human capital, entrepreneurial capital based on new technologies. **Outputs:** intellectual assets, medium tech, and high-tech exports.
DEA Model Used	Bootstrap DEA model
Key Findings	Seven EU countries as innovation leaders based on the analysed sample.

Author(s)	**Carayannis et al. (2016)**
Objective	To introduce a framework for assessing national and regional innovation efficiency.
Dataset	23 European countries and their 185 corresponding regions.
Inputs and outputs used in DEA Analysis	**Inputs:** Science graduates in tertiary education; Participation in lifelong learning; Total R&D expenditure; R&D capital stock; Citable documents; Patent applications; Employment in knowledge intensive services/manufacturing; SMEs collaborating with others and Venture capital investment. **Outputs:** High tech exports; Sales of new to market and new to firm innovation; License and patent revenues from abroad; Number of trademark applications in national offices.
DEA Model Used	VRS-multistage, multilevel 2 stages
Key Findings	large disparities related to the efficiency scores of the different stages and levels

Author(s)	**Lu et al. (2014)**
Objective	Assess R&D efficiency and the economic efficiency of NIS in 30 countries. Then, examine the effect of intellectual capital on the NIS of countries.
Dataset	Average value for the period from 2007 to 2009.
Inputs and outputs used in DEA Analysis	Each stage has its own inputs and outputs. The outputs of R&D efficiency stage are the inputs for economic efficiency stage. In the economic efficiency stage: **Inputs:** published scientific articles; patents granted to residents and patents secured abroad by country residents.

Author(s)	**Lu et al. (2014)**
	Outputs: Gross Domestic Product, purchasing power parity and Productivity.
DEA Model Used	Network DEA and truncated regression
Key Findings	In terms of the R&D efficiency stage, 24 countries are deemed efficient, accounting for 80% of the sample. Additionally, America NIS is the most efficient system in the sample of countries in terms of both R&D efficiency and economic efficiency.

Author(s)	**Foddi and Usai (2013)**
Objective	To assess how efficiently 29 EU countries use inputs to produce new knowledge
Dataset	2000 to 2007.
Inputs and outputs used in DEA Analysis	**Inputs:** Total intramural R&D expenditure, economically active population with tertiary education attainment (15 years and over) Number of people on 1st January (as a control variable) **Outputs:** Number of the European Patent Office (EPO) patent applications per priority year and residence region of inventors.
DEA Model Used	CCR, BCC and Malmquist productivity index
Key Findings	Using CCR and BCC models, the efficient regions are those located in the strategic areas of the continent. Additionally, the result of the Malmquist index shows considerably differentiated productivity dynamics across regions. The significant differences are between the core and periphery of Europe.

Author(s)	**Matei and Aldea (2012)**
Objective	Estimate NIS technical efficiency for 31 countries
Dataset	Innovation Union Scoreboard 2011 database
Inputs and outputs used in DEA Analysis	**Inputs:** New doctorate graduates (ISCED 6) per 1000 population; International scientific Co-publications per million populations; Public R&D expenditures as % of GDP; Business R&D expenditures as % of GDP; patents applications per billion GDP. Trademarks per billion GDP; Trademarks per billion GDP. **Outputs:** Employment in knowledge intensive activities (manufacturing and services) as % of total employment; Medium and high-tech product exports as % total product exports; Knowledge-intensive services exports as % total service exports.
DEA Model Used	Output oriented BCC DEA Model
Key Findings	Malta has the most efficient innovation system.

Author(s)	**Guan and Chen (2010)**
Objective	Estimate the efficiency of high-tech innovations in the 26 China's provinces.
Dataset	in 2002 and 2003
Inputs and outputs used in DEA Analysis	**Inputs:** R&D expenditure; Technology import **Outputs:** Patent applications; High-tech export. Two stages: R&D efficiency and commercial efficiency
DEA Model Used	Two stages Network DEA
Key Findings	Based on the empirical results the Chinese provinces are divided into four subgroups with respect to their strength or weakness in R&D capability and commercial capability.

Author(s)	**Nasierowski and Arcelus (2003)**
Objective	To assess the role of R&D on a country's productivity for 46 countries included in the World Competitiveness Report.
Dataset	for 1993 and 1997
Inputs and outputs used in DEA Analysis	**Inputs:** Imports of goods and commercial products, GDP expenditure on research, private business involvement in R&D, Employment in R&D, expenses in Education. **Outputs:** external Patents by resident, patents by residents, national productivity
DEA Model Used	CRS DEA model input orientation
Key Findings	Eight countries are efficient countries and the study concluded that further research is needed.

Author(s)	**Guan and Chen (2012)**
Objective	Evaluate the innovation efficiency of the national innovation systems in 22 OECD Countries.
Dataset	1999 -2003
Inputs and outputs used in DEA Analysis	**Inputs:** Number of full-time equivalent scientists and engineers; Incremental R&D expenditure funding; Innovation activities; Prior accumulated knowledge stock breeding upstream knowledge production; Consumed full-time equivalent labour for non-R&D activities. **Outputs:** Number of patents granted; Number of patents granted; International scientific papers; Added value of industries; Export of new products in high-tech industries.
DEA Model Used	Output oriented DEA CCR and BCC models, two stage network super efficiency and Tobit regression.
Key Findings	Considerable attention should be paid to the efficiency assessment of national innovation activities for the sake of KBE development.

Appendix (VIIII): The Empirical Studies that Employed DEA for Measuring R&D Efficiency.

Author(s)	Karadayi and Ekinci (2019)
Objective	Evaluate the relative R&D efficiencies of 28 EU countries.
Dataset	2011-2013
Inputs and outputs used in DEA Analysis	**Inputs:** Total full time equivalent research and development personnel; Persons with tertiary education and employed in science and technology; Employment in high and medium-high technology manufacturing sectors and knowledge-intensive service sectors (% of total employment; R&D expenditures conducted by government; R&D expenditures conducted by business enterprises; R&D expenditures conducted by high education sector. **Outputs:** Total number of citable and non-citable documents; Total number of patents granted by European Patent Office; Total number of patents granted by US Patent and Trademark Office.
DEA Model Used	Output-oriented CCR and BCC Categorical DEA
Key Findings	17 EU countries out of the 28 EU Countries in the sample are efficient during 2011–2013.

Author(s)	Gavurová et al. (2019)
Objective	Assess the potential of R&D efficiency in 28 European Union countries.
Dataset	2010–2015
Inputs and outputs used in DEA Analysis	**Inputs:** were R&D expenditure in the higher education and the business enterprise sector as % of GDP, human labour indicators as total researchers, human resources in science and technology as % of active population and share of employment in service-intensive sectors. **Outputs:** were high-tech export as % of total export and the number of scientific publications.
DEA Model Used	super-efficient non-oriented non-radial slack-based DEA model
Key Findings	Bulgaria, Romania, Cyprus, Croatia, and United Kingdom are the best efficient countries in both of the analysed period.

Author(s)	Han et al. (2016)
Objective	Assess the regional R&D efficiency in 15 Korean regions from the static perspective and the dynamic one as well.
Dataset	2005-2009
Inputs and outputs used in DEA Analysis	**Inputs:** R&D expenditure (after inflation adjustment). **Outputs:** Number of PCT applications and Number of SCIE publications.
DEA Model Used	CCR super efficiency and Malmquist productivity index.
Key Findings	Most Korean regions suffer from declining R&D productivity over time because of their inability to catch up with the best practices.

Author(s)	Afzal and Lawrey (2014)
Objective	Assess how effective ASEAN countries are utilizing their public research and development expenditures.
Dataset	2010
Inputs and outputs used in DEA Analysis	**Inputs:** public R&D expenditure as a percentage of GDP. **Outputs:** real GDP growth and high-tech goods export as a percentage of total manufacturing exports
DEA Model Used	CCR and BCC
Key Findings	The CCR model proves that Philippines and Indonesia are the top performers in 2010. in contrast, Singapore and Thailand were the most efficient countries by applying the BCC model.

Author(s)	Roman (2010)
Objective	The relative R&D efficiency for 13 regions form Romania and Bulgaria is evaluated.
Dataset	2003 and 2005
Inputs and outputs used in DEA Analysis	Inputs: R&D expenditures, the number of researchers and employment in high- and medium-skilled Labor Outputs: number of patents
DEA Model Used	CCR and BCC
Key Findings	Bulgarian regions are more relatively efficient in R&D activities with respect to their Romanian regions

Author(s)	Cullmann et al. (2009)
Objective	To measure the comparative efficiency of R & D in 28 OECD countries.
Dataset	1995 to 2004
Inputs and outputs used in DEA Analysis	**Inputs:** R&D expenditures and labour invested in R&D **Outputs:** number of patents
DEA Model Used	CCR and BCC
Key Findings	The most efficient countries are Germany, Sweden, and United States. Further, procedure. High regulation and barriers to entry lowers R&D efficiency in the economy.

Author(s)	Schmidt-Ehmcke and Zloczysti (2009)
Objective	To assess R & D relative efficiency in 17 European countries.
Dataset	From 2000 to 2004
Inputs and outputs used in DEA Analysis	**Inputs:** R&D expenditures and high- and medium-skilled labour **Outputs**: number of patents
DEA Model Used	CCR and BCC
Key Findings	Germany, the United States, and Denmark have the highest efficiency scores on average in total manufacturing. The most interesting is small countries such as Belgium have high efficiency, while large countries such as United Kingdom lag.

Author(s)	Sharma and Thomas (2008)
Objective	To assess R & D relative efficiency for 22 developed and developing countries.
Dataset	
Inputs and outputs used in DEA Analysis	**Inputs:** R&D expenditures, researchers, gross domestic product, population **Outputs:** patents granted, and publications counts Four models with different numbers of inputs and outputs are applied in the study.
DEA Model Used	CCR and BCC
Key Findings	The DEA result varies considerably with different models applied. Based on DEA CCR model 3 countries are efficient namely, Japan, Republic of Korea, China lie on the while 6 out of 22 countries are efficient by applying the BCC model.

Author(s)	**Wang and Huang (2007)**
Objective	To measure the relative efficiency of R&D activities in 30 countries (OECD and non-OECD economies)
Dataset	1997–2002
Inputs and outputs used in DEA Analysis	**Inputs:** R&D net capital stock, researchers, technicians **Outputs:** patents granted, publications count Environmental Variables: enrolment rate of tertiary education, the PC density, and the English proficiency
DEA Model Used	Input-oriented DEA – BCC model, three stage DEA Model and Tobit regression.
Key Findings	-Roughly around half of the countries are efficient in their R&D activities. -Two-thirds are at increasing returns to scale stage. -Most of the countries published scientific publications and have advantage over Patents.

Author(s)	**Roman (2010)**
Objective	The relative R&D efficiency for 13 regions form Romania and Bulgaria is evaluated.
Dataset	2003 and 2005
Inputs and outputs used in DEA Analysis	Inputs: R&D expenditures, the number of researchers and employment in high- and medium-skilled Labor Outputs: number of patents
DEA Model Used	CCR and BCC
Key Findings	Bulgarian regions are more relatively efficient in R&D activities with respect to their Romanian regions

Author(s)	**Lee and Park (2005)**
Objective	Assess the relative efficiency of twenty-seven Asian countries.
Dataset	**Inputs:** average from1994-1998 **Outputs** :1999
Inputs and outputs used in DEA Analysis	**Inputs:** R&D expenditure; Average number of researchers. **Outputs:** Technology balance of receipts.; Number of scientific and technical journal articles.; Number of triadic patent families
DEA Model Used	output oriented CCR model
Key Findings	Singapore is the most efficient country. China, Korea, and Taiwan are relatively inefficient in R&D

Author(s)	Rousseau and Rousseau (1998)
Objective	To evaluate the relative efficiency of R&D process in 18 countries
Dataset	1993
Inputs and outputs used in DEA Analysis	**Inputs:** GDP, active population, and R&D expenditure. **Outputs:** publications and patents.
DEA Model Used	CCR but with output and input weights
Key Findings	Switzerland is the most efficient country

Author(s)	Rousseau and Rousseau (1997)
Objective	To evaluate the relative efficiency of R&D process in 18 countries.
Dataset	1993
Inputs and outputs used in DEA Analysis	**Inputs:** GDP, active population and R&D expenditure (1993) **Outputs:** publications and patents (1995)
DEA Model Used	CCR
Key Findings	Seven countries are fully efficient.

Appendix (X): Developing Countries According to the World Bank classification based on Gross National Income (GNI) per capita in 2020[2]

Low-Income Countries ($1,035 or Less)			Total Number of Countries: 29		
Afghanistan	Congo, Dem. Rep	Guinea-Bissau	Malawi	Sierra Leone	Tajikistan
Burkina Faso	Eritrea	Haiti	Mali	Somalia	Togo
Burundi	Ethiopia	Korea, Dem. People's Rep.	Mozambique	South Sudan	Uganda
Central African Republic	Gambia	Liberia	Niger	Sudan	Yemen, Rep.
Chad	Guinea	Madagascar	Rwanda	Syrian Arab Republic	

Upper-Middle Income Countries ($4,046 TO $12,535)				Total Number of Countries: 56	
Albania	Bulgaria	Gabon	Kazakhstan	North Macedonia	Thailand
American Samoa	China	Georgia	Kosovo	Paraguay	Tonga
Argentina	Colombia	Grenada	Lebanon	Peru	Turkey
Armenia	Costa Rica	Guatemala	Libya	Russian Federation	Turkmenistan
Azerbaijan	Cuba	Guyana	Malaysia	Samoa	Tuvalu
Belarus	Dominica	Indonesia	Maldives	Serbia	Venezuela, RB
Belize	Dominican Republic	Iran, Islamic Rep.	Marshall Islands	South Africa	
Bosnia and Herzegovina	Equatorial Guinea	Iraq	Mexico	St. Lucia	
Botswana	Ecuador	Jamaica	Montenegro	St. Vincent and the Grenadines	
Brazil	Fiji	Jordan	Namibia	Suriname	

Lower-Middle Income Countries ($1,036 TO $4,045)			Total Number of Countries: 50	
Angola	Congo, Rep.	Kiribati	Nepal	Tanzania
Algeria	Côte d'Ivoire	Kyrgyz Republic	Nicaragua	Timor-Leste
Bangladesh	Djibouti	Lao PDR	Nigeria	Tunisia
Benin	Egypt, Arab Rep.	Lesotho	Pakistan	Ukraine
Bhutan	El Salvador	Mauritania	Papua New Guinea	Uzbekistan
Bolivia	Eswatini	Micronesia, Fed.	Philippines	Vanuatu
Cabo Verde	Ghana	Moldova	São Tomé and Principe	Vietnam
Cambodia	Honduras	Mongolia	Senegal	West Bank and Gaza
Cameroon	India	Morocco	Solomon Islands	Zambia
Comoros	Kenya	Myanmar	Sri Lanka	Zimbabwe

(2) The main grouping provided by the WB are by geographic region, by income group, and by the operational lending categories, the study adopts the income grouping which classifies countries into four income groups namely, low, lower-middle, upper-middle, and high-income countries. Developing Countries are referred to in the WB and elsewhere as the low- and middle-income groups. The classifications are updated every year on the first of July. This classification is built based on GNI per capita in current USD by using the Atlas method exchange rates for the previous year (i.e. the previous calendar year in this case was 2019).

- **The final selection of the developing countries given data availability (65 countries)**

Low-income countries	Lower-middle income countries		Upper-middle income countries	
Burkina Faso	Algeria	Nepal	Albania	Kazakhstan
Burundi	Angola	Nicaragua	Argentina	Mexico
Ethiopia	Cambodia	Nigeria	Armenia	Namibia
Gambia	Côte d'Ivoire	Pakistan	Azerbaijan	North Macedonia
Georgia	Egypt, Arab Rep.	Philippines	Botswana	Paraguay
Mali	El Salvador	Senegal	Brazil	Peru
Mozambique	Ghana	Sri Lanka	Bulgaria	Russian Federation
Rwanda	Honduras	Tunisia	China	Serbia
Uganda	India	Ukraine	Colombia	South Africa
	Kenya	Vietnam	Costa Rica	Thailand
	Kyrgyz Republic	Zambia	Ecuador	Turkey
	Lao PDR		Guatemala	
	Lesotho		Indonesia	
	Madagascar		Iran, Islamic Rep	
	Mauritania		Jamaica	
	Mongolia		Jordan	
	Morocco		Malaysia	
9	**28**		**28**	

Appendix (XI): Methodology for Choosing Variables for KBE Dimensions.

1- Methodology for choosing variables for knowledge acquisition dimension.

Beta coefficient technique is the methodology adopted in this study for variable selection. A standardized beta coefficient compares the strength of the effect of each individual independent variable to the dependent variable. The higher the absolute value of the beta coefficient, the stronger the effect.

1- Descriptive statistics to the inputs and outputs

Descriptive Statistics						
		N	Minimum	Maximum	Mean	Std. deviation
Inputs	Trade openness	129	9.955	293.775	73.282	39.528
	Ease of doing a business	130	20.040	83.734	57.825	12.877
	Transparency	135	.000	92.7884	35.061	22.661
	Government Effectiveness	135	.000	82.212	33.643	20.821
	Rule of Law	135	.000	86.057690	33.853	21.142
	Regulatory Quality	135	.000	83.654	33.123	20.247
	Foreign direct investment, net inflows (% of GDP)	132	-11.625	32.765	3.471	4.863
Outputs	Real GDP Growth	129	-59.7	43.5	-4.176	8.9093
	Competitiveness	87	35.0846	79.619	53.680	9.003

2- OLS multiple regression

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.340[a]	.116	.062	8.7463
Predictors: (Constant), Foreign direct investment, net inflows (% of GDP), Transparency (in Percentile Rank), Trade openness (Exports + imports)/GDP Trade as % of GDP 2019, Ease of doing a business, Regulatory Quality (in Percentile Rank), Rule of Law (in Percentile Rank), Government Effectiveness (in Percentile Rank) Dependent Variable: Real GDP Growth				

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.902[a]	.814	.797	3.792680624219437
Predictors: (Constant), Foreign direct investment, net inflows (% of GDP), Transparency (in Percentile Rank), Trade openness (Exports + imports)/GDP Trade as % of GDP 2019, Ease of doing a business, Regulatory Quality (in Percentile Rank), Rule of Law (in Percentile Rank), Government Effectiveness (in Percentile Rank) Dependent Variable: Competitiveness				

3- Estimating the standardized beta coefficient

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-16.660	5.075		-3.283	.001
	Trade openness (Exports + imports)/GDP Trade as % of GDP 2019	-.035	.023	-.153	-1.555	.123
	Ease of doing a business	.325	.115	.462	2.829	.006
	Transparency (in Percentile Rank)	.089	.074	.211	1.198	.233
	Government Effectiveness (in Percentile Rank)	-.060	.090	-.135	-.662	.510
	Rule of Law (in Percentile Rank)	-.013	.090	-.028	-.143	.886
	Regulatory Quality (in Percentile Rank)	-.192	.088	-.416	-2.190	.031
	Foreign direct investment, net inflows (% of GDP)	.546	.182	.296	2.996	.003
a. Dependent Variable: Real GDP Growth						

4- Determining the variables structure for the knowledge acquisition dimension

As explained in the methodology section, we select the dependent variable that yields the highest adjusted R square (.797) and the greatest reduction of the residual sum of squares. So, comparing adjusted R2 of these two models, we decided to use selected factors with the highest significance level (Mutanov et al., 2020). Thus, in this case we shall choose Competitiveness. Nonetheless, in terms of data availability, which is taken as a complementary criterion in this study to include as many as possible of developing countries in our sample, thus, we will select Real GDP growth as the output variable for Knowledge acquisition.

In terms of inputs, a proxy for the business environment and economic openness is required. Thus, ease of doing business is selected with a standardized beta coefficient of (.462). For economic openness, so we must choose the most appropriate variable that can be used as a proxy for economic openness. Thus, we must choose between FDI net inflows and trade openness. In our sample, FDI net inflows achieve both criteria that is it has the highest data availability compared with trade openness (132 compared with 129) and the higher standardized beta coefficient compared trade openness as we neglect the sign and focus on the value (coefficient: .296 compared with - .135).

2- Methodology for choosing variables for Knowledge production dimension.

1- Descriptive statistics to the inputs and outputs

Descriptive Statistics						
		N	Minimum	Maximum	Mean	Std. Deviation
Inputs	R &D expenditure as % GDP	90	.0108	2.141	.371	.3390
	Researchers in R&D (per million people)	80	10.565	2784.332	449.924	615.540
	Intellectual Property Rights (IPR)	86	1.868	5.390	3.737	.648
Outputs	Scientific and technical publications per 1000 pop	134	.62	528263.25	8297.0954	47866.082
	Trademarks application, total	111	14	2104414	39356.85	204045.756
	Patents Granted per million people	87	.000	461.151	6.041	49.395

2- OLS multiple regression

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.767[a]	.588	.568	1.375178764949
Predictors: (Constant), Intellectual Property Rights (IPR), Researchers in R&D (per million people), R &D expenditure as % GDP Dependent Variable: Patents Granted per million people				

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.723[a]	.523	.499	188248.995
Predictors: (Constant), Intellectual Property Rights (IPR), Researchers in R&D (per million people), R &D expenditure as % GDP Dependent Variable: Trademarks application, total				

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.724[a]	.524	.502	47288.00132
Predictors: (Constant), Intellectual Property Rights (IPR), Researchers in R&D (per million people), R &D expenditure as % GDP Dependent Variable: Scientific and technical publications per 1000 pop				

3- Estimating the standardized beta coefficient

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.523	1.054		-1.444	.154
	R & D expenditure as % GDP	3.951	.649	.686	6.089	<.001
	Researchers in R&D (per million people)	.000	.000	.093	.871	.387
	Intellectual Property Rights (IPR)	.145	.293	.043	.493	.624
a. Dependent Variable: Patents Granted per million people						

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-6424.397	36254.448		-.177	.860
	R&D expenditure as % GDP	168930.286	22186.779	.916	7.614	<.001
	Researchers in R&D (per million people)	-32.981	11.719	-.321	-2.814	.007
	Intellectual Property Rights (IPR)	-8555.258	10078.403	-.080	-.849	.399
a. Dependent Variable: Scientific and technical publications per 1000 pop						

4- Determining the variables structure of the knowledge production dimension

Given the observed results of the OLS multiple regressions analysis, we sorted patent followed by the scientific and technical publications as the output variables for the DEA model as they have the highest adjusted R Square compared with other dependent variables. We added two outputs here compared to all other knowledge dimensions in the study because sometimes the scientific and technical publications are criticism by many authors as explained in the main text.

R&D expenditure is taken as the first input variable as it has the highest standardized beta coefficient in both models. Concerning the second input, we should discriminate between intellectual property rights and number of R&D.

we opt for on intellectual property rights for two reasons; data availability criteria on one hand and need for including all factors that are highly important for knowledge production on the other hand. That is why we included R&D expenditure as a proxy for human capital and we need a different proxy for institutions and rules governing knowledge production. That is why intellectual property rights as a proxy is used as the second proxy.

3- Methodology for choosing variables for knowledge distribution dimension.

1. Descriptive statistics to the inputs and outputs

Descriptive Statistics						
Inputs		N	Minimum	Maximum	Mean	Std. Deviation
	Education expenditure as % GDP	130	1.300	14.700000	4.412	2.313
	ICT Price Basket	113	2.590	1101.5300	45.722	109.569
	ICT Access 2017	117	1.38	7.87	4.434	1.594
	Net enrollment ratio at secondary school	124	.000	99.83989	58.289	25.093
Outputs	ICT use	117	.04	6.54	2.914	1.739
	percentage of households with a computer	131	1.0	83.8	28.757	22.115
	School enrolment, tertiary (% gross)	130	.7498	115.042	28.410	24.759
	Government Online Service Index	127	.0000	.9235	.475	.221
Source: Author’s calculations using SPSS software						

2. OLS multiple regression

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.925[a]	.856	.850	.65443
Predictors: (Constant), ICT Access 2017, Education expenditure as % GDP, ICT Price Basket, Net enrollment ratio at secondary school Dependent Variable: ICT use				

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.599[a]	.358	.329	.1729673
Predictors: (Constant), ICT Access 2017, Education expenditure as % GDP, ICT Price Basket, Net enrollment ratio at secondary school Dependent Variable: Government Online Service Index				

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.883[a]	.780	.771	10.836
Predictors: (Constant), ICT Access 2017, Education expenditure as % GDP, ICT Price Basket, Net enrollment ratio at secondary school Dependent Variable: percentage of households with a computer				

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.777[a]	.603	.586	16.405
Predictors: (Constant), ICT Access 2017, Education expenditure as % GDP, ICT Price Basket, Net enrollment ratio at secondary school Dependent Variable: School enrolment, tertiary (% gross)				

3. Estimating the standardized beta coefficient

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-30.862	4.724		-6.533	<.001
	Education expenditure as % GDP	-.050	.598	-.004	-.083	.934
	Net enrollment ratio at secondary school	.075	.072	.076	1.052	.296
	ICT Price Basket	.004	.010	.020	.369	.713
	ICT Access 2017	12.396	1.074	.834	11.544	<.001
a. Dependent Variable: percentage of households with a computer						

4. Determining the variables structure of the knowledge distribution dimension

As observed, from the OLS multiple regressions analysis. Certainly, the dependent variable in the regression model with the highest adjusted R Square is ICT use followed by percentage of households with a computer. Given data availability, we accept percentage of households with a computer as the output variable for knowledge distribution dimension.

In terms of inputs, we need to select a proxy for ICT and another proxy for education as they are the main channels for distributing knowledge. Therefore, we take ICT access and education expenditures as the inputs for knowledge distribution dimension.

4-Methodology for choosing variables for Knowledge utilization dimension

1- Descriptive statistics to the inputs and outputs

Descriptive Statistics						
		N	Minimum	Maximum	Mean	Std. Deviation
Inputs	Knowledge transfer rate (university to industry)	129	.00	68.50	29.856	14.298
	FDI net outflows % GDP	131	-38.10	14.66	.402	3.917
	High-Tech Imports, % of Total Trade	102	.0	27.7	8.106	5.178

Descriptive Statistics						
		N	**Minimum**	**Maximum**	**Mean**	**Std. Deviation**
	Intellectual property payments (BoP, current US$)	121	.0	37781733949.9	638146688.8	3574135544.7
Outputs	High-tech Exports % of manufactured exports	109	96	62.247	7.321	10.252
	Medium and high-tech manufacturing value added (% manufacturing value added)	112	0	47	16.90	11.934
Source: Author’s calculations using SPSS software						

2- OLS multiple regression

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.547[a]	.299	.260	10.252
Predictors: (Constant), Intellectual property payments (BoP, current US$), FDI net outflows % GDP, Knowledge transfer rate (university to industry), High-Tech Imports, % of Total Trade Dependent Variable: Medium and high-tech manufacturing value added (% manufacturing value added)				

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.727[a]	.528	.506	7.026726448761938
Predictors: (Constant), Knowledge transfer rate (university to industry), FDI net outflows % GDP, Intellectual property payments (BoP, current US$), High-Tech Imports, % of Total Trade Dependent Variable: High-tech Exports % of manufactured exports				
Source: Author’s calculations using SPSS software				

3- Estimating the standardized beta coefficient

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-6.412	2.064		-3.107	.003
	High-Tech Imports, % of Total Trade	1.392	.175	.675	7.949	<.001
	Intellectual property payments (BoP, current US$)	4.022E-11	.000	.017	.201	.841
	FDI net outflows % GDP	.208	.409	.038	.507	.614
	Knowledge transfer rate (university to	.071	.056	.102	1.271	.207

	industry)					
a. Dependent Variable: High-tech Exports % of manufactured exports						
Source: Author's calculations using SPSS software						

4- Determining the variables structure of the knowledge utilization dimension

As indicated above, we have run OLS multiple regressions analysis and opt for the model with the highest adjusted R Square. Therefore, the output variable for knowledge utilization dimension is high-tech exports as percentage of manufactured exports.

Concerning the input variables, high-tech imports% of total trade has the highest standardized beta coefficient but the lowest data availability so we excluded it from the analysis as we need to include as many as possible of developing countries.

The second highest variable in terms of standardized beta coefficient is knowledge transfer followed by the third highest FDI outflows. Thus, Knowledge transfer and FDI outflows are chosen as the inputs for knowledge utilization dimension as they have both the second and third largest standardized beta coefficients as well as the highest data availability.

Appendix (XII): Selected KBE Pillars and Their Respective Proxies

	Input Variables for Each Knowledge Dimension		
	Variable	**Definition (According to the data source)**	**Source of the data**
Knowledge Acquisition	**Foreign direct investment, net inflows (% of GDP)**	It is defined as the total sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. The Foreign direct investment, net inflows (% of GDP) series shows the net inflows (new investment inflows less disinvestment) in the reporting economy from foreign investors and is divided by country's GDP. These net inflows of investment are to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor.	World Bank – World Development Indicators, available at: https://databank.worldbank.org/source/world-development-indicators
	Easy of doing a business	The ease of doing business scores is an indicator that benchmarks countries with respect to regulatory best practice, i.e., by showing the proximity to the analysed country to the best regulatory performance on each Doing Business indicator. An economy's score is identified on a scale started from 0= lowest (worst) regulatory performance to 100= best performance). It is worth mentioning that Doing Business report has been discontinued as of 9/16/2021. Further details are available in: https://bit.ly/3CLCbme	World Bank, Doing Business project (http://www.doingbusiness.org/)
Knowledge Production	**R &D expenditure as % GDP**	Gross domestic expenditures on research and development (R&D), expressed as a percent of GDP includes both capital and current expenditures in the four main sectors. These four sectors are: Business enterprise, Government, Higher education and Private non-profit. R&D covers basic research, applied research, and experimental development.	World Bank – World Development Indicators, available at: https://databank.worldbank.org/source/world-development-indicators
	Intellectual Property Rights (IPR)	This indicator is a response to a survey question which is "In your country, to what extent is intellectual property protected?" [1 = not at all; 7 = to a great extent]	World Economic Forum, Executive Opinion Survey, 2019
Knowledge Distribution	**Education expenditure as % GDP**	General government expenditure on education (current, capital, and transfers) is calculated as a percentage of total general government expenditure on all sectors (including health, education, social services, etc.).	World Bank – World Development Indicators, available at: https://databank.worldbank.org/source/world-development-

	Input Variables for Each Knowledge Dimension		
	Variable	**Definition (According to the data source)**	**Source of the data**
		It includes expenditure funded by transfers from international sources to government. General government usually refers to local, regional, and central governments.	indicators
	ICT Access	It is an index to reflecting the level of use of ICTs in the society. This index is a sub-index of the ICT Development Index (IDI), which has been published annually since 2009, is a composite index that until 2017 combined 11 indicators into one benchmark measure. It is used to monitor and compare developments in information and communication technology (ICT) between countries and over time.	International Telecommunication Union (ITU), Measuring the information society report, 2018, available at: https://www.itu.int/en/ITUD/Statistics/Pages/publications/mis r2018.aspx
Knowledge Utilization	**Knowledge transfer rate**	It is an index used to reflect the transfer rate from university to industry i.e., the research collaboration. It is a score from Max=100 strength to 0 =Weakest.	Global Innovation Index report,2020, https://www.wipo.int/edocs/pubdocs/en/wipo_pub_gii_2020.pdf
	FDI net outflows % GDP	Foreign direct investment means direct investment equity flows in an economy. It is equal to the sum of equity capital, reinvestment of earnings, and other capital. Direct investment is a category of cross-border investment associated with a resident in one economy having control or a significant degree of influence on the management of an enterprise that is resident in another economy. Ownership of 10 percent or more of the ordinary shares of voting stock is the criterion for determining the existence of a direct investment relationship. This series shows net outflows of investment from the reporting economy to the rest of the world and is divided by GDP.	World Bank – World Development Indicators, available at: https://databank.worldbank.org/source/world-development-indicators

	Output Variables for Each Knowledge Dimension		
Knowledge dimension	Variable	Definition (according to the data source)	Source of the data
Knowledge Acquisition	**Real GDP Growth**	It is the most used measure of a country's overall economic activity. It shows the total value at constant prices of final goods and services produced within a country during a specific time (e.g.one year).	IMF, World Economic Outlook (October 2021), Latest available date 2020, available at: https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG
Knowledge Production	**Scientific and technical journal articles**	Scientific and technical journal articles refer to the number of scientific and engineering articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences.	World Bank – World Development Indicators, available at: https://databank.worldbank.org/source/world-development-indicators

Knowledge dimension	Output Variables for Each Knowledge Dimension		
	Variable	Definition (according to the data source)	Source of the data
	Patent applications per million pop.	Total number of patent families per million populations filed in at least two of the major 5 (IP5) offices in the World: The European Patent Office (EPO), the Japan Patent Office (JPO), the Korean Intellectual Property Office (KIPO), the State Intellectual Property Office of the People's Republic of China (SIPO), and the United States Patent and Trademark Office (USPTO).	World Economic Forum Global Competitiveness Index; available at: https://govdata360.worldbank.org/indicators/h5d4e7989?country=BRA&indicator=41467&viz=line_chart&years=2017,2019
Knowledge Distribution	**Percentage of households with a computer**	Is an indication of computers penetration i.e., the Percentage of households equipped with a personal computer	International Telecommunication Union (ITU), Measuring the Information Society Report, 2018.
Knowledge Utilization	**High-tech Exports % of manufactured exports**	High-technology exports are products with high R&D intensity, such as in aerospace, computers, pharmaceuticals, scientific instruments, and electrical machinery.	World Bank – World Development Indicators, available at: https://databank.worldbank.org/source/world-development-indicators

APPENDIX (XIII): Robustness Test for KAM 2012

1-1 Data Collection

- The objective here is to re-calculate the KEI for all countries in 2012 using the same data sources and methodological considerations to compare the published and observed KAM results.
- For this current version of the KAM, KAM 2012, countries are included in the KAM database only if, the 12 variables of the basic scorecard are available. If at most one variable from each of the four KE pillars is not available, then this country is not included in KAM 2012.
- As an example, if Country X does not have data for the secondary and tertiary gross enrollment rates, thus in this case the education pillar index cannot be computed because it is the simple average of three variables of which secondary and tertiary gross enrollment rates. Subsequently, the KI and KEI cannot be calculated as well because the education index is part of these calculations. So, finally, so, a pillar index is not calculated if more than one variable from the pillar is missing and country X is excluded from the KAM database.

1-2 Variables Description, Definition, AND Sources of Data in KAM 2012

Indicators	Year	Source of Data	Definition
The Institutional Pillar Index Is calculated as the average of the normalised values of 1-1, 1-2, and 1-3			
1-1Tariff & Nontariff Barriers	2011	Heritage Foundation	This score is given to each country based on an analysis of its tariff and non-tariff barriers to trade. Import bans and quotas; strict labelling and licensing requirements are among these barriers. The Trade Freedom score as proxied by tariff and non-tariff barriers is based on the Heritage Foundation's Trade Freedom score, and it ranged from (0 -100). 0 means restrictive barriers (Repressed) and 100 means free barriers. Available at: https://www.heritage.org/index/explore
1-2 Regulatory Quality	2009	Governance Indicators, World Bank	This indicator evaluates the existence of market-unfriendly policies. Price controls; Inadequate bank supervision; Perceptions of the burdens imposed by excessive regulation in areas such as foreign trade and business development are among these policies. Countries are ranked in a score from 0 the lowest to 100 the highest. The higher the score, the best is the regulatory quality situation in a country. Available at: https://info.worldbank.org/governance/wgi/
1-3 Rule of law	2009	Governance Indicators, World Bank	This indicator includes several indicators which measure the extent to which agents have confidence in and adhere to society's rules as well as the extent

Indicators	Year	Source of Data	Definition
			of crime and violence in a country. These include perceptions of the incidence of both violent and non-violent crime, the effectiveness and predictability of the judiciary as well as the quality of contract enforcement. Countries are ranked in a score from 0 the lowest to 100 the highest. The highest score indicates the best situation in a particular country. Available at: https://info.worldbank.org/governance/wgi/
The Education Pillar Index **Is calculated as the average of the normalised values of 2-1,2-2 and 2-3**			
2-1 Average years of schooling (Age 15 years old and above)	2010	Barro-Lee Educational Attainment Dataset	This variable is used as an aggregate measure of educational stock in a particular country. Available at: https://databank.worldbank.org/source/education-statistics-%5E-all-indicators#
2-2 Gross secondary enrollment rate (%)	2009	World Bank Data Bank. Original source: UNESCO Institute for Statistics	This variable is defined as the ratio of total enrollment, regardless of their age, to the population of the age group that is eligibly officially at the secondary level of education (school-age population) Available at: https://databank.worldbank.org/source/world-development-indicators
2-3 Gross Tertiary enrollment rate School enrollment, tertiary (% gross)	2009	World Bank Data Bank. Original source: UNESCO Institute for Statistics	This variable is defined as the ratio of total enrollment, regardless of their age, to the population of the age group that is eligibly officially at the tertiary level of education (school-age population) Available at: https://databank.worldbank.org/source/world-development-indicators
The Innovation Pillar index **Is calculated as the average of the normalised values of 3-1,3-2 and 3-3**			
3-1 Royalty and License Fees Payments and Receipts (US$ millions)	2009	World Bank Data Bank. Original source: International Monetary Fund, Balance of Payments Statistics Yearbook, and data files.	This variable is calculated as the sum of Royalty and License Fees Payments (US$ mil.) which is also called charges for the use of intellectual property payments and the Royalty and License Fees Receipts (US$ mil.) which are also called charges for the use of intellectual property receipts. Available at: https://databank.worldbank.org/source/world-development-indicators
3-2 Scientific and technical journal articles	2007	World Bank Data Bank. Original source: Thomson Reuters, SCI and SSCI; The Patent Board; and National Science Foundation, Division of Science Resources Statistics,	Scientific and technical journal articles refer to the number of scientific and engineering articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences. Available at: https://databank.worldbank.org/source/world-development-indicators

Indicators	Year	Source of Data	Definition
		special tabulations.	
3-3 Patent Applications Granted by the USPTO	Average 2005-2009	World Bank	This variable presents the number of worldwide patent applications filed through the Patent Cooperation Treaty procedure or with a national patent office. A patent is generally defined as an exclusive right granted for a specified period (generally 20 years) for a new way of doing something or a new technical solution to a problem - an invention. The invention must be of practical use and display a characteristic unknown in the existing body of knowledge in its field. Most countries have systems to protect patentable inventions. Available at: https://knoema.com/WBWDI2019Jan/world-development-indicators-wdi
The ICT Pillar Index Is calculated as the average of the normalized values of 4-1,4-2 and 4-3			
4-1Telephones Per 1000 people	2009	World Bank Data Bank. Original source: International Telecommunication Union (ITU); World Telecommunication/ ICT Indicators Database	This variable consists of the sum of telephone mainlines and mobile phones. Telephone mainlines are telephone lines connecting a customer's equipment to the public switched telephone network. And Mobile telephone subscribers are subscribers to a public mobile telephone service using cellular technology. The available indicators are per 100 people, so it is multiplied by 10 to be per 1000 people. Available at: http://knoema.com/ITUKIICT2019Apr/global-ict-developments
4-2 Internet users per 1000 people	2009	World Bank Data Bank. Original source: International Telecommunication Union (ITU); World Telecommunication/ ICT Indicators Database	This indicator refers to the reported Internet Service Provider subscriber counts. Generally, this indicator is obtained from nationally reported data, but in some cases, it is based on national surveys. Available at : https://knoema.com/WBMDG2017/millennium-development-goals-discontinued
4-3 Computer per 100 people	2008	World Bank Data Bank. Original source: International Telecommunication Union (ITU); World Telecommunication/ ICT Indicators Database	This indicator refers to personal computers which are self-contained computers designed to be used by a single individual. Available at : https://knoema.com/WBEDS2017Jun/education-statistics

1-3 Countries Included in KAM 2012

Regions	Countries included in KAM 2012	Number of Countries included in every region
North America	Canada; United States.	**2**
Europe and Central Asia	Albania; Armenia; Austria; Azerbaijan; Belarus; Belgium; Bosnia & Herzegovina; Bulgaria; Croatia; Cyprus; Czech Republic; Demark; Estonia; Finland; France; Germany; Greece; Georgia; Hungary; Iceland; Ireland; Italy; Kazakhstan; Kyrgyz Republic; Latvia; Lithuania; Luxemburg; Macedonia, FYR; Moldova; Netherlands; Norway; Poland; Portugal; Romania; Russian Federation; Serbia; Slovak Republic; Slovenia; Spain; Sweden; Switzerland; Tajikistan; Turkey; Ukraine; United Kingdom; Uzbekistan.	**46**
East Asia and the Pacific	Australia; Cambodia; China; Fiji; Hong Kong, China; Indonesia; Japan; Korea, Rep.; Lao PDR; Malaysia; Mongolia; Myanmar; New Zealand; Philippines; Singapore; Taiwan, China; Thailand; Vietnam.	**18**
South Asia	Bangladesh; India; Nepal; Pakistan; Sri Lanka.	**5**
Latin America and the Caribbean	Argentina; Aruba; Barbados; Bolivia; Brazil; Chile; Colombia; Costa Rica; Cuba; Dominica; Dominican Republic; Ecuador; El Salvador; Guatemala; Guyana; Haiti; Honduras; Jamaica; Mexico; Nicaragua; Panama; Paraguay; Peru Trinidad and Tobago; Uruguay; Venezuela, RB.	**26**
The Middle East and North Africa	Algeria; Bahrain; Djibouti; Egypt, Arab Rep.; Iran, Islamic Rep.; Israel; Jordan; Kuwait; Lebanon; Malta; Morocco; Oman; Qatar; Saudi Arabia; The Syrian Arab Republic; Tunisia; United Arab Emirates; Yemen, Rep.	**18**
Sub-Saharan Africa	Angola; Benin; Botswana; Burkina Faso; Cameroon; Cape Verde; Cote d'Ivoire; Eritrea; Ethiopia; Ghana; Guinea; Kenya; Lesotho; Madagascar; Malawi; Mali; Mauritania; Mauritius; Mozambique, Namibia; Nigeria; Rwanda; Senegal; Sierra Leone; South Africa, Sudan; Swaziland; Tanzania; Uganda; Zambia; Zimbabwe.	**31**

1-4 Calculating the sub-indices for each of the four KBE pillars

1-4-1 The Institutional Sub-Index

1-The economic incentives and institutional regime Pillar							
Countries in KAM 2012	1-1 Tariff & Nontariff Barriers 2011		1-2 Regulatory Quality 2009		1-3 Rule of law 2009		The Institutional sub-index
	Actual	Normalised	Actual	Normalised	Actual	Normalised	
Albania	79.80	4.90	0.24	5.45	-0.50	3.79	4.71
Algeria	72.80	3.01	-1.07	0.90	-0.79	2.28	2.06
Angola	70.20	2.38	-1.03	0.97	-1.23	0.83	1.39
Argentina	69.50	1.96	-0.85	1.52	-0.68	2.97	2.15
Armenia	85.50	7.06	0.30	5.86	-0.48	4.00	5.64
Aruba	n/a	n/a	1.29	8.34	1.43	8.55	8.45
Australia	84.40	6.57	1.82	9.79	1.74	9.17	8.51
Austria	87.60	9.23	1.45	8.83	1.78	9.38	9.15
Azerbaijan	77.10	4.27	-0.31	3.52	-0.88	1.79	3.19
Bahrain	82.80	6.22	0.69	7.10	0.52	6.55	6.63
Bangladesh	58.00	0.28	-0.86	1.4	-0.79	2.21	1.31
Barbados	60.50	0.56	0.59	6.83	1.01	7.93	5.11
Belarus	80.30	5.03	-1.12	0.69	-1.03	1.31	2.34
Belgium	87.60	9.16	1.31	8.48	1.38	8.48	8.71
Benin	58.80	0.35	-0.35	3.10	-0.65	3.10	2.19
Bolivia	77.60	4.41	-0.88	1.38	-1.11	1.10	2.30
Bosnia & Herzegovina	86.00	7.20	-0.09	4.55	-0.36	4.62	5.46
Botswana	75.20	3.78	0.49	6.41	0.67	7.10	5.76
Brazil	69.80	2.17	0.10	4.97	-0.16	5.24	4.12
Bulgaria	87.60	9.09	0.67	6.97	-0.04	5.66	7.24
Burkina Faso	76.20	4.13	-0.11	4.48	-0.21	5.03	4.55
Cambodia	70.00	2.31	-0.49	2.55	-1.12	1.03	1.96
Cameroon	59.60	0.49	-0.76	1.66	-1.12	0.97	1.04
Canada	88.10	9.51	1.70	9.52	1.80	9.45	9.49
Cape Verde	67.60	1.54	0.04	4.83	0.54	6.69	4.35
Chile	88.00	9.44	1.46	8.90	1.30	8.41	8.92
China	71.60	2.66	-0.22	3.86	-0.41	4.34	3.62
Colombia	73.20	3.29	0.15	5.17	-0.39	4.41	4.29
Costa Rica	85.20	6.92	0.42	6.28	0.56	6.83	6.68
Cote d'Ivoire	72.20	2.87	-0.97	1.03	-1.23	0.76	1.55
Croatia	87.60	9.02	0.56	6.69	0.16	6.14	7.28
Cuba	62.20	0.84	-1.60	0.28	-0.71	2.76	1.29
Cyprus	82.60	6.15	1.36	8.55	1.21	8.28	7.66
Czech Republic	87.60	8.95	1.31	8.41	0.96	7.79	8.39
Denmark	87.60	8.88	1.88	9.93	1.92	9.72	9.51

1-The economic incentives and institutional regime Pillar							
Djibouti	59.60	0.42	-0.61	2.21	-0.68	2.90	1.84
Dominica	74.30	3.50	0.59	6.76	0.71	7.17	5.81
Dominican Republic	79.80	4.83	-0.19	4.00	-0.77	2.48	3.77
Ecuador	76.00	4.06	-1.30	0.48	-1.25	0.62	1.72
Egypt, Arab Rep.	74.00	3.43	-0.20	3.93	-0.11	5.45	4.27
El Salvador	85.00	6.78	0.32	5.93	-0.75	2.62	5.11
Eritrea	69.10	1.89	-2.24	0.07	-1.31	0.48	0.81
Estonia	87.60	8.81	1.40	8.76	1.13	8.14	8.57
Ethiopia	65.60	1.33	-0.93	1.31	-0.83	2.00	1.55
Fiji	69.80	2.10	-0.96	1.17	-0.77	2.41	1.89
Finland	87.60	8.74	1.81	9.66	1.97	9.93	9.44
France	82.60	6.08	1.22	8.28	1.45	8.62	7.66
Georgia	89.20	9.65	0.50	6.48	-0.20	5.10	7.08
Germany	87.60	8.67	1.52	9.03	1.66	8.97	8.89
Ghana	67.80	1.61	0.08	4.90	-0.04	5.59	4.03
Greece	82.60	6.01	0.84	7.24	0.65	7.03	6.76
Guatemala	84.60	6.64	-0.15	4.21	-1.02	1.38	4.08
Guinea	61.20	0.70	-1.14	0.62	-1.54	0.14	0.49
Guyana	71.30	2.59	-0.61	2.14	-0.56	3.59	2.77
Haiti	74.80	3.64	-0.93	1.24	-1.32	0.41	1.76
Honduras	77.00	4.20	-0.30	3.72	-0.90	1.66	3.19
Hong Kong, China	90.00	9.93	1.82	9.72	1.50	8.76	9.47
Hungary	87.60	8.60	1.08	8.00	0.80	7.38	7.99
Iceland	88.20	9.58	1.02	7.79	1.71	9.03	8.80
India	64.20	1.12	-0.33	3.31	0.01	5.72	3.38
Indonesia	73.80	3.36	-0.36	3.03	-0.60	3.24	3.21
Iran, Islamic Rep.	44.80	0.07	-1.72	0.21	-0.97	1.52	0.60
Ireland	87.60	8.53	1.70	9.45	1.75	9.31	9.10
Israel	87.80	9.30	1.10	8.14	0.84	7.52	8.32
Italy	87.60	8.46	0.97	7.59	0.40	6.41	7.49
Jamaica	72.20	2.80	0.27	5.59	-0.43	4.14	4.17
Japan	82.60	5.94	1.10	8.07	1.29	8.34	7.45
Jordan	78.80	4.69	0.27	5.52	0.25	6.28	5.49
Kazakhstan	80.90	5.17	-0.32	3.45	-0.65	3.03	3.89
Kenya	72.80	2.94	-0.15	4.14	-1.01	1.45	2.84
Korea, Rep.	70.80	2.45	0.84	7.17	0.99	7.86	5.83
Kuwait	81.60	5.45	0.15	5.10	0.59	6.90	5.82
Kyrgyz Republic	63.20	0.98	-0.33	3.24	-1.33	0.28	1.50
Lao PDR	68.40	1.75	-1.07	0.83	-1.05	1.24	1.27
Latvia	87.60	8.39	0.99	7.72	0.81	7.45	7.85
Lebanon	80.50	5.10	-0.05	4.69	-0.68	2.83	4.21
Lesotho	63.60	1.05	-0.62	2.07	-0.21	4.97	2.69
Lithuania	87.60	8.32	0.95	7.52	0.73	7.31	7.72

1-The economic incentives and institutional regime Pillar							
Luxemburg	87.60	8.25	1.65	9.31	1.83	9.59	9.05
Macedonia, FYR	83.60	6.50	0.29	5.72	-0.26	4.76	5.66
Madagascar	73.20	3.22	-0.52	2.48	-0.73	2.69	2.80
Malawi	71.00	2.52	-0.45	2.62	-0.11	5.38	3.51
Malaysia	78.70	4.62	0.30	5.79	0.46	6.48	5.63
Mali	73.20	3.15	-0.41	2.90	-0.37	4.55	3.53
Malta	87.60	8.18	1.37	8.62	1.48	8.69	8.50
Mauritania	69.90	2.24	-0.68	1.86	-0.80	2.07	2.06
Mauritius	88.00	9.37	0.86	7.31	0.94	7.72	8.14
Mexico	81.20	5.31	0.22	5.38	-0.56	3.52	4.74
Moldova	80.20	4.97	-0.13	4.34	-0.44	4.07	4.46
Mongolia	79.80	4.76	-0.30	3.66	-0.26	4.69	4.37
Morocco	75.80	3.92	-0.06	4.62	-0.21	4.90	4.48
Mozambique	81.00	5.24	-0.39	2.97	-0.59	3.31	3.84
Myanmar	n/a	n/a	-2.24	0.00	-1.53	0.21	0.10
Namibia	86.40	7.41	0.11	5.03	0.19	6.21	6.22
Nepal	61.40	0.77	-0.71	1.79	-0.86	1.86	1.47
Netherlands	87.60	8.11	1.70	9.38	1.81	9.52	9.00
New Zealand	86.60	7.48	1.83	9.86	1.93	9.79	9.05
Nicaragua	84.80	6.71	-0.43	2.83	-0.79	2.14	3.89
Nigeria	65.00	1.19	-0.75	1.72	-1.15	0.90	1.27
Norway	89.40	9.72	1.47	8.97	1.88	9.66	9.45
Oman	83.60	6.43	0.53	6.55	0.56	6.76	6.58
Pakistan	67.00	1.47	-0.58	2.28	-0.83	1.93	1.89
Panama	75.80	3.85	0.37	6.00	-0.09	5.52	5.12
Paraguay	83.00	6.36	-0.44	2.76	-0.88	1.72	3.62
Peru	86.00	7.13	0.39	6.14	-0.61	3.17	5.48
Philippines	77.80	4.55	-0.11	4.41	-0.57	3.45	4.14
Poland	87.60	8.04	0.95	7.45	0.63	6.97	7.49
Portugal	87.60	7.97	0.99	7.66	1.06	8.00	7.88
Qatar	82.40	5.73	0.68	7.03	0.91	7.59	6.78
Romania	87.60	7.90	0.60	6.90	0.05	5.86	6.89
Russian Federation	68.20	1.68	-0.34	3.17	-0.78	2.34	2.40
Rwanda	77.80	4.48	-0.32	3.38	-0.50	3.72	3.86
Saudi Arabia	82.20	5.59	0.16	5.24	0.05	5.79	5.54
Senegal	73.20	3.08	-0.30	3.59	-0.37	4.48	3.72
Serbia	75.20	3.71	-0.13	4.28	-0.41	4.28	4.09
Sierra Leone	62.80	0.91	-0.79	1.59	-0.90	1.59	1.36
Singapore	90.00	9.86	1.78	9.59	1.57	8.83	9.42
Slovak Republic	87.60	7.83	1.05	7.93	0.54	6.62	7.46
Slovenia	87.60	7.76	0.92	7.38	1.08	8.07	7.74
South Africa	77.20	4.34	0.41	6.21	0.12	6.00	5.51
Spain	87.60	7.69	1.19	8.21	1.16	8.21	8.04

1-The economic incentives and institutional regime Pillar							
Sri Lanka	72.20	2.73	-0.28	3.79	-0.11	5.31	3.94
Sudan	37.00	0.00	-1.26	0.55	-1.24	0.69	0.62
Swaziland	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Sweden	87.60	7.62	1.65	9.24	1.97	9.86	8.91
Switzerland	90.00	9.79	1.55	9.10	1.75	9.24	9.38
Syrian Arab Republic	65.40	1.26	-0.96	1.10	-0.57	3.38	1.91
Taiwan, China	86.20	7.27	1.04	7.86	0.94	7.66	7.60
Tajikistan	82.50	5.80	-1.07	0.76	-1.27	0.55	2.37
Tanzania	69.60	2.03	-0.44	2.69	-0.48	3.93	2.88
Thailand	75.90	3.99	0.22	5.31	-0.23	4.83	4.71
Trinidad and Tobago	81.70	5.52	0.56	6.62	-0.18	5.17	5.77
Tunisia	53.50	0.21	0.00	4.76	0.13	6.07	3.68
Turkey	85.40	6.99	0.28	5.66	0.10	5.93	6.19
Uganda	74.80	3.57	-0.18	4.07	-0.41	4.21	3.95
Ukraine	85.20	6.85	-0.57	2.34	-0.76	2.55	3.92
United Arab Emirates	82.60	5.87	0.44	6.34	0.40	6.34	6.19
United Kingdom	87.60	7.55	1.58	9.17	1.74	9.10	8.61
United States	86.40	7.34	1.40	8.69	1.60	8.90	8.31
Uruguay	83.00	6.29	0.38	6.07	0.72	7.24	6.53
Uzbekistan	66.20	1.40	-1.47	0.41	-1.32	0.34	0.72
Venezuela, RB	61.20	0.63	-1.59	0.34	-1.62	0.07	0.35
Vietnam	68.90	1.82	-0.62	2.00	-0.54	3.66	2.49
Yemen, Rep.	81.60	5.38	-0.65	1.93	-1.09	1.17	2.83
Zambia	82.40	5.66	-0.53	2.41	-0.48	3.86	3.98
Zimbabwe	45.00	0.14	-2.12	0.14	-1.85	0.00	0.09

1-4-2 The Education Sub-Index

2-The education pillar							
Countries in KAM 2012	**2-1Average Years of Schooling, 2010**		**2-2 Gross secondary enrollment rate 2009**		**2-3 Gross Tertiary enrollment rate 2009**		**The Education Index**
	Actual	**Normalised**	**Actual**	**Normalised**	**Actual**	**Normalised**	
Albania	9.93	5.98	85.69	4.57	33.39	5.00	5.18
Algeria	6.68	2.52	92.88	6.23	29.91	4.70	4.48
Angola	n/a	n/a	22.69	0.22	2.38	0.30	0.26
Argentina	9.51	5.35	96.62	7.25	70.21	8.43	7.01
Armenia	10.73	7.24	100.13	8.33	51.33	6.72	7.43
Aruba	n/a	n/a	74.00	3.26	35.36	5.30	4.28
Australia	11.54	8.58	152.94	9.86	80.91	9.33	9.26
Austria	9.60	5.59	99.65	8.04	68.11	8.28	7.31
Azerbaijan	n/a	n/a	73.85	3.19	19.06	3.36	3.27
Bahrain	7.06	2.83	91.98	5.94	22.79	3.73	4.17
Bangladesh	5.91	1.89	49.99	2.10	10.86	2.24	2.08
Barbados	9.45	5.28	103.23	8.91	75.70	9.18	7.79
Belarus	n/a	n/a	110.75	9.35	74.46	9.03	9.19
Belgium	10.69	7.09	156.64	9.93	65.27	8.06	8.36
Benin	4.43	0.71	28.89	0.65	10.23	1.94	1.10
Bolivia	8.25	4.17	83.46	4.06	n/a	n/a	4.12
Bosnia & Herzegovina	n/a	n/a	N/A	N/A	23.34	3.96	N/A
Botswana	9.55	5.43	79.92	3.55	23.68	4.10	4.36
Brazil	7.89	3.86	96.67	7.32	37.04	5.60	5.59
Bulgaria	11.24	7.95	88.74	5.29	54.24	7.01	6.75
Burkina Faso	n/a	n/a	20.29	0.07	3.53	0.52	0.30
Cambodia	4.72	1.02	45.22	1.67	11.77	2.54	1.74
Cameroon	6.15	2.05	40.48	1.45	9.05	1.57	1.69
Canada	12.32	9.53	102.73	8.62	63.07	7.84	8.66
Cape Verde	n/a	n/a	83.99	4.13	15.15	2.76	3.45
Chile	9.78	5.83	88.98	5.43	60.91	7.54	6.27
China	7.51	3.23	85.45	4.42	22.44	3.58	3.74
Colombia	8.95	4.96	95.27	6.74	37.52	5.67	5.79
Costa Rica	7.97	3.94	98.09	7.61	26.66	4.48	5.34
Cote d'Ivoire	4.65	0.94	24.06	0.36	8.36	1.42	0.91
Croatia	11.30	8.11	99.85	8.19	48.79	6.34	7.55
Cuba	10.16	6.22	92.78	6.16	114.10	9.93	7.44
Cyprus	11.07	7.80	98.39	7.75	52.00	6.87	7.47
Czech Republic	12.80	9.69	93.85	6.30	61.08	7.61	7.87
Denmark	11.30	8.03	117.98	9.64	74.28	8.88	8.85
Djibouti	n/a	n/a	34.99	1.16	3.54	0.60	0.88
Dominica	n/a	n/a	92.27	6.01	n/a	n/a	N/A
Dominican Republic	7.85	3.78	80.90	3.77	34.10	5.07	4.21

2-The education pillar							
Ecuador	7.60	3.46	88.64	5.22	38.78	5.90	4.86
Egypt, Arab Rep.	7.15	2.99	67.16	2.83	30.54	4.78	3.53
El Salvador	7.77	3.70	67.34	2.90	25.61	4.33	3.64
Eritrea	n/a	n/a	49.03	2.03	2.67	0.37	1.20
Estonia	12.11	9.29	102.74	8.70	66.63	8.21	8.73
Ethiopia	n/a	n/a	33.60	1.01	5.37	1.12	1.07
Fiji	9.96	6.06	86.66	4.78	16.14	2.99	4.61
Finland	11.62	8.82	107.48	9.28	91.29	9.78	9.29
France	10.68	7.01	106.24	9.13	52.77	6.94	7.69
Georgia	n/a	n/a	95.13	6.59	28.88	4.63	5.61
Germany	12.37	9.61	103.16	8.77	47.79	6.27	8.21
Ghana	7.00	2.68	48.80	1.96	8.80	1.49	2.04
Greece	10.30	6.46	98.20	7.68	87.40	9.55	7.90
Guatemala	4.57	0.87	47.51	1.81	17.32	3.13	1.94
Guinea	4.26	0.55	33.88	1.09	9.57	1.79	1.14
Guyana	8.79	4.65	87.09	5.00	10.99	2.31	3.99
Haiti	5.11	1.57	N/A	N/A	n/a	n/a	N/A
Honduras	6.19	2.20	60.02	2.54	17.71	3.28	2.67
Hong Kong, China	11.38	8.35	86.90	4.93	56.41	7.16	6.81
Hungary	11.85	8.98	96.25	7.17	64.61	7.99	8.05
Iceland	11.05	7.72	106.51	9.20	74.42	8.96	8.62
India	6.24	2.28	59.61	2.46	16.03	2.91	2.55
Indonesia	7.61	3.62	74.62	3.33	22.99	3.88	3.61
Iran, Islamic Rep.	8.88	4.88	82.16	3.91	37.91	5.75	4.85
Ireland	12.03	9.13	114.39	9.49	56.50	7.24	8.62
Israel	12.32	9.45	103.18	8.84	63.15	7.91	8.73
Italy	9.63	5.67	101.42	8.55	66.55	8.13	7.45
Jamaica	9.87	5.91	94.53	6.45	23.41	4.03	5.46
Japan	11.60	8.74	N/A	N/A	n/a	n/a	N/A
Jordan	9.59	5.51	85.90	4.64	41.74	6.04	5.40
Kazakhstan	11.33	8.27	99.95	8.26	58.19	7.39	7.97
Kenya	6.14	1.97	56.76	2.32	3.99	0.90	1.73
Korea, Rep.	12.05	9.21	95.98	7.03	104.28	9.85	8.70
Kuwait	6.34	2.36	97.72	7.54	19.21	3.43	4.44
Kyrgyz Republic	10.71	7.17	86.84	4.86	44.35	6.19	6.07
Lao PDR	5.02	1.42	45.44	1.74	16.39	3.06	2.07
Latvia	10.65	6.85	99.42	7.90	73.05	8.73	7.83
Lebanon	n/a	n/a	n/a	n/a	n/a	n/a	N/A
Lesotho	5.85	1.81	50.93	2.17	3.60	0.67	1.55
Lithuania	10.89	7.48	104.76	8.99	89.25	9.70	8.72
Luxemburg	10.99	7.64	97.48	7.39	10.61	2.09	5.71
Macedonia, FYR	n/a	n/a	81.01	3.84	39.30	5.97	4.91
Madagascar	n/a	n/a	30.65	0.80	3.49	0.45	0.62

2-The education pillar							
Malawi	4.81	1.10	32.73	0.87	0.50	0.00	0.66
Malaysia	10.44	6.61	76.12	3.41	35.49	5.37	5.13
Mali	1.97	0.08	36.67	1.23	5.94	1.19	0.83
Malta	10.52	6.69	100.21	8.48	35.51	5.45	6.87
Mauritania	4.53	0.79	20.49	0.14	3.85	0.75	0.56
Mauritius	8.86	4.72	88.80	5.36	32.16	4.93	5.00
Mexico	8.79	4.57	85.94	4.71	26.59	4.40	4.56
Moldova	10.40	6.54	88.60	5.14	38.29	5.82	5.83
Mongolia	9.20	5.12	97.62	7.46	51.41	6.79	6.46
Morocco	4.96	1.26	60.97	2.61	13.68	2.69	2.19
Mozambique	1.93	0.00	23.24	0.29	3.89	0.82	0.37
Myanmar	4.85	1.18	47.93	1.88	10.61	2.16	1.74
Namibia	6.17	2.13	65.78	2.68	9.20	1.64	2.15
Nepal	4.23	0.47	51.79	2.25	11.16	2.39	1.70
Netherlands	11.39	8.43	120.61	9.71	61.17	7.69	8.61
New Zealand	10.98	7.56	124.66	9.78	59.26	7.46	8.27
Nicaragua	6.61	2.44	71.76	3.12	17.42	3.21	2.92
Nigeria	n/a	n/a	39.23	1.30	10.49	2.01	1.66
Norway	11.59	8.66	111.31	9.42	73.18	8.81	8.96
Oman	n/a	n/a	99.78	8.12	22.96	3.81	5.96
Pakistan	5.02	1.34	32.86	0.94	6.79	1.27	1.18
Panama	9.27	5.20	69.99	2.97	43.32	6.12	4.76
Paraguay	7.57	3.39	66.79	2.75	36.67	5.52	3.89
Peru	8.88	4.80	90.84	5.72	34.22	5.15	5.23
Philippines	8.43	4.41	84.12	4.28	28.49	4.55	4.41
Poland	11.32	8.19	96.24	7.10	72.31	8.66	7.98
Portugal	7.52	3.31	105.90	9.06	62.64	7.76	6.71
Qatar	8.43	4.33	93.97	6.38	9.31	1.72	4.14
Romania	10.67	6.93	95.29	6.81	68.59	8.36	7.37
Russian Federation	11.53	8.50	84.77	4.35	75.33	9.10	7.32
Rwanda	4.36	0.63	26.15	0.58	5.27	1.04	0.75
Saudi Arabia	8.53	4.49	94.79	6.52	31.56	4.85	5.29
Senegal	2.74	0.16	30.32	0.72	7.94	1.34	0.74
Serbia	10.85	7.40	91.48	5.80	49.85	6.49	6.56
Sierra Leone	4.23	0.39	24.25	0.43	1.96	0.15	0.33
Singapore	10.81	7.32	n/a	n/a	n/a	n/a	N/A
Slovak Republic	12.82	9.76	91.68	5.87	56.05	7.09	7.57
Slovenia	11.89	9.06	98.75	7.83	86.44	9.48	8.79
South Africa	9.69	5.75	92.51	6.09	n/a	n/a	5.92
Spain	10.27	6.30	115.03	9.57	71.58	8.58	8.15
Sri Lanka	10.06	6.14	87.22	5.07	n/a	n/a	5.61
Sudan	3.21	0.24	42.32	1.52	15.59	2.84	1.53
Swaziland	5.06	1.50	n/a	n/a	n/a	n/a	N/A
Sweden	11.64	8.90	99.49	7.97	70.74	8.51	8.46

2-The education pillar							
Switzerland	13.02	9.84	95.60	6.96	50.15	6.57	7.79
Syrian Arab Republic	6.70	2.60	71.37	3.04	24.14	4.25	3.30
Taiwan, China	n/a	n/a	n/a	n/a	n/a	n/a	N/A
Tajikistan	10.30	6.38	84.08	4.20	22.79	3.66	4.75
Tanzania	5.81	1.73	5.72	0.00	1.51	0.07	0.60
Thailand	7.99	4.02	80.82	3.70	49.40	6.42	4.71
Trinidad and Tobago	10.63	6.77	85.51	4.49	11.95	2.61	4.63
Tunisia	7.48	3.15	90.60	5.65	34.99	5.22	4.68
Turkey	7.05	2.76	80.04	3.62	23.86	4.18	3.52
Uganda	5.70	1.65	24.64	0.51	4.32	0.97	1.04
Ukraine	11.15	7.87	95.32	6.88	81.97	9.40	8.05
United Arab Emirates	9.07	5.04	79.18	3.48	n/a	n/a	4.26
United Kingdom	12.24	9.37	100.17	8.41	57.90	7.31	8.36
United States	13.18	9.92	95.22	6.67	87.62	9.63	8.74
Uruguay	8.17	4.09	90.19	5.58	50.93	6.64	5.44
Uzbekistan	n/a	n/a	89.47	5.51	9.99	1.87	3.69
Venezuela, RB	8.41	4.25	82.70	3.99	79.30	9.25	5.83
Vietnam	7.15	2.91	58.26	2.39	20.23	3.51	2.94
Yemen, Rep.	3.68	0.31	43.02	1.59	11.34	2.46	1.46
Zambia	7.32	3.07	N/A	N/A	2.27	0.22	1.65
Zimbabwe	7.61	3.54	39.98	1.38	n/a	n/a	2.46

1-4-3 The Innovation Sub-Index

3-The innovation pillar							
Countries in KAM 2012	**3-1 Royalty Payments and receipts 2009**		**3-2 S&E Journal Articles 2007**		**3-3 Patent Applications Granted by the USPTO (Average 2005-2009)**		**The Innov -ation Index**
	Actual	**Normalise d**	**Actual**	**Normalised**	**Actual**	**Normalised**	
Albania	31586025.92	4.17	40.88	1.62	n/a	n/a	2.90
Algeria	19004491.66	3.31	1404.92	6.13	67.00	3.04	4.16
Angola	12020000.00	2.83	10.16	0.42	n/a	n/a	1.63
Argentina	1632860850.3	7.64	5684.67	7.54	890.40	6.76	7.31
Armenia	N/A	N/A	391.91	4.72	175.00	4.51	4.61
Aruba	13184357.54	2.91	n/a	n/a	n/a	n/a	n/a
Australia	3622140221.1	8.50	36024.47	9.15	2685.00	8.43	8.70
Austria	2717913187.5	8.19	9902.90	8.24	2297.40	8.14	8.19
Azerbaijan	21029000.00	3.46	414.86	4.93	260.80	5.10	4.50
Bahrain	N/A	N/A	172.91	3.31	n/a	n/a	n/a
Bangladesh	8718834.94	2.68	992.89	5.70	43.20	2.35	3.58
Barbados	39295890.36	4.41	49.82	1.83	2.00	0.39	2.21
Belarus	85500000.00	5.35	1300.93	6.06	1404.40	7.25	6.22
Belgium	4492836016.1	8.82	13798.70	8.59	541.00	6.08	7.83
Benin	3014054.96	1.81	93.03	2.32	n/a	n/a	2.07

3-The innovation pillar							
Bolivia	21150000.00	3.54	85.28	2.25	n/a	n/a	2.90
Bosnia & Herzegovina	18358200.43	3.23	312.53	4.15	60.00	2.94	3.44
Botswana	9376293.37	2.76	149.26	3.10	n/a	n/a	2.93
Brazil	2945851900.0	8.35	31059.14	9.08	4151.00	8.73	8.72
Bulgaria	127267331.16	5.67	2451.79	6.62	241.20	5.00	5.76
Burkina Faso	523077.70	1.02	111.78	2.68	1.00	0.10	1.27
Cambodia	8456000.00	2.60	51.93	1.90	n/a	n/a	2.25
Cameroon	8248042.20	2.52	337.68	4.30	n/a	n/a	3.41
Canada	12527019746	9.21	52152.72	9.44	5166.20	8.82	9.16
Cape Verde	0.00	0.63	2.67	0.07	n/a	n/a	0.35
Chile	621960112.26	6.93	3265.02	6.90	385.80	5.88	6.57
China	11494723602	9.13	215206.94	9.86	158507.60	9.71	9.57
Colombia	558606751.95	6.77	1584.54	6.27	124.60	3.73	5.59
Costa Rica	119400565.11	5.59	227.19	3.73	19.80	1.76	3.69
Cote d'Ivoire	20567988.72	3.39	120.02	2.75	n/a	n/a	3.07
Croatia	244854637.81	6.06	3345.26	6.97	320.80	5.49	6.17
Cuba	N/A	N/A	1102.09	5.99	80.20	3.43	4.71
Cyprus	71326540.10	5.28	417.12	5.00	10.00	1.08	3.79
Czech Republic	1020459655.9	7.40	9939.57	8.31	688.80	6.47	7.39
Denmark	3987432461.4	8.66	9007.63	8.03	1594.60	7.55	8.08
Djibouti	N/A	N/A	2.28	0.00	n/a	n/a	n/a
Dominica	435029.63	0.94	3.44	0.14	n/a	n/a	0.54
Dominican Republic	53400000.00	4.80	20.32	0.92	16.40	1.67	2.46
Ecuador	47457318.40	4.65	142.56	2.96	6.20	0.69	2.76
Egypt, Arab Rep.	284500000.00	6.30	4547.63	7.18	478.75	5.98	6.49
El Salvador	26490000.00	3.78	14.59	0.77	n/a	n/a	2.28
Eritrea	N/A	N/A	16.55	0.85	n/a	n/a	n/a
Estonia	70327620.93	5.20	1065.71	5.85	48.20	2.55	4.53
Ethiopia	4983715.25	2.05	336.85	4.23	6.00	0.59	2.29
Fiji	2079293.75	1.57	85.21	2.18	n/a	n/a	1.88
Finland	3212173293.6	8.43	9448.99	8.10	1811.00	7.94	8.15
France	21058652971	9.45	63610.50	9.58	14467.20	9.22	9.42
Georgia	16023505.98	3.15	354.30	4.44	237.40	4.90	4.16
Germany	14221493377	9.29	89413.66	9.65	48266.20	9.51	9.48
Ghana	0.00	0.55	239.77	3.80	n/a	n/a	2.18
Greece	702703791.94	7.09	11151.57	8.38	579.00	6.18	7.22
Guatemala	97393800.00	5.51	30.89	1.27	13.20	1.37	2.72
Guinea	280000.00	0.71	14.11	0.70	n/a	n/a	0.71
Guyana	67661428.90	5.12	10.95	0.56	n/a	n/a	2.84
Haiti	3796950.90	1.97	10.85	0.49	n/a	n/a	1.23
Honduras	26491000.00	3.86	12.07	0.63	n/a	n/a	2.25
Hong Kong, China	2083147640.6	8.03	n/a	n/a	162.00	4.22	6.13
Hungary	3682609785	8.58	5877.07	7.61	710.40	6.57	7.59

3-The innovation pillar							
Iceland	210729942.35	5.98	382.36	4.51	53.40	2.65	4.38
India	2052009616.7	7.95	43627.40	9.37	6078.00	8.92	8.75
Indonesia	1568235429.8	7.56	689.57	5.49	321.60	5.59	6.21
Iran, Islamic Rep.	N/A	N/A	13352.19	8.52	9651.20	9.12	8.82
Ireland	36742589468	9.69	5419.29	7.39	n/a	n/a	8.54
Israel	1661200000.0	7.80	11192.87	8.45	1508.20	7.35	7.87
Italy	9412697642.8	8.98	54056.39	9.51	8885.67	9.02	9.17
Jamaica	53958028.71	4.88	174.37	3.38	13.80	1.47	3.24
Japan	38532661905	9.76	109981.96	9.79	334788.60	9.90	9.82
Jordan	0.00	0.47	1073.46	5.92	58.60	2.84	3.08
Kazakhstan	65089100.00	5.04	216.01	3.59	1517.00	7.45	5.36
Kenya	40721991.79	4.49	554.96	5.35	45.40	2.45	4.10
Korea, Rep.	10611000000.	9.06	41496.30	9.23	126159.00	9.61	9.30
Kuwait	0.00	0.39	724.09	5.56	n/a	n/a	2.98
Kyrgyz Republic	7352407.00	2.36	38.24	1.48	145.30	4.02	2.62
Lao PDR	0.00	0.31	28.22	1.13	2.75	0.49	0.64
Latvia	32210035.42	4.25	494.93	5.14	162.20	4.31	4.57
Lebanon	942199.40	1.26	648.10	5.42	n/a	n/a	3.34
Lesotho	358796.36	0.79	9.75	0.35	n/a	n/a	0.57
Lithuania	29455104.25	4.02	1703.50	6.34	74.60	3.14	4.50
Luxemburg	524321297.76	6.69	219.60	3.66	34.60	2.25	4.20
Macedonia, FYR	26405831.76	3.70	254.32	3.94	n/a	n/a	3.82
Madagascar	45753162.50	4.57	106.01	2.46	7.00	0.98	2.67
Malawi	429555.61	0.87	130.44	2.82	n/a	n/a	1.84
Malaysia	1398844040.2	7.48	3876.96	7.11	755.00	6.67	7.09
Mali	2849393.53	1.73	69.10	2.04	n/a	n/a	1.89
Malta	2780118765.8	8.27	106.35	2.54	10.67	1.17	3.99
Mauritania	n/a	n/a	9.21	0.28	n/a	n/a	n/a
Mauritius	5305919.88	2.13	54.09	1.97	2.00	0.29	1.46
Mexico	278548222.00	6.14	9611.38	8.17	658.80	6.27	6.86
Moldova	14970000.00	3.07	148.15	3.03	284.00	5.29	3.80
Mongolia	985003.54	1.34	110.19	2.61	55.80	2.75	2.23
Morocco	50762950.19	4.72	1044.23	5.77	156.00	4.12	4.87
Mozambique	3747303.10	1.89	41.50	1.69	7.00	0.88	1.49
Myanmar	0.00	0.24	38.23	1.41	n/a	n/a	0.82
Namibia	6884138.65	2.28	40.10	1.55	n/a	n/a	1.92
Nepal	N/A	N/A	391.72	4.65	n/a	n/a	n/a
Netherlands	61120483735	9.84	25669.59	8.94	2292.00	8.04	8.94
New Zealand	763821945.61	7.32	6064.43	7.75	1749.80	7.84	7.64
Nicaragua	800000.00	1.18	23.12	1.06	n/a	n/a	1.12
Nigeria	208441257.40	5.91	2411.91	6.55	n/a	n/a	6.23
Norway	441906533.66	6.61	7730.01	7.89	1176.60	7.16	7.22
Oman	N/A	N/A	410.46	4.86	n/a	n/a	n/a

3-The innovation pillar							
Pakistan	95000000.00	5.43	3384.71	7.04	128.25	3.82	5.43
Panama	62500000.00	4.96	100.51	2.39	n/a	n/a	3.68
Paraguay	1700000.00	1.42	29.48	1.20	22.00	1.86	1.49
Peru	154605000.00	5.75	399.52	4.79	32.40	2.16	4.23
Philippines	413719061.34	6.54	500.28	5.21	209.20	4.71	5.49
Poland	1645000000.0	7.72	22172.08	8.87	2392.80	8.24	8.28
Portugal	713438402.14	7.17	7654.28	7.82	308.80	5.39	6.79
Qatar	N/A	N/A	241.07	3.87	n/a	n/a	n/a
Romania	560200087.58	6.85	5250.00	7.32	921.20	6.96	7.04
Russian Federation	4367810000.0	8.74	30268.45	9.01	26468.60	9.41	9.05
Rwanda	N/A	N/A	20.71	0.99	0.00	0.00	0.49
Saudi Arabia	0.00	0.16	2068.13	6.41	122.00	3.63	3.40
Senegal	13395892.20	2.99	206.94	3.52	n/a	n/a	3.26
Serbia	206916013.20	5.83	2875.14	6.83	380.80	5.78	6.15
Sierra Leone	1750566.95	1.50	4.97	0.21	n/a	n/a	0.85
Singapore	14868601740	9.37	8281.13	7.96	686.80	6.37	7.90
Slovak Republic	284105902.36	6.22	2803.45	6.76	186.00	4.61	5.86
Slovenia	323605684.57	6.38	2688.84	6.69	327.20	5.69	6.25
South Africa	1733727964	7.87	5938.90	7.68	893.20	6.86	7.47
Spain	n/a	n/a	42297.40	9.30	3329.20	8.63	8.96
Sri Lanka	0.00	0.08	438.99	5.07	171.20	4.41	3.19
Sudan	2819188.59	1.65	140.16	2.89	136.80	3.92	2.82
Swaziland	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Sweden	6455304528.65	8.90	16771.10	8.66	2446.00	8.33	8.63
Switzerland	24787410122.34	9.61	16914.50	8.73	1670.60	7.65	8.66
Syrian Arab Republic	30000000.00	4.09	153.03	3.17	114.50	3.53	3.60
Taiwan, China	N/A	N/A	n/a	n/a	n/a	n/a	n/a
Tajikistan	705800.00	1.10	32.13	1.34	22.33	1.96	1.47
Tanzania	0.00	0.00	311.92	4.08	n/a	n/a	2.04
Thailand	2311690000.00	8.11	4889.91	7.25	960.60	7.06	7.47
Trinidad and Tobago	N/A	N/A	168.21	3.24	1.33	0.20	1.72
Tunisia	38806909.70	4.33	2338.97	6.48	78.00	3.24	4.68
Turkey	648000000.00	7.01	21729.57	8.80	1717.20	7.75	7.85
Uganda	6301105.96	2.20	273.35	4.01	6.67	0.78	2.33
Ukraine	756000000.00	7.24	5488.86	7.46	3142.20	8.53	7.75
United Arab Emirates	N/A	N/A	757.57	5.63	n/a	n/a	n/a
United Kingdom	23628221965.7	9.53	91212.76	9.72	17040.00	9.31	9.52
United States	115151000000	9.92	391909.59	9.93	225499.60	9.80	9.88
Uruguay	22098555.73	3.62	386.69	4.58	30.60	2.06	3.42
Uzbekistan	n/a	n/a	346.50	4.37	282.20	5.20	4.78
Venezuela, RB	352000000.00	6.46	1410.33	6.20	79.20	3.33	5.33
Vietnam	n/a	n/a	521.62	5.28	211.40	4.80	5.04

3-The innovation pillar							
Yemen, Rep.	28620000.00	3.94	45.48	1.76	15.00	1.57	2.42
Zambia	n/a	n/a	69.27	2.11	12.60	1.27	1.69
Zimbabwe	7756168.60	2.44	185.25	3.45	n/a	n/a	2.95

1-4-4 The Information and Communication Technology Sub-Index

4-The information and communication technology pillar							
Countries in KAM 2012	**4-1 Telephones Per 1,000 People 2009**		**4-2 Internet Users Per 1,000 people 2009**		**4-3 Computers Per 1,000 Persons 2008**		**The ICT Index**
	Actual	**Normalised**	**Actual**	**Normalised**	**Actual**	**Normalised**	
Albania	950.79	4.04	412.00	6.34	49.20	3.24	4.54
Algeria	999.21	4.38	112.30	3.17	10.52	1.20	2.92
Angola	373.66	1.37	23.00	0.97	5.97	0.56	0.97
Argentina	1537.71	7.88	340.00	5.66	89.41	4.72	6.08
Armenia	966.52	4.11	153.00	3.52	98.51	5.14	4.26
Aruba	1623.38	8.29	580.00	7.52	99.18	5.21	7.01
Australia	1513.00	7.47	742.50	8.97	601.41	8.94	8.46
Austria	1754.16	9.11	734.50	8.90	607.21	9.01	9.01
Azerbaijan	1026.20	4.59	274.00	4.90	79.70	4.58	4.69
Bahrain	1383.86	6.30	530.00	7.31	518.38	8.45	7.35
Bangladesh	360.42	1.23	31.00	1.17	24.16	2.39	1.60
Barbados	1681.80	8.70	647.00	8.21	145.98	6.27	7.72
Belarus	1449.08	6.78	274.30	4.97	8.18	0.92	4.22
Belgium	1511.18	7.33	700.00	8.62	377.34	8.10	8.02
Benin	576.93	2.12	22.40	0.83	6.89	0.77	1.24
Bolivia	735.33	2.88	168.00	3.66	24.11	2.32	2.95
Bosnia & Herzegovina	1139.17	5.34	377.40	6.00	63.05	4.01	5.12
Botswana	1029.70	4.66	61.50	1.79	60.98	3.87	3.44
Brazil	1087.66	4.93	392.20	6.28	159.17	6.41	5.87
Bulgaria	1694.01	8.77	450.00	6.83	111.53	5.56	7.05
Burkina Faso	262.60	0.62	11.30	0.48	6.51	0.63	0.58
Cambodia	448.59	1.71	5.30	0.14	3.79	0.21	0.69
Cameroon	426.46	1.64	38.40	1.31	11.03	1.41	1.45
Canada	1260.00	5.89	803.00	9.24	945.64	9.86	8.33
Cape Verde	744.85	2.95	210.00	4.28	143.37	6.20	4.47
Chile	1184.73	5.62	415.60	6.48	142.89	6.13	6.08
China	779.44	3.08	289.00	5.24	56.53	3.52	3.95
Colombia	1109.13	5.07	300.00	5.38	112.75	5.63	5.36
Costa Rica	763.13	3.01	343.30	5.79	235.41	7.04	5.28
Cote d'Ivoire	671.33	2.74	20.00	0.76	17.81	1.90	1.80
Croatia	1505.14	7.26	505.80	7.10	181.35	6.69	7.02
Cuba	155.07	0.21	143.30	3.45	55.80	3.38	2.34
Cyprus	1620.42	8.15	498.10	7.03	309.07	7.82	7.67
Czech Republic	1486.39	7.05	644.30	8.14	274.21	7.75	7.65
Denmark	1738.57	8.97	868.40	9.59	549.31	8.66	9.07

4-The information and communication technology pillar							
Djibouti	175.91	0.27	40.00	1.45	39.52	2.89	1.54
Dominica	1623.13	8.22	420.20	6.62	184.86	6.83	7.22
Dominican Republic	1001.93	4.45	277.20	5.10	21.72	2.18	3.91
Ecuador	1032.53	4.73	246.00	4.55	122.43	5.77	5.02
Egypt, Arab Rep.	809.33	3.22	200.00	4.07	40.48	2.96	3.42
El Salvador	1407.25	6.51	121.10	3.31	58.85	3.73	4.52
Eritrea	60.77	0.14	5.40	0.28	11.11	1.48	0.63
Estonia	1544.23	7.95	725.00	8.83	255.78	7.46	8.08
Ethiopia	58.27	0.07	5.40	0.21	6.58	0.70	0.33
Fiji	909.97	3.70	170.00	3.72	60.84	3.80	3.74
Finland	1709.01	8.84	824.90	9.45	500.37	8.38	8.89
France	1580.55	8.08	715.80	8.76	628.72	9.08	8.64
Georgia	839.18	3.36	200.70	4.14	58.30	3.66	3.72
Germany	1961.68	9.73	790.00	9.10	655.53	9.30	9.38
Ghana	636.15	2.33	54.40	1.59	10.82	1.27	1.73
Greece	17600.65	9.93	424.00	6.69	94.82	4.93	7.18
Guatemala	1307.65	6.03	93.00	2.69	19.87	2.11	3.61
Guinea	325.35	0.96	9.40	0.34	4.65	0.35	0.55
Guyana	850.02	3.42	239.00	4.41	35.67	2.75	3.53
Haiti	382.24	1.44	81.00	2.34	52.32	3.31	2.36
Honduras	1117.33	5.27	98.00	2.83	25.05	2.46	3.52
Hong Kong, China	2436.87	9.86	694.00	8.48	694.94	9.44	9.26
Hungary	1492.17	7.12	620.00	7.79	255.74	7.39	7.44
Iceland	1676.51	8.63	930.00	9.93	526.69	8.59	9.05
India	461.64	1.78	51.20	1.52	31.36	2.68	1.99
Indonesia	831.81	3.29	69.20	2.00	19.67	2.04	2.44
Iran, Islamic Rep.	1074.52	4.86	138.00	3.38	104.63	5.49	4.58
Ireland	1521.03	7.74	673.80	8.34	580.31	8.80	8.30
Israel	1715.99	8.90	631.20	7.93	255.17	7.32	8.05
Italy	1906.34	9.59	488.30	6.97	370.64	8.03	8.19
Jamaica	1165.49	5.48	243.00	4.48	67.71	4.23	4.73
Japan	1424.21	6.58	780.00	9.03	411.08	8.24	7.95
Jordan	945.21	3.97	260.00	4.62	76.32	4.44	4.34
Kazakhstan	1303.98	5.96	182.00	3.93	n/a	n/a	4.94
Kenya	489.68	1.85	61.00	1.72	13.92	1.69	1.75
Korea, Rep.	1516.55	7.53	816.00	9.38	573.82	8.73	8.55
Kuwait	1115.51	5.21	508.00	7.17	265.06	7.61	6.66
Kyrgyz Republic	934.53	3.90	160.00	3.59	19.37	1.97	3.15
Lao PDR	542.38	1.99	60.00	1.66	17.41	1.83	1.82
Latvia	1335.92	6.16	668.40	8.28	337.19	7.89	7.44
Lebanon	663.63	2.53	301.40	5.45	103.52	5.42	4.47
Lesotho	352.24	1.16	37.20	1.24	2.60	0.07	0.83
Lithuania	1802.47	9.25	597.60	7.72	254.02	7.25	8.07
Luxemburg	1980.96	9.79	873.10	9.66	672.82	9.37	9.61
Macedonia,	1150.54	5.41	517.70	7.24	365.48	7.96	6.87

4-The information and communication technology pillar							
FYR							
Madagascar	314.55	0.89	16.30	0.55	5.58	0.49	0.65
Malawi	183.82	0.34	10.70	0.41	1.97	0.00	0.25
Malaysia	1249.97	5.82	559.00	7.45	229.98	6.97	6.75
Mali	311.72	0.82	18.00	0.62	7.27	0.85	0.76
Malta	1625.49	8.36	588.60	7.59	n/a	n/a	7.97
Mauritania	665.03	2.60	22.80	0.90	42.88	3.10	2.20
Mauritius	1175.18	5.55	225.10	4.34	178.28	6.62	5.50
Mexico	913.17	3.84	263.40	4.69	134.67	5.99	4.84
Moldova	799.30	3.15	275.00	5.03	118.25	5.70	4.63
Mongolia	911.77	3.77	100.00	3.03	247.18	7.18	4.66
Morocco	902.85	3.63	413.00	6.41	57.42	3.59	4.55
Mozambique	264.39	0.68	26.80	1.10	13.38	1.62	1.14
Myanmar	18.83	0.00	0.00	0.00	8.94	1.06	0.35
Namibia	855.46	3.49	65.00	1.93	240.02	7.11	4.18
Nepal	238.45	0.48	19.70	0.69	5.18	0.42	0.53
Netherlands	1648.29	8.49	896.30	9.72	911.53	9.79	9.34
New Zealand	1519.66	7.60	797.00	9.17	525.74	8.52	8.43
Nicaragua	626.44	2.26	73.00	2.07	40.90	3.03	2.45
Nigeria	492.47	1.92	93.00	2.62	8.60	0.99	1.84
Norway	1476.22	6.85	920.80	9.86	628.88	9.15	8.62
Oman	1484.85	6.99	268.00	4.83	177.45	6.55	6.12
Pakistan	572.49	2.05	75.00	2.21	4.54	0.28	1.51
Panama	1844.83	9.38	390.80	6.21	61.45	3.94	6.51
Paraguay	974.37	4.18	189.00	4.00	79.37	4.51	4.23
Peru	981.12	4.32	314.00	5.52	101.41	5.28	5.04
Philippines	862.28	3.56	90.00	2.55	71.92	4.37	3.49
Poland	1389.76	6.37	589.70	7.66	169.27	6.48	6.83
Portugal	1520.49	7.67	482.70	6.90	183.60	6.76	7.11
Qatar	1351.53	6.23	531.00	7.38	158.83	6.34	6.65
Romania	1445.39	6.71	366.00	5.93	198.44	6.90	6.51
Russian Federation	1921.69	9.66	290.00	5.31	132.82	5.85	6.94
Rwanda	251.74	0.55	77.00	2.28	3.03	0.14	0.99
Saudi Arabia	1841.34	9.32	380.00	6.07	643.16	9.23	8.20
Senegal	582.10	2.19	75.00	2.14	22.18	2.25	2.19
Serbia	1442.71	6.64	381.00	6.14	258.50	7.54	6.77
Sierra Leone	190.16	0.41	2.60	0.07	n/a	n/a	0.24
Singapore	1774.99	9.18	690.00	8.41	720.62	9.51	9.03
Slovak Republic	1243.69	5.68	700.00	8.55	583.73	8.87	7.70
Slovenia	1494.51	7.19	640.00	8.07	425.15	8.31	7.86
South Africa	1016.38	4.52	100.00	2.97	83.76	4.65	4.04
Spain	1530.52	7.81	624.00	7.86	390.03	8.17	7.95
Sri Lanka	981.01	4.25	87.80	2.48	37.37	2.82	3.18
Sudan	365.99	1.30	86.60	2.41	102.71	5.35	3.02
Swaziland	671.03	2.67	n/a	n/a	n/a	n/a	n/a
Sweden	1672.92	8.56	910.00	9.79	881.01	9.72	9.36
Switzerland	1873.81	9.52	813.00	9.31	962.38	9.93	9.59

4-The information and communication technology pillar							
Syrian Arab Republic	655.15	2.47	173.00	3.79	92.66	4.86	3.71
Taiwan, China	1852.61	9.45	289.00	5.17	55.88	3.45	6.03
Tajikistan	712.48	2.81	100.70	3.10	12.43	1.55	2.49
Tanzania	409.59	1.51	24.00	1.03	9.11	1.13	1.22
Thailand	1094.07	5.00	201.00	4.21	66.93	4.15	4.45
Trinidad and Tobago	1627.32	8.42	443.00	6.76	134.05	5.92	7.03
Tunisia	1052.24	4.79	340.70	5.72	96.54	5.00	5.17
Turkey	1112.06	5.14	364.00	5.86	64.04	4.08	5.03
Uganda	306.17	0.75	97.80	2.76	17.24	1.76	1.76
Ukraine	1477.78	6.92	179.00	3.86	45.34	3.17	4.65
United Arab Emirates	1547.49	8.01	640.00	8.00	270.73	7.68	7.90
United Kingdom	1750.59	9.04	835.60	9.52	798.73	9.58	9.38
United States	1394.53	6.44	710.00	8.69	806.02	9.65	8.26
Uruguay	1512.15	7.40	418.00	6.55	135.31	6.06	6.67
Uzbekistan	651.14	2.40	119.00	3.24	31.33	2.61	2.75
Venezuela, RB	1248.27	5.75	327.00	5.59	92.46	4.79	5.38
Vietnam	1327.92	6.10	265.50	4.76	97.44	5.07	5.31
Yemen, Rep.	413.48	1.58	99.60	2.90	28.44	2.54	2.34
Zambia	340.29	1.03	63.10	1.86	10.88	1.34	1.41
Zimbabwe	349.34	1.10	40.00	1.38	70.39	4.30	2.26

1-4-5 Calculation of the Knowledge Index (KI) and Knowledge Economy Index (KEI)

Countries included in KAM 2012	Institutional Sub-Index	Education Sub-Index	Innovation Sub-Index	ICT Sub-Index	Knowledge Index (KI)	Knowledge-Economy Index (KEI)
Albania	4.71	5.18	2.90	4.54	4.21	4.33
Algeria	2.06	4.48	4.16	2.92	3.85	3.40
Angola	1.39	0.26	1.63	0.97	0.95	1.06
Argentina	2.15	7.01	7.31	6.08	6.80	5.64
Armenia	5.64	7.43	4.61	4.26	5.43	5.49
Aruba	8.45	4.28	n/a	7.01	5.64	6.58
Australia	8.51	9.26	8.70	8.46	8.80	8.73
Austria	9.15	7.31	8.19	9.01	8.17	8.41
Azerbaijan	3.19	3.27	4.50	4.69	4.15	3.91
Bahrain	6.63	4.17	n/a	7.35	5.76	6.05
Bangladesh	1.31	2.08	3.58	1.60	2.42	2.14

Countries included in KAM 2012	Institutional Sub-Index	Education Sub-Index	Innovation Sub-Index	ICT Sub-Index	Knowledge Index (KI)	Knowledge-Economy Index (KEI)
Barbados	5.11	7.79	2.21	7.72	5.91	5.71
Belarus	2.34	9.19	6.22	4.22	6.54	5.49
Belgium	8.71	8.36	7.83	8.02	8.07	8.23
Benin	2.19	1.10	2.07	1.24	1.47	1.65
Bolivia	2.30	4.12	2.90	2.95	3.32	3.07
Bosnia & Herzegovina	5.46	N/A	3.44	5.12	4.28	4.67
Botswana	5.76	4.36	2.93	3.44	3.58	4.12
Brazil	4.12	5.59	8.72	5.87	6.73	6.08
Bulgaria	7.24	6.75	5.76	7.05	6.52	6.70
Burkina Faso	4.55	0.30	1.27	0.58	0.71	1.67
Cambodia	1.96	1.74	2.25	0.69	1.56	1.66
Cameroon	1.04	1.69	3.41	1.45	2.18	1.90
Canada	9.49	8.66	9.16	8.33	8.72	8.91
Cape Verde	4.35	3.45	0.35	4.47	2.76	3.16
Chile	8.92	6.27	6.57	6.08	6.30	6.96
China	3.62	3.74	9.57	3.95	5.75	5.22
Colombia	4.29	5.79	5.59	5.36	5.58	5.26
Costa Rica	6.68	5.34	3.69	5.28	4.77	5.25
Cote d'Ivoire	1.55	0.91	3.07	1.80	1.92	1.83
Croatia	7.28	7.55	6.17	7.02	6.91	7.01
Cuba	1.29	7.44	4.71	2.34	4.83	3.94
Cyprus	7.66	7.47	3.79	7.67	6.31	6.65
Czech Republic	8.39	7.87	7.39	7.65	7.64	7.82
Denmark	9.51	8.85	8.08	9.07	8.67	8.88
Djibouti	1.84	0.88	n/a	1.54	1.21	1.42
Dominica	5.81	N/A	0.54	7.22	3.88	4.53
Dominican Republic	3.77	4.21	2.46	3.91	3.53	3.59
Ecuador	1.72	4.86	2.76	5.02	4.21	3.59
Egypt, Arab Rep.	4.27	3.53	6.49	3.42	4.48	4.43
El Salvador	5.11	3.64	2.28	4.52	3.48	3.89
Eritrea	0.81	1.20	n/a	0.63	0.92	0.88
Estonia	8.57	8.73	4.53	8.08	7.11	7.48
Ethiopia	1.55	1.07	2.29	0.33	1.23	1.31
Fiji	1.89	4.61	1.88	3.74	3.41	3.03
Finland	9.44	9.29	8.15	8.89	8.78	8.94
France	7.66	7.69	9.42	8.64	8.58	8.35
Georgia	7.08	5.61	4.16	3.72	4.50	5.14
Germany	8.89	8.21	9.48	9.38	9.02	8.99
Ghana	4.03	2.04	2.18	1.73	1.98	2.49
Greece	6.76	7.90	7.22	7.18	7.43	7.26
Guatemala	4.08	1.94	2.72	3.61	2.75	3.09
Guinea	0.49	1.14	0.71	0.55	0.80	0.72

Countries included in KAM 2012	Institutional Sub-Index	Education Sub-Index	Innovation Sub-Index	ICT Sub-Index	Knowledge Index (KI)	Knowledge-Economy Index (KEI)
Guyana	2.77	3.99	2.84	3.53	3.45	3.28
Haiti	1.76	N/A	1.23	2.36	1.80	1.79
Honduras	3.19	2.67	2.25	3.52	2.81	2.91
Hong Kong, China	9.47	6.81	6.13	9.26	7.40	7.92
Hungary	7.99	8.05	7.59	7.44	7.69	7.77
Iceland	8.80	8.62	4.38	9.05	7.35	7.71
India	3.38	2.55	8.75	1.99	4.43	4.17
Indonesia	3.21	3.61	6.21	2.44	4.09	3.87
Iran, Islamic Rep.	0.60	4.85	8.82	4.58	6.08	4.71
Ireland	9.10	8.62	8.54	8.30	8.49	8.64
Israel	8.32	8.73	7.87	8.05	8.22	8.24
Italy	7.49	7.45	9.17	8.19	8.27	8.08
Jamaica	4.17	5.46	3.24	4.73	4.48	4.40
Japan	7.45	N/A	9.82	7.95	8.88	8.41
Jordan	5.49	5.40	3.08	4.34	4.27	4.58
Kazakhstan	3.89	7.97	5.36	4.94	6.09	5.54
Kenya	2.84	1.73	4.10	1.75	2.53	2.61
Korea, Rep.	5.83	8.70	9.30	8.55	8.85	8.09
Kuwait	5.82	4.44	2.98	6.66	4.69	4.98
Kyrgyz Republic	1.50	6.07	2.62	3.15	3.95	3.34
Lao PDR	1.27	2.07	0.64	1.82	1.51	1.45
Latvia	7.85	7.83	4.57	7.44	6.61	6.92
Lebanon	4.21	N/A	3.34	4.47	3.90	4.01
Lesotho	2.69	1.55	0.57	0.83	0.98	1.41
Lithuania	7.72	8.72	4.50	8.07	7.10	7.25
Luxemburg	9.05	5.71	4.20	9.61	6.50	7.14
Macedonia, FYR	5.66	4.91	3.82	6.87	5.20	5.31
Madagascar	2.80	0.62	2.67	0.65	1.31	1.68
Malawi	3.51	0.66	1.84	0.25	0.92	1.56
Malaysia	5.63	5.13	7.09	6.75	6.32	6.15
Mali	3.53	0.83	1.89	0.76	1.16	1.75
Malta	8.50	6.87	3.99	7.97	6.28	6.83
Mauritania	2.06	0.56	n/a	2.20	1.38	1.61
Mauritius	8.14	5.00	1.46	5.50	3.99	5.03
Mexico	4.74	4.56	6.86	4.84	5.42	5.25
Moldova	4.46	5.83	3.80	4.63	4.75	4.68
Mongolia	4.37	6.46	2.23	4.66	4.45	4.43
Morocco	4.48	2.19	4.87	4.55	3.87	4.02
Mozambique	3.84	0.37	1.49	1.14	1.00	1.71
Myanmar	0.10	1.74	0.82	0.35	0.97	0.76
Namibia	6.22	2.15	1.92	4.18	2.75	3.62
Nepal	1.47	1.70	n/a	0.53	1.12	1.24

Countries included in KAM 2012	Institutional Sub-Index	Education Sub-Index	Innovation Sub-Index	ICT Sub-Index	Knowledge Index (KI)	Knowledge-Economy Index (KEI)
Netherlands	9.00	8.61	8.94	9.34	8.96	8.97
New Zealand	9.05	8.27	7.64	8.43	8.11	8.35
Nicaragua	3.89	2.92	1.12	2.45	2.16	2.60
Nigeria	1.27	1.66	6.23	1.84	3.24	2.75
Norway	9.45	8.96	7.22	8.62	8.27	8.56
Oman	6.58	5.96	n/a	6.12	6.04	6.22
Pakistan	1.89	1.18	5.43	1.51	2.71	2.51
Panama	5.12	4.76	3.68	6.51	4.98	5.02
Paraguay	3.62	3.89	1.49	4.23	3.20	3.31
Peru	5.48	5.23	4.23	5.04	4.83	4.99
Philippines	4.14	4.41	5.49	3.49	4.46	4.38
Poland	7.49	7.98	8.28	6.83	7.70	7.64
Portugal	7.88	6.71	6.79	7.11	6.87	7.12
Qatar	6.78	4.14	n/a	6.65	5.40	5.86
Romania	6.89	7.37	7.04	6.51	6.98	6.95
Russian Federation	2.40	7.32	9.05	6.94	7.77	6.43
Rwanda	3.86	0.75	0.49	0.99	0.74	1.52
Saudi Arabia	5.54	5.29	3.40	8.20	5.63	5.61
Senegal	3.72	0.74	3.26	2.19	2.06	2.48
Serbia	4.09	6.56	6.15	6.77	6.49	5.89
Sierra Leone	1.36	0.33	0.85	0.24	0.47	0.70
Singapore	9.42	N/A	7.90	9.03	8.47	8.79
Slovak Republic	7.46	7.57	5.86	7.70	7.05	7.15
Slovenia	7.74	8.79	6.25	7.86	7.63	7.66
South Africa	5.51	5.92	7.47	4.04	5.81	5.74
Spain	8.04	8.15	8.96	7.95	8.35	8.27
Sri Lanka	3.94	5.61	3.19	3.18	3.99	3.98
Sudan	0.62	1.53	2.82	3.02	2.46	2.00
Swaziland	n/a	N/A	n/a	n/a	n/a	N/A
Sweden	8.91	8.46	8.63	9.36	8.82	8.84
Switzerland	9.38	7.79	8.66	9.59	8.68	8.85
Syrian Arab Republic	1.91	3.30	3.60	3.71	3.53	3.13
Taiwan, China	7.60	N/A	n/a	6.03	n/a	N/A
Tajikistan	2.37	4.75	1.47	2.49	2.90	2.77
Tanzania	2.88	0.60	2.04	1.22	1.29	1.69
Thailand	4.71	4.71	7.47	4.45	5.55	5.34
Trinidad and Tobago	5.77	4.63	1.72	7.03	4.46	4.79
Tunisia	3.68	4.68	4.68	5.17	4.84	4.55
Turkey	6.19	3.52	7.85	5.03	5.47	5.65
Uganda	3.95	1.04	2.33	1.76	1.71	2.27
Ukraine	3.92	8.05	7.75	4.65	6.82	6.09
United Arab	6.19	4.26	n/a	7.90	6.08	6.11

Countries included in KAM 2012	Institutional Sub-Index	Education Sub-Index	Innovation Sub-Index	ICT Sub-Index	Knowledge Index (KI)	Knowledge-Economy Index (KEI)
Emirates						
United Kingdom	8.61	8.36	9.52	9.38	9.09	8.97
United States	8.31	8.74	9.88	8.26	8.96	8.80
Uruguay	6.53	5.44	3.42	6.67	5.18	5.52
Uzbekistan	0.72	3.69	4.78	2.75	3.74	2.98
Venezuela, RB	0.35	5.83	5.33	5.38	5.51	4.22
Vietnam	2.49	2.94	5.04	5.31	4.43	3.94
Yemen, Rep.	2.83	1.46	2.42	2.34	2.07	2.26
Zambia	3.98	1.65	1.69	1.41	1.58	2.18
Zimbabwe	0.09	2.46	2.95	2.26	2.55	1.94

1-5 Difference Between Applied KAM and Published KAM in 2012

Country	Applied KAM in 2012	Published KAM in 2012	Comparing Results
Albania	4.33	4.30	0.03
Algeria	3.40	4.11	-0.71
Angola	1.06	1.11	-0.05
Argentina	5.64	5.65	-0.01
Armenia	5.49	4.88	0.61
Aruba	6.58	5.47	1.11
Australia	8.73	8.93	-0.20
Austria	8.41	8.50	-0.09
Azerbaijan	3.91	4.56	-0.65
Bahrain	6.05	6.41	-0.36
Bangladesh	2.14	2.05	0.09
Barbados	5.71	6.19	-0.48
Belarus	5.49	5.63	-0.14
Belgium	8.23	8.64	-0.41
Benin	1.65	1.86	-0.21
Bolivia	3.07	3.73	-0.66
Bosnia & Herzegovina	4.67	4.88	-0.21
Botswana	4.12	3.97	0.15
Brazil	6.08	6.14	-0.06
Bulgaria	6.70	6.66	0.04
Burkina Faso	1.67	1.98	-0.31
Cambodia	1.66	1.8	-0.14
Cameroon	1.90	1.82	0.08
Canada	8.91	8.97	-0.06
Cape Verde	3.16	3.44	-0.28
Chile	6.96	7.25	-0.29
China	5.22	5.26	-0.04
Colombia	5.26	5.37	-0.11
Costa Rica	5.25	5.73	-0.48
Cote d'Ivoire	1.83	1.62	0.21
Croatia	7.01	7.04	-0.03

Country	Applied KAM in 2012	Published KAM in 2012	Comparing Results
Cuba	3.94	4.35	-0.41
Cyprus	6.65	6.9	-0.25
Czech Republic	7.82	8.08	-0.26
Denmark	8.88	8.92	-0.04
Djibouti	1.42	1.3	0.12
Dominica	4.53	4.8	-0.27
Dominican Republic	3.59	4.12	-0.53
Ecuador	3.59	3.89	-0.30
Egypt, Arab Rep.	4.43	4.4	0.03
El Salvador	3.89	4.13	-0.24
Eritrea	0.88	1.1	-0.22
Estonia	7.48	7.94	-0.46
Ethiopia	1.31	1.68	-0.37
Fiji	3.03	3.42	-0.39
Finland	8.94	9.09	-0.15
France	8.35	8.44	-0.09
Georgia	5.14	5.01	0.13
Germany	8.99	9.07	-0.08
Ghana	2.49	2.87	-0.38
Greece	7.26	7.47	-0.21
Guatemala	3.09	3.83	-0.74
Guinea	0.72	1.24	-0.52
Guyana	3.28	4.19	-0.91
Haiti	1.79		
Honduras	2.91	3.11	-0.20
Hong Kong, China	7.92	8.38	-0.46
Hungary	7.77	7.96	-0.19
Iceland	7.71	7.87	-0.16
India	4.17	4.13	0.04
Indonesia	3.87	3.96	-0.09
Iran, Islamic Rep.	4.71	4.33	0.38
Ireland	8.64	8.73	-0.09
Israel	8.24	7.93	0.31
Italy	8.08	8.19	-0.11
Jamaica	4.40	5.3	-0.90
Japan	8.41	8.49	-0.08
Jordan	4.58	4.83	-0.25
Kazakhstan	5.54	5.21	0.33
Kenya	2.61	3.31	-0.70
Korea, Rep.	8.09	8.13	-0.04
Kuwait	4.98	5.11	-0.13
Kyrgyz Republic	3.34	3.74	-0.40
Lao PDR	1.45	1.7	-0.25
Latvia	6.92	6.96	-0.04
Lebanon	4.01	4.4	-0.39
Lesotho	1.41	1.84	-0.43
Lithuania	7.25	7.49	-0.24
Luxemburg	7.14	7.73	-0.59
Macedonia, FYR	5.31	5.29	0.02
Madagascar	1.68	1.86	-0.18
Malawi	1.56	1.98	-0.42

Country	Applied KAM in 2012	Published KAM in 2012	Comparing Results
Malaysia	6.15	6.26	-0.11
Mali	1.75	1.92	-0.17
Malta	6.83	7.01	-0.18
Mauritania	1.61	1.6	0.01
Mauritius	5.03	5.05	-0.02
Mexico	5.25	5.61	-0.36
Moldova	4.68	4.73	-0.05
Mongolia	4.43	4.19	0.24
Morocco	4.02	3.99	0.03
Mozambique	1.71	1.89	-0.18
Myanmar	0.76	1.12	-0.36
Namibia	3.62	3.79	-0.17
Nepal	1.24	1.78	-0.54
Netherlands	8.97	9.06	-0.09
New Zealand	8.35	8.73	-0.38
Nicaragua	2.60	2.57	0.03
Nigeria	2.75	2.87	-0.12
Norway	8.56	8.87	-0.31
Oman	6.22	5.81	0.41
Pakistan	2.51	3.24	-0.73
Panama	5.02	5.02	0.00
Paraguay	3.31	3.87	-0.56
Peru	4.99	5.33	-0.34
Philippines	4.38	4.61	-0.23
Poland	7.64	7.63	0.01
Portugal	7.12	7.53	-0.41
Qatar	5.86	5.18	0.68
Romania	6.95	7	-0.05
Russian Federation	6.43	6.25	0.18
Rwanda	1.52	1.85	-0.33
Saudi Arabia	5.61	6.14	-0.53
Senegal	2.48	2.72	-0.24
Serbia	5.89	5.9	-0.01
Sierra Leone	0.70	0.95	-0.25
Singapore	8.79	8.06	0.73
Slovak Republic	7.15	7.44	-0.29
Slovenia	7.66	7.62	0.04
South Africa	5.74	5.46	0.28
Spain	8.27	8.53	-0.26
Sri Lanka	3.98	3.75	0.23
Sudan	2.00	1.61	0.39
Swaziland	N/A	2.77	
Sweden	8.84	9.25	-0.41
Switzerland	8.85	8.66	0.19
Syrian Arab Republic	3.13	3.01	0.12
Taiwan, China	N/A	8.78	
Tajikistan	2.77	3.08	-0.31
Tanzania	1.69	1.95	-0.26
Thailand	5.34	5.66	-0.32
Trinidad and Tobago	4.79	5.33	-0.54
Tunisia	4.55	4.6	-0.05

Country	Applied KAM in 2012	Published KAM in 2012	Comparing Results
Turkey	5.65	5.61	0.04
Uganda	2.27	2.57	-0.30
Ukraine	6.09	6.1	-0.01
United Arab Emirates	6.11	6.73	-0.62
United Kingdom	8.97	8.91	0.06
United States	8.80	8.9	-0.10
Uruguay	5.52	6.07	-0.55
Uzbekistan	2.98	3.41	-0.43
Venezuela, RB	4.22	4.51	-0.29
Vietnam	3.94	3.96	-0.02
Yemen, Rep.	2.26	2.13	0.13
Zambia	2.18	2.6	-0.42
Zimbabwe	1.94	2.25	-0.31

Appendix (XIV): - Selected Empirical Studies on the Determinants of Innovation.

❖ At the Regional Level

Author (s): Qureshi et al. (2021)

Study Objective: Compare innovation performance in two regions, namely the Asia-Pacific region and Latin America and the Caribbean region.

Innovation Measures:

Regional Innovation Inputs: (Independent variables): R&D expenditure; Secondary school enrolment; Openness (exports plus imports as a share of GDP); Import of manufactured goods, the share of total trade in manufactured goods; Total trade with the United States, the share of GDP (IMF Direction of Trade Statistics); Financial development index (IMF); Percent of population with access to electricity, a proxy for infrastructure access/availability; Institutional quality/good governance rating, Worldwide Governance Indicators.

Regional Innovation Outputs: (Dependent variable): Patent flows (number of patent applications by residents, World Development Indicators.

Sample of Countries Included: The Asia-Pacific region and Latin America and the Caribbean region.

Findings of the Study: The Asia-Pacific innovates better than Latin America and the Caribbean region.

Author (s): Buesa et al. (2010)

Study Objective: Investigate the determinants of regional innovation in Europe (146 regions of the EU-15 countries) by using a knowledge production function approach which includes factorial analysis and regression.

Innovation Measures:

Regional Innovation Inputs: (Independent variables): 21 variables to explain five important aspects of the innovation system, namely national environment; regional environment; innovating firms; universities, and the R&D done by public administration.

Regional Innovation Outputs: (Dependent variable): Patents registered in European Patents Office (EPO).

Findings of the Study: All factors (aspects of the innovation system) have a statistically significant effect on the production of knowledge measured by (patents). However, they have varied very different impacts.

❖ At the Country Level using the GCI

Author (s)	Objective	Methodology	Indicators Used	Sample Used
Barrichello et al. (2020)	Determining the innovation drivers at the country level.	Using the Global Competitiveness Index and the seven items representing the innovation pillars, the study investigated the effect of each item individually and collectively.	Quality of scientific research, institutions" and patent applications are equally important for the countries' innovation development.	137 countries as classified by the global competitiveness report.

❖ At the Country Level using the GII

Author (s)	Objective	Methodology	Indicators Used	Sample Used
Bate et al. (2023)	Assess the determinants of innovation performance.	The Global Innovation Index pillars.	Human capital and research, infrastructure, and business sophistication are the key pillars determining innovation performance	63 countries

Author (s)	Objective	Methodology	Indicators Used	Sample Used
Hamidi and Berrado (2017)	Analyze the most important determinants of innovation performance in a country.	The Global Innovation Index Framework.	(i) The assessment in reading, mathematics, and science for 15-year-old students (ii) The patent families filed in at least three offices (iii) The researchers' full-time equivalence	142 countries included in the GII report in 2015

❖ At the Country Level using Innovation-Related Variables

Author (s)	Objective	Methodology	Sample Used	Finding(s)
Sandu and Ciocanel (2014)	Assess the relationship between high-tech exports and the main determinants of innovation at the country level in EU countries for the period 2006-2010.	Innovation performance is measured by: R&D expenditure in the public sector as % of GDP. R&D expenditure in the business sector as % of GDP Employment in knowledge-intensive activities (production and services) is a % of total employment.	26 EU countries (except for Luxembourg)	A positive correlation exists between total R&D expenditure volume, and the level of high-tech exports, with variability between countries. The influence of private R&D expenditure on high-tech exports is stronger than public R&D expenditure.

Author (s)	Objective	Methodology	Sample Used	Finding(s)
Ang and Madsen (2013)	Analyze the effects of domestic R&D stock and foreign knowledge spillovers on total factor productivity in six Asian countries, namely China, India, Japan, Korea, Singapore, and Taiwan for the period from 1955 to 2006.	Innovation variables with patents as a proxy of innovative outputs.	26 OECD countries in addition to China and India over a period from 1870 to 2010.	There is a Positive relationship between patenting and R&D investments. Furthermore, negative correlation between patenting and GDP.

Author (s)	Objective	Methodology	Sample Used	Finding(s)
Seidel et al. (2013)	Introduce an indicator-based analysis of the determinant of NIS in Manaus, Brazil.	Innovation drivers are grouped as a three-level hierarchy macro, meso, and micro levels with 30 determinants.	Manaus and Brazil in 2010.	Building a NIS is crucial, particularly for developing economies.

❖ Building a National Innovative Capacity at the Country Level

Author (s)	Objective	Methodology	Sample Used	Finding(s)
Furman et al., (2002)	Empirically determine the factors of national innovative capacity**.**	**Innovation Output:** International patents International patents per million of the population. **Innovation Inputs:** variables to represent different sources of national innovative capacity, namely the quality of the common innovation infrastructure. The cluster-specific innovation environment. The linkages between these two sources. The time lag is three years	17 OECD countries for the period from 1973 to 1996.	The empirical factors that determine the international patenting activity within the analyzed countries are more complex than the factors suggested by the ideas-driven growth theory. The study also concluded that public policy in every country is crucial in shaping the country's national innovative capacity.

Author (s)	Objective	Methodology	Sample Used	Finding(s)
Andrijauskiene et al. (2021)	Analyze the effects of the national innovative capacity framework on innovation performance for EU countries.	**Innovation Outputs:** three groups: Technologically innovative outputs Non-technologically innovative outputs Commercialization of innovation. **Innovation Inputs:** seven dimensions: Common innovation infrastructure. Quality of linkages. Cluster-specific environment for innovation. International economic activities. Diversity and equality Legal and political strength General social-economic conditions.	EU countries for the period from 2000 to 2018.	The study empirically determines the most critical innovation determinants in EU countries.

❖ Building a national innovation System at the country level

Author (s)	Objective	Methodology	Sample Used	Finding(s)
Ibrahim and Marah (2018)	Empirically determine the factors of NISs in the BRICS economies as well as their impacts on specific economic and social development.	20 variables are divided into five NIS dimensions, namely the innovation dimension, the infrastructural dimension, the institutional dimension and the educational dimension, and another dimension for economic and social performance.	Five BRICS countries for the period from 2000 to 2015.	Structural variations in NIS dimensions between the BRICS nations

Appendix (XV): Classification of Demand-Oriented Measures.

Instrument	Role of the State	Mode of Functioning	Examples of Cases
1. Public Demand: state buys for its own use and/or to catalyse the private market			
General procurement	Buy and Use	State actors consider innovation in general procurement as the main criterion (e.g., the definition of needs, not products, in tenders)	In Australia, the government has established consolidated communication platforms with industries and target training since 2008. (Lember et al., 2013)
Strategic procurement	Buy and Use	State actors specifically demand an already existing innovation to accelerate the market introduction and particularly the diffusion.	In the UK, the Procurement of new catheters in the UK by the NHS (Rolfstam, 2009)
		State actors stimulate deliberately the development and market introduction of innovations by formulating new, demanding needs (including forward commitment procurement).	In Denmark, the government has Procured an innovative intelligent hospital bed by adopting the elements of competitive dialogue in the procurement process. (TemaNord, 2011)
Co-operative and catalytic procurement	Buy, Use, and moderation	State actors are part of a group of demanders and organize the coordination of the procurement and the specification of needs.	Ethanol-fuelled lorries in Stockholm (Lember et al., 2011)
		Special form: catalytic procurement: the state does not utilize the innovation itself, but organizes only the private procurement	The government has employed policies for the diffusion of wind energy in Denmark (Neij & Andersen, 2012)
2. Support for Private Demand			
Direct support for private demand			
Demand subsidies	Co-financing	The purchase of innovative technologies by consumers or industrial demanders is directly subsidized, lowering the entry cost of innovation.	Subsidies for solar water heaters in Germany (Nemet, 2014)
Tax incentives	Co-financing	Amortization possibilities for certain innovative technologies, in different	In the US, the government has introduced tax incentives for solar water

Instrument	Role of the State	Mode of Functioning	Examples of Cases
		forms (tax credit, rebate, waiver, etc.)	heaters (Nemet, 2012)
Indirect support for private demand: information and enabling (soft steering): State mobilizes, informs, connects			
Awareness building measures	informing	State actors start information campaigns, advertise new solutions, conduct demonstration projects (or support them) and try to create confidence in certain innovations (in the general public, opinion leaders)	The awareness campaigns regarding new energy-efficient building appliances in Southern Sweden using energy-efficient light bulbs (Bertoldi et al., 2012).
Labels or information campaigns	Supporting and informing	The state supports a co-ordinated private marketing activity that signals performance and safety features.	Heat pump programs in Switzerland and Sweden (Kiss et al., 2012)
Training and further education	Enabling	Consumers are made aware of innovative possibilities and simultaneously placed in a position to use them.	The Department of Trade and Industry in the UK with the Office of Government Commerce designed a training program for decision-makers and public procurers in 2003 to enhance their ability to cope with the needs of Government departments in the future (NESTA, 2010)
Articulation and foresight	Organizing discourse	Societal groups and potential consumers are given a voice in the marketplace, and signals as to future preferences (and fears) are articulated and signalled to the marketplace. Various variations (including constructive technology assessment bringing).	Possible examples could be: UK Technology Foresight Programme US Critical Technologies Programme Futuris exercise in France was an industry-driven exercise (Georghiou & Cassingena Harper, 2011)
User–producer interaction	Organizing discourse	The state supports firms to include user needs in innovation activity or organizes fora of targeted discourse (innovation platforms etc.)	Creating a network of Living Labs network in Finland to support interaction between users and producers (Breznitz et al.,2009)
Regulation of demand or of the interface demander – producer			
Regulation of product	Regulating, controlling	The state sets requirements for the production and	Possible cases could be: 1-regulation of green

Instrument	Role of the State	Mode of Functioning	Examples of Cases
performance and manufacturing	(Command and control)	introduction of innovations (e.g., market approval, recycling requirements). Thus, demanders know reliably how certain products perform and how they are manufactured.	construction in Nordic countries (Sand et al., 2012) 2-the introduction of new emission standards in the US auto industry to improve its competitiveness (Blind, 2012)
Regulation of product information	Regulating, controlling (Command and control)	Smart regulation leaves freedom to choose technologies, but changes the incentive structures for those choices (e.g., quota systems)	
Process and "Usage" norms	Regulating, controlling (Command and control)	The state creates legal security by setting up clear rules on the use of innovations (e.g., electronic signatures)	The adoption of the Digital Signature Act 1997 in Malaysia to regulate the use of digital signatures and ensures the security of legal issues related to electronic transactions. (Saripan & Hamin, 2011).
Support of innovation-friendly private regulation activities	moderating	The state stimulates self-regulation (norms, standards) of firms and supports/moderates this process, and plays a role as a catalyst by using standards	To facilitate the certification in the services sector in Northern European to support cross borderer trade in services (Grimsby & Grünfeld (2008)
Regulations to create a market	Moderating, organizing	State action creates markets for the consequences of the use of technologies (most strongly through the institutional setup of emission trading) or sets market conditions that intensify the demand for innovations	UK governments aimed to reduce greenhouse gas emissions by 80 percent by 2050; this would expect to enlarge the demand for adopting low-carbon technologies (NESTA, 2010).
3- Systemic Approaches			
Integrated demand measures	Combination of roles	Strategically coordinated measures that combine various demand-side instruments	Applied Renewable energy policy in Germany. The policy includes a combination of demand-side measures such as regulation, subsidies, tax incentives, and loan facilities adopt green energy technology

Instrument	Role of the State	Mode of Functioning	Examples of Cases
			(Bechberger & Reiche, 2004)
Integration of demand- and supply-side logic and measures	Combination of roles	Combination of supply-side instruments and demand-side impulses for selected technologies or services (including clusters integrating users and supply chains) Conditional supporting of user-producer interaction (R&D grants if user involved)	In Finland, the government has introduced strategic Centres for Science, Technology, and Innovation based on existing industry clusters by deploying demand and supply-side policy instruments (Nikulainen &Tahvanainen, 2009)
		Specific instrument : Pre-commercial Procurement	Pre-Commercial procurement for intelligent transport systems. (Lindholm, 2011); (Rigby, 2013); (Edquist & Zabala-Iturriagagoitia;2015)

Sources: Cunningham (2009); Lember et al. (2013); Elder (2013)

APPENDIX (XVI): GII for the Developing MENA Countries and Its Pillars and Sub-Pillars in 2020

	Country	Algeria	Egypt	Iran	Jordon	Lebanon	Morocco	Tunisia
1	**Institutions**	**52.5**	**49.3**	**45.3**	**64.4**	**50.1**	**61.6**	**61.4**
1.1	**Political environment**	44.6	47.1	41.0	57.3	33.3	54.0	53.1
1.1.1	Political and operational stability	55.4	58.9	46.4	66.1	35.7	66.1	62.5
1.1.2	Government effectiveness	39.2	41.2	38.3	52.9	32.1	48.0	48.4
1.2	**Regulatory environment**	**49.4**	**35.8**	**43.4**	**73.7**	**63.5**	**57.7**	**56.7**
1.2.1	Regulatory quality	9.4	21.9	6.3	44.4	32.4	38.0	32.1
1.2.2	Rule of law	25.2	35.6	27.0	50.5	24.1	43.1	48.4
1.2.3	Cost of redundancy dismissal	17.3	36.8	23.1	8.0	8.7	20.7	21.6
1.3	**Business environment**	**63.6**	**65.0**	**51.4**	**62.1**	**53.6**	**73.0**	**74.4**
1.3.1	Ease of starting a business	78.0	87.8	67.8	84.5	78.2	93.0	94.6
1.3.2	Ease of resolving insolvency	49.2	42.2	35.1	39.7	29.1	52.9	54.2
2	**Human Capital & Research**	**29.8**	**21.8**	**37.3**	**26.2**	**24.9**	**27.5**	**42.7**
2.1	**Education**	**41.2**	**40.7**	**44.5**	**32.9**	**24.8**	**53.2**	**71.2**
2.1.1	Expenditure on education, % GDP	n/a	n/a	4	3.1	2.4	n/a	6.6
2.1.2	Government funding/pupil, secondary, % GDP/cap	n/a	11.8	17.5	15.5	6.4	36.4	52.4
2.1.3	School life expectancy, years	14.3	13.6	14.8	10.6	n/a	14.0	15.1
2.1.4	PISA scales in reading, maths, & science	361.7	n/a	n/a	416.0	376.8	367.9	371.4
2.1.5	Pupil-teacher ratio, secondary	n/a	15.8	19.0	14.4	7.7	18.8	13.6
2.2	**Tertiary education**	43.2	13.9	52.9	36.3	35.7	22.6	48.6
2.2.1	Tertiary enrolment, % gross	52.6	38.9	62.8	33.1	n/a	38.5	31.8
2.2.2	Graduates in science & engineering, %	34.2	11.2	40.2	26.4	23.4	19.0	43.3
2.2.3	Tertiary inbound mobility, %	0.5	1.8	0.6	14.0	9.6	2.0	2.2
2.3	**Research & development (R&D)**	5.1	10.7	14.6	9.5	14.3	6.7	8.2
2.3.1	Researchers, FTE/MN pop	819.3	686.7	1,474.9	596.0	n/a	1,073.5	1,771.6
2.3.2	Gross expenditure on R&D, % GDP	0.5	0.7	0.8	0.7	n/a	0.7	0.6
2.3.3	Global R&D companies, avg. exp. top 3, MN $US	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2.3.4	QS university ranking, average score top 3	0.0	20.4	24.2	17.0	28.6	0.0	0.0
3	**Infrastructure**	**31.8**	**33.5**	**40.9**	**30.1**	**30.4**	**36.3**	**34.2**
3.1	**Information & communication technologies (ICTs)**	**39.1**	**52.5**	**60.1**	**41.4**	**45.4**	**54.8**	**61.7**
3.1.1	ICT access	60.2	58.8	79.2	45.9	62.8	66.6	61.5

	Country	Algeria	Egypt	Iran	Jordon	Lebanon	Morocco	Tunisia
3.1.2	ICT use	53.0	43.1	56.0	50.4	43.7	49.1	53.8
3.1.3	Government's online service	27.6	57.1	58.8	35.9	41.8	52.3	62.4
3.1.4	E-participation	15.5	51.2	46.4	33.3	33.3	51.2	69.0
3.2	**General infrastructure**	32.4	21.4	41.5	20.5	21.2	25.0	11.0
3.2.1	Electricity output, kWh/MN pop	1,815.5	1,971.8	3,787.8	2,057.2	3,100.6	1,131.3	1,816.7
3.2.2	Logistics performance	18.6	36.1	37.4	29.8	31.1	22.9	24.3
3.2.3	Gross capital formation, % GDP	37.5	19.0	40.7	19.8	n/a	28.1	10.3
3.3	**Ecological sustainability**	24.1	26.7	21.2	28.5	24.6	29.1	30.0
3.3.1	GDP/unit of energy use	10.2	12.1	5.9	9.8	9.9	14.5	12.0
3.3.2	Environmental performance	44.8	43.3	48.0	53.4	45.4	42.3	46.7
3.3.3	ISO 14001 environmental certificates/bn PPP$ GDP	0.3	0.8	0.7	1.2	0.6	0.8	1.9
4	**Market Sophistication**	**23.7**	**40.9**	**43.4**	**49.7**	**42.0**	**41.9**	**40.7**
4.1	**Credit**	9.4	29.5	38.1	51.7	34.1	33.1	35.9
4.1.1	Ease of getting credit	10.0	65.0	50.0	95.0	40.0	45.0	50.0
4.1.2	Domestic credit to private sector, % GDP	25.9	24.0	66.1	76.9	106.3	87.8	86.6
4.1.3	Microfinance gross loans, % GDP	n/a	0.1	n/a	0.4	0.2	0.2	0.5
4.2	**Investment**	**10.0**	**19.6**	**24.6**	**26.3**	**26.2**	**23.3**	**22.3**
4.2.1	Ease of protecting minority investors	20.0	64.0	40.0	50.0	44.0	70.0	62.0
4.2.2	Market capitalization, % GDP	0.2	17.0	27.6	52.7	18.0	55.8	21.8
4.2.3	Venture capital investors, deals/bn PPP$ GDP	n/a	0.0	n/a	0.1	0.1	0.0	0.0
4.2.4	Venture capital recipients, deals/bn PPP$ GDP	n/a	0.0	n/a	0.0	0.1	0.0	0.0
4.3	**Trade, diversification, and market scale**	**51.7**	**73.6**	**67.5**	**71.2**	**65.7**	**69.2**	**63.9**
4.3.1	Applied tariff rate, weighted avg., %	10.0	10.4	15.4	4.4	3.3	3.6	9.4
4.3.2	Domestic industry diversification	45.8	92.2	93.5	94.8	80.7	77.5	88.5
4.3.3	Domestic market scale, bn PPP$	488.3	1,292.5	1,006.7	102.2	78.9	273.5	123.6
5	**Business Sophistication**	**14.7**	**18.0**	**16.5**	**21.9**	**25.4**	**18.1**	**16.5**
5.1	**Knowledge workers**	13.3	13.9	18.1	23.1	34.0	22.1	19.6
5.1.1	Knowledge-intensive employment, %	17.9	29.6	19.8	21.4	27.6	6.9	20.9
5.1.2	Firms offering formal training, %	n/a	7.9	n/a	16.9	20.8	35.7	19.1
5.1.3	GERD performed by business, % GDP	0.0	0.0	0.2	n/a	n/a	0.2	0.1
5.1.4	GERD financed by business, %	6.7	3.9	n/a	n/a	n/a	29.9	18.9
5.1.5	Females employed w/advanced degrees, %	8.1	5.8	7.9	7.6	14.6	n/a	8.8
5.2	**Innovation linkages**	**15.2**	**20.7**	**16.2**	**26.5**	**21.3**	**14.0**	**13.9**
5.2.1	University/industry	37.1	44.3	26.7	46.8	42.6	29.2	32.8

	Country	Algeria	Egypt	Iran	Jordon	Lebanon	Morocco	Tunisia
	research collaboration							
5.2.2	State of cluster development and depth	48.3	67.2	42.9	57.6	47.5	42.9	39.0
5.2.3	GERD financed by abroad, % GDP	0.0	0.0	n/a	n/a	n/a	0.0	0.0
5.2.4	JV-strategic alliance deals/bn PPP$ GDP	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5.2.5	Patent families 2+ offices/bn PPP$ GDP	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5.3	**Knowledge absorption**	**15.6**	**19.6**	**15.1**	**16.2**	**21.0**	**18.0**	**16.1**
5.3.1	Intellectual property payments, % total trade	0.3	0.3	0.2	0.1	0.1	0.3	0.1
5.3.2	High-tech imports, % total trade	8.9	9.3	3.8	7.0	4.0	8.5	9.3
5.3.3	ICT services imports, % total trade	0.6	1.0	0.5	0.2	2.5	0.7	0.4
5.3.4	FDI net inflows, % GDP	0.8	3.1	0.8	3.0	4.6	2.3	2.2
5.3.5	Research talent, % in business enterprise	0.5	6.3	19.2	n/a	n/a	7.0	5.2
6	**knowledge & Technology Outputs**	**8.1**	**19.4**	**26.9**	**18.0**	**14.1**	**20.1**	**24.0**
6.1	**Knowledge creation**	7.4	13.8	50.6	16.6	21.5	11.3	24.2
6.1.1	Patents by origin/bn PPP$ GDP	0.2	0.8	11.1	0.2	1.1	0.7	1.4
6.1.2	PCT patents by origin/bn PPP$ GDP	0.0	0.0	0.3	0.2	n/a	0.2	0.0
6.1.3	Utility models by origin/bn PPP$ GDP	n/a	n/a	n/a	n/a	n/a	n/a	n/a
6.1.4	Scientific & technical articles/bn PPP$ GDP	9.3	15.9	46.2	29.2	28.4	14.4	40.9
6.1.5	Citable documents H-index	10.2	17.7	20.5	10.0	12.8	11.4	11.2
6.2	Knowledge Impact	13.7	33.0	24.9	26.8	5.7	31.6	29.7
6.2.1	Labour productivity growth, %	−0.6	4.5	−4.9	−0.8	−10.0	0.1	−1.4
6.2.2	New businesses/th pop. 15-64	0.4	n/a	0.4	0.5	n/a	1.9	1.7
6.2.3	software spending, % GDP	0.0	0.2	0.3	0.3	0.0	0.2	0.3
6.2.4	ISO 9001 quality certificates/bn PPP$ GDP	1.2	1.9	2.1	5.6	5.7	3.7	8.6
6.2.5	High-tech manufacturing, %	4.1	21.8	38.6	22.1	n/a	38.5	24.3
6.3	**Knowledge diffusion**	**3.3**	**11.3**	**5.2**	**10.7**	**15.2**	**17.4**	**18.0**
6.3.1	Intellectual property receipts, % total trade	0.0	0.0	0.0	0.1	0.1	0.0	0.1
	Production and export complexity	13.6	42.5	27.6	47.8	52.1	30.9	51.6
6.3.2	High-tech net exports, % total trade	0.0	0.5	0.1	1.4	0.2	2.1	4.0
6.3.3	ICT services exports, % total trade	0.4	1.2	0.1	0.1	2.1	3.3	1.2
7	**Creative Outputs**	**10.3**	**15.5**	**31.3**	**18.3**	**17.2**	**22.8**	**20.6**
7.1	**Intangible assets**	**16.6**	**21.3**	**53.8**	**22.0**	**18.7**	**38.7**	**30.5**
7.1.1	Trademarks by origin/bn PPP$ GDP	14.3	18.7	419	25.7	12.7	58.7	n/a

	Country	Algeria	Egypt	Iran	Jordon	Lebanon	Morocco	Tunisia
7.1.2	Global brand value, top 5,000, % GDP	0.0	3.1	1.0	7.9	14.6	17.8	n/a
7.1.3	Industrial designs by origin/bn PPP$ GDP	2.7	1.4	16.7	0.7	n/a	12.5	1.3
7.1.4	ICTs & organizational model creation	41.3	56.0	47.4	52.6	42.4	51.3	42.7
7.2	**Creative goods and services**	**1.0**	**8.2**	**2.8**	**13.8**	**13.7**	**5.1**	**12.9**
7.2.1	Cultural & creative services exports, % total trade	0.0	n/a	0.1	0.0	1.6	0.4	n/a
7.2.2	National feature films/MN pop. 15-69	0.4	0.6	1.7	n/a	3.3	1.5	1.4
7.2.3	Entertainment & Media market/th pop. 15-69	1.3	0.8	3.0	1.8	0.9	1.1	1.2
7.2.4	Printing and other media, % manufacturing	0.3	0.5	0.3	2.4	n/a	0.7	n/a
7.2.5	Creative goods exports, % total trade	0.0	1.3	0.1	0.9	0.6	0.1	2.0
7.3	**Online creativity**	**7.1**	**11.4**	**14.9**	**15.4**	**17.6**	**8.8**	**8.3**
7.3.1	Generic top-level domains (TLDs)/th pop. 15-69	0.5	1.2	1.8	4.8	5.9	1.5	2.8
7.3.2	Country-code TLDs/th pop. 15-69	0.1	0.0	6.2	0.2	0.3	1.1	1.7
7.3.3	Wikipedia edits/MN pop. 15-69	30.4	45.1	50.7	45.5	44.4	31.8	31.1
7.3.4	Mobile app creation/bn PPP$ GDP	0.0	0.2	0.8	11.6	20.5	3.3	0.1

Source: Global Innovation Index Database, WIPO, 2021

APPENDIX (XVII): Effect of Different Institutional Channels on Innovation Development.

Author(s)	Study objective	Level of analysis	Institutional measure(s)	Methodology	Findings of the study
Rodríguez-Pose & Di Cataldo (2015)	To empirically investigate how institutions affect innovation capacity in regions of Europe	Regional level	The sub-national Quality of Government (QoG) index of Charron et al. (2014) is used as a proxy for regional government institutions. The four QoG index Institutional dimensions are control of corruption, rule of law, government, effectiveness, and government accountability	Dependent variable: patent applications to the European Patent Office per million inhabitants in every region. Fixed effect and GMM are utilized in the study. The institution dimension is treated as an endogenous variable.	A strong relationship between the effectiveness of government and the ability of regions to innovate
Bariş (2019)	To empirically assess how institution quality affects innovation capacity in OECD countries	Country level	The six dimensions of the World Bank's Worldwide Governance Indicators are used separately as a proxy for institutional quality.	Dependent variable: number of patent applications. The six institutional dimensions are used individually. The fixed effect model is the consistent model used.	On the one hand, innovation is positively related to three dimensions, namely voice and accountability, absence of violence and political stability and rule of law. On the other hand, innovation is negatively related to the control of corruption. For the government's effectiveness and regulatory quality, there has been no relationship determined between these two dimensions and innovation.

Appendix (XVIII): Summarizing the Explanations for all Variables Used in the Empirical Model.

Variable Name	Definition	Measurement	Source	Abbreviation
Dependent Variable				
Innovation output sub-index	Innovation is proxy by the innovation output sub-Index which provides information about outputs that are the results of innovative activities within the economy.	Score	GII	INN
Independent Variables				
Foreign direct investment, net inflows (BoP, current US$)	Is defined as the summation of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the balance of payments. This series shows total net FDI. In BPM6, financial account balances are calculated as the change in assets minus the change in liabilities. Net FDI outflows are assets and net FDI inflows are liabilities. Data are in current U.S. dollars.	(BoP, current US$)	WDI	FDI
Institutional quality index	It is defined as the simple average of the six indicators included in the WGI, namely control of corruption, government effectiveness, political stability and absence of violence & terrorism, regulatory quality, rule of law and voice and accountability.	Average score	WGI	IQI
Entrepreneurship	Is measured by the new business density rate, which is defined as the number of newly registered corporations per 1,000 working-age people (those ages 15–64).	Rate	WB	ENT
Controlled Variables				
Human capital	It is defined as the average of education and tertiary education scores in the global innovation index	Average score	GII	HC
Gross domestic product (Growth rates)	It is the annual percentage growth rate of GDP at market prices based on constant local currency.	Percentage	WDI	GDPg

DBibliography

Abd El-Fattah, M. A. (2011). The endogenous growth theory and innovation in Egypt. Journal of Agricultural Biotechnology and Sustainable Development, 3(5), 90-99.

Abderrezzak, B., Wafaa, B., & Benabbou, S. (2016). Key determinants of innovation in the Algerian SMEs. Topics in Middle Eastern and North African Economies, 18(1).

Abdu, M., & Jibir, A. (2018). Determinants of firms innovation in Nigeria. Kasetsart Journal of Social Sciences, 39(3), 448-456.

Abramson, B. D. (2006). Word matters: Multicultural perspectives on information societies-by Alain Ambrosi, Valérie Peugeot, & Daniel Pimienta.

Acemoglu, D., & Robinson, J. A. (2000). Political losers as a barrier to economic development. American Economic Review, 90(2), 126-130.

Acs, Z. J., Desai, S. and Klapper, L. F. (2008), What does "entrepreneurship" data really show? Small Business Economics 31, 265–281.

Acs, Z., ˚Astebro, T., Audretsch, D. and Robinson, D. T. (2016), Public policy to promote entrepreneurship: a call to arms, small business economics 47, 35–51.

Adhikary, B. K. (2017). Factors influencing foreign direct investment in South Asian economies: A comparative analysis. South Asian Journal of Business Studies.

Affortunato, F., Bucciarelli, E., Ciommi, M., & Giulioni, G. (2010). Assessing local knowledge dynamics: Regional knowledge economy indicators. International Journal of Human and Social Sciences, 5(11), 703-708.

Aflaki, S., Basher, S. A., & Masini, A. (2021). Technology-push, demand-pull and endogenous drivers of innovation in the renewable energy industry. Clean Technologies and Environmental Policy, 23(5), 1563-1580.

Afzal, M. N. I., & Lawrey, R. (2014). Measuring the importance and efficiency of research and development expenditures in the transformation of knowledge-based economies: A case study of the ASEAN region. International Journal of Asia-Pacific Studies, 10(1), 33-47.

Afzal, M. N. I. and Lawrey, R. (2012a). Evaluating the comparative performance of technical and scale efficiencies in knowledge-based economies (KBEs) in ASEAN: A data envelopment analysis (DEA) application, European Journal of Economics, Finance and Administrative Sciences 2(51), 81–95.

Afzal, M. N. I., & Lawrey, R. (2012b). Knowledge-based economy (KBE) frameworks and empirical investigation of KBE input-output indicators for ASEAN. International Journal of Economics and Finance, 4(9), 13-22

Afzal, M. N. I., & Lawrey, R. (2012c). Investigating World Bank knowledge assessment methodology (KAM) using data envelopment analysis (DEA): a study in the ASEAN region. Research Journal of Science & IT Management, 1(12), 33-38.

Afzal, M. N. I., & Lawrey, R. (2012d). Evaluating the comparative performance of knowledge-based economies (KBEs) in ASEAN: a data envelopment analysis (DEA) application of additive efficiency. Research Journal of Social Science

& Management, 2(6), 48-55.

Afzal, M. N. I., & Lawrey, R. (2012e). KBE frameworks and their applicability to a resource-based country: The case of Brunei Darussalam. Asian Social Science, 8(7), 208-218.

Agénor, P. R., & Canuto, O. (2017). Access to finance, product innovation and middle-income traps. Research in Economics, 71(2), 337-355.

Ahmad, M. and Hall, S. G. (2023), The growth effects of economic and political institutions: new evidence from spatial econometrics analysis using historical based institutional matrix', Economic Change and Restructuring 56(2), 749–780.

Ahmad, N., & Hoffmann, A. (2008). A framework for addressing and measuring entrepreneurship.

Ahmed, A. and Alfaki, I. M. A. (2013), Transforming the United Arab Emirates into a knowledge-based economy: The role of science, technology and innovation, World Journal of Science, Technology and Sustainable Development 10(2), 84–102.

Ahmed, A. and AlRoubaie, A. (2012), Building a knowledge-based economy in the Muslim world: The critical role of innovation and technological learning, World Journal of Science, Technology and Sustainable Development 9(2), 76–98.

Ahmed, E. M., & Krishnasamy, G. (2013). Human capital investment to achieve knowledge-based economy in ASEAN5: DEA applications. Journal of the Knowledge Economy, 4(4), 331-342.

Al Majali, I., & Almomani, S. N. (2020). Human Capital Development in a Knowledge Economy.

Al Shami, A., Lotfi, A., & Coleman, S. (2012, June). Unified knowledge-based economy neural forecasting map. In The 2012 International Joint Conference on Neural Networks (IJCNN) (pp. 1-8). IEEE.

Al Shami, A., Lotfi, A., Lai, E., & Coleman, S. (2011, April). Unified knowledge economy competitiveness index using fuzzy clustering model. In 2011 IEEE Symposium on Computational Intelligence for Financial Engineering and Economics (CIFEr) (pp. 1-6). IEEE.

Alamtabriz, A. and Imanipour, M. (2011). Measuring the relative efficiency of health care offered in hospitals of Shahid Beheshti University of medical sciences using Data Envelopment Analysis (DEA) technique.

Albulescu, C. T., & Tămăşilă, M. (2016). Exploring the role of FDI in enhancing the entrepreneurial activity in Europe: a panel data analysis. International Entrepreneurship and Management Journal, 12(3), 629-657.

Al-Busaidi, K. A. (2020). Fostering the development of Oman's knowledge economy pillars through ICT. VINE Journal of Information and Knowledge Management Systems.

Aldulaimi, S., Kharabsheh, R., & Alazzawi, A. (2020, October). Investment in Human Capital to Promote Knowledge-Based Economy: Data Analysis in the GCC. In 2020 International Conference on Data Analytics for Business and Industry: Way Towards a Sustainable Economy (ICDABI) (pp. 1-6). IEEE.

Alexander, R. (2021), The fourth industrial revolution and national innovation sys tems: Key concepts and snapshot of south Africa, Technical report, SARChI in dustrial Development Working Paper Series WP 20218a. Johannesburg.

Alguliyev, R. M., & Aliyev, A. G. (2017, September). The development of indicators and indices system characterizing information and knowledge economy. In 2017 IEEE 11th International Conference on Application of Information and Communication Technologies (AICT) (pp. 1-6). IEEE.

Alirezaee, M. R., Howland, M. and Van de Panne, C. (1998). Sampling size and efficiency bias in data envelopment analysis, Journal of Applied Mathematics and Decision Sciences 2(1), 51–64.

Aliyev, A. G. (2021). Development system of hierarchical indicators for analyzing and measuring the level of growth of information and knowledge economy. Management dynamics in the knowledge economy, 9(1), 65-80.

Alizadeh, P., & Salami, R. (2015). Assessment of knowledge economy: A comparative study between Iran and Turkey and lessons for policymaking. Journal of Science & Technology Policy Management.

Allard, G., Martinez, C. A., & Williams, C. (2012). Political instability, pro-business market reforms and their impacts on national systems of innovation. Research Policy, 41(3), 638-651.

Almoli, A., & Tok, M. E. (2020). Knowledge-Based Development and Economic Diversification: The Case of Qatar. In Economic Development in the Gulf Cooperation Council Countries (pp. 43-73). Springer, Singapore.

Alnafrah, I. (2021). Efficiency evaluation of BRICS's national innovation systems based on bias-corrected network data envelopment analysis. Journal of Innovation and Entrepreneurship, 10(1), 1-28.

Alnafrah, I., & Mouselli, S. (2019). The knowledge society vis-à-vis the knowledge economy and their potential development impacts in Russia. Journal of the Knowledge Economy, 10(1), 205-220.

Al-Rahbi, I. A. (2008), An empirical study of the key knowledge economy factors for sustainable economic development in Oman, PhD thesis, Victoria Unversity.

Alrashidi, A. N. (2016), Data envelopment analysis for measuring the efficiency of head trauma care in England and Wales, University of Salford (United Kingdom).

Al-Sudairi, M., & Haj Bakry, S. (2014). Knowledge issues in the global innovation index: Assessment of the state of Saudi Arabia versus countries with distinct development. Innovation, 16(2), 176-183.

Álvarez, I., Barbero, J., & Zofío, J. L. (2016). A data envelopment analysis toolbox for MATLAB (No. 2016/03). Universidad Autónoma de Madrid (Spain), Department of Economic Analysis (Economic Theory and Economic History).

Amirat, A., & Zaidi, M. (2020). Estimating GDP growth in Saudi Arabia under the government's vision 2030: a knowledge-based economy approach. Journal of the Knowledge Economy, 11(3), 1145-1170

Andersen, P. and Petersen, N. C. (1993). A procedure for ranking efficient units in data envelopment analysis, Management science 39(10), 1261–1264.

Andres, A. R., Otero, A. and Amavilah, V. H. (2021). Using deep learning neural networks to predict the knowledge economy index for developing and emerging economies, Expert Systems with Applications 184, 115514.

Andrijauskiene, M., Dumciuviene, D., & Vasauskaite, J. (2021). Redeveloping the national innovative capacity framework: European Union perspective. Economies, 9(4), 201.

Ang, J. B., & Madsen, J. B. (2013). International R&D spillovers and productivity trends in the Asian miracle economies. Economic Inquiry, 51(2), 1523-1541.

Anokhin, S., & Schulze, W. S. (2009). Entrepreneurship, innovation, and corruption. Journal of business venturing, 24(5), 465-476.

Aparicio, G., Iturralde, T. and Rodr´ıguez, A. V. (2023). Developments in the knowledge-based economy research field: a bibliometric literature review, Management Review Quarterly 73(1), 317–352.

APEC Economic Committee (2000). Towards knowledge-based economies in APEC. Report by APEC Economic Committee, November.

Arellano, M. and Bond, S. (1991), Some tests of specification for panel data: Monte-carlo evidence and an application to employment equations, The review of economic studies 58(2), 277–297.

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error components models, Journal of econometrics 68(1), 29–51.

Aristovnik, A. (2012a). The relative efficiency of education and R&D expenditures in the new EU member states. Journal of business economics and management, 13(5), 832-848.

Aristovnik, A. (2012b). The impact of ICT on educational performance and its efficiency in selected EU and OECD countries: a non-parametric analysis. Available at SSRN 2187482.

Aristovnik, A. (2014a). Development of the information society and its impact on the education sector in the EU: efficiency at the regional (NUTS 2) level.

Aristovnik, A. (2014b). Efficiency of the R&D Sector in the EU-27 at the Regional Level: An Application of DEA.

Arocena, R., & Sutz, J. (2012). Research and innovation policies for social inclusion: an opportunity for developing countries. Innovation and Development, 2(1), 147-158.

Arrow, K. (1962). Economic welfare and the allocation of resources for invention. In The rate and direction of inventive activity: Economic and social factors (pp. 609-626). Princeton University Press.

Arshed, N., Ahmad, W., & Hanif, U. (2021). A spatial temporal exploration of factors motivating academia-industry collaboration. Journal of the Knowledge Economy, 1-20.

Arshed, N., Hanif, N., Aziz, O., & Croteau, M. (2022). Exploring the potential of institutional quality in determining technological innovation. Technology in Society, 68, 101859.

Arthur, W. B. (1994). Increasing returns and path dependence in the economy. University of Michigan Press.

Arundel, A., Cruysen, v. A., Hansen, W., Kanerva, M. and Kemp, R. (2008), Defining the knowledge-based economy: final synthesis report: deliverable 1.5, Knowledge Economy Indicators, Workpackage 1.

Arundel, A., Kanerva, M., Van Cruysen, A. and Hollanders, H. (2007), Innovation statistics for the European service sector, European Commission.

Arvanitidis, P. A., & Petrakos, G. (2011). Defining knowledge-driven economic dynamism in the world economy: a methodological perspective. In Innovation, growth and competitiveness (pp. 15-39). Springer, Berlin, Heidelberg.

Asian Development Bank (2007). Moving Towards Knowledge-based Economies: Asian Experiences. © Asian Development Bank. http://hdl.handle.net/11540/2557. License: CC BY 3.0 IGO.

Asian Development Bank 2014. Innovative Asia: Advancing the Knowledge-Based Economy: Country Case Studies for the PRC, India, Indonesia, and Kazakhstan. ADB Reports RPT146810-3, Asian Development Bank (ADB).

Asongu, S. A. (2017). The comparative economics of knowledge economy in Africa: policy benchmarks, syndromes, and implications. Journal of the Knowledge Economy, 8(2), 596-637.

Asongu, S. A., & Andrés, A. R. (2020). Trajectories of knowledge economy in SSA and MENA countries. Technology in Society, 63, 101119.

Asongu, S. A., & Kuada, J. (2020). Building knowledge economies in Africa: an introduction. Contemporary Social Science, 15(1), 1-6.

Asongu, S. A., & Odhiambo, N. M. (2019). Building knowledge-based economies in Africa: A systematic review of policies and strategies. Journal of the Knowledge Economy, 1-18.

Asongu, S. A., Amavilah, V. H., & Andres, A. R. (2020a). Business dynamics, knowledge economy, and the economic performance of African countries. Information Development, 36(1), 128-152.

Asongu, S.A., Tchamyou, V.S. & Acha-Anyi, P.N. (2020b) Who Is Who in Knowledge Economy in Africa?. J Knowl Econ 11, 425–457 (2020). https://doi.org/10.1007/s13132-018-0547-8

Atkinson, A. B. and Stiglitz, J. E. (1969), A new view of technological change, The Economic Journal 79(315), 573–578.

Atkinson, R. D., & Coduri, R. (2002). The 2002 state new economy index: Benchmarking economic transformation in the states. Washington, DC: Progressive Policy Institute.

Attia, A. M. (2015). National innovation systems in developing countries: barriers to university–industry collaboration in Egypt. International Journal of Technology Management & Sustainable Development, 14(2), 113-124.

Aubert, J. E., & Reiffers, J. L. (Eds.). (2003). Knowledge economies in the Middle East and North Africa: Toward new development strategies. World Bank Publications.

Australia. Steering Committee for the Review of Commonwealth/State Service Provision, & Scales, B. (1997). Data envelopment analysis: a technique for measuring the efficiency of government service delivery. Industry Commission.

Avilés-Sacoto, S. V., Cook, W. D., Güemes-Castorena, D., & Zhu, J. (2020). Modelling efficiency in regional innovation systems: A two-stage data envelopment analysis problem with shared outputs within groups of decision-making units. European Journal of Operational Research, 287(2), 572-582.

Avkiran, N. K., Tone, K., & Tsutsui, M. (2008). Bridging radial and non-radial measures of efficiency in DEA. Annals of Operations Research, 164(1), 127-138.

Azzman Shariffadeen, T. M. (2009, June). Developing a Values-based Knowledge Societey and Knowledge Economy–A Malaysian Experiment. In Presentation to Austrian Conference on Knowledge Politics organised by Knowledge Management Austria (Vol. 19).

Bach, L. and Matt, M. (2005). From economic foundations to S&T policy tools: a comparative analysis of the dominant paradigms. In ‘Innovation policy in a knowledge-based economy: theory and practice’, Springer, pp. 17–45.

Baesu, V., Albulescu, C. T., Farkas, Z. B., & Drăghici, A. (2015). Determinants of the high-tech sector innovation performance in the European Union: a review. Procedia Technology, 19, 371-378.

Bakhsh, S., Yin, H., & Shabir, M. (2021). Foreign investment and CO2 emissions: do technological innovation and institutional quality matter? Evidence from system GMM approach. Environmental Science and Pollution Research, 28(15), 19424-19438.

Bakırcı, F. (2018), Knowledge and innovation economy: An evaluation of turkey, in ‘German-Turkish Perspectives on IT and Innovation Management: Challenges and Approaches’, Springer, pp. 21–42.

Baltagi, B. H. (2008). Econometric analysis of panel data (Vol. 4). Chichester: Wiley.

Balzat, M. and Hanusch, H. (2004). Recent trends in the research on national innovation systems. Journal of evolutionary economics 14, 197–210.

Banerjee, A. V. and Duflo, E. (2005). Growth theory through the lens of development economics. Handbook of economic growth 1, 473–552.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management science, 30(9), 1078-1092.

Bano, S., & Taylor, J. (2015). Universities and the knowledge-based economy: Perceptions from a developing country. Higher Education Research & Development, 34(2), 242-255.

Bardhan, I., WF, B., WW, C., & Sueyoshi, T. (1996). Models and measures for efficiency dominance in DEA part I: additive models and MED measures. Journal of the operations Research Society of Japan, 39(3), 322-332.

Bardhan, P. (1995). The contributions of endogenous growth theory to the analysis of development problems: an assessment. Handbook of Development Economics, 3, 2983-2998.

Bariş, S. (2019). Innovation and institutional quality: Evidence from OECD countries. Global Journal of Business, Economics and Management: Current Issues, 9(3), 165-176.

Barkhordari, S., Fattahi, M., & Azimi, N. A. (2019). The impact of knowledge-based economy on growth performance: Evidence from MENA countries. Journal of the Knowledge Economy, 10(3), 1168-1182.

Barr, R. S. (2004). DEA software tools and technology. In Handbook on data envelopment analysis (pp. 539-566). Springer, Boston, MA.

Barra, C., & Ruggiero, N. (2022). How do dimensions of institutional quality improve Italian regional innovation system efficiency? The Knowledge production function using SFA. Journal of Evolutionary Economics, 32(2), 591-642.

Barrichello, A., dos Santos, E. G., & Morano, R. S. (2020). Determinant and priority factors of innovation for the development of nations. Innovation & Management Review, 17(3), 307-320.

Bashir, M. (2013a). Knowledge economy index (KEI) 2012 rankings for Islamic countries and assessment of KEI indicators for Pakistan. International Journal of Academic Research in Economics and Management Sciences, 2(6), 28.

Bashir, M. (2013b). Knowledge-based Economy (KBE) Frameworks and Investigation of KBE Input-output Indicators for Pakistan. Science, 2(8).

Baskarada, S., & Koronios, A. (2013). Data, information, knowledge, wisdom (DIKW): A semiotic theoretical and empirical exploration of the hierarchy and its quality dimension. Australasian Journal of Information Systems, 18(1).

Bastani, M., Ketabi, S., Maddahi, R., & Ahari, R. M. (2021). Data Envelopment Analysis in the Presence of Correlated Evaluation Variables. Jordan Journal of Mechanical & Industrial Engineering, 15(3).

Batagan, L. (2007). Indicators for Knowledge Economy. Informatica Economica, 11(4), 60-63.

Bate, A. F., Wachira, E. W., & Danka, S. (2023). The determinants of innovation performance: an income-based cross-country comparative analysis using the Global Innovation Index (GII). Journal of Innovation and Entrepreneurship, 12(1), 1-27.

Bell, D. (1973). The coming of postindustrial society. New york: Basic books.

Belloc, F. (2012). Corporate governance and innovation: A survey. Journal of Economic Surveys, 26(5), 835-864.

Belussi, F., & Caldari, K. (2009). At the origin of the industrial district: Alfred Marshall and the Cambridge school. Cambridge Journal of economics, 33(2), 335-355.

Bemelmans-Videc, M. L., Rist, R. C., & Vedung, E. (2017). Policy instruments: typologies and theories. In Carrots, sticks & sermons (pp. 21-58). Routledge.

Bemelmans-Videc, M. L., Rist, R. C., & Vedung, E. O. (Eds.). (2011). Carrots, sticks, and sermons: Policy instruments and their evaluation (Vol. 1). Transaction Publishers.

Ben Hassen, T. (2020), The state of the knowledge-based economy in the Arab world: cases of Qatar and Lebanon. EuroMed Journal of Business 16(2), 129–153.

Benhabib, J., & Spiegel, M. M. (1994). The role of human capital in economic development evidence from aggregate cross-country data. Journal of Monetary economics, 34(2), 143-173.

Benhabib, J., & Spiegel, M. M. (2000). The role of financial development in growth and investment. Journal of economic growth, 5, 341-360.

Benítez, R., Coll-Serrano, V., & Bolós, V. J. (2021). deaR-Shiny: An Interactive Web App for Data Envelopment Analysis. Sustainability, 13(12), 6774.

Bento, N., Sousa, C., Trindade, P., Mamede, R. P., Fontes, M., & Alves, T. (2022). Robust relation between public procurement for innovation and economic development. Economics Letters, 211, 110241.

Berger, M., & Diez, J. R. (2008). Can host innovation systems in late industrializing countries benefit from the presence of transnational corporations? Insights from Thailand's manufacturing industry. European Planning Studies, 16(8), 1047-1074.

Bettencourt, L. M., Trancik, J. E., & Kaur, J. (2013). Determinants of the pace of global innovation in energy technologies. PloS one, 8(10), e67864.

Bindé, J. (2005). Towards knowledge societies: UNESCO world report.

Blind, K. (2009). Standardisation as a Catalyst for Innovation.

Blind, K. (2012). The impact of regulation on innovation: Compendium of evidence on the effectiveness of innovation policy intervention. Manchester Institute of Innovation Research, Manchester Business School, University of Manchester.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of econometrics, 87(1), 115-143.

Boekholt, P. (2010). The evolution of innovation paradigms and their influence on research, technological development and innovation policy instruments. In The Theory and Practice of Innovation Policy. Edward Elgar Publishing.

Bokachev, I. N. (2020). The process of a national innovation system concept formulation: Key problems. RUDN Journal of Economics, 28(1), 98-109.

Bond, S. R. (2002). Dynamic panel data models: a guide to micro data methods and practice. Portuguese economic journal, 1, 141-162.

Boni, A., Giachi, S., & Molas-Gallart, J. (2019). Towards a framework for transformative innovation policy evaluation. TIPC Research Report. Science Policy Research Unit (SPRU), University of Sussex Business School.

Boon, T. H., Foong, W. M., & Hon, L. Y. (2014). Efficiency And Productivity Gains in Knowledge-Based Production: The Case Of East Asian Economies. Economic Studies, 23(2).

Borrás, S., & Edquist, C. (2013). The choice of innovation policy instruments. Technological forecasting and social change, 80(8), 1513-1522.

Borrás, S., & Laatsit, M. (2019). Towards system-oriented innovation policy evaluation? Evidence from EU28 member states. Research Policy, 48(1), 312-321.

Boschma, R. (2005). Role of proximity in interaction and performance: Conceptual and empirical challenges.

Bouchoucha, N. and Benammou, S. (2020). Does institutional quality matter foreign direct investment? evidence from african countries. Journal of the Knowledge Economy 11, 390–404.

Boudreaux, C. J. (2017). Institutional quality and innovation: some cross-country evidence. Journal of Entrepreneurship and Public Policy.

Boukerche, A., Zheng, L., & Alfandi, O. (2020). Outlier detection: Methods, models, and classification. ACM Computing Surveys (CSUR), 53(3), 1-37.

Bound, J., Jaeger, D. A., & Baker, R. M. (1995). Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. Journal of the American statistical association, 90(430), 443-450.

Boussetta, O., Aissaoui, N., & Sellaouti, F. (2022). MENA Countries Face the Challenge of the Knowledge-Based Economy. In Cases on Applying Knowledge Economy Principles for Economic Growth in Developing Nations (pp. 150-202). IGI Global.

Bowlin, W. F. (1998). Measuring performance: An introduction to data envelopment analysis (DEA). The Journal of Cost Analysis, 15(2), 3-27.

Bratianu, C. (Ed.). (2015). Organizational knowledge dynamics: Managing knowledge creation, acquisition, sharing, and transformation: Managing knowledge creation, acquisition, sharing, and transformation. IGI Global.

Braunerhjelm, P., Acs, Z. J., Audretsch, D. B., & Carlsson, B. (2010). The missing link: knowledge diffusion and entrepreneurship in endogenous growth. Small Business Economics, 34, 105-125.

Breitenecker, R. J., Harms, R., Weyh, A., Maresch, D., & Kraus, S. (2017). When the difference makes a difference–the regional embeddedness of entrepreneurship. Entrepreneurship & Regional Development, 29(1-2), 71-93.

Breuss, F., Luptacik, M., & Mahlberg, B. (2000). How far away are the CEECs from the EU economic standards. A Data Envelopement Analysis of the economic performance of the CEECs. In EI Working Papers/Europainstitut, 35. Vienna: Vienna University of Economics and Business.

Bring, J. (1994). How to standardize regression coefficients. The American Statistician, 48(3), 209-213.

Brinkley, I. (2006). Defining the knowledge economy (Vol. 19). London: The work foundation.

Brinkley, I. (2008), The knowledge economy: How knowledge is reshaping the economic life of nations, Work Foundation.

Brockmann, C., & Roztocki, N. (2017). The six pillars of knowledge economics.

Brown, C., & Thornton, M. (2013). How entrepreneurship theory created economics. Quarterly Journal of Austrian Economics, 16(4).

Bruhn, N. C. P., Calegario, C. L. L., & Mendonça, D. (2020). Foreign direct investment in developing economies A study on the productivity spillover effects in Latin America. RAUSP Management Journal, 55, 40-54.

Bryl, Ł. (2012). Measurement Methods of New Economy-Macroeconomic Level. Comparative Analysis. Zeszyty Naukowe/Uniwersytet Ekonomiczny w Poznaniu, (246), 253-267.

Brynjolfsson, E. and Hitt, L. M. (2000). Beyond computation: Information tech nology, organizational transformation and business performance. Journal of Economic perspectives 14(4), 23–48.

Bučar, M. (2003). Slovenia's potential for knowledge-based economy with foucs on R&D and innovation policy.

Buesa, M., Heijs, J., & Baumert, T. (2010). The determinants of regional innovation in Europe: A combined factorial and regression knowledge production function approach. Research policy, 39(6), 722-735.

Burange, L. G., Ranadive, R. R., & Karnik, N. N. (2019). Trade openness and economic growth nexus: A case study of BRICS. Foreign Trade Review, 54(1), 1-15.

Burdenko, E. V. and Mudrova, S. V. (2018), Indicators system as a measure of development level of knowledge economy: Application of world bank methodology, in 'Global Practices in Knowledge Management for Societal and Organizational Development', IGI Global, pp. 74–105.

Burnett, D. (2000). The supply of entrepreneurship and economic development. com : http://www. asiaentrepreneurshipjournal. Com/AJESII-I1Adegbite. pdf [10-04-12].

Bush, V. (1945). Science, the endless frontier: Washington. DC: US Government.

Cader, H. A. (2008). The evolution of the knowledge economy. Journal of Regional Analysis and Policy, 38(1100-2016-90010).

Cameron, A. C., & Trivedi, P. K. (2005). Micro econometrics: methods and applications. Cambridge university press.

Camisón-Zornoza, C., Lapiedra-Alcamí, R., Segarra-Ciprés, M., & Boronat-Navarro, M. (2004). A meta-analysis of innovation and organizational size. Organization studies, 25(3), 331-361.

Campos, J. E., Lien, D., & Pradhan, S. (1999). The impact of corruption on investment: Predictability matters. World development, 27(6), 1059-1067.

Canh, N. P., Schinckus, C., & Thanh, S. D. (2019). Do economic openness and institutional quality influence patents? Evidence from GMM systems estimates. International Economics, 157, 134-169.

Capello, R. (1999). Spatial transfer of knowledge in high technology milieux: learning versus collective learning processes. Regional studies, 33(4), 353-365.

Capello, R., & Faggian, A. (2005). Collective learning and relational capital in local innovation processes. Regional studies, 39(1), 75-87.

Capello, R., & Lenzi, C. (2018). Regional innovation patterns from an evolutionary perspective. Regional Studies, 52(2), 159-171.

Carayannis, E. G., Grigoroudis, E., & Goletsis, Y. (2016). A multilevel and multistage efficiency evaluation of innovation systems: A multiobjective DEA approach. Expert Systems with Applications, 62, 63-80.

Carlaw, K., Oxley, L., Walker, P., Thorns, D., & Nuth, M. (2006). Beyond the hype: Intellectual property and the knowledge society/knowledge economy. Journal of Economic Surveys, 20(4), 633-690.

Carpenter, M. P., & Narin, F. (1981). The adequacy of the Science Citation Index (SCI) as an indicator of international scientific activity. Journal of the American Society for Information Science, 32(6), 430-439.

Carvalho, N., Carvalho, L., & Nunes, S. (2015). A methodology to measure innovation in European Union through the national innovation system. International Journal of Innovation and Regional Development, 6(2), 159-180.

Casson, M. C. (2003). The entrepreneur: an economic theory 2nd ed. Elgar, Cheltenham.

Castellacci, F., Oguguo, P. C., & Freitas, I. M. B. (2022). Quality of pro-market national institutions and firms' decision to invest in R&D: evidence from developing and transition economies. Eurasian Business Review, 12(1), 35-57.

Cavusoglu, B. (2018, September). Knowledge Based Economy: Where Does North Cyprus Stand? In European Conference on Knowledge Management (pp. 132-XVII). Academic Conferences International Limited.

Ceruti, M., Williams, A., & Bedford, D. (2019). Building Knowledge Capacity for a Knowledge Economy. In Translating Knowledge Management Visions into Strategies (pp. 3-21). Emerald Publishing Limited.

Çetin, M. (2013). The hypothesis of innovation-based economic growth: a causal relationship. Volume (11), 1-16.

Chambers, D., & Munemo, J. (2019). Regulations, institutional quality, and entrepreneurship. Journal of Regulatory Economics, 55, 46-66.

Chaminade, C., Lundvall, B. Å., Vang, J., & Joseph, K. J. (2009). Designing innovation policies for development: towards a systemic experimentation-based approach. In Handbook of innovation systems and developing countries. Edward Elgar Publishing.

Chaminade, C., Lundvall, B.˚A. and Haneef, S. (2018). Advanced introduction to national innovation systems. Edward Elgar Publishing.

Charles, V., Aparicio, J., & Zhu, J. (2019). The curse of dimensionality of decision-making units: A simple approach to increase the discriminatory power of data envelopment analysis. European Journal of Operational Research, 279(3), 929-940.

Charnes, A., Cooper, W. W., & Li, S. (1989). Using data envelopment analysis to evaluate efficiency in the economic performance of Chinese cities. Socio-Economic Planning Sciences, 23(6), 325-344.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. European journal of operational research, 2(6), 429-444.

Charnes, A., Cooper, W. W., Golany, B., Seiford, L., & Stutz, J. (1985). Foundations of data envelopment analysis for Pareto-Koopmans efficient empirical production functions. Journal of econometrics, 30(1-2), 91-107.

Charnes, A., Cooper, W. W., Lewin, A. Y., & Seiford, L. M. (1994A). Extensions to DEA models. In Data envelopment analysis: Theory, methodology, and applications (pp. 49-61). Springer, Dordrecht.

Charnes, A., Cooper, W. W., Lewin, A. Y., & Seiford, L. M. (1994B). DEA software packages. In Data Envelopment Analysis: Theory, Methodology, and Applications (pp. 89-94). Springer, Dordrecht.

Charnes, A., Cooper, W., Lewin, A. Y., & Seiford, L. M. (1997). Data envelopment analysis theory, methodology and applications. Journal of the Operational Research society, 48(3), 332-333.

Chen, C. (2017a). Introduction: A Critical Assessment. In Foreign Direct Investment and the Chinese Economy. Edward Elgar Publishing.

Chen, C. C. (2017b). Measuring departmental and overall regional performance: applying the multi-activity DEA model to Taiwan′ s cities/counties. Omega, 67, 60-80.

Chen, C. J., Wu, H. L., & Lin, B. W. (2006). Evaluating the development of high-tech industries: Taiwan's science park. Technological Forecasting and Social Change, 73(4), 452-465.

Chen, C. K. (2008a). Construct Model of the Knowledge-Based Economy Indicators. Transformations in Business & Economics, 7(2).

Chen, C. K. (2008b). Causal modeling of knowledge-based economy. Management Decision.

Chen, C. K. (2010). Short-form knowledge-based economy scorecards. Journal of Information and Optimization Sciences, 31(4), 789-807.

Chen, C. P., Hu, J. L., & Yang, C. H. (2011). An international comparison of R&D efficiency of multiple innovative outputs: The role of the national innovation system. Innovation, 13(3), 341-360.

Chen, D. H., & Dahlman, C. J. (2005). The knowledge economy, the KAM methodology and World Bank operations. World Bank Institute Working Paper, (37256).

Chen, T. Y., & Yeh, T. L. (1998). A study of efficiency evaluation in Taiwan’s banks. International Journal of Service Industry Management.

Cheng, G. (2014). Data envelopment analysis: methods and Max-DEA software. Beijing: Publishing House Co. Ltd.

Cheng, G., Qian, Z., & Zervopoulos, P. (2011). Overcoming the infeasibility of super-efficiency DEA model: A model with generalized orientation.

Cheng, G., Zervopoulos, P., & Qian, Z. (2013). A variant of radial measure capable of dealing with negative inputs and outputs in data envelopment analysis. European Journal of Operational Research, 225(1), 100-105.

Cherchye, L., Moesen, W., Rogge, N., & Van Puyenbroeck, T. (2011). Constructing composite indicators with imprecise data: A proposal. Expert Systems with Applications, 38(9), 10940-10949.

Chesher, A. (1979). Testing the law of proportionate effect. The Journal of industrial economics 27(4), 403–411.

Chi-ang Lin, B. (2007). A new vision of the knowledge economy. Journal of Economic Surveys, 21(3), 553-584.

Choi, H., & Zo, H. (2019). Assessing the efficiency of national innovation systems in developing countries. Science and Public Policy, 46(4), 530-540.

Choi, S. B., Park, B. I., & Hong, P. (2012). Does ownership structure matter for firm technological innovation performance? The case of Korean firms. Corporate Governance: An International Review, 20(3), 267-288.

Choong, K. K., & Leung, P. W. (2021). A critical review of the precursors of the knowledge economy and their contemporary research: implications for the computerized new economy. Journal of the Knowledge Economy, 1-38.

Christopoulos, D. K. (2007). Explaining country's efficiency performance. Economic Modelling, 24(2), 224-235.

Chun, D., Chung, Y., & Bang, S. (2015). Impact of firm size and industry type on R&D efficiency throughout innovation and commercialisation stages: evidence from Korean manufacturing firms. Technology Analysis & Strategic Management, 27(8), 895-909.

Clermont, M., & Schaefer, J. (2019). Identification of outliers in data envelopment analysis. Schmalenbach Business Review, 71(4), 475-496.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. Administrative science quarterly, 128-152.

Cole, M. A. (2004). Trade, the pollution haven hypothesis and the environmental Kuznets curve: examining the linkages. Ecological economics, 48(1), 71-81.

Coleman, J. S. (1988). Social capital in the creation of human capital. American journal of sociology, 94, S95-S120.

Collin, E., Sandström, C., & Wennberg, K. (2022). Evaluating Evaluations of Innovation Policy: Exploring Reliability, Methods, and Conflicts of Interest. Questioning the Entrepreneurial State, 157.

Collins, J. M., & Troilo, M. L. (2015). National factor effects on firm competitiveness and innovation. Competitiveness Review. comparative analysis', Zeszyty Naukowe/Uniwersytet Ekonomiczny w Poznaniu (246), 253–267.

Conceicao, P., & Heitor, M. V. (1999). On the role of the university in the knowledge economy. Science and Public Policy, 26(1), 37-51.

Connolly, M. (2003). The dual nature of trade: measuring its impact on imitation and growth. Journal of Development Economics, 72(1), 31-55.

Cook, W. D., & Seiford, L. M. (2009). Data envelopment analysis (DEA)–Thirty years on. European journal of operational research, 192(1), 1-17.

Cook, W. D., & Zhu, J. (2007). Classifying inputs and outputs in data envelopment analysis. European journal of operational research, 180(2), 692-699.

Cook, W. D., Harrison, J., Imanirad, R., Rouse, P., & Zhu, J. (2015). Data envelopment analysis with non-homogeneous DMUs. In Data Envelopment Analysis (pp. 309-340). Springer, Boston, MA.

Cooper, W. W., Park, K. S., & Pastor, J. T. (1999). RAM: a range adjusted measure of inefficiency for use with additive models, and relations to other models and measures in DEA. Journal of Productivity analysis, 11(1), 5-42.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). Data envelopment analysis: a comprehensive text with models, applications, references, and DEA-solver software (Vol. 2, p. 489). New York: Springer.

Cooper, W.W., Seiford, L.M. & Zhu, J. (Eds.) (2004). Handbook on Data Envelopment Analysis. Boston: Kluwer Academic

Cortright, J. (2001). New growth theory, technology and learning: A practitioner's guide, Portland, OR: Impresa.

Council, P. (2007). Turning Qatar into a Competitive Knowledge-Based Economy. Government of Qatar Planning, Qatar Knowledge Economy Project

Cowan, R., David, P. A., & Foray, D. (2000). The explicit economics of knowledge codification and tacitness. Industrial and corporate change, 9(2), 211-253.

Cowen, T., & Tabarrok, A. (2009). Modern principles of economics. Macmillan.

Coyle, D., & Quah, D. (2002). Getting the measure of the new economy. London: Work Foundation.

Crisan, D. (2020). Buying with Intent: Public Procurement for Innovation by Provincial and Municipal Governments. The School of Public Policy Publications.

Crivits, M., de Krom, M. P., Dessein, J., & Block, T. (2014). Why innovation is not always good: innovation discourses and political accountability. Outlook on AGRICULTURE, 43(3), 147-155.

Crnogaj, K., & Bradač Hojnik, B. (2016). Institutional determinants and entrepreneurial action. Management: Journal of Contemporary Management Issues, 21(Special issue), 131-150.

Cullinane, K., Ji, P., & Wang, T. F. (2005). The relationship between privatization and DEA estimates of efficiency in the container port industry. Journal of economics and business, 57(5), 433-462.

Cullman, A., Schmidt-Ehmcke, J., & Zloczysti, P. (2009). Innovation, R&D Efficiency and the Impact of the Regulatory Environment: A Two Stage Semi-Parametric DEA Approach. German Institute for Economic Research: Discussions Papers of DIW Berlin, 883.

Cunningham, P. (2009). Demand-side innovation policies, Policy Brief No. 1. Pro Inno Europe, Inno Policy Trendchart.

D'Este, P., Rentocchini, F. and VegaJurado, J. (2014). The role of human capital in lowering the barriers to engaging in innovation: evidence from the spanish innovation survey. Industry and innovation 21(1), 1–19.

D'Ingiullo, D., & Evangelista, V. (2020). Institutional quality and innovation performance: evidence from Italy. Regional Studies, 54(12), 1724-1736.

Dahlman, C. and Andersson, T. (2000). Korea and the knowledge-based economy making the transition: Making the transition. OECD publishing.

Dahlman, C. J. and Aubert, J.E. (2001). China and the knowledge economy: Seizing the 21st century. World Bank Publications.

Dahlman, C. J. and Utz, A. (2005). India and the knowledge economy: leveraging strengths and opportunities. World Bank Publications.

Damanpour, F. and Gopalakrishnan, S. (2001). The dynamics of the adoption of product and process innovations in organizations, Journal of management studies 38(1), 45–65.

Daniele, V., & Marani, U. (2011). Organized crime, the quality of local institutions and FDI in Italy: A panel data analysis. European Journal of Political Economy, 27(1), 132-142.

Daraio, C., Kerstens, K. H., Nepomuceno, T. C. C., & Sickles, R. (2019). Productivity and efficiency analysis software: an exploratory bibliographical survey of the options. Journal of Economic Surveys, 33(1), 85-100.

Dašić, P., Dašić, J., Antanasković, D., & Pavićević, N. (2020). Statistical analysis and modeling of global innovation index (GII) of Serbia. In New Technologies, Development and Application III 6 (pp. 515-521). Springer International Publishing.

Daugėlienė, R. (2004). Towards knowledge-based economy: Modelling knowledge expression assessment. European Union Enlargement of, 451-469.

David, P. A. and Foray, D. (1995), Accessing and expanding the science and tech nology knowledge base, technical report.

David, P. A., & Foray, D. (2003). Economic fundamentals of the knowledge society. Policy futures in education, 1(1), 20-49.

Dawid, H., Pellegrino, G. and Vivarelli, M. (2021). The role of demand in fostering product vs process innovation: a model and an empirical test. Journal of Evolutionary Economics 31, 1553–1572.

De Mello Jr, L. R. (1997). Foreign direct investment in developing countries and growth: A selective survey. The journal of development studies, 34(1), 1-34.

De Waldemar, F. S. (2012). New products and corruption: evidence from Indian firms. The Developing Economies, 50(3), 268-284.

Debreu, G. (1951). The coefficient of resource utilization. Econometrica: Journal of the Econometric Society, 273-292.

Dehnokhalaji, A., Khezri, S., & Emrouznejad, A. (2022). A box-uncertainty in DEA: A robust performance measurement framework. Expert Systems with Applications, 187, 115855.

Deliktas, E., & Balcilar, M. (2005). A comparative analysis of productivity growth, catch-up, and convergence in transition economies. Emerging Markets Finance and Trade, 41(1), 6-28.

Dellnitz, A., Kleine, A., & Rödder, W. (2018). CCR or BCC: what if we are in the wrong model? Journal of Business Economics, 88(7), 831-850.

Demir, O., Genc, E. G., Alp, E. A., & Yildirim, F. (2015). A new knowledge society index: Global tendencies and an analysis of Turkey. Educational Sciences: Theory & Practice, 15(2).

Demircioglu, M. A., & Vivona, R. (2021). Positioning public procurement as a procedural tool for innovation: an empirical study. Policy and Society, 40(3), 379-396.

Department for Business, Energy & Industrial Strategy (2021). UK innovation survey, available at: https://www.gov.uk/government/collections/uk-innovation-survey

Desai, S. (2011). Measuring entrepreneurship in developing countries. In Entrepreneurship and economic development (pp. 94-107). London: Palgrave Macmillan UK.

Despotis, D. K. (2005). Measuring human development via data envelopment analysis: the case of Asia and the Pacific. Omega, 33(5), 385-390.

Dharmapala, P. S. (2021). Detecting outliers in DEA after correcting biases in efficiency scores using simulated beta samples. International Journal of Mathematics in Operational Research, 19(3), 387-400.

Di Stefano, G., Gambardella, A., & Verona, G. (2012). Technology push and demand-pull perspectives in innovation studies: Current findings and future research directions. Research policy, 41(8), 1283-1295.

Diaconu, M. (2011). Technological Innovation: Concept, Process, Typology and Implications in the Economy. Theoretical & Applied Economics, 18(10).

Dima, A. M., Begu, L., Vasilescu, M. D., & Maassen, M. A. (2018). The relationship between the knowledge economy and global competitiveness in the European Union. Sustainability, 10(6), 1706.

Dincer, O. (2019). Does corruption slow down innovation? evidence from a co-integrated panel of us states, European Journal of Political Economy 56, 1–10.

Diskaya, F., Emir, S., & Orhan, N. (2011). Measuring the technical efficiency of telecommunication sector within global crisis: comparison of G8 countries and Turkey. Procedia-Social and Behavioral Sciences, 24, 206-218.

Diyamett, B. D. (2009). Building systems of innovation in an African setting: the cluster initiative development approach. African journal of science, technology, innovation and development, 1(1), 167-189.

Doğan, E. (2016). The effect of innovation on competitiveness. Istanbul University Econometrics and Statistics e-Journal, (24), 60-81.

Dollar, D., & Kraay, A. (2003). Institutions, trade, and growth. Journal of monetary economics, 50(1), 133-162.

Donlagic, S., Fazlic, S., & Nuhanovic, A. (2015). Introducing a Framework for Knowledge Economy Development in Transition Countries: The Case of Bosnia and Herzegovina. Ekonomski Vjesnik, 28(1), 257.

Dosi, G. (1982). Technological paradigms and technological trajectories: a suggested interpretation of the determinants and directions of technical change. Research policy, 11(3), 147-162.

Dosi, G., Freeman, C., Nelson, R., Silverberg, G., & Soete, L. (1988). Technical change and economic theory. Laboratory of Economics and Management (LEM), Sant'Anna School of Advanced Studies, Pisa, Italy.

Dowrick, S., & Rogers, M. (2002). Classical and technological convergence: Beyond the Solow-Swan growth model. Oxford Economic Papers, 54(3), 369-385.

Doyle, J., & Green, R. (1994). Efficiency and cross-efficiency in DEA: Derivations, meanings and uses. Journal of the Operational Research Society, 45(5), 567-578.

Doytch, N. (2012). FDI and entrepreneurship in developing countries. GSTF Business Review (GBR), 1(3), 120.

Driouchi, A., Azelmad, E. M., & Anders, G. C. (2006). An econometric analysis of the role of knowledge in economic performance. The Journal of Technology Transfer, 31(2), 241-255.

Droit, R. P. (2005). Towards knowledge societies (Vol. 1). Unesco.

Drucker, P. F. (1969). The Age of Discontinuity (1969). Unter: http://www. peter. drucker. at.

Drucker, P. F. (1993). Postcapitalist society. new york: Harperbusiness, 1993), Chapter 6, 123.

Đsmail, S. E. K. Đ. (2008). The importance of ICT for the knowledge economy: A total factor productivity analysis for selected OECD countries. Emerging Economic Issues in a Globalizing World, 72.

Du, J., Liang, L., & Zhu, J. (2010). A slacks-based measure of super-efficiency in data envelopment analysis: a comment. European Journal of Operational Research, 204(3), 694-697.

Du, Z. (2018). A literature review on institutional environment and technological innovation. American Journal of Industrial and Business Management, 8(9), 1941-1950.

Dutta, S., Lanvin, B., & Wunsch-Vincent, S. (Eds.). (2016). Global Innovation Index 2016: Winning the Global Innovation. WIPO.

Dutta, S., Lanvin, B., & Wunsch-Vincent, S. (Eds.). (2020). Global innovation index 2020. Johnson Cornell University.

Dyson, R. G., Allen, R., Camanho, A. S., Podinovski, V. V., Sarrico, C. S., & Shale, E. A. (2001). Pitfalls and protocols in DEA. European Journal of operational research, 132(2), 245-259.

Dziallas, M., & Blind, K. (2019). Innovation indicators throughout the innovation process: An extensive literature analysis. Technovation, 80, 3-29.

ECE, U. (2002). Towards a knowledge-based economy: Georgia: country readiness assessment report.

Edler, J. (2013). Review of policy measures to stimulate private demand for innovation. Concepts and effects. Compendium of evidence on the effectiveness of innovation policy intervention, 13, 44.

Edler, J. (2016). The impact of policy measures to stimulate private demand for innovation. Handbook of innovation policy impact.

Edler, J. and Georghiou, L. (2007). Public procurement and innovation—resurrecting the demand side, Research policy 36(7), 949–963.

Edler, J., & Fagerberg, J. (2017). Innovation policy: what, why, and how. Oxford Review of Economic Policy, 33(1), 2-23.

Edler, J., Berger, M., Dinges, M., & Gök, A. (2012). The practice of evaluation in innovation policy in Europe. Research Evaluation, 21(3), 167-182.

Edler, J., Cunningham, P., Gök, A., Rigby, J., Amanatidou, E., Garefi, I., ... & Guy, K. (2010). INNO-Appraisal. Understanding Evaluation of Innovation Policy in Europe.

Edler, J., Georghiou, L., Uyarra, E., & Yeow, J. (2015). The meaning and limitations of public procurement for innovation: a supplier's experience. In Public procurement for innovation (pp. 35-64). Edward Elgar Publishing.

Edler, J., Gök, A., Cunningham, P., & Shapira, P. (2016a). Introduction: Making sense of innovation policy. In Handbook of Innovation Policy Impact (pp. 1-

17). Edward Elgar Publishing.

Edler, J., Shapira, P., Cunningham, P., & Gök, A. (2016b). Conclusions: Evidence on the effectiveness of innovation policy intervention. In Handbook of Innovation Policy Impact (pp. 543-564). Edward Elgar Publishing.

Edquist, C. (1997). Systems of innovation approaches–their emergence and characteristics. Systems of innovation: Technologies, institutions, and organizations, 1989, 1-35.

Edquist, C. (2011). Design of innovation policy through diagnostic analysis: identification of systemic problems (or failures). Industrial and corporate change, 20(6), 1725-1753.

Edquist, C., & Hommen, L. (2000). Public technology procurement and innovation theory. In Public technology procurement and innovation (pp. 5-70). Springer, Boston, MA.

Edquist, C., & Zabala-Iturriagagoitia, J. M. (2012). Public Procurement for Innovation as mission-oriented innovation policy. Research policy, 41(10), 1757-1769.

Edwards, D., Hudson, H., Anderson, C., McGee, R., & Brock, K. (2018). Supporting innovation and the use of technologies in accountability initiatives: lessons from Making All Voices Count

Efendic, A., Pugh, G., & Adnett, N. (2009). Institutions and economic performance: System GMM modelling of institutional effects in transition. Unpublished Paper, Staffordshire University Business School, Stoke-on-Trent, UK. Accessed June 10, 2009.

Ege, A., & Ege, A. Y. (2019). How to create a friendly environment for innovation? A case for Europe. Social indicators research, 144(1), 451-473.

Ejdemo, T., & Örtqvist, D. (2021). Exploring a leading and lagging regions dichotomy: does entrepreneurship and diversity explain it? Journal of Innovation and Entrepreneurship, 10(1), 1-26.

El Hadidi, H. H., & Kirby, D. A. (2017). University–industry collaboration in a factor-driven economy: The perspective of Egyptian industry. Industry and Higher Education, 31(3), 195-203.

El Harbi, S., & Anderson, A. R. (2010). Institutions and the shaping of different forms of entrepreneurship. The Journal of socioeconomics, 39(3), 436-444.

Elhini, M., & Mourad, Y. (2022). The relationship between knowledge-based economies and economic growth: an empirical analysis on the Asia-Pacific region 2011–2018. Journal of Chinese Economic and Foreign Trade Studies.

Emrouznejad, A., & Yang, G. L. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. Socio-economic planning sciences, 61, 4-8.

Emrouznejad, A., Tavana, M., & Hatami-Marbini, A. (2014). The state of the art in fuzzy data envelopment analysis. In Performance measurement with fuzzy data envelopment analysis (pp. 1-

Erdal, L., & Göçer, İ. (2015). The effects of foreign direct investment on R&D and innovations: Panel data analysis for developing Asian countries. Procedia-

Social and Behavioral Sciences, 195, 749-758.

Ergas, H. (1986). Does technology policy matter? Available at SSRN 1428246.

Erika, K.M. and Watu, W. (2010), Innovation and the development agenda, OECD Publishing.

ESCWA, U. (2014). Arab integration: a 21st century development imperative.

Esmaeeli, J., Amiri, M., & Taghizadeh, H. (2021). A new approach in the DEA technique for measurement of productivity of decision-making units through efficiency and effectiveness. Scientia Iranica.

European Commission, Directorate-General for Research, and Innovation, (2016). Supply and demand side innovation policies: first policy brief, Publications Office. https://data.europa.eu/doi/10.2777/298996

European Commission. (2013). Lessons from a Decade of Innovation Policy—What Can Be Learnt from the INNO Policy Trend Chart and the Innovation Union Scoreboard.

Evangelista, R., & Sirilli, G. (1995). Measuring innovation in services. Research evaluation, 5(3), 207-215.

Fagerberg, I., 2014. Innovation Policy: In Search for a Useful Theoretical Framework. Presentation at the Lundvall Symposium, Aalborg

Fagerberg, J. (2003). Schumpeter and the revival of evolutionary economics: an appraisal of the literature. Journal of evolutionary economics, 13(2), 125-159.

Fagerberg, J. (2015). Innovation policy, national innovation systems and economic performance: In search of a useful theoretical framework. Working Papers on Innovation Studies, 20150321.

Fagerberg, J. (2017). Innovation policy: Rationales, lessons and challenges. Journal of Economic Surveys, 31(2), 497-512.

Fagerberg, J., & Sapprasert, K. (2011). National innovation systems: the emergence of a new approach. Science and public policy, 38(9), 669-679.

Fagerberg, J., Laestadius, S., & Martin, B. R. (2016). The triple challenge for Europe: the economy, climate change, and governance. Challenge, 59(3), 178-204.

Fan, P. (2011). Innovation capacity and economic development: China and India. Economic change and restructuring, 44(1), 49-73.

Fang, V. W., Tian, X., & Tice, S. (2014). Does stock liquidity enhance or impede firm innovation? The Journal of finance, 69(5), 2085-2125.

Färe, R., Grosskopf, S., & Lovell, C. K. (1985). The measurement of efficiency of production (Vol. 6). Springer Science & Business Media.

Färe, R., Grosskopf, S., & Whittaker, G. (2007). Network DEA. In Modeling data irregularities and structural complexities in data envelopment analysis (pp. 209-240). Springer, Boston, MA.

Farrell, M. J. (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society: Series A (General), 120(3), 253-281.

Fartash, K., Jahangirnia, M., & Sadabadi, A. A. (2021). Three frames for innovation policy: R&D, systems of innovation and transformative change. Science and Technology Policy Letters, 11(2), 152-178.

Feldman, M. P., & Link, A. N. (Eds.). (2001). Innovation policy in the knowledge-based economy (Vol. 23). Springer Science & Business Media

Fernandes, A. J., & Ferreira, J. J. (2022). Entrepreneurial ecosystems and networks: a literature review and research agenda. Review of Managerial Science, 16(1), 189-247.

Fernández, S., Torrecillas, C., & Labra, R. E. (2021). Drivers of eco-innovation in developing countries: the case of Chilean firms. Technological Forecasting and Social Change, 170, 120902.

Fernandez-Palacin, F., Lopez-Sanchez, M. A., & Munõz-Márquez, M. (2018). Stepwise selection of variables in DEA using contribution loads. Pesquisa Operacional, 38, 31-52.

Ferrier, G. D., Kerstens, K., & Eeckaut, P. V. (1994). Radial and nonradial technical efficiency measures on a DEA reference technology: a comparison using US banking data. Recherches Économiques de Louvain/Louvain Economic Review, 60(4), 449-479.

Filippetti, A., & Guy, F. (2020). Labor market regulation, the diversity of knowledge and skill, and national innovation performance. Research Policy, 49(1), 103867.

Filippetti, A., Frenz, M., & Ietto-Gillies, G. (2017). The impact of internationalization on innovation at countries' level: The role of absorptive capacity. Cambridge Journal of economics, 41(2), 413-439.

Firsova, A., Chernyshova, G., & Tugusheva, R. (2022). Approaches to Efficiency Assessing of Regional Knowledge-Intensive Services Sector Development Using Data Envelopment Analysis. Mathematics, 10(2), 173.

Flanagan, K., & Uyarra, E. (2016). Four dangers in innovation policy studies–and how to avoid them. Industry and Innovation, 23(2), 177-188.

Flanagan, K., Uyarra, E., & Laranja, M. (2011). Reconceptualising the 'policy mix 'for innovation. Research policy, 40(5), 702-713.

Foddi, M., & Usai, S. (2013). Technological catching up among European regions. Lessons from Data Envelopment Analysis (Vol. 2). SEARCH WORKING PAPER, paper No. WP4.

Fontana, R., & Guerzoni, M. (2008). Incentives and uncertainty: an empirical analysis of the impact of demand on innovation. Cambridge Journal of Economics, 32(6), 927-946.

Foray, D. (2004). Economics of knowledge. MIT press.

Foray, D., & Mairesse, J. (2001). The Remarkable Properties of Knowledge as an Economic Good: a Note. Hec.Edu,

Førsund, F. R., & Sarafoglou, N. (2002). On the origins of data envelopment analysis. Journal of Productivity Analysis, 17(1), 23-40.

Foss, N. J. (2002). Economic organization in the knowledge economy: An Austrian perspective. Entrepreneurship and the Firm: Austrian Perspectives on Economic Organization, 48-71.

Foxon, T. J. (2005). Inducing innovation for a low carbon future: drivers, barriers, and policies.

Fredström, A., Peltonen, J., & Wincent, J. (2021). A country-level institutional perspective on entrepreneurship productivity: The effects of informal economy and regulation. Journal of Business Venturing, 36(5), 106002.

Freeman, C. (1987). Technology policy and economic performance/C. London: London Printer.

Freeman, C., & Perez, C. (1988). Structural crises of adjustment: business cycles. Technical change and economic theory. Londres: Pinter.

Frické, M. H. (2018). Data-information-knowledge-wisdom (DIKW) pyramid, framework, continuum. Encyclopedia of Big Data, 1-4.

Fu, X., & Yang, Q. G. (2009). Exploring the cross-country gap in patenting: A stochastic frontier approach. Research Policy, 38(7), 1203-1213.

Fukugawa, N. (2018). Theoretical framework for innovation policy in ASEAN. Innovation policy in ASEAN, ERIA Research Project Report. Jakarta: Economic Research Institute for ASEAN and East Asia (ERIA), 23-60.

Furman, J. L., Porter, M. E., & Stern, S. (2002). The determinants of national innovative capacity. Research policy, 31(6), 899-933.

Gabsi, F., M'henni, H., & Koouba, K. (2008). Innovation determinants in emerging countries: an empirical study at the Tunisian firm’s level.

Gale, D. (2007). Linear programming and the simplex method. Notices of the AMS, 54(3), 364-369.

Gao, Y., Zang, L., Roth, A., & Wang, P. (2017). Does democracy cause innovation? An empirical test of the popper hypothesis. Research Policy, 46(7), 1272-1283.

Garcia, C. (2020). Sustainable Knowledge Economy Index. Journal of Educational and Human Research Development 8:1-15

García-Valderrama, T., Mulero-Mendigorri, E., & Revuelta-Bordoy, D. (2009). Relating the perspectives of the balanced scorecard for R&D by means of DEA. European Journal of Operational Research, 196(3), 1177-1189.

Gault, F. (2016, September). Defining and measuring innovation in all sectors of the economy: Policy relevance. In Proceedings of the OECD Blue Sky Forum III, Ghent, Belgium (pp. 19-21).

Gavurová, B., Halásková, M., & Koróny, S. (2019). Research and development indicators of EU28 countries from viewpoint of super-efficiency DEA analysis. Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 67(1), 225-242.

Gentzoglanis, A. (2000). Innovation and Growth in the Knowledge-based Economy. CIENCIA ergo-sum, Revista Científica Multidisciplinaria de Prospectiva, 7(3).

Georghiou, L. (1998). Issues in the evaluation of innovation and technology policy. evaluation, 4(1), 37-51.

Giudici, G., & Paleari, S. (2000). The provision of finance to innovation: a survey conducted among Italian technology-based small firms. Small Business Economics, 14(1), 37-53.

Gocer, I. (2013). Effects of R&D expenditures on high technology exports, balance of foreign trade and economic growth. Maliye Dergisi, 165, 215-240.

Godin, B. (2006). The knowledge-based economy: conceptual framework or buzzword? The Journal of technology transfer, 31(1), 17-30.

Godin, B. (2009). National innovation system: The system approach in historical perspective. Science, Technology, & Human Values, 34(4), 476-501.

Godin, B. (2010). The knowledge economy: Fritz Machlup’s construction of a synthetic concept. In The Capitalization of Knowledge. Edward Elgar Publishing.

Godin, B., & Lane, J. P. (2013). Pushes and pulls: Hi (S) tory of the demand pull model of innovation. Science, Technology, & Human Values, 38(5), 621-654.

Goedhuys, M., Mohnen, P., & Taha, T. (2016). Corruption, innovation and firm growth: firm-level evidence from Egypt and Tunisia. Eurasian Business Review, 6, 299-322.

Gok, A., Li, Y., Cunningham, P., Edler, J., & Laredo, P. (2016). Towards a Taxonomy of Science and Innovation Policy Instruments. Paper presented at 2016 Annual Conference of the Eu-SPRI Forum, Lund, Sweden.

Golany, B., & Roll, Y. (1989). An application procedure for DEA. Omega, 17(3), 237-250.

Golany, B., & Thore, S. (1997). Restricted best practice selection in DEA: An overview with a case study evaluating the socio-economic performance of nations. Annals of Operations Research, 73, 117-140.

Goodridge, P. (2014). Measuring the Contribution of Knowledge. Imperial College Business School, Imperial College London

Gordon, R. J. (2000). Does the “new economy” measure up to the great inventions of the past?, Journal of economic perspectives 14(4), 49–74.

Gorji, E. and Alipourian, M. (2011), The knowledge economy and the knowledge assessment methodology, Iranian Economic Review 15(29), 43–72.

Graham, M., Ojanperä, S., Anwar, M. A., & Friederici, N. (2017). Digital Connectivity and African Knowledge Economies. Questions de communication, (2), 345-360.

Grandia, J., & Meehan, J. (2017). Public procurement as a policy tool: using procurement to reach desired outcomes in society. International Journal of Public Sector Management.

Greenacre, P., Gross, R., & Speirs, J. (2012). Innovation Theory: A review of the literature. Imperial College Centre for Energy Policy and Technology, London.

Griliches, Z. (1979). Issues in Assessing the Contribution of Research and Development to. Bell Journal of Economics, 10, 92-116.

Guaita Martínez, J. M., Martín Martín, J. M., Ostos Rey, M. S., & de Castro Pardo, M. (2020). Constructing Knowledge Economy Composite Indicators using an MCA-DEA approach. Economic Research-Ekonomska Istraživanja, 1-21.

Guan, J., & Chen, K. (2010). Measuring the innovation production process: A cross-region empirical study of China’s high-tech innovations. Technovation, 30(5-6), 348-358.

Guan, J., & Chen, K. (2012). Modeling the relative efficiency of national innovation systems. Research policy, 41(1), 102-115.

Guerzoni, M., & Raiteri, E. (2015). Demand-side vs. supply-side technology policies: Hidden treatment and new empirical evidence on the policy mix. Research Policy, 44(3), 726-747

Guillard, C., & Salazar, M. (2017). The Experience in Innovation Surveys of Selected Latin American Countries. Inter-American Development Bank.

Gujarati, D. N. (2022). Basic econometrics. Prentice Hall.

Guloglu, B., & Tekin, R. B. (2012). A panel causality analysis of the relationship among research and development, innovation, and economic growth in high-income OECD countries. Eurasian Economic Review, 2(1), 32-47.

Gunay, E. N. and Kazazoglu, G. N. (2016). National innovation efficiency during the global crisis: A crosscountry analysis. Springer.

Gürak, H. (2005). Creative Intelligence & Productive Knowledge (Technology) (No. 0508001). University Library of Munich, Germany.

Gust-Bardon, N. I. (2014). Regional development in the context of an innovation process, International Journal of Innovation and Regional Development 5(4 5), 349–366.

Gyekye, A. B., & Oseifuah, E. K. (2015). Knowledge and economic growth: a comparative analysis of three regional blocks in sub-Saharan Africa. Environmental economics, (6, Iss. 4 (contin.)), 196-208.

Hadad, S. (2017). Knowledge Economy: Characteristics and Dimensions. Management Dynamics in the Knowledge Economy. Vol.5 (2017) no.2, pp.203-225; DOI 10.25019/MDKE/5.2.03

Haddad, C. R., & Bergek, A. (2020, August). A functions approach for evaluating transformative innovation policy. In 11th International Sustainability Transitions Conference (online), Vienna, Austria.

Hadhri, W., Arvanitis, R., & M'henni, H. (2016). Determinants of innovation activities in small and open economies: the Lebanese business sector 1. Journal of Innovation Economics & Management, (3), 77-107.

Hakimi, A., & Inglesi-Lotz, R. (2020). Examining the differences in the impact of climate change on innovation between developed and developing countries: evidence from a panel system GMM analysis. Applied Economics, 52(22), 2353-2365.

Halkos, G., & Tzeremes, N. (2005). A DEA approach to regional development. MPRA Paper 3992

Hamidi, S., & Berrado, A. (2017). A framework for National Innovation Determinants. In Proceedings of the International Conference on Industrial Engineering and Operations Management (pp. 1222-1230).

Hamilton, B. H. (2000). Does entrepreneurship pay? An empirical analysis of the returns to self-employment. Journal of Political economy, 108(3), 604-631.

Han, U., Asmild, M., & Kunc, M. (2016). Regional R&D efficiency in Korea from static and dynamic perspectives. Regional Studies, 50(7), 1170-1184.

Hansen, L. P. (1982). Large sample properties of generalized method of moments estimators. Econometrica: Journal of the econometric society, 1029-1054.

Hansen, N. (1992). Competition, trust, and reciprocity in the development of innovative regional milieux. Papers in Regional Science, 71(2), 95-105.

Haq, N. U. (2023). Impact of FDI and Its Absorption Capacity on the National Innovation Ecosystems: Evidence from the Largest FDI Recipient Countries of the World. Foreign Trade Review, 58(2), 259-288.

Harris, R. G. (2001). The knowledge-based economy: intellectual origins and new economic perspectives. International journal of management reviews, 3(1), 21-40.

Harvey, D. (1989). From managerialism to entrepreneurialism: the transformation in urban governance in late capitalism. Geografiska Annaler: series B, human geography, 71(1), 3-17.

Hasan, I., & Tucci, C. L. (2010). The innovation–economic growth nexus: Global evidence. Research policy, 39(10), 1264-1276.

Hausman, A., & Johnston, W. J. (2014). The role of innovation in driving the economy: Lessons from the global financial crisis. Journal of Business Research, 67(1), 2720-2726.

Hausman, J. A. (1978). Specification tests in econometrics. Econometrica: Journal of the econometric society, 1251-1271.

Hayek, F. A. (2009). The use of knowledge in society. In Knowledge management and organizational design (pp. 7-15). Routledge.

Hébert, R. F., & Link, A. N. (1989). In search of the meaning of entrepreneurship. Small business economics, 1(1), 39-49.

Hekkert, M. P., Janssen, M. J., Wesseling, J. H., & Negro, S. O. (2020). Mission-oriented innovation systems. Environmental Innovation and Societal Transitions, 34, 76-79.

Hekkert, M. P., Suurs, R. A., Negro, S. O., Kuhlmann, S., & Smits, R. E. (2007). Functions of innovation systems: A new approach for analysing technological change. Technological forecasting and social change, 74(4), 413-432.

Hey, J. (2004). The data, information, knowledge, wisdom chain: the metaphorical link. Intergovernmental Oceanographic Commission, 26, 1-18.

Hippe, R., & Fouquet, R. (2018). The knowledge economy in historical perspective. World Economics, 18(1), 75-107.

Hjalmarsson, L., Kumbhakar, S. C., & Heshmati, A. (1996). DEA, DFA and SFA: a comparison. Journal of Productivity Analysis, 7(2), 303-327.

Hoff, A. (2007). Second stage DEA: Comparison of approaches for modelling the DEA score. European journal of operational research, 181(1), 425-435.

Hong, S., Reed, W. R., Tian, B., Wu, T., & Chen, G. (2021). Does FDI promote entrepreneurial activities? A meta-analysis. World Development, 142, 105436.

Hoseini, S. A., Fallahpour, A., Wong, K. Y., & Antuchevičienė, J. (2021). Developing an integrated model for evaluating R&D organizations' performance: Combination of dea-anp. Technological and Economic Development of Economy, 27(4), 970-991.

Hossain, A. (2015). Evolution of mutual knowledge-based economy in regional integration: an experience from the Cooperation Council of Arab States of the

Gulf. Journal of the Knowledge Economy, 6(4), 790-817.

Houghton, J., & Sheehan, P. (2000). A primer on the knowledge economy. Victoria University.

Howells, J. (2005). Innovation and regional economic development: A matter of perspective? Research policy, 34(8), 1220-1234.

Howlett, M. (2019). Designing public policies: Principles and instruments. Routledge.

Hsiao, C., & Tahmiscioglu, A. K. (2008). Estimation of dynamic panel data models with both individual and time-specific effects. Journal of Statistical Planning and Inference, 138(9), 2698-2721.

Hsu, M., Luo, X., & Chao, G. H. (2008). The fog of OECD and non-OECD country efficiency: a data envelopment analysis approach. The Journal of Developing Areas, 81-93.

Hu, J. L., Yang, C. H., & Chen, C. P. (2014). R&D efficiency and the national innovation system: An international comparison using the distance function approach. Bulletin of Economic Research, 66(1), 55-71.

Hudson, B., Hunter, D., & Peckham, S. (2019). Policy failure and the policy-implementation gap: can policy support programs help? Policy Design and Practice.

Huntington, S. P. (2006). Political order in changing societies. Yale university press.

Hvidt, M. (2015). Transformation of the Arab Gulf economies into knowledge economies: Motivational issues related to the tertiary educational sector. Arab Center for Research & Policy Studies.

Iamsiraroj, S. (2016). The foreign direct investment–economic growth nexus. International Review of Economics & Finance, 42, 116-133.

Ibrahim, A., & Marah, A. (2018). A comparative analysis of national innovation systems’ structures and their developmental impacts (Evidence from BRICS countries)., (1), 13-20.

Ibrahim, C. (2021). Toward a knowledge-based economy: evidence from the MENA region. International Journal of Competitiveness, 2(1), 33-41.

Iliyasu, A., Mohamed, Z. A. and Terano, R. (2015). Data envelopment analysis mod els and software packages for academic purposes, Pertanika Journal of Scholarly Research Reviews 1(1).

Industry Analysis Branch of the Department of Industry, Science and Resources. (1999). Measuring the knowledge-based economy. How does Australia compare?

Inglesi-Lotz, R., Hakimi, A., & Pouris, A. (2018). Patents vs publications and R&D: Three sides of the same coin? Panel Smooth Transition Regression (PSTR) for OECD and BRICS countries. Applied Economics, 50(45), 4912-4923.

Iqbal, N., & Daly, V. (2014). Rent seeking opportunities and economic growth in transitional economies. Economic Modelling, 37, 16-22.

Isaksen, A., & Trippl, M. (2017). Innovation in space: the mosaic of regional innovation patterns. Oxford Review of Economic Policy, 33(1), 122-140.

Ismail, I., Ramalingam, S., Azahan, A. H., & Khezrimotlagh, D. (2014). Relative efficiency of public universities in Malaysia. Scholars Journal of Economics, Business and Management, 1(11), 606-612.

Jackson, F. H., Sara, T., Kahai, S. K. et al. (2014). Determinants of innovative capability of a country and its role in economic growth, International Business & Economics Research Journal (IBER) 13(5), 1141–1148.

Jamali, D. and Lanteri, A. (2016), Social Entrepreneurship in the Middle East: Volume 1, Vol. 1, Springer.

Janger, J., Schubert, T., Andries, P., Rammer, C., & Hoskens, M. (2017). The EU 2020 innovation indicator: A step forward in measuring innovation outputs and outcomes? Research Policy, 46(1), 30-42.

Javorcik, B. S. (2004). Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages. American economic review, 94(3), 605-627.

Jiao, H., Koo, C. K., & Cui, Y. (2015). Legal environment, government effectiveness and firms' innovation in China: examining the moderating influence of government ownership. Technological Forecasting and Social Change, 96, 15-24.

Johansson, B., Lööf, H., & Savin, M. (2015). European R&D efficiency. Economics of Innovation and New Technology, 24(1-2), 140-158.

Joumard, R., & Boughédaoui, M. (2010). Research typology and knowledge needs for development in Africa. African Journal of Science, Technology, Innovation and Development, 2(3), 186-206.

Juřičková, E., Pilik, M., & Kwarteng, M. A. (2019). Efficiency measurement of national innovation systems of the European Union countries: DEA model application. Journal of International Studies.

Kaasa, A., Kaldaru, H., & Parts, E. (2007). Social capital and institutional quality as factors of innovation: evidence from Europe. University of Tartu Faculty of Economics and Business Administration Working Paper, (55-2007).

Kadakia, K., Patel, B., & Shah, A. (2020). Advancing digital health: FDA innovation during COVID-19. Npj Digital Medicine, 3(1), 1-3.

Kafi, A., Daneshian, B., & Rostamy-Malkhalifeh, M. (2021). Forecasting the confidence interval of efficiency in fuzzy DEA. Operations Research and Decisions, 31.

Kahin, B., & Foray, D. (2006). Measuring knowledge and its economic effects: The role of official statistics.

Kaiser, R., & Kripp, M. (2010, June). Demand-orientation in national systems of innovation: a critical review of current European innovation policy concepts. In DRUID Summer Conference.

Kalai, M. (2019). Nonparametric measures of capacity utilization of the Tunisian manufacturing industry: Short-and long-run dual approach. Journal of the Knowledge Economy, 10(1), 318-334.

Kamien, M. I., & Schwartz, N. L. (1982). Market structure and innovation. Cambridge University Press.

Kao, C., & Liu, S. T. (2007). Data envelopment analysis with missing data. In Modeling data irregularities and structural complexities in data envelopment analysis (pp. 291-304). Springer, Boston, MA.

Karadayi, M. A., & Ekinci, Y. (2019). Evaluating R&D performance of EU countries using categorical DEA. Technology Analysis & Strategic Management, 31(2), 227-238.

Karadayi, M. A., & Ekinci, Y. (2019). Evaluating R&D performance of EU countries using categorical DEA. Technology Analysis & Strategic Management, 31(2), 227-238.

Karahan, O¨. (2012), 'Input output indicators of knowledge-based economy and turkey', Journal of Business Economics and Finance 1(2), 21–36.

Karami Khorramabadi, M., Yarahmadi, M., & Ghiyasi, M. (2020). Cost Efficiency Evaluation Based on a Data Envelopment Analysis Approach by Considering Undesirable Outputs on the Basis of the Semi-Disposability Assumption. Mathematical and Computational Applications, 25(1), 4.

Karkazis, J., & Thanassoulis, E. (1998). Assessing the effectiveness of regional development policies in Northern Greece using data envelopment analysis. Socio-Economic Planning Sciences, 32(2), 123-137.

Karri, R., & Goel, S. (2006). Demand and supply side perspective of entrepreneurial action in emerging economies. In Conference on Entrepreneurship in Emerging Regions.

Kassicieh, S. (2010). The knowledge economy and entrepreneurial activities in technology-based economic development. Journal of the Knowledge Economy, 1(1), 24-47.

Kaufmann, D., Kraay, A., & Mastruzzi, M. (2005). Governance matters IV: governance indicators for 1996-2004. World bank policy research working paper series, (3630).

Kaur, M., & Singh, L. (2016). Knowledge in the economic growth of developing economies. African Journal of Science, Technology, Innovation and Development, 8(2), 205-212.

Kaur, V. (2019). Knowledge-based dynamic capabilities. Springer Cham: Springer NaturSwitzerland: Springer International Publishing.

Kawabata, M. K., & Camargo Junior, A. S. (2020). Innovation and institutions' quality: a comparative study between countries. International Journal of Innovation Science, 12(2), 169-185.

Keely, L. C. (2002). Pursuing problems in growth. Journal of Economic Growth, 7(3), 283-308.

Khaliq, A., & Noy, I. (2007). Foreign direct investment and economic growth: Empirical evidence from sectoral data in Indonesia. Journal of Economic Literature, 45(1), 313-325

Khan, A. W. (2003). Measuring and Monitoring the Information and Knowledge Societies: A Statistical Challenge. UNESCO.

Khan, Z. U., Hussain, A., & Iqbal, N. (2017). Institutions and innovation: Evidence from countries at different stages of development. The Pakistan Development Review, 297-317.

Khezrimotlagh, D., Cook, W. D., & Zhu, J. (2021). Number of performance measures versus number of decision-making units in DEA. Annals of Operations Research, 303(1), 529-562.

Khodabakhshi, M., Gholami, Y., & Kheirollahi, H. (2010). An additive model approach for estimating returns to scale in imprecise data envelopment analysis. Applied Mathematical Modelling, 34(5), 1247-1257.

Khumalo, B. (2006). Measuring a Society's Knowledge Base.

Kim, H., & Lee, C. W. (2018). Efficiency analysis for nonprofit organizations using DEA: Focused on humanitarian assistance organizations in South Korea. Asia Pacific Journal of Innovation and Entrepreneurship.

Kirkman, G. S., Osorio, C. A., & Sachs, J. D. (2002). The networked readiness index: Measuring the preparedness of nations for the networked world. Korea, 4, 20.

Kirzner, I. M. (2015). Competition and entrepreneurship. University of Chicago press.

Klapper, L., Amit, R., & Guillén, M. F. (2010). Entrepreneurship and firm formation across countries. In International differences in entrepreneurship (pp. 129-158). University of Chicago Press.

Kleszcz, A. et al. (2021), Principal components of innovation performance in European union countries, Wiadomo´sci Statystyczne. The Polish Statistician 66(08), 24–45.

Klevenhusen, A., Coelho, J., Warszawski, L., Moreira, J., Wanke, P., & Ferreira, J. J. (2021). Innovation efficiency in OECD countries: A non-parametric approach. Journal of the Knowledge Economy, 12(3), 1064-1078.

Kline, S. and Rosenberg, N. (2009). An overview of innovation. studies on science and the innovation process.

Kline, S. J., & Rosenberg, N. (1986). An overview of innovation. The positive sum strategy. Harnessing technology for economic growth, 14, 640.

Knight, F. H. (1921). Risk, uncertainty and profit (Vol. 31). Houghton Mifflin.

Koçak, E. (2017). Does institutional quality drive innovation? Evidence from system-GMM estimates.

Kontolaimou, A., Giotopoulos, I., & Tsakanikas, A. (2016). A typology of European countries based on innovation efficiency and technology gaps: The role of early-stage entrepreneurship. Economic Modelling, 52, 477-484.

Kotsemir, M. (2013). Measuring national innovation systems efficiency–a review of DEA approach. Higher School of Economics Research Paper No. WP BRP, 16.

Kowalski, A. M. (2021). Dynamics and factors of innovation gap between the European Union and China. Journal of the Knowledge Economy, 12(4), 1966-1981.

Krammer, S. M. (2009). Drivers of national innovation in transition: Evidence from a panel of Eastern European countries. Research Policy, 38(5), 845-860.

Krasnokutska, N. S. (2012). Comparative analysis of the knowledge-based potential on the level of countries and regions, (12), 46-49.

Kripfganz, S., & Schwarz, C. (2019). Estimation of linear dynamic panel data models with time-invariant regressors. Journal of Applied Econometrics, 34(4), 526-546.

Kriščiūnas, K., & Daugėlienė, R. (2006). The assessment models of knowledge-based economy penetration. Engineering economics, 50(5).

Kumar, S. and Gulati, R. (2008). An examination of technical, pure technical, and scale efficiencies in indian public sector banks using data envelopment analysis, Eurasian Journal of Business and Economics 1(2), 33–69.

Kuntz, L., & Vera, A. (2007). Modular organization and hospital performance. Health Services Management Research, 20(1), 48-58.

Kurz, H. D., & Salvadori, N. (2003). Theories of economic growth: old and new. The Theory of Economic Growth: A 'Classical' Perspective, Cheltenham: Edward Elgar, 1-22.

Kuznets, S. (1955). Economic growth and income inequality. The American economic review, 45(1), 1-28.

Kuznetsov, Y. N., & Dahlman, C. J. (2008). Mexico's transition to a knowledge-based economy: Challenges and opportunities. World Bank Publications.

Lagzouli, A., LAgzouli, A., & Lakhal, P. T. (2020). Conceptual Foundations of the Knowledge Economy and Presentation of Its Performance Indicators. IOSR Journal of Economics and Finance (IOSR-JEF). e-ISSN: 2321-5933, p-ISSN: 2321-5925.Volume 11, Issue 4 Ser. III (Jul. – Aug. 2020), PP 15-25

Landström, H., Åström, F., & Harirchi, G. (2015). Innovation and entrepreneurship studies: One or two fields of research? International Entrepreneurship and Management Journal, 11, 493-509.

Larédo, P., Köhler, C., & Rammer, C. (2016). The impact of fiscal incentives for R & D. In Handbook of innovation policy impact (pp. 18-53). Edward Elgar Publishing.

Law, S. H., Lee, W. C., & Singh, N. (2018). Revisiting the finance-innovation nexus: Evidence from a non-linear approach. Journal of Innovation & Knowledge, 3(3), 143-153.

Leadbeater, C., & London, D. (1999, June). New measures for the new economy. In International symposium on measuring and reporting intellectual capital: Experience, issues, and prospects.

Lee, C. C., Wang, C. W., & Ho, S. J. (2020). Country governance, corruption, and the likelihood of firms' innovation. Economic Modelling, 92, 326-338.

Lee, H. S. (2021). An integrated model for SBM and Super-SBM DEA models. Journal of the Operational Research Society, 72(5), 1174-1182.

Lee, H. Y., & Park, Y. T. (2005). An international comparison of R&D efficiency: DEA approach. Asian Journal of Technology Innovation, 13(2), 207-222.

Lee, H., Park, Y., & Choi, H. (2009). Comparative evaluation of performance of national R&D programs with heterogeneous objectives: A DEA approach. European journal of operational research, 196(3), 847-855.

Lee, K., & Yoon, B. (2015). The idiosyncrasy of research and development efficiency across types of small-and medium-sized enterprises: evidence from

Korea. R&D Management, 45(3), 250-266.

Lee, L. F. (2007). GMM and 2SLS estimation of mixed regressive, spatial autoregressive models. Journal of Econometrics, 137(2), 489-514.

Lee, S. K. (2001, January). Economic development through knowledge creation-the case of Korea. In Proceedings of the 34th Annual Hawaii International Conference on System Sciences (pp. 7-pp). IEEE.

Lehne, J., Mo, J., & Plekhanov, A. (2014). What determines the quality of economic institutions? Cross-country evidence.

LêKhang, T., & Thành, N. C. (2018, April). Economic growth, entrepreneurship, and institutions: evidence in emerging Countries. In The 5th IBSM international conference on business, management and accounting (pp. 19-21).

Lema, R., Kraemer-Mbula, E., & Rakas, M. (2021). Innovation in developing countries: examining two decades of research. Innovation and Development, 11(2-3), 189-210.

Lember, V., Cepilovs, A., & Kattel, R. (2013). Demand-side innovation policy in Estonia: rationales, limits and future paths (No. 56). TUT Ragnar Nurkse Department of Innovation and Governance.

Lenihan, H., McGuirk, H., & Murphy, K. R. (2019). Driving innovation: Public policy and human capital. Research policy, 48(9), 103791.

Leon, R. D. (2017). Measuring the knowledge economy: a national and organizational perspective. Management Dynamics in the Knowledge Economy, 5(2), 227-249.

Leppälä, S. (2015). Economic analysis of knowledge: the history of thought and the central themes. Journal of Economic Surveys, 29(2), 263-286.

Lerner, J. (2009). The empirical impact of intellectual property rights on innovation: Puzzles and clues. American Economic Review, 99(2), 343-348.

Leung, S. K. (2004, November). Statistics to measure the knowledge-based economy: The case of Hong Kong, China. In Asia Pacific Technical Meeting on Information and Communication Technology (ICT) Statistics, Wellington, November.

Levchenko, A. A. (2007). Institutional quality and international trade. The Review of Economic Studies, 74(3), 791-819.

Levin, R. C., Klevorick, A. K., Nelson, R. R., Winter, S. G., Gilbert, R., & Griliches, Z. (1987). Appropriating the returns from industrial research and development. Brookings papers on economic activity, 1987(3), 783-831.

Leydesdorff, L., & Meyer, M. (2006). Triple Helix indicators of knowledge-based innovation systems: Introduction to the special issue. Research policy, 35(10), 1441-1449.

Leys, C. (1965). What is the Problem about Corruption? The Journal of Modern African Studies, 3(2), 215-230.

Lhuillery, S., Raffo, J., & Hamdan-Livramento, I. (2017). Measurement of innovation. In The Elgar companion to innovation and knowledge creation (pp. 99-118). Edward Elgar Publishing.

Liang, C., Shah, S. A., & Bifei, T. (2021). The role of FDI inflow in economic growth: Evidence from developing countries. Journal of Advanced Research in Economics and Administrative Sciences, 2(1), 68-80.

Liang, L., Wu, J., Cook, W. D., & Zhu, J. (2008). Alternative secondary goals in DEA cross-efficiency evaluation. International Journal of Production Economics, 113(2), 1025-1030.

Lightfoot, M. (2011). Promoting the knowledge economy in the Arab world. Sage Open, 1(2), 2158244011417457.

Lin, R., & Chen, Z. (2015). Super-efficiency measurement under variable return to scale: an approach based on a new directional distance function. Journal of the Operational Research Society, 66(9), 1506-1510.

Lin, R., Yang, W., & Huang, H. (2019). A modified slacks-based super-efficiency measure in the presence of negative data. Computers & Industrial Engineering, 135, 39-52.

Lind, J. T., & Mehlum, H. (2010). With or without U? The appropriate test for a U-shaped relationship. Oxford bulletin of economics and statistics, 72(1), 109-118.

Liping, Y., & Shudong, Z. Research on Efficiency of China's Regional Knowledge-Based Economy (2007). In 2007 International Conference on Wireless Communications, Networking and Mobile Computing. (pp. 5688-5691). IEEE.

Liu, J. S., Lu, L. Y., & Lu, W. M. (2016). Research fronts in data envelopment analysis. Omega, 58, 33-45.

Liu, X., & Huang, J. (2022). China's high-tech industry efficiency measurement with virtual frontier data envelopment analysis and Malmquist productivity index. Expert Systems, 39(2), e12450.

Livingstone, D. W., & Guile, D. (2012). The knowledge economy and lifelong learning: A critical reader. BRILL.

Loukil, K. (2016). Foreign direct investment and technological innovation in developing countries. Oradea Journal of Business and Economics, 1(2), 31-40.

Loury, G. C. (1979). Market structure and innovation. The quarterly journal of economics, 395-410.

Lovell, C. K. (1995). Measuring the macroeconomic performance of the Taiwanese economy. International Journal of Production Economics, 39(1-2), 165-178.

Lozić, J. (2022). Application of Data Envelopment Analysis (DEA) in Information and Communication Technologies. Tehnički glasnik, 16(1), 129-134.

Lu, W. M., Kweh, Q. L., & Huang, C. L. (2014). Intellectual capital and national innovation systems performance. Knowledge-based systems, 71, 201-210.

Lu, Y. H., Shen, C. C., Ting, C. T., & Wang, C. H. (2010). Research and development in productivity measurement: An empirical investigation of the high technology industry. African Journal of Business Management, 4(13), 2871-2884.

Lundvall, B. A. (1992). National systems of innovation: towards a theory of innovation and interactive learning.

Lundvall, B. Å. (2002). The learning economy: challenges to economic theory and policy. A Modern Reader in Institutional and Evolutionary Economics: Key Concepts. Cheltenham: Edward Elgar, 26-47.

Lundvall, B. Å. (2004). The economics of knowledge and learning. In Product inovation, interactive learning, and economic performance. Emerald Group Publishing Limited.

Lundvall, B. Å. (2006). Knowledge management in the learning economy. Aalborg: Danish Research Unit for Industrial Dynamics.

Lundvall, B. Å. (2007). National innovation systems—analytical concept and development tool. Industry and innovation, 14(1), 95-119.

Lundvall, B. A. (2016). From the economics of knowledge to the learning economy. The learning economy and the economics of hope, 133.

Lundvall, B. Å., & Nielsen, P. (2007). Knowledge management and innovation performance. International Journal of Manpower.

Lundvall, B. Å., Vang, J., & Joseph, K. J. (2009). Innovation system research and developing countries. In Handbook of innovation systems and developing countries. Edward Elgar Publishing.

Lundvall, B.¨a. and Johnson, B. (1994). The learning economy, Journal of industry studies 1(2), 23–42.

Luo, M., & Yip, T. L. (Eds.). (2017). Ports and the Environment: Maritime policy and management. Routledge.

Luptacik, M. (2010). Mathematical optimization and economic analysis (p. 307). New York, NY, USA: Springer.

Lyotard, J. F. (1984). The Postmodern Condition: A Report on Knowledge; Theory and History of Literature; Bennington, G., Massumi, B., Eds.

Machlup, F. (1962). The production and distribution of knowledge in the United States (Vol. 278). Princeton university press.

Madbouly, A., Reyad, S., & Chinnasamy, G. (2021). Analysis for the knowledge economy in GCC countries. In The Fourth Industrial Revolution: Implementation of Artificial Intelligence for Growing Business Success (pp. 403-416). Springer, Cham.

Mahagaonkar, P. (2008). Corruption and innovation: a grease or sand relationship? (No. 2008, 017). Jena Economic Research Papers.

Maharajh, R. (2009). Science, Technology & Innovation for Development.

Mairesse, J., & Robin, S. (2009). Innovation and productivity: a firm-level analysis for French Manufacturing and Services using CIS3 and CIS4 data (1998-2000 and 2002-2004). Paris: Crest-Ensae.

Malerba, F. (Ed.). (2004). Sectoral systems of innovation: concepts, issues and analyses of six major sectors in Europe. Cambridge University Press.

Malhotra, R., & Malhotra, D. K. (2009). Evaluating the efficiency of European Union integration. International Journal of Commerce and Management.

Malik, S. (2023). Macroeconomic determinants of innovation: Evidence from Asian countries. Global Business Review, 24(1), 137-151.

Manniche, J., & Testa, S. (2018). Towards a multi-levelled social process perspective on firm innovation: Integrating micro, meso and macro concepts of knowledge creation. Industry and Innovation, 25(4), 365-388.

Manoharan, T. R., Muralidharan, C., & Deshmukh, S. G. (2009). Employee Performance Appraisal Using Data Envelopment Analysis: A Case Study. Research & Practice in Human Resource Management, 17(1).

Mansell, R., & Wehn, U. (1998). Knowledge societies: Information technology for sustainable development. Oxford University Press.

Maradana, R. P., Pradhan, R. P., Dash, S., Zaki, D. B., Gaurav, K., Jayakumar, M., & Sarangi, A. K. (2019). Innovation and economic growth in European Economic Area countries: The Granger causality approach. IIMB Management Review, 31(3), 268-282.

Markatou, M. (2013). Innovation in sustainable-new and emerging-technological fields: a patent-based perspective for Greece. International Journal of Innovation and Regional Development, 5(1), 26-40.

Marouf, L., & Chaudhry, A. S. (2013). Performance Measures for the Knowledge-Based Economy (KBE): A Case of Kuwait. Journal of the Social Sciences, 41(4).

Marshall, A. and Marshall, M. P. (1920). The economics of industry, Macmillan, and Company.

Marti, M. M., Novakovi, M. S., & Baggia, A. (2009). Data envelopment analysis-basic models and their utilization. iji, 1000, 1i.

Martić, M., & Savić, G. (2001). An application of DEA for comparative analysis and ranking of regions in Serbia with regards to social-economic development. European Journal of Operational Research, 132(2), 343-356.

Martin, B. R. (2012). The evolution of science policy and innovation studies. Research policy, 41(7), 1219-1239.

Martin, B. R. (2016). R&D policy instruments–a critical review of what we do and don't know. Industry and innovation, 23(2), 157-176.

Matei, M. M., & Aldea, A. (2012). Ranking national innovation systems according to their technical efficiency. Procedia-Social and Behavioral Sciences, 62, 968-974.

Matošková, J. (2016). Measuring Knowledge. Journal of Competitiveness.

Mazzocchitti, M., Quaglione, D., & Sarra, A. (2016). DEA approaches to handle environmental factors. L'industria, 37(3), 515-524.

Mazzucato, M., & Semieniuk, G. (2017). Public financing of innovation: new questions. Oxford Review of Economic Policy, 33(1), 24-48.

McArthur, J. W., & Sachs, J. D. (2001). The growth competitiveness index: measuring technological advancement and the stages of development. *The global competitiveness report*, *2002*, 28-51.

Mêgnigbêto, E. (2018). Correlation between transmission power and some indicators used to measure the knowledge-based economy: case of six OECD countries. Journal of the Knowledge Economy, 9(4), 1168-1183.

Meissner, D., & Kergroach, S. (2021). Innovation policy mix: mapping and measurement. The Journal of Technology Transfer, 46, 197-222.

Melecký, L., Staníčková, M., & Hančlová, J. (2019). Nonparametric approach to evaluation of economic and social development in the EU28 member states by DEA efficiency. Journal of Risk and Financial Management, 12(2), 72.

Menna, A., Walsh, P. R., & Ekhtari, H. (2019). Identifying enablers of innovation in developed economies: A National Innovation Systems approach. Journal of Innovation Management, 7(1), 108-128.

Meressa, H. A. (2022). Determinants of foreign direct investment inflows to COMESA member countries: an integration of institutional and socio-economic factors. Journal of Innovation and Entrepreneurship, 11(1), 1-16.

Mestre-Ferrandiz, J., Shaw, B., Chatterjee, C., Ding, J., Singh, P., & Hopkins, M. M. (2022). Policy instruments (non-price) for medical innovation. Oslo Medicines Initiative technical report. Copenhagen: WHO Regional Office for Europe.

Metcalfe, J. S. (2005). Systems failure and the case for innovation policy. In Innovation policy in a knowledge-based economy (pp. 47-74). Springer, Berlin, Heidelberg.

Metcalfe, J. S., & Foster, J. (2010). Evolutionary growth theory. In Handbook of alternative theories of economic growth. Edward Elgar Publishing.

Mihaiu, D. M., Opreana, A., & Cristescu, M. P. (2010). Efficiency, effectiveness and performance of the public sector. Romanian journal of economic forecasting, 4(1), 132-147.

Mileva, E. (2007). Using Arellano-Bond dynamic panel GMM estimators in Stata. Economics Department, Fordham University, 64, 1-10.

Mimis, A., & Georgiadis, T. (2013). Economic clustering of countries in the Asia-Pacific region. International Journal of Social Economics.

Mises, L. V. (1998). Human action: A treatise on economics. The Scholar's Edition. Auburn, Ala.: Ludwig von Mises Institute.

Mohamad, A., & Bani, Y. (2017). Foreign Direct Investment, absorptive capacity and technological innovation: Empirical evidence in developing economies. In Glob. Conf. Bus. Econ. Res (Vol. 8, pp. 14-15).

Mohamad, N. (2007). A linear programming formulation of macroeconomic performance: the case of Asia Pacific. MATEMATIKA: Malaysian Journal of Industrial and Applied Mathematics, 29-40.

Mohamed, M. M. A., Liu, P., & Nie, G. (2022). Do Knowledge Economy Indicators Affect Economic Growth? Evidence from Developing Countries. Sustainability, 14(8), 4774.

Mohammed bin Rashid Al Maktoum Foundation (MBRF) and the United Nations Development Programme/Regional Bureau for Arab States (UNDP/RBAS), 2015. Al Ghurair Printing and Publishing House., Dubai – United Arab Emirates

Mohnen, P., & Dagenais, M. (1998). The Construction of Innovation Intensity Indexes.

Molas-Gallart, J., & Davies, A. (2006). Toward theory-led evaluation: The experience of European science, technology, and innovation policies. American Journal of Evaluation, 27(1), 64-82.

Morrar, R. (2018). Innovation in the MENA Region. Strategic Sectors| Economy & Territory.

Moustafa, E. (2021). The relationship between perceived corruption and FDI: a longitudinal study in the context of Egypt. Transnational Corporations Journal, 28(2).

Moutinho, V., Vale, J., Bertuzi, R., Bandeira, A. M., & Palhares, J. (2021). A Two-Stage DEA Model to Evaluate the Performance of Iberian Banks. Economies, 9(3), 115.

Mowery, D. C. (2011). Federal policy and the development of semiconductors, computer hardware, and computer software: a policy model for climate change R&D? In Accelerating energy innovation: insights from multiple sectors (pp. 159-188). University of Chicago Press.

Mowery, D., & Rosenberg, N. (1979). The influence of market demand upon innovation: a critical review of some recent empirical studies. Research policy, 8(2), 102-153.

Murat, D., Betül, İ. N. A. M., & Güzel, S. (2017). Relationship between knowledge economy performance indicators and selected macroeconomic variables: an application for OECD countries. Yönetim Bilimleri Dergisi, 15(30), 9-26.

Mutanov, G., Zhuparova, A., & Zhaisanova, D. (2020). Measuring the Knowledge-Based Performance Efficiency in the Oil-Exported Countries. Montenegrin Journal of Economics, 16(3), 109-122.

Myers, S., & Marquis, D. G. (1969). Successful industrial innovations: A study of factors underlying innovation in selected firms (Vol. 69, No. 17). National Science Foundation.

Naceur, M. S. B., Blotevogel, M. R., Fischer, M. M., & Shi, H. (2017). Financial development and source of growth: new evidence. International Monetary Fund.

Nachef, T., Jantan, M. B., & Boularas, A. (2014). Fuzzy modelling for Qatar knowledge-based economy and its characteristics. Modern Economy, 2014.

Nadeem, M. A., Jiao, Z., Nawaz, K., & Younis, A. (2020). Impacts of voice and accountability upon innovation in pakistan: evidence from ARDL and Maki Cointegration approaches. Mathematical Problems in Engineering, 2020, 1-18.

Napiorkowski, T. M. (2018). The impact of Framework Programs on innovativeness in the European Union. Strengthening the Knowledge Base for Innovation in the European Union. Edited by Marzenna Anna Weresa. Warszawa: Polish Scientific Publishers PWN, 59-99.

Naqvi, R. (2016). Global Innovative Index and India: Current Trends and Opportunities. International Journal of Science Technology and Management, 5(9).

Nasierowski, W., & Arcelus, F. J. (2003). On the efficiency of national innovation systems. Socio-Economic Planning Sciences, 37(3), 215-234.

Nataraja, N. R., & Johnson, A. L. (2011). Guidelines for using variable selection techniques in data envelopment analysis. European Journal of Operational Research, 215(3), 662-669.

National Science Board (2018). Science & Engineering Indicators 2018. https://www.nsf.gov/statistics/2018/nsb20181/downloads

Naude, W., Szirmai, A., & Goedhuys, M. (2011). Innovation and entrepreneurship in developing countries. UNU.

Neef, D. (2009). Introduction: Rethinking economics in the knowledge-based economy. In The economic impact of knowledge (pp. 3-16). Routledge.

Nelson, R. R. (1959). The simple economics of basic scientific research. Journal of political economy, 67(3), 297-306.

Nelson, R. R. (1993b), National innovation systems: a comparative analysis, Oxford University Press, USA.

Nelson, R. R. (2008), ‘Economic development from the perspective of evolutionary economic theory’, Oxford development studies 36(1), 9–21.

Nelson, R. R. and Romer, P. M. (1996).Science, economic growth, and public policy Challenge. 39(1), 9–21.

Nelson, R. R., & Winter, S. G. (1977). In search of a useful theory of innovation. In Innovation, economic change and technology policies (pp. 215-245). Birkhäuser, Basel.

Nelson, R. R., & Winter, S. G. (2002). Evolutionary theorizing in economics. Journal of economic perspectives, 16(2), 23-46.

Nelson, R., & Winter, S. (1982). An Evolutionary Theory of Economic Change, Cambr.

Nemet, G. F. (2007). Policy and innovation in low-carbon energy technologies. University of California, Berkeley.

Nemet, G. F. (2009). Demand-pull, technology-push, and government-led incentives for non-incremental technical change. Research policy, 38(5), 700-709.

Neter, J., Wasserman, W., & Kutner, M. H. (1989). Applied Linear Regression Models. Irwin, Homewood. Chap, 11, 386-432.

Nicholas, T. (2003). Why Schumpeter was right: innovation, market power, and creative destruction in 1920s America. The Journal of Economic History, 63(4), 1023-1058.

Nickell, S. (1981). Biases in dynamic models with fixed effects. Econometrica: Journal of the econometric society, 1417-1426.

Nonaka, I. and Takeuchi, H. (1995), The knowledge creating company, new york oxford university.

Nordhaus, W., & Romer, P. (2018). Integrating nature and knowledge into economics. Royal Swedish Academy of Sciences Nobel Prize Lecture.

North, D. C. (1991). Institutions. Journal of economic perspectives, 5(1), 97-112.

Nour, S. (2014a). Challenges and opportunities for transition to knowledge-based economy in Arab Gulf countries (No. 030). United Nations University-Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT).

Nour, S. (2014b). Transition to a knowledge-based economy in Saudi Arabia (No. 029). United Nations University-Maastricht Economic and Social Research Institute on Innovation and Technology (MERIT).

Nour, S. S. O. M. (2014c). Prospects for transition to a knowledge-based economy in the Arab region. World Journal of Science, Technology and Sustainable Development.

Nour, S. S. O. M. (2015). Overview of knowledge economy in the Arab region. Journal of the Knowledge Economy, 6(4), 870-904.

Noyelle, T. J. (1990), Skills, wages, and productivity in the service sector, Westview Press.

Nurunnabi, M. (2017). Transformation from an oil-based economy to a knowledge-based economy in Saudi Arabia: The Direction of Saudi Vision 2030. Journal of the Knowledge Economy, 8, 536–564.

Nyhan, R. C., & Cruise, P. L. (2000). Comparative performance assessment in managed care: data envelopment analysis for health care managers. Managed Care Quarterly, 8(1), 18-27.

Nyhan, R. C., & Martin, L. L. (1999). Comparative performance measurement: A primer on data envelopment analysis. Public Productivity & Management Review, 348-364.

O'Donovan, N. (2020). From knowledge economy to automation anxiety: a growth regime in crisis? New political economy, 25(2), 248-266.

O'Sullivan, M. (2006), 'Finance and innovation'.

Obunike, C. F., & Udu, A. A. (2021). Innovativeness And Growth: A Study Of Small-Scale Manufacturing Firms In Lagos State.

OECD (1992). Technology and the economy: The key relationships (Vol. 22). Organization for Economic.

OECD (2011), Demand-side Innovation Policies, OECD Publishing, Paris, https://doi.org/10.1787/9789264098886-en.

OECD (2015). Innovation policies for inclusive development, scaling up inclusive innovations.

OECD, E. (2018). Oslo manual 2018. The Measurement of Scientific, Technological and Innovation Activities, guidelines for collecting, reporting, and using data on innovation. 258.

OECD/Eurostat (2018). Oslo Manual 2018: Guidelines for Collecting, Reporting and Using Data on Innovation, 4th Edition, The Measurement of Scientific, Technological and Innovation Activities, OECD Publishing, Paris/Eurostat, Luxembourg, https://doi.org/10.1787/9789264304604-en.

Ojanperä, S., Graham, M., & Zook, M. (2019). The digital knowledge economy index: mapping content production. The Journal of Development Studies, 55(12), 2626-2643.

Olsson, O. (2000). Knowledge as a set in idea space: An epistemological view on growth. Journal of economic growth, 5(3), 253-275.

Oluwatobi, S., Olurinola, I., Alege, P., & Ogundipe, A. (2020). Knowledge-driven economic growth: the case of Sub-Saharan Africa. Contemporary Social Science, 15(1), 62-81.

Omar, N. S. (2019). Innovation and economic performance in MENA region. Review of Economics and Political Science.

Omidi, V., Shahabadi, A., & Mehregan, N. (2020). Innovation drivers in developing countries. Journal of the Knowledge Economy, 11(2), 707-720.

Onea, I. A. (2020). Innovation indicators and the innovation process-evidence from the European innovation scoreboard. Management & Marketing. Challenges for the Knowledge Society, 15(4), 605-620.

Organisation For Economic Co-Operation and Development (OECD).The Knowledge-Based Economy. General Distribution OECD/GD (96)102, OECD, 1996: Http://Www.Oecd.Org/Science/Scitech/1913021.Pdf., Pp. 3, 7, 9, 18-19.

Organisation for Economic Co-operation and Development. (2013). Measuring the internet economy: a contribution to the research agenda. OECD Publishing. WRITE IT AS OECD

Ortega, A. M., & Serna, M. (2020). Determinants of innovation performance of organizations in a regional innovation system from a developing country. International Journal of Innovation Science, 12(3), 345-362.

Ortigueira-Sánchez, L. C., Welsh, D. H., & Stein, W. C. (2022). Innovation drivers for export performance. Sustainable Technology and Entrepreneurship, 1(2), 100013.

Osman, I. H. (Ed.). (2013). Handbook of research on strategic performance management and measurement using data envelopment analysis. IGI global.

Oxley, L., Walker, P., Thorns, D., & Wang, H. (2008). The Knowledge Economy/Society: The Latest Example of “Measurement Without Theory”. The journal of philosophical economics, 2(1), 20-54.

Pakhnenko, O. M., Liuta, O. V., & Pihul, N. H. (2018). Methodological approaches to assessment of the efficiency of business entities activity.

Pansera, M., & Martinez, F. (2017). Innovation for development and poverty reduction: an integrative literature review. Journal of Management Development.

Panwar, A., Olfati, M., Pant, M., & Snasel, V. (2022). A Review on the 40 Years of Existence of Data Envelopment Analysis Models: Historic Development and Current Trends. Archives of Computational Methods in Engineering, 1-30.

Papaconstantinou, G., & Polt, W. (1997, June). Policy evaluation in innovation and technology: an overview. In Conference Policy Evaluation in Innovation and Technology, Capítulo (Vol. 1, pp. 9-14).

Papageorgiadis, N., & Sharma, A. (2016). Intellectual property rights and innovation: A panel analysis. Economics Letters, 141, 70-72.

Paradi, J. C., Sherman, H. D., & Tam, F. K. (2017). Data envelopment analysis in the financial services industry: A guide for practitioners and analysts working in operations research using DEA (Vol. 266). Springer.

Parcero, O. J., & Ryan, J. C. (2017). Becoming a knowledge economy: the case of Qatar, UAE, and 17 benchmark countries. Journal of the knowledge economy, 8(4), 1146-1173.

Parisi, M. L., Schiantarelli, F., & Sembenelli, A. (2006). Productivity, innovation and R&D: Micro evidence for Italy. European Economic Review, 50(8), 2037-2061.

Parkan, C. (1987). Measuring the efficiency of service operations: an application to bank branches. Engineering Costs and Production Economics, 12(1-4), 237-242.

Parker, S. C. (2004). The economics of self-employment and entrepreneurship. Cambridge university press.

Passerini, K. (2007). Knowledge-driven development indicators: still an eclectic panorama. Journal of Knowledge Management.

Patel, P., & Pavitt, K. (1994). National innovation systems: why they are important, and how they might be measured and compared. Economics of innovation and new technology, 3(1), 77-95.

Paul, J., & Feliciano-Cestero, M. M. (2021). Five decades of research on foreign direct investment by MNEs: An overview and research agenda. Journal of business research, 124, 800-812.

Paunov, C. (2016). Corruption's asymmetric impacts on firm innovation. Journal of Development Economics, 118, 216-231.

Pavitt, K. (2005). Innovation processes. In The Oxford handbook of innovation.

Pece, A. M., Simona, O. E. O., & Salisteanu, F. (2015). Innovation and economic growth: An empirical analysis for CEE countries. Procedia Economics and Finance, 26, 461-467.

Pedersen, L. F. (2008). On the Road to the Knowledge Economy. An Analysis of the Case of Mozambique in the Introduction of Knowledge and Skills as a Foundation for Economic Growth (master's Thesis Aalborg University 2008).

Pellegrino, G., & Savona, M. (2017). No money, no honey? Financial versus knowledge and demand constraints on innovation. Research policy, 46(2), 510-521.

Peters, M. (2001). National education policy constructions of the "knowledge economy": towards a critique. The Journal of Educational Enquiry, 2(1).

Peters, M. A. (2010). Three forms of the knowledge economy: Learning, creativity, and openness. Economics, Management, and Financial Markets, 5(4), 63-92.

Peters, M. A. (2022). A post-marxist reading of the knowledge economy: open knowledge production, cognitive capitalism, and knowledge socialism. Analysis and Metaphysics, (21), 7-23.

Peters, M., Schneider, M., Griesshaber, T., & Hoffmann, V. H. (2012). The impact of technology-push and demand-pull policies on technical change–Does the locus of policies matter? Research policy, 41(8), 1296-1308.

Phale, K., Li, F., Adjei Mensah, I., OmariSasu, A. Y. and Musah, M. (2021), 'Knowledgebased economy capacity building for developing countries: a panel analysis in southern african development community', Sustainability 13(5), 2890.

Pham, T. T. T., Nguyen, K. S., Nguyen, H. H., Nguyen, L. T., & Vo, V. X. (2021). Dynamic entrepreneurship, planned innovation, and firm profitability:

evidence from a Southeast Asian country. Heliyon, 7(7), e07599.

Piech, K. (2004). The knowledge-based economy in transition countries: assessing the place of new EU member states [in:] K. The Knowledge-Based Economy in Transition Countries: selected issues, University College London–School of Slavonic and East European Studies, London, 1-56.

Pierce, J. L., & Delbecq, A. L. (1977). Organization structure, individual attitudes and innovation. Academy of management review, 2(1), 27-37.

Podinovski, V. V., & Thanassoulis, E. (2007). Improving discrimination in data envelopment analysis: Some practical suggestions. Journal of Productivity Analysis, 28(1), 117-126.

Poorfaraj, A., & Keshavarz, H. (2011). Knowledge and economic growth: Evidence from some developing countries. Journal of Education and Vocational Research, 1(1), 21-25.

Popov, E. V., & Kochetkov, D. M. (2019). Developing the Regional Knowledge Economy Index: a Case of Russian Regions. Journal of the Knowledge Economy, 10(4), 1860-1878.

Porat, M. (1977). The information economy.us department of commerce wash.

Porter, M. E. (2011), Competitive advantage of nations: creating and sustaining superior performance, simon and schuster.

Pourhabib Yekta, A., Kordrostami, S., Amirteimoori, A., & Kazemi Matin, R. (2018). Data envelopment analysis with common weights: the weight restriction approach. Mathematical Sciences, 12(3), 197-203.

Powell, W. W., & Snellman, K. (2004). The knowledge economy. Annual review of sociology, 199-220.

Pradhan, R. P., Arvin, M. B., & Bahmani, S. (2018). Are innovation and financial development causative factors in economic growth? Evidence from a panel granger causality test. Technological Forecasting and Social Change, 132, 130-142.

Pradhan, R. P., Arvin, M. B., Bahmani, S., & Bennett, S. E. (2017). The innovation-growth link in OECD countries: Could other macroeconomic variables matter? Technology in Society, 51, 113-123.

Pradhan, R. P., Arvin, M. B., Hall, J. H., & Nair, M. (2016). Innovation, financial development and economic growth in Eurozone countries. Applied Economics Letters, 23(16), 1141-1144.

Pradhan, R. P., Arvin, M. B., Nair, M., & Bennett, S. E. (2020). Sustainable economic growth in the European Union: The role of ICT, venture capital, and innovation. Review of Financial Economics, 38(1), 34-62.

Prokop, V., Stejskal, J., & Hajek, P. (2018). Effectiveness of selected knowledge-based determinants in macroeconomics development of EU 28 economies. In Finance & Economics Readings (pp. 69-83). Springer, Singapore.

Proksch, D., Haberstroh, M. M., & Pinkwart, A. (2017). Increasing the national innovative capacity: Identifying the pathways to success using a comparative method. Technological Forecasting and Social Change, 116, 256-270.

Prusak, L. (1997), 'Knowledge in organisations'.

Qamruzzaman, M., & Ferdaous, J. (2014). Building a Knowledge-Based Economy in Bangladesh. Asian Business Review, 4(3), 119-128.

Qian, Y. (2007). Do national patent laws stimulate domestic innovation in a global patenting environment? A cross-country analysis of pharmaceutical patent protection, 1978–2002. The Review of Economics and Statistics, 89(3), 436-453.

Quah, D. (2003). Digital goods and the new economy. Available at SSRN 410604.

Quah, D. T. (1999). The weightless economy in growth. Business Economist, 30, 40-53.

Qureshi, I., Park, D., Crespi, G. A., & Benavente, J. M. (2021). Trends and determinants of innovation in Asia and the Pacific vs. Latin America and the Caribbean. Journal of Policy Modeling, 43(6), 1287-1309.

Raab, R. A., & Kotamraju, P. (2006). The efficiency of the high-tech economy: Conventional development indexes versus a performance index. Journal of Regional Science, 46(3), 545-562.

Rabar, D. (2013). Assessment of regional efficiency in Croatia using data envelopment analysis. Croatian operational research review, 4(1), 76-88.

Rabar, D. (2017). An overview of data envelopment analysis application in studies on the socio-economic performance of OECD countries. Economic research-Ekonomska istraživanja, 30(1), 1770-1784.

Rabie, M. (2016). A theory of sustainable sociocultural and economic development. Springer.

Raheli, H., Rezaei, R. M., Jadidi, M. R., & Mobtaker, H. G. (2017). A two-stage DEA model to evaluate sustainability and energy efficiency of tomato production. Information Processing in Agriculture, 4(4), 342-350.

Rahimić, Z., & Kožo, A. (2009). Building and development of the knowledge-based economy in Bosnia and Herzegovina. Journal of Inerdisciplinary Management Research, 5, 111-122.

Ramanathan, R. (2003). An introduction to data envelopment analysis: a tool for performance measurement. Sage.

Ramanathan, R. (2006). Evaluating the comparative performance of countries of the Middle East and North Africa: A DEA application. Socio-Economic Planning Sciences, 40(2), 156-167.

Ramli, N. A., & Munisamy, S. (2013). Modeling undesirable factors in efficiency measurement using data envelopment analysis: A review.

Rantisi, N. M. (2002). The local innovation system as a source of'variety': openness and adaptability in New York City's garment district. Regional studies, 36(6), 587-602.

Ray, A. (1984). Cost-benefit analysis: Issues and methodologies. The World Bank.

Ray, S. C. (2004). Data envelopment analysis: theory and techniques for economics and operations research. Cambridge university press.

Ray, S. C. (2019). Data Envelopment Analysis with Alternative Returns to Scale. In The Palgrave Handbook of Economic Performance Analysis (pp. 145-188).

Palgrave Macmillan, Cham.

Ray, S. C. (2020). Choice of Inputs and Outputs for Production Analysis (pp. 1-34). Springer Singapore.

Ray, S. C., & Chen, L. (2015). Data envelopment analysis for performance evaluation: A child's guide. In Benchmarking for Performance Evaluation (pp. 75-116). Springer, New Delhi.

Ray, S. C., Kumbhakar, S. C. and Dua, P. (2015), Benchmarking for performance evaluation, Springer.

Reddy, G. T. (2015). Comparison and Correlation Coefficient between CRS and VRS models of OC Mines. International Journal of Ethics in Engineering & Management Education, 2(1), 2348-4748.

Rehman, N. U. (2016). FDI and economic growth: empirical evidence from Pakistan. Journal of Economic and Administrative Sciences.

Reynolds, P., Bosma, N., Autio, E., Hunt, S., De Bono, N., Servais, I., ... & Chin, N. (2005). Global entrepreneurship monitor: Data collection design and implementation 1998–2003. Small business economics, 24(3), 205-231.

Rezny, L., White, J. B., & Maresova, P. (2019). The knowledge economy: Key to sustainable development? Structural Change and Economic Dynamics, 51, 291-300.

Ribeiro, V. M., Varum, C., & Daniel, A. D. (2021). Introducing microeconomic foundation in data envelopment analysis: effects of the ex-ante regulation principle on regional performance. Journal of the Knowledge Economy, 12(3), 1215-1244.

Rim, G. N., Kim, G. S., Hwang, S. H., & Ko, U. D. (2019). Some problems in statistically assessing the level of knowledge economy. Journal of the Knowledge Economy, 10(3), 974-996.

Robertson, J., Caruana, A., & Ferreira, C. (2021). Innovation performance: The effect of knowledge-based dynamic capabilities in cross-country innovation ecosystems. International Business Review, 101866.

Robertson, S. L. (2008). Producing knowledge economies: The World Bank, the KAM, education and development. Re-reading Education Policies: Studying the Policy Agenda of the 21st Century. Netherlands: Sense Publishers.

Rock, M. T., & Bonnett, H. (2004). The comparative politics of corruption: accounting for the East Asian paradox in empirical studies of corruption, growth and investment. World Development, 32(6), 999-1017.

Rodríguez-Pose, A. (2013). Do institutions matter for regional development? Regional studies, 47(7), 1034-1047.

Rodríguez-Pose, A., & Di Cataldo, M. (2015). Quality of government and innovative performance in the regions of Europe. Journal of economic geography, 15(4), 673-706.

Rodríguez-Pose, A., & Storper, M. (2006). Better rules or stronger communities? On the social foundations of institutional change and its economic effects. Economic geography, 82(1), 1-25.

Rodríguez-Pose, A., & Wilkie, C. (2019). Innovating in less developed regions: What drives patenting in the lagging regions of Europe and North America. Growth and Change, 50(1), 4-37.

Rogge, K. S., & Reichardt, K. (2016). Policy mixes for sustainability transitions: An extended concept and framework for analysis. Research Policy, 45(8), 1620-1635.

Roghanian, P., Rasli, A., & Gheysari, H. (2012). Productivity through effectiveness and efficiency in the banking industry. Procedia-Social and Behavioral Sciences, 40, 550-556.

Roman, M. (2010). Regional efficiency of knowledge economy in the new EU countries: The Romanian and Bulgarian case.

Romer, P. M. (1990). Endogenous technological change. Journal of political Economy, 98(5, Part 2), S71-S102.

Romer, P. M. (1994). The origins of endogenous growth. Journal of Economic perspectives, 8(1), 3-22.

Roodman, D. (2009a). How to do xtabond2: An introduction to difference and system GMM in Stata. The stata journal, 9(1), 86-136.

Roodman, D. (2009b). A note on the theme of too many instruments. Oxford Bulletin of Economics and Statistics, 71(1), 135-158.

Roodman, D. (2020). xtabond2: Stata module to extend xtabond dynamic panel data estimator.

Rose, J., & Winter, K. (2015). A gap analysis of the South African innovation system for water. Water SA, 41(3), 406-415.

Rose, K. (2009). Enhancing innovation in developing country systems: A synthesis of case studies and lessons from Uganda. African Journal of Science, Technology, Innovation and Development, 1(2_3), 89-114.

Rosenberg, N. (1982). Inside the black box: technology and economics. cambridge university press.

Rosenberg, N. (1984), Perspectives on technology, technical report, ME Sharpe. Rosenberg, N. (2006), ‘Innovation and economic growth’.

Rosenberg, N. (2006). Innovation and economic growth.

Roser, M. (2014). Human development index (HDI). *Our World in Data*.

Rostamzadeh, R., Akbarian, O., Banaitis, A., & Soltani, Z. (2021). Application of DEA in benchmarking: a systematic literature review from 2003–2020. Technological and Economic Development of Economy, 27(1), 175-222.

Rothwell, R., & Zegveld, W. (1981). Government regulations and innovation—industrial Innovation and Public Policy. Industrial Innovation and Public Policy. Frances Pinter, London, 116-147.

Rothwell, R., Freeman, C., Horlsey, A., Jervis, V. T. P., Robertson, A. B., & Townsend, J. (1974). SAPPHO updated-project SAPPHO phase II. Research policy, 3(3), 258-291.

Rousseau, S., & Rousseau, R. (1997). Data envelopment analysis as a tool for constructing scientometric indicators. Scientometrics, 40(1), 45-56.

Rousseau, S., & Rousseau, R. (1998). The scientific wealth of European nations: Taking effectiveness into account. Scientometrics, 42(1), 75-87.

Rowley, J. (2007). The wisdom hierarchy: representations of the DIKW hierarchy. Journal of information science, 33(2), 163-180.

Roztocki, N., & Weistroffer, H. R. (2015). Information and communication technology in transition economies: An assessment of research trends. Information Technology for Development, 21(3), 330-364.

Ruttan, V. W. (2000). Technology, growth, and development: an induced innovation perspective. OUP Catalogue.

Sabau, G. L. (2010). Know, live, and let live: Towards a redefinition of the knowledge-based economy—sustainable development nexus. Ecological Economics, 69(6), 1193-1201.

Salahi, M., Toloo, M., & Hesabirad, Z. (2019). Robust Russell and enhanced Russell measures in DEA. Journal of the Operational Research Society, 70(8), 1275-1283.

Saljoughian, M., Ghandehari, M., Shirouyehzad, H., Dabestani, R., & Balouei, H. (2013). Performance evaluation of OECD countries by data envelopment analysis based on science and technology factors. Journal of Applied Science and Engineering Management, 1(1), 24-35.

Samadi, A. H. (2019). Institutions and entrepreneurship: unidirectional or bidirectional causality? Journal of Global Entrepreneurship Research, 9(1), 3.

Samuelson, P., & Varian, H. (2001). The ' New Economy Information Technology: A Review of Information Policy in the 1990s. Harvard University, 27.

Sandu, S., & Ciocanel, B. (2014). Impact of R&D and Innovation on High-tech Export. Procedia Economics and Finance, 15, 80-90.

Santana, N. B., Mariano, E. B., Camioto, F. D. C., & Rebelatto, D. A. D. N. (2015). National innovative capacity as determinant in sustainable development: a comparison between the BRICS and G7 countries. International Journal of Innovation and Sustainable Development, 9(3-4), 384-405.

Sarangi, A. K., Pradhan, R. P., Nath, T., Maradana, R. P., & Roy, H. (2022). How Does Innovation Affect Economic Growth? Evidence from G20 Countries. The Indian Economic Journal, 70(1), 8-21.

Sargan, J. D. (1958). The estimation of economic relationships using instrumental variables. Econometrica: Journal of the econometric society, 393-415.

Sarkis, J. (2007). Preparing your data for DEA. In Modeling data irregularities and structural complexities in data envelopment analysis (pp. 305-320). Springer, Boston, MA.

Saudi Arabian Ministry of Economy and Planning (2010). Ninth Development Plan: Chapter 5 Available at: https://www.mep.gov.sa/DocumentsLibrary/NinthDevelopmentPlan/Ninth%20Development%20Plan%20-%20Chapter%205%20-%20Knowledge-Based%20Economy.pdf.

Schmidt-Ehmcke, J., & Zloczysti, P. (2009). Research efficiency in manufacturing: An application of DEA at the industry level. DIW Discussion Papers, No. 884, Deutsches Institut für Wirtschaftsforschung (DIW), Berlin

Schmookler, J. (1966). Invention and economic growth. In Invention and Economic

Growth. Harvard University Press.

Schneider, P. H. (2005). International trade, economic growth and intellectual property rights: A panel data study of developed and developing countries. Journal of Development Economics, 78(2), 529-547.

Schultz, T. W. (1980). Investment in entrepreneurial ability. The Scandinavian Journal of Economics, 437-448.

Schumpeter, J. (1934). The theory of economic development. in 'Joseph Alois Schumpeter: Entrepreneurship, Style and Vision', Springer, pp. 61–116.

Schumpeter, J. A. (1942). Socialism, capitalism and democracy. Harper and Brothers.

Schwab, K. (2018, November). The global competitiveness report 2018. In World Economic Forum (Vol. 671).

Šegota, A., Tomljanović, M., & Huđek, I. (2017). Contemporary approaches to measuring competitiveness–the case of EU member states. Journal of Economics and Business, 35(1), 123-150.

Seidel, U., Müller, L., Köcker, G. M. Z., & Filho, G. D. A. (2013). A new approach for analysing national innovation systems in emerging and developing countries. Industry and Higher Education, 27(4), 279-285.

Seiford, L. M., & Zhu, J. (1999). Infeasibility of super-efficiency data envelopment analysis models. INFOR: Information Systems and Operational Research, 37(2), 174-187.

Sener, S., & Tunali, C. B. (2017). Is innovation conducive to economic growth? The case of Central and Eastern European countries. In Innovation, Governance and Entrepreneurship: How Do They Evolve in Middle Income Countries? (pp. 35-51). Palgrave Macmillan, Cham.

Sepehrdoust, H., & Zamani Shabkhaneh, S. (2015). Impact of knowledge-based components on total factor productivity of MENA countries. Iranian Economic Review, 19(2), 149-163.

Shahabadi, A., Nemati, M., & Hosseinidoust, S. E. (2017). The effect of knowledge economy factors on income inequality in the selected Islamic Countries. Journal of the knowledge economy, 8(4), 1174-1188.

Shao, Q., Yuan, J., Lin, J., Huang, W., Ma, J., & Ding, H. (2021). A SBM-DEA based performance evaluation and optimization for social organizations participating in community and home-based elderly care services. PloS one, 16(3), e0248474.

Shapira, P., Youtie, J., Yogeesvaran, K., & Jaafar, Z. (2006). Knowledge economy measurement: Methods, results and insights from the Malaysian Knowledge Content Study. Research Policy, 35(10), 1522-1537.

Sharma, M. J., & Yu, S. J. (2015). Stepwise regression data envelopment analysis for variable reduction. Applied Mathematics and Computation, 253, 126-134.

Sharma, N (2008). The Origin of Data Information Knowledge Wisdom (DIKW) Hierarchy. Google Inc. Archived at: https://doi. org/10.17605/OSF. IO/N7G9X.

Sharma, S., & Thomas, V. (2008). Inter-country R&D efficiency analysis: An application of data envelopment analysis. Scientometrics, 76(3), 483-501.

Shen, Y., Shen, M., & Chen, Q. (2016). Measurement of the new economy in China: big data approach. China Economic Journal, 9(3), 304-316.

Shepherd, D. A., & Patzelt, H. (2011). The new field of sustainable entrepreneurship: Studying entrepreneurial action linking “what is to be sustained” with “what is to be developed”. Entrepreneurship theory and practice, 35(1), 137-163.

Sherman, H. D., & Zhu, J. (2006). Service productivity management: Improving service performance using data envelopment analysis (DEA). Springer science & business media.

Shewell, P., & Migiro, S. (2016). Data envelopment analysis in performance measurement: A critical analysis of the literature. Problems and Perspectives in Management, (14, Iss. 3 (contin. 3)), 705-713.

Shibata, T. (2006), Japan, Moving Toward a More Advanced Knowledge Economy, 1: Assessment and Lessons, World Bank Publications.

Shiryaev, D. V., Artemova, E. I., Zelinskaya, M. V., Novoselov, S. N., Galiullina, S. D., & Pismennaya, E. E. (2016). " Knowledge economy" as a resource for the intensification of socio-economic transformation of the regional economic space. *International review of management and marketing*, *6*(1S).

Shrieves, R. E. (1978). Market structure and innovation: a new perspective. The Journal of Industrial Economics, 329-347.

Sickles, R. C. and Zelenyuk, V. (2019), Measurement of productivity and efficiency, Cambridge University Press.

Siddiqui, S. A., & Afzal, M. N. I. (2022). Sectoral diversification of UAE toward a knowledge-based economy. Review of Economics and Political Science.

Sinha, D. (2008). Patents, innovations and economic growth in Japan and South Korea: evidence from individual country and panel data, Applied Econometrics, and International Development 8(1).

Širá, E., Vavrek, R., Kravčáková Vozárová, I., & Kotulič, R. (2020). Knowledge economy indicators and their impact on the sustainable competitiveness of the EU countries. Sustainability, 12(10), 4172.

Sivak, R., Caplanova, A., & Hudson, J. (2011). The impact of governance and infrastructure on innovation. Post-Communist Economies, 23(02), 203-217.

Sivalogathasan, V., & Wu, X. (2014). The effect of foreign direct investment on innovation in south Asian emerging markets. Global Business and Organizational Excellence, 33(3), 63-76.

Škare, M., & Rabar, D. (2016). Measuring economic growth using data envelopment analysis. Amfiteatru Economic Journal, 18(42), 386-406.

Skrodzka, I. (2016). Knowledge-based economy in the European Union–Cross-country analysis. Statistics in Transition. New Series, 17(2), 281-294.

Smith, K. (2000). Innovation indicators and the knowledge economy: concepts, results and policy challenges. Oslo: STEP Group.

Smith, K. H. (2002a). What is the 'Knowledge Economy'? Knowledge intensity and distributed knowledge bases. United Nations University. Institute for New Technologies

Smith, P. (1997). Model misspecification in data envelopment analysis. Annals of Operations Research, 73, 233-252.

Smits, R., & Kuhlmann, S. (2004). The rise of systemic instruments in innovation policy. International journal of foresight and innovation policy, 1(1-2), 4-32.

Solow, R. M. (1956). A contribution to the theory of economic growth. The quarterly journal of economics, 70(1), 65-94.

Soumitra, D., Lanvin, B., & Wunsch-Vincent, S. (Eds.). (2020). Global innovation index 2020: who will finance innovation? WIPO.

Spaapen, J., & Van Drooge, L. (2011). Introducing 'productive interactions' in social impact assessment. Research evaluation, 20(3), 211-218.

Spencer, A. B. (2001). Antitrust and the Information Age: Section 2 Monopolization Analyses in the New Economy. Harvard Law Review.

Spitsin, V. V., Mikhalchuk, A., Vukovic, D. B., & Spitsina, L. Y. (2022). Technical Efficiency of High-Technology Industries in the Crisis: Evidence from Russia. Journal of the Knowledge Economy, 1-26.

Stam, E. (2008). Entrepreneurship and innovation policy. Jena Economic Research Paper, (2008-006).

Staničkova, M. (2013). DEA Method for Evaluation of EU Performance. International Journal of Economics and Management Engineering, 7(6), 1730-1736.

Staníčková, M., & Skokan, K. (2011, December). Evaluation of the EU member states competitive potential by data envelopment analysis. In Proceedings of the 2nd international conference on Mathematical Models for Engineering Science, and proceedings of the 2nd international conference on Development, Energy, Environment, Economics, and proceedings of the 2nd international conference on Communication and Management in Technological Innovation and Academic Globalization (pp. 190-195).

Steedman, I. (2002). On 'measuring' knowledge in new (endogenous) growth theory. Manchester Metropolitan University.

Stiglitz, J. (1999). Public policy for a knowledge economy. Remarks at the Department for Trade and Industry and Center for Economic Policy Research, 27(3), 3-6.

Stojčić, N., Srhoj, S., & Coad, A. (2020). Innovation procurement as capability-building: Evaluating innovation policies in eight Central and Eastern European countries. European Economic Review, 121, 103330.

Storey, D. J. (1991). The birth of new firms—does unemployment matter? a review of the evidence, Small business economics 3, 167–178.

Su, W., Wang, D., Xu, L., Zeng, S., & Zhang, C. (2020). A non-radial super efficiency DEA framework using a MCDM to measure the research efficiency of disciplines at Chinese universities. IEEE Access, 8, 86388-86399.

Sueyoshi, T. (1992). Measuring the industrial performance of Chinese cities by data envelopment analysis. Socio-Economic Planning Sciences, 26(2), 75-88.

Suh, J., & Chen, D. H. C. (Eds.). (2007). Korea as a knowledge economy: Evolutionary process and lessons learned. The World Bank.

Sukharev, O. (2021). Measuring the contribution of the "knowledge economy" to the economic growth rate: Comparative analysis. Journal of the Knowledge Economy, 12(4), 1809-1829.

Summad, E., Al-Kindi, M., Shamsuzzoha, A., Piya, S., & Ibrahim, M. K. (2018, January). A Framework to Assess a Knowledge-Based Economy: Special Focus to Higher Educational Institutions. In Proceedings of the International Conference on Industrial Engineering and Operations Management Paris, France, July (pp. 26-27).

Sun, S. (2002). Measuring the relative efficiency of police precincts using data envelopment analysis. Socio-economic planning sciences, 36(1), 51-71.

Sunley, P., Pinch, S., Reimer, S., & Macmillen, J. (2008). Innovation in a creative production system: the case of design. Journal of economic geography, 8(5), 675-698.

Sweet, C. M., & Maggio, D. S. E. (2015). Do stronger intellectual property rights increase innovation? World Development, 66, 665-677.

Tadros, M. E. (2015). The Arab Gulf states and the knowledge economy: Challenges and opportunities. Arab Gulf States Institute in Washington.

Taghizadech, R., & Ahmadi, M. (2019). Statistical and econometrical analysis of knowledge-based economy indicators affecting economic growth in Iran: The new evidence of principal component analysis—Tukey and ARDL bound test. Preprint: January 10.

Tan, H. B., & Hooy, C. W. (2007). The development of East Asian countries towards a knowledge-based economy: a DEA analysis. Journal of the Asia Pacific Economy, 12(1), 17-33.

Tan, H. B., Hooy, C. W., Islam, S. M., & Manzoni, A. (2008). Relative efficiency measures for the knowledge economies in the Asia Pacific region. Journal of modelling in management.

Tang, J., Liu, J., Chen, J., & Wei, F. (2020). Performance Ranking Method Based on Super efficiency with Directional Distance Function in DEA. Mathematical Problems in Engineering, 2020.

Tarnawska, K., & Mavroeidis, V. (2015). Efficiency of the knowledge triangle policy in the EU member states: DEA approach. Triple Helix, 2(1), 1-22.

Tasnim, N., & Afzal, M. N. I. (2018). An empirical investigation of country-level efficiency and national systems of entrepreneurship using Data Envelopment Analysis (DEA) and the TOBIT model. Journal of Global Entrepreneurship Research, 8(1), 1-17.

Taylor, W. E. (1980). Small sample considerations in estimation from panel data. Journal of Econometrics, 13(2), 203-223.

Tchamyou, V. S. (2017). The role of knowledge economy in African business. Journal of the Knowledge Economy, 8(4), 1189-1228.

Tebaldi, E., & Elmslie, B. (2008). Institutions, innovation and economic growth. MPRA Paper no 9683.

Tebaldi, E., & Elmslie, B. (2013). Does institutional quality impact innovation? Evidence from cross-country patent grant data. Applied Economics, 45(7), 887-900.

Tellis, G. J., Eisingerich, A. B., Chandy, R. K., & Prabhu, J. C. (2008). Competing for the future: Patterns in the global location of R&D centers by the world's largest firms. ISBM Report, 6.

Terzić, L. (2017). The role of innovation in fostering competitiveness and economic growth: Evidence from developing economies. Comparative Economic Research. Central and Eastern Europe, 20(4), 65-81.

Thanassoulis, E. (1993). A comparison of regression analysis and data envelopment analysis as alternative methods for performance assessments. Journal of the operational research society, 44(11), 1129-1144.

Thanassoulis, E. (2001). Introduction to the theory and application of data envelopment analysis. Dordrecht: Kluwer Academic Publishers.

Thanassoulis, E., & Silva, M. C. A. (2018). Measuring efficiency through data envelopment analysis. Impact, 2018(1), 37-41.

Thanassoulis, E., Boussofiane, A., & Dyson, R. G. (1996). A comparison of data envelopment analysis and ratio analysis as tools for performance assessment. Omega, 24(3), 229-244.

Thomas, A., & Carl, D. (Eds.). (2001). Korea and the knowledge-based economy making the transition: Making the transition. OECD publishing.

Thomas, M. A. (2010). What do the worldwide governance indicators measure? The European Journal of Development Research, 22, 31-54.

Thomas, V. J., Jain, S. K., & Sharma, S. (2009, October). Analyzing R&D efficiency in Asia and the OECD: An application of the Malmquist productivity index. In 2009 Atlanta Conference on Science and Innovation Policy (pp. 1-10). IEEE.

Thomas, V. J., Sharma, S., & Jain, S. K. (2011). Using patents and publications to assess R&D efficiency in the states of the USA. World Patent Information, 33(1), 4-10.

Thrall, R. M. (1996). Duality, classification and slacks in DEA. Annals of Operations Research, 66(2), 109-138.

Thurik, A. R., Carree, M. A., Van Stel, A., & Audretsch, D. B. (2008). Does self-employment reduce unemployment? Journal of business venturing, 23(6), 673-686.

Tocan, M. C. (2012). Knowledge-based economy assessment. Journal of Knowledge Management, Economics and Information Technology, 2(5), 1-13.

Toimbek, D. (2022). Problems and perspectives of transition to the knowledge-based economy in Kazakhstan. Journal of the Knowledge Economy, 13(2), 1088-1125.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. European journal of operational research, 130(3), 498-509.

Tone, K. (2016). On the Consistency of Slacks Based Measure Max Model and Super Slacks Based Measure Model (No. 16-24). National Graduate Institute for Policy Studies.

Tone, K., Toloo, M., & Izadikhah, M. (2020). A modified slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, 287(2), 560-571.

Tong, L., & Liping, C. (2009, December). Research on the evaluation of innovation efficiency for China's regional innovation system by utilizing DEA. In 2009 International Conference on Information Management, Innovation Management, and Industrial Engineering (Vol. 1, pp. 192-195). IEEE.

Toselli, M. (2017). Knowledge sources and integration ties toward innovation. A food sector perspective. Eurasian Business Review, 7(1), 43-65.

Tran-Nguyen, N. (2015). Innovation And Institutional Quality on Economic Growth in Asia.

Trewin, D. (2002). Measuring a knowledge-based economy and society: An Australian framework, 2002. Australian Bureau of Statistics.

Tsipouri, L. (2013, March). Innovation strategies articulating supply side and demand side aspects. In Research and Innovation Policies Seminar.

Tyshchenko, V. (2013). Diagnosis of knowledge economy vector: A regional aspect. Economic Annals, XXI.

Udovič, B., & Bučar, M. (2008). Building the knowledge society: The case of European Union new member states. Revija za sociologiju, 39(1-2), 29-49.

United Nations (2020). World Economic Situation and Prospects, Department of Economic and Social Affairs-Economic Analysis

Urbano, D., Aparicio, S., & Audretsch, D. (2019). Twenty-five years of research on institutions, entrepreneurship, and economic growth: what has been learned? Small Business Economics, 53(1), 21-49.

Uyarra, E. (2016). The impact of public procurement of innovation. In Handbook of innovation policy impact (pp. 355-381). Edward Elgar Publishing.

Uyarra, E., & Ramlogan, R. (2016). The impact of cluster policy on innovation. In Handbook of innovation policy impact (pp. 196-238). Edward Elgar Publishing.

Vadra, R. (2017). Knowledge economy in BRICS: a case of South Africa. Journal of the knowledge economy, 8(4), 1229-1240.

Valenta, R., Idsø, J., & Opstad, L. (2021). Evidence of a Threshold Size for Norwegian Campsites and Its Dynamic Growth Process Implications—Does Gibrat’s Law Hold? Economies, 9(4), 175.

van den Besselaar, P. A., Flecha, R., & Radauer, A. (2018). Monitoring the impact of EU Framework Programmes.

Varga, A., & Sebestyén, T. (2017). Does EU Framework Program participation affect regional innovation? The differentiating role of economic development. International Regional Science Review, 40(4), 405-439.

Varsakelis, N. C. (2006). Education, political institutions, and innovative activity: A cross-country empirical investigation. Research policy, 35(7), 1083-1090.

Vera, A., & Kuntz, L. (2007). Process-based organization design and hospital efficiency. Health care management review, 32(1), 55-65.

Veracierto, M. (2008). Corruption and innovation. Economic Perspectives, 32(1).

Vincova, K. (2005). Using DEA models to measure efficiency. Biatec, 13(8), 24-28.

VINNyChUK, O., SKRAShChUK, L., & VINNyChUK, I. (2014). Research of

Economic Growth in the context of Knowledge Economy. Intellectual economics, 8(1), 116-127.

Vinutha, H. P., Poornima, B., & Sagar, B. M. (2018). Detection of outliers using interquartile range technique from intrusion dataset. In Information and Decision Sciences: Proceedings of the 6th International Conference on FICTA (pp. 511-518). Springer Singapore.

Visbal-Cadavid, D., Martínez-Gómez, M., & Guijarro, F. (2017). Assessing the efficiency of public universities through DEA. A case study. Sustainability, 9(8), 1416.

Vukoszavlyev, S. (2019). The connenction between global innovation index and economic well-being indexes. Applied Studies in Agribusiness and Commerce, 13(3-4), 87-92.

Waguespack, D. M., Birnir, J. K., & Schroeder, J. (2005). Technological development and political stability: Patenting in Latin America and the Caribbean. Research policy, 34(10), 1570-1590.

Wakelin, K. (2001). Productivity growth and R&D expenditure in UK manufacturing firms. Research policy, 30(7), 1079-1090.

Wang, C. and Kafouros, M. I. (2009), 'What factors determine innovation per formance in emerging economies? evidence from china', International Business Review 18(6), 606–616.

Wang, C. N., Dang, T. T., Tibo, H., & Duong, D. H. (2021). Assessing renewable energy production capabilities using DEA window and fuzzy TOPSIS model. Symmetry, 13(2), 334.

Wang, E. C., & Huang, W. (2007). Relative efficiency of R&D activities: A cross-country study accounting for environmental factors in the DEA approach. Research policy, 36(2), 260-273.

Wang, P., & Li, F. (2021). Science, technology and innovation policy in Russia and China–Mapping and comparisons in objectives, instruments, and implementation. Technological Forecasting and Social Change, 162, 120386.

Wei, F., Song, J., Jiao, C., & Yang, F. (2019). A modified slacks-based ranking method handling negative data in data envelopment analysis. Expert Systems, 36(1), e12329.

Weil, D. N., & Wilde, J. (2009). How relevant is Malthus for economic development today? American Economic Review, 99(2), 255-60.

Weisberg, S. (2005). Applied linear regression (Vol. 528). John Wiley & Sons.

Weitzman, M. L. (1998). Recombinant growth. The Quarterly Journal of Economics, 113(2), 331-360.

Welch, W. (2000). The Information Society Index (ISI) 2000. Development Outreach.

Wen, J., Deng, P., Zhang, Q., & Chang, C. P. (2021). Is higher government efficiency bringing about higher innovation? Technological and economic development of economy, 27(3), 626-655.

Wennekers, S., & Thurik, R. (1999). Linking entrepreneurship and economic growth. Small business economics, 13(1), 27-56.

Wilson, P. W. (2008). FEAR: A software package for frontier efficiency analysis with R. Socio-economic planning sciences, 42(4), 247-254.

Winskel, M., & Moran, B. (2008). Innovation theory and low carbon innovation: Innovation processes and innovations systems. Edinburgh University.

Winter, S. G. (1987). Knowledge and competence as strategic assets. DJ Teece, ed. The Competitive Challenge: Strategies for Industrial Innovation and Renewal. Cambridge Ma.: Ballinger, 1-13.

Wintjes, R. (2015). Demand-side innovation policies at regional level.

Wirba, A. V. (2022). Transforming Cameroon into knowledge-based economy (KBE): the role of education, especially higher education. Journal of the Knowledge Economy, 13(2), 1542-1572.

Witt, U. (2002). How evolutionary is Schumpeter’s theory of economic development? Industry and innovation 9(12), 7–22.

Womer, N. K., Bougnol, M. L., Dula, J. H., & Retzlaff-Roberts, D. (2006). Benefit-cost analysis using data envelopment analysis. Annals of Operations Research, 145(1), 229-250.

Wong, W. P. (2021). A Global Search Method for Inputs and Outputs in Data Envelopment Analysis: Procedures and Managerial Perspectives. Symmetry, 13(7), 1155.

Wooldridge, J. M. (2015). Introductory econometrics: A modern approach. Cengage learning.

World Bank (2003). Lifelong learning in the global knowledge economy: Challenges for developing countries. The World Bank.

World Bank (2007a). Building knowledge economies: Advanced strategies for development. The World Bank.

World Bank, A. D. (2007b). Moving towards knowledge-based economies: Asian experiences.

Wu, J., Ma, Z., & Zhuo, S. (2017). Enhancing national innovative capacity: The impact of high-tech international trade and inward foreign direct investment. International Business Review, 26(3), 502-514.

Wu, J., Tsai, H., & Zhou, Z. (2011). Improving efficiency in international tourist hotels in Taipei using a non-radial DEA model. International Journal of Contemporary Hospitality Management.

Wu, P. C., Huang, T. H., & Pan, S. C. (2014). Country performance evaluation: The DEA model approach. Social indicators research, 118(2), 835-849.

Yaffee, R. (2003). A primer for panel data analysis. Connect: Information Technology at NYU, 8(3), 1-11.

Yakici Ayan, T. and Pabu¸ccu, H. (2018). The assessment of knowledge economy efficiency: Comparing turkey with the European Union countries. 36(2), 443–464.

Yang, C. H. (2006). Is innovation the story of Taiwan's economic growth? Journal of Asian Economics, 17(5), 867-878.

Yang, S., & Li, L. (2021). A Study on Evaluation on Innovation Efficiency of Advanced Manufacturing in China. In E3S Web of Conferences (Vol. 235, p. 02074). EDP Sciences.

Yao, S., & Han, Z. (2010). Performance of the Chinese insurance industry under economic reforms.

Yeo, Y., Lee, J.D. and Jung, S. (2023). Winners and losers in a knowledge based economy: investigating the policy packages for an inclusive growth based on a computable general equilibrium analysis of Korea, Journal of the Asia Pacific Economy 28(2), 420–456.

Youssef, A. B., Boubaker, S., & Omri, A. (2018). Entrepreneurship and sustainability: The need for innovative and institutional solutions. Technological Forecasting and Social Change, 129, 232-241.

Yue, W. (2022). Foreign direct investment and the innovation performance of local enterprises. Humanities and Social Sciences Communications, 9(1), 1-9.

Zabala-Iturriagagoitia, J. M., Aparicio, J., Ortiz, L., Carayannis, E. G., & Grigoroudis, E. (2021). The productivity of national innovation systems in Europe: Catching up or falling behind? Technovation, 102, 102215.

Żak, K. (2016). The knowledge economy-the diagnosis of its condition in selected countries. Studia Ekonomiczne, 271, 176-188.

Zang, L., Xiong, F., Lao, X., & Gao, Y. (2019). Does governance efficiency matter for national innovative capacity? One tale from different countries. Technology Analysis & Strategic Management, 31(2), 239-252.

Zarbakhshnia, N., & Jaghdani, T. J. (2018). Sustainable supplier evaluation and selection with a novel two-stage DEA model in the presence of uncontrollable inputs and undesirable outputs: a plastic case study. The International Journal of Advanced Manufacturing Technology, 97(5), 2933-2945.

Zeb, S. (2022). The role of knowledge economy in Asian business. Future Business Journal, 8(1), 1-13.

Zelenyuk, V. (2020). Aggregation of inputs and outputs prior to Data Envelopment Analysis under big data. European Journal of Operational Research, 282(1), 172-187.

Zelinska, H., Andrusiv, U., & Simkiv, L. (2020). Knowledge economy: trends in the world and analysis of Ukraine. Journal of Eastern European and Central Asian Research (JEECAR), 7(1), 104-113.

Zemtsov, S., & Kotsemir, M. (2019). An assessment of regional innovation system efficiency in Russia: the application of the DEA approach. Scientometrics, 120(2), 375-404.

Zhang, X., & Shi, W. (2019). Research about the university teaching performance evaluation under the data envelopment method. Cognitive Systems Research, 56, 108-115.

Zhao, F. (2005). Exploring the synergy between entrepreneurship and innovation. International Journal of Entrepreneurial Behavior & Research.

Zhong, K., Li, C. and Wang, Q. (2021).Evaluation of bank innovation efficiency with data envelopment analysis: From the perspective of uncovering the black box between input and output, Mathematics 9(24), 3318.

Zhou, P., Poh, K. L., & Ang, B. W. (2007). A non-radial DEA approach to measuring environmental performance. European journal of operational research, 178(1), 1-9.

Zhu, J. (1996). Data envelopment analysis with preference structure. Journal of the Operational Research Society, 47(1), 136-150.

Zhu, J. (1998). Data envelopment analysis vs. principal component analysis: An illustrative study of economic performance of Chinese cities. European journal of operational research, 111(1), 50-61.

Zhu, J. (2015). Data Envelopment Analysis a Handbook of Models and Methods. Springer.

Zhu, N., Zhu, C., & Emrouznejad, A. (2020). A combined machine learning algorithms and DEA method for measuring and predicting the efficiency of Chinese manufacturing listed companies. Journal of Management Science and Engineering.

Zhuparova, A., Sagiyeva, R., & Zhaisanova, D. (2019). The Impact of the Knowledge Economy Indicators on Regional Economic Growth: Evidence From Kazakhstan. In Proceedings of the International Management Conference (Vol. 13, No. 1, pp. 514-520). Faculty of Management, Academy of Economic Studies, Bucharest, Romania.

Ziari, S., & Raissi, S. (2016). Ranking efficient DMUs using minimizing distance in DEA. Journal of Industrial Engineering International, 12(2), 237-242.

Zins, C. (2007). Conceptual approaches for defining data, information, and knowledge. Journal of the American society for information science and technology, 58(4), 479-493.

Zuo, G., & Chen, Q. (2014). Study on R and D Efficiencies of Chinese Science Parks: An Application of DEA Model and Malmquist Index. Journal of Applied Sciences, 14(8), 784-790.