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"High Spending, Poor Productivity Gains!" Assessing Public Health System (In)Efficiency and Hospital Performance In The State Of Kuwait: Would More Private Delivery Improve Healthcare?

Aljawhara Alsabah

“HIGH SPENDING, POOR PRODUCTIVITY GAINS!” ASSESSING PUBLIC HEALTH SYSTEM (IN)EFFICIENCY AND HOSPITAL PERFORMANCE IN THE STATE OF KUWAIT: WOULD MORE PRIVATE DELIVERY IMPROVE HEALTHCARE?

By

ALJAWHARA MOHAMMAD ALKHALED ALSABAH

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Student Name: AlJawhara Al-Sabah

The signatures below certify that this dissertation has been examined and accepted with the following conditions:

__✓__Approved no revisions

_____Approved minor revisions

_____Approved major revisions

_____Not Approved

Name	Signature	Date
Adam E. Block, PhD	[signature]	7/27/22
Kenneth A. Knapp, PhD	[signature]	27 July 2022
Naser H. Al-Sabti, M.D.	[signature]	7/28/22

Abstract

The healthcare sector in the State of Kuwait has been nurtured for many decades by the government, where the majority of health services in the country are controlled by the Ministry of Health (MoH). Public general and specialized hospitals represent a significant proportion of health expenditures in Kuwait; amidst the backdrop of dwindling health resources, a declining global oil market in an oil-dependent welfare state, and a heavy reliance on a non-national clinical workforce. Although healthcare services in public sector hospitals are at highly subsidized rates, causing private sector involvement in healthcare to be considerably low, the growing demands for private delivery of care burgeoned participation of private hospitals in Kuwait, and improving hospital efficiency and productivity is more critical and timelier than ever. This dissertation aims to analyze public health system efficiency and hospital performance in the State of Kuwait; where we begin by evaluating the input-oriented technical efficiency (TE) of MoH hospitals in 2015-2019 and identifying potential areas for efficiency improvement by exploring influencing institutional and environmental factors. We further conduct an output-oriented comparative study of public-private productivity in view of ownership, hospital management, and other external variables to understand drivers of productive efficiency and potential factors of output maximization disparities in 2019/2020. As robustness checks, we adjusted activity differences in general and specialized hospitals to obtain balanced and weighted sets of outputs and used bootstrapping to control for bias and account for small sample sizes. Over the five years between 2015 and 2019, TE in MoH hospitals has decreased by an average of 2.98% solely based on technical regress, where the six MoH general hospitals reported a pooled mean efficiency of 86.58%, and the nine sampled MoH specialized hospitals had a five-year pooled average of 65.47% efficiency. Inefficient (< 1 variable returns to scale) MoH general hospitals in 2019/2020 registered a higher deterioration in output productivity (79.4%) than inefficient private hospitals (85.4%). The second-stage Tobit regression for our comparative analysis in 2019/2020 found that ownership had a significant impact on pure/managerial efficiency in MoH general hospitals that influenced their ability to maximize their outputs and better allocate their given inputs for optimum performance on the scale; indicating a higher degree of leakage and waste in the public sector. The differences between public and private healthcare services suggest MoH policymakers should focus on improving allocative efficiency in the public health system, and healthcare policy reforms should focus on strengthening management structures in Kuwait's public hospitals to improve production efficiency and financial sustainability.

Keywords: technical efficiency, productivity, data envelopment analysis, public hospital, private hospital, Kuwait

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To my parent: At times this felt like a never-ending journey rather than an ultimate destination, and now that we're here, my greatest gratitude and love goes out to you both for coming along on this wonderful (and at times crazy) ride. A big thank you to the A-team, my doctoral committee: Dr. Adam Block, Dr. Kenneth Knapp, and Dr. Naser Al-Sabti; your support went above and beyond, and your patience throughout the dissertation process was truly remarkable. Our Department Chair, Dr. Mark Kittleson: Thank you for your unwavering encouragement!

Lastly, healthcare is a right and not a privilege; this right must be protected by governments and not influenced by politics or personal interests. Each year nearly 6 million people die in developing countries from inefficient healthcare services – this research is also for them, the families they've left behind, and the millions of others today still facing health inequities and access to high-quality healthcare.

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Chapter 1

Amid dwindling resources and growing demands, global pursuits for cost-effectiveness in delivering quality care and interventions are intensifying as recent efforts shift towards optimizing essential medical supply chains. Yet, a viable balance of equity and efficiency in the allocation of health resources – without compromising one for the other – remain among the major implementation challenges in global public health systems. Public health system reforms must commit to achieving effective, efficient, and equitable healthcare for all; prioritizing the Sustainable Development Goal 3 (SDG 3) targets and indicators for Universal Health Coverage (UHC) when opting for allocation efficiency (World Health Organization, 2015).

In 2010, the World Health Report projected that 20 percent to 40 percent of all health spending (between $1.3 and $2.6 trillion) was squandered globally due to inefficiencies in healthcare systems (WHO, 2015). Furthermore, it was projected that the yearly loss of health resources owing to hospital-related inefficiencies is approximately $300 billion (Elovainio & Evans, 2013). Since hospitals are the primary consumers of health resources, hospital efficiency is crucial before the overall health system can be deemed efficient. According to Hanson et al. (2002) , public hospitals in Sub-Saharan African nations absorb a considerable portion (about 40 percent) of the entire health budget. Kelly et al. (2016) also claimed that public hospitals in the United Kingdom (UK) accounted for roughly 44 percent of national health spending in 2012/13. Similar findings have been reported in a wide range of publications and systematic reviews conducted internationally (Hollingsworth, 2008; Kiadaliri et al., 2013; Li et al., 2014; Varabyova & Müller, 2016). As a result, conducting an efficiency analysis of public hospitals and identifying the cause(s) of inefficiency is critical in order to make decisions that facilitate optimal use of public resources (Jacobs et al., 2006).

As a welfare state with elaborate subsidies exclusively for its own citizens, the Kuwaiti government essentially provides the citizenry with extensive social welfare programs therefore becoming an allocation or distributive state. The budget, in effect, is little more than an expenditure program. National health accounts and time-series data reveal Kuwait's unsustainable health expenditure (as a percent of general government expenditure) drastically increasing between 2010-2019, while government health spending as a share of gross domestic product (GDP) further growing over the same 2010-2019 fiscal periods (Table 1 & Table 2) (Central Bank of Kuwait, 2021). Despite the majority of government expenditures going towards healthcare and the Ministry of Health's (MoH) annual budget, life expectancy of Kuwaitis and other population health indicators are not any better compared to similar countries in the region that spend considerably less on healthcare; indicating possible inefficiency in the utilization of scarce resources (World Bank, 2019).

Table 1

General Health Expenditures and Government Spending, FY 2009/2010 – FY 2018/2019 in Million Current US$

Time	Current Health Expenditure (CHE)	Domestic General Government Health Expenditure (GGHE-D)	Domestic Private Health Expenditure (PVT-D)	General government expenditure
Units	**million current US$**	**million current US$**	**million current US$**	**million current US$**
2010	3091.7643	2603.2898	488.4745	51638.7307
2011	3593.8248	3035.8112	558.0136	60164.0089
2012	4060.7201	3389.1370	671.5831	67554.8306
2013	4333.0949	3638.4287	694.6662	66437.5914
2014	4742.8876	4011.9529	730.9347	72025.1793
2015	4829.7165	4098.4600	731.2565	62339.6159
2016	5176.0127	4415.9778	760.0349	58814.2952
2017	5615.9859	4813.4188	802.5671	62014.2241
2018	7173.3092	6326.7425	846.5667	69470.2714
2019	7398.8880	6434.1573	964.7307	72029.6316

Note. State of Kuwait National Health Accounts (NHA) 2010-2019 time series. WHO Global Health Expenditure Database – NHA Indicators. Available at: http://apps.who.int/nha/database/ViewData/Indicators/en

Table 2

General Health Expenditures and Government Spending, FY 2009/2010 – FY 2018/2019 in Percentage

Time	Current Health Expenditure (CHE) as % Gross Domestic Product (GDP)	Domestic General Government Health Expenditure (GGHE-D) as % Current Health Expenditure (CHE)	Domestic Private Health Expenditure (PVT-D) as % Current Health Expenditure (CHE)	Domestic General Government Health Expenditure (GGHE-D) as % General Government Expenditure (GGE)	Domestic General Government Health Expenditure (GGHE-D) as % Gross Domestic Product (GDP)
Units	**%**	**%**	**%**	**%**	**%**
2010	2.68	84.20	15.80	5.04	2.26
2011	2.33	84.47	15.53	5.05	1.97
2012	2.33	83.46	16.54	5.02	1.95
2013	2.49	83.97	16.03	5.48	2.09
2014	2.92	84.59	15.41	5.57	2.47
2015	4.21	84.86	15.14	6.57	3.58
2016	4.73	85.32	14.68	7.51	4.04
2017	4.65	85.71	14.29	7.76	3.99
2018	5.10	88.20	11.80	9.11	4.50
2019	5.50	86.96	13.04	8.93	4.78

Note. State of Kuwait National Health Accounts (NHA) 2010-2019 time series. WHO Global Health Expenditure Database – NHA Indicators. Available at: http://apps.who.int/nha/database/ViewData/Indicators/en

Overview

Health Reform Policies: Kuwait National Development Plan

In early 2017, the Government of Kuwait unveiled its vision and plan of transforming the country into a regional financial, cultural, and institutional leader by the year 2035 through 164 strategic development programs; all in the hope of diversifying the Kuwaiti economy and reducing its reliance on oil revenues (Kuwait Supreme Council of Development and Planning, 2017; Olver-Ellis, 2020). According to Kuwait Vision 2035, launched as 'New Kuwait' national development plan, high-quality medical care is one of the seven pillars included in the development agenda to improve the quality of services at a lower cost and develop national cadres in the healthcare system (Kuwait Ministry of Foreign Affairs, 2021).

The overarching theme of health in the 'New Kuwait' development plan is essentially met with better, modernized treatments for high-quality healthcare; a majority of national development plans are aimed at expanding the clinical capacity of hospitals by improving the average physician-to-patient ratio and increasing the number of hospital beds per 1,000 people through several new construction projects in the country (Kuwait Ministry of Foreign Affairs, 2021). In the delivery of routine health services, public hospitals within the health system need to be further strengthened to deliver effective and efficient medical services. Given the scarcity of scientific studies on the efficiency of the public health sector (MoH) in relation to the private health sector (for-profit), or the performance of government hospitals just prior to the onset of the COVID-19 pandemic, further research is particularly relevant to identifying efficiency determinants and eliminating internal/external factors of inefficiencies; thus informing policymakers to work towards better healthcare resource allocation in order to achieve health system efficiency and self-reliant healthcare service delivery that can prove resilient in times of unpredictable global emergencies. This dissertation aims to assess healthcare efficiency in government hospitals and identify factors of hospital inefficiency resulting from internal factors, such as resource allocation and utilization within the hospitals and external factors in the community. Subsequently, the research study will compare the relative efficiency of public and private health sectors in Kuwait to assess whether ownership type (government vs. privately-owned) affects efficiency levels of healthcare delivering facilities.

Enhancing Hospital Performance & Productivity in Kuwait's Public Health Sector

Kuwait's national health system encompasses six autonomous, decentralized administrative divisions known as health areas or regions: (i) Capital (Asima); (ii) Hawalli; (iii) Ahmadi; (iv) Jahra; (v) Farwaniya; and (vi) Sabah (MOH, 2021). Many primary healthcare centers and a secondary general hospital serve each of these health areas. Kuwait has a three-tiered healthcare delivery system, including primary health centers (PHC or clinics), secondary (general hospitals) and tertiary (specialist hospitals) facilities that are either linked with the Ministry of Health (MoH), other governmental divisions, or the private sector (Al-Homayan et al., 2013; Albejaidi, 2010). Treatment of chronic conditions (such as hypertension and diabetes), dental care, prescriptions and medications are all provided by PHCs. Hospitals in Kuwait provide secondary healthcare, such as surgical operations, specialised medical interventions for clinical illnesses, rehabilitation services, emergency medicine, and critical care services for those in need of medical attention. Patients who require more extensive medical attention and care are frequently sent to specialty hospitals (Al-Homayan et al., 2013; Almalki et al., 2011).

For years, patients from Gulf Cooperation Council (GCC) nations have traveled abroad to pursue medical treatment (medical tourism). Historically, GCC countries have lacked expertise in specific specialized fields; therefore, governments have opted to finance their sick citizens' travels abroad, where quality healthcare services are available for the most complex medical cases. While the exact number of outbound patients is often not disclosed, it was estimated that around 650 Kuwaiti patients were sent abroad for medical treatment each month between 2017 and 2018, prompting outrage over the reckless spending of public funds and causing the Minister of Health to resign. This essentially awakened people to the surge in medical expenditures, which are borne by the Kuwaiti government in the midst of dwindling oil prices. By the time COVID-19 paralyzed the world in 2020, the number of outbound medical tourists from Kuwait had already declined. This is the byproduct of the governments' national development plan ('New Kuwait' vision 2035), which aims to increase domestic healthcare capacity to make the national health system more sustainable, effectively decreasing the need for overseas treatment. Furthermore, Kuwait has been overhauling its healthcare infrastructure with state-of-the-art treatment facilities so that people can soon have access to quality healthcare services at home.

Indeed, the COVID-19 pandemic is a stark reminder for the government on why Kuwait's vision 2035 national development plan – especially investment in the health sector – is so vital and why hospitals and healthcare delivery systems that are not doing enough must do more, while the MoH must continuously strive to do even better. When the pandemic brought international travel to a halt, the risk of Kuwait's unsustainable healthcare system, which relies heavily on overseas treatments and foreign medical workers, quickly became exposed. Thus, following the pandemic, Kuwait will likely amplify its efforts to ensure more self-reliance on its own national healthcare system. With national healthcare strategies already laid out, it will be more critical than ever that health governance, organizational structures, effective financing, and hospital productivity are well aligned to ensure access to adequate healthcare services in the face of any unexpected crisis. As is typical with public sector enterprises, particularly in high-income developing countries, the public healthcare system in Kuwait is perceived to be somewhat inefficient relative to neighboring Arab Gulf states. Therefore, instead of reductions in public expenditure on healthcare and the financing of overseas treatments for high-risk medical cases, both of which can have severe implications for the health status of the population, a more logical means of controlling the total public expenditure on healthcare would be to improve the overall efficiency of the public healthcare system. Due to the significance of the problem, this research will provide probable factors associated with public hospital inefficiencies and other variables impacting the efficiency of public health sector delivery of care compared with private health sector indicators.

Statement of the Problem

Despite recent nationwide efforts and community-based initiatives promoting awareness and education, the health burden in Kuwait continues to rise against a backdrop of limited public commitment and political will; thereby increasing the demand for healthcare funding. Since domestic finances and general government expenditure are virtually entirely dependent on hydrocarbons and fossil fuels, the state's capacity to satisfy rising healthcare demands will be contingent on increasing oil revenues at an equal rate, cutting costs in other areas of public spending, sectors, or social programs, rationing medical services, or improving health spending efficiency.

Purpose of the Study

Relative efficiency and total productivity change over time are used to measure performance of the panel data of MoH public hospitals and identify inefficiency related to internal factors, such as resource allocation and utilization within hospitals as well as external factors in the environment or community. To determine performance efficiency in any production process, the value of the input (i.e., what is being used in production) is evaluated by the output (i.e., what is obtained) (Afonso & St Aubyn, 2011). The purpose of this research is to assess (in)efficient delivery of care in government-funded, MoH-operated, public health sector managed, secondary and tertiary level hospitals in the State of Kuwait. The study further aims to better understand performance differences in the healthcare sector between public and private hospitals in Kuwait; the second part of our research focuses on efficiency in delivering healthcare services and analyzes whether public hospitals outperform private ones.

Theoretical Framework

In economic research, analyzing the efficiency of actions, productions, or organizational units are considerable feats (Kleine, 2003). Applying frontier-based techniques, we follow the analytical framework of non-parametric data envelopment analysis (DEA), a widely used method in operations research and economics, for the estimation of production frontiers and empirically measure productive efficiency of decision-making units (DMUs) represented by individual (hospital) units in our sample; identifying *efficient* hospitals as those that reach the boundary of efficiency and *inefficient* hospitals as those that fall under the frontier (Imamgholi et al., 2014).

Drawing on the theoretical framework of efficiency in frontier-based evaluations such as DEA in healthcare is expected to lead us to some challenging yet fundamental follow-up questions to consider, namely: If private organizations providing public services could lower costs and increase efficiency, what would happen to their public counterparts? Would the private delivery of social services and public goods serve the public interest? If the simple transfer of ownership from public to private hands could reduce healthcare spending and enhance the quality of services, would the future of Kuwait's public health system be obsolete?

Aims and Objectives

In an attempt to touch on the considerations mentioned above as well as the main aims of this dissertation, the following objectives and their accompanying research questions are outlined below.

Objective 1

To understand the application and factors influencing efficiency assessments of hospitals in the regional Middle East and North Africa (MENA), with a specific focus on efficiency evaluations from Gulf Cooperation Council (GCC) member states; comparing studies to those published across the world, high-income and low- middle-income countries, and emerging markets or fully-developed economies.

Research Questions 1-2

1. What can be learned and applied from previous, global studies on hospital performance measures in diverse countries regarding methods used and effects on efficiency measurement application in public hospitals?
2. Are the methods used in previous studies on efficiency and performance different for public and private hospitals within MENA countries or Arab Gulf states?

Objective 2

To measure the technical efficiency of hospitals and identify the causes of inefficiency while estimating the optimal levels of resources.

Research Questions 3-5

3. What is the level of efficiency and performance in secondary and tertiary public hospitals between 2015 and 2019? Are there any changes in performance? Does efficiency improve for one year compared to the year before?
4. What is the pooled average efficiency of public hospitals over the five-year period?
5. What are the optimal levels of resource utilization in public MoH hospitals?

Objective 3

To identify all external factors that determine differences in public and private hospitals' efficiency levels.

Research Question 6

6. What are the environmental, institutional, patient demographic factors -- as well as community characteristics -- that influence hospital efficiency?

Objective 4

It can often be asserted that the private health sector produces health services more efficiently than the governmental health sector; this is especially true in Kuwait. The commonly cited argument among Kuwaitis is based on the premise that because public MoH hospitals are government-funded and operated, they are not profit-driven and therefore do not provide the proper incentives for managers to optimize resource utilization. Thus, to estimate the public and private sector's productivity and scale efficiency for 2019-2020. In addition, another attempt will be made to estimate the magnitudes of output increases and/or input reductions that would have been required to make relatively inefficient health sector facilities more efficient, and Tobit regression analysis will be used once again to estimate the effect of hospital ownership on hospital efficiency.

Research Questions 7-8

7. Compared to the public sector as a whole, was the private sector of the Kuwaiti health system in 2019 more technically efficient?
8. Is the efficiency of a health sector affected by its type of ownership? Does regressing DEA efficiency scores against hospital ownership impact the efficiency of the government-owned hospitals?

Background

Health Indicators

With its long history as a regional sheikdom, Kuwait is a constitutional, hereditary emirate former British protectorate Since its independence as a former British protectorate in 1961, Kuwait has offered its citizens universal health coverage through its National Health Service (NHS), which provides complete healthcare services, including overseas treatment if the level of disease complexity required more advanced, cutting-edge medicine (Chun, 2017). Following the 1990 Gulf War, rapid population growth and periodic economic downturns placed financial pressure on the NHS. The system faces enormous challenges, and many institutional gaps are emerging in the country's current health system – even before the onset of the COVID-19 pandemic.

The rapid "globalization" of Kuwait in many respects has caused profound changes in the nature and health of its society. An interdisciplinary set of challenges that transcends national boundaries is surfacing, involving the determinants of health and the related organized social responses that are needed, both within and outside of health systems (Huynen et al., 2005). Changes in attitudes, behaviors, and lifestyles in a brief period have led to lifestyle-related diseases that have detrimental effects on people's health and well-being and current public healthcare delivery (Chun, 2017b). In response to growing medical needs, the government of Kuwait has sought to emphasize a treatment-oriented health care infrastructure. The preference for private medical services and a focus on treatment (rather than prevention) have led to challenges that threaten to degrade the quality of public healthcare services further and to exacerbate inequalities in the provision of such services.

Like most other countries, Kuwait is prone to multiple public health issues, with research showing personal choices and behaviors, as well as environmental and social factors, to be behind several health issues in the country (Salman et al., 2020). There are severe gaps in the country's health-related needs and the policies and programs currently in place to help minimize those health risks. Kuwait is one of the leading countries in tobacco use and obesity, which means that cardiovascular diseases and associated diseases are rampant, and risks spreading across society impact the male population significantly. As of 2016, the physical inactivity rate in Kuwait was 73 percent for females and 60 percent for males, with obesity rates equaling 44 percent for males and 33 percent for females. Smoking was also prevalent in 40 percent of the male population ages 15 years and over (WHO, 2018).

Among the reasons for high rates of physical inactivity is social stigma regarding outdoor walking, sedentary school and work environments, limited sports facilities and parks, and inadequately structured bicycle paths and sidewalks (Behbehani, 2014; Klautzer, Becker, Mattke, 2014). Estimates show that the population of Kuwait above 60 years will significantly increase by 2030, which means the chronic diseases' prevalence will also increase and become a burden for the country's healthcare system. This burden has largely been overlooked (Behbehani, 2014).

Improving the efficiency of Kuwait's public health system is a major priority. The Kuwaiti government recently acknowledged the need to examine the relative efficiency of both public vs. private hospital models for differences in health sector performance; this dissertation will go further by assessing whether efficiency levels between the private and public health sectors are significantly influenced by the type of ownership precisely, and what that effectively tells us about government-owned, MoH-operated health facilities. This study will provide the necessary research to establish a difference in cost-effectiveness and quality of services. This dissertation will also contribute to knowledge about the economic issues arising from increased healthcare costs. Healthcare decision-makers need empirical data to control healthcare costs without reducing access to high-quality healthcare (Rice, 2002).

Government leaders and policymakers may use the results from this study to determine the efficiency of public hospitals and examine possible internal and external factors for inefficiencies in Kuwait’s public health sector. An examination of the research may also determine if hospitals provide cost-effective healthcare services for patients while limiting wastage. Through policies, regulations, and third-party funding, governments are vested in the healthcare decision-making process (Jerrett et al., 2003). Policies and regulations will allow governments to control healthcare expenditures (Landreanau, 2003). Government leaders will then be able to make informed choices about alternative health service delivery methods and cost-containment strategies.

Resources & Challenges

Healthcare in Kuwait has dramatically evolved over the past two decades. The MoH continues to be the principal provider of healthcare through three main levels of care:

***Primary Care*:** Services are offered across community health facilities, including general medicine, dentistry, childcare, maternity care, and preventive medicine, in addition to school health, laboratory and radiology.

Secondary Care: Services delivered across six (6) public general hospitals, including Al-Amiri Hospital, Al-Adan Hospital, Al-Sabah Hospital, Mubarak Al-Kabeer Hospital, Al-Farwaniya Hospital, and Al-Jahra Hospital. The new Jaber Al-Ahmed Hospital is the latest facility now included in 2019/2020 annual statistical reports but was not operating at the start of our observation period.

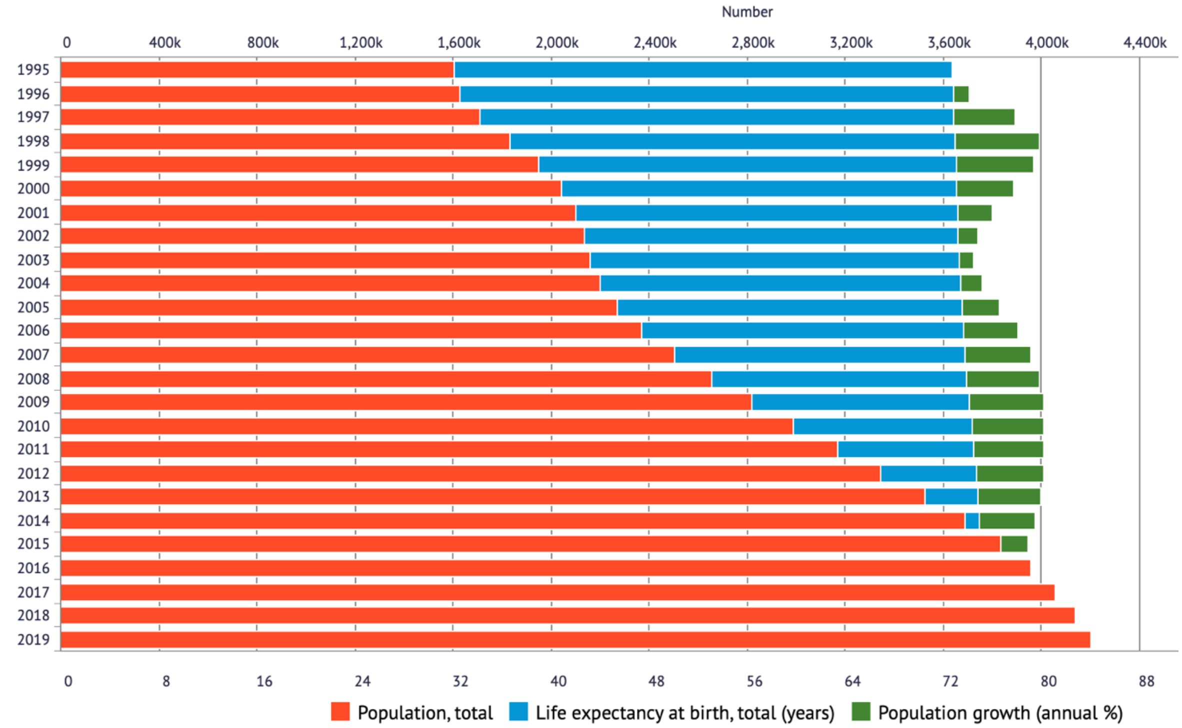
Tertiary Care: Services offered through specialized hospitals and medical centers, including psychiatry, Ibn Sina, communicable diseases, physical medicine and rehabilitation system.

Despite the Kuwaiti government's high investment in the healthcare sector in the past decades, several persisting issues pose challenges to the public health system. For instance, resource limitations, unpredictable global oil markets, changing disease patterns, poor management of public hospital resources and capacity planning, lack of a national health information system, and shortage of Kuwaiti health professionals (Olver-Ellis, 2020).

Most concerning is that the country's economy is experiencing a decline caused by the drop in oil revenues (International Monetary Fund, 2019), the primary source of healthcare financing. In addition, a rapid increase in health expenditure in the country, due to increased demand for services, has made the situation more challenging (MOH, 2019). The rise in healthcare demand has been attributed to multiple factors, including an increase in total population from approximately 1.6 million in 1995 to about 4.2 million in 2019, in addition to an aging population due to an increase in total life expectancy at birth since 1995 (72.8 years) and 2019 (75.5 years) (Figure 1) (World Bank, 2020). Furthermore, the growing demand for advanced services is thought to be the outcome of increased public health awareness (MOH, 2020).

Figure 1

Kuwait – Population Dynamics, 1995-2019



Note. Kuwait national demographics, annual estimates 1995-2019. World Bank collection of development indicators. Available at: https://datacatalog.worldbank.org/dataset/world-development-indicators

In 2016, the Kuwaiti government responded to these challenges by issuing sweeping economic reforms outlining broad, ambiguous policy goals; ranging from improving the efficiency of the public sector, to initiating administrative and institutional reforms dedicated towards general and financial administration efficiency (Kuwait Ministry of Finance, 2016). Indeed, Kuwait is experiencing record fiscal deficits on the back of declining oil revenues, all of which are contained within an economy plagued by two major structural imbalances – heavy reliance on oil production and public ownership dominance – and urgently needs to diversify its resource-dependent financial base and make serious attempts to transition to a genuine post-oil economy (Gelan et al., 2021). In order to successfully respond to the tremendous fiscal pressures and ongoing economic volatility that have buffeted Kuwait since oil prices first began to fall in

July 2014, the Kuwaiti government must embrace a series of long-term, comprehensive economic reforms underpinned by a set of plans that spell out the detail and mechanics of the policy changes (Ulrichsen, 2016; Durand-Lasserve & Karanfil, 2021).

Even so, several challenges linger within sustainable healthcare financing schemes. Regardless of a country's income level or stage of development, increasing demand for healthcare services and the inflationary spiral that these services are likely to bring should be a source of major concern for policymakers (Osmani, 2012). Since hospitals consume a sizable share of the healthcare budget and are extensive health-production facilities that require a variety of resource inputs, including buildings, health and administrative staff, pharmaceuticals, and medical equipment, the attention of health decisionmakers is frequently called to the facility's efficiency in equitably dispersing human resources and capital assets (Chisholm & Evans, 2010; Oxley & MacFarlan, 1994; Sefiddashti et al., 2016; Zhou et al., 2017).

According to the 2019/2020 annual bulletin of health statistics, Kuwait (public and private sectors; not including the oil sector) had 1.9 beds per 1,000 population in which the MoH had 1.7 beds per 1,000 populations; a lower ratio than the global average of 2.7 beds per 1,000 population. Therefore, the capacity of public healthcare services is clearly challenged, and Kuwait is on track for numerous expansion projects that will double its total bed capacity as part of the country's many national health reforms. Again, efficiency considers factors such as costs associated with the possible excess of empty hospital beds that represent wasteful expenses; the inappropriate bed occupancy rate is regarded as a waste of resources, and proper utilization of existing assets effectively is the key to efficient hospital performance.

Furthermore, Kuwait's health system is challenged by the shortage of local Kuwaiti healthcare professionals, such as physicians, nurses, pharmacists, and other allied health personnel. The majority of clinicians and health workers are expatriates, which leads to a high rate of turnover and instability in the clinical workforce. In essence, the health system in Kuwait suffers from a lack of trained Kuwaiti healthcare professionals and a heavy reliance on foreign nationals instead. Among the noted issues in the delivery of treatment is reducing patient wait times owing to a high patient load and overworked medical staff. Other challenges include developing a system for routinely assessing the quality of services delivered by primary healthcare centers, hospitals, and specialized clinics; establishing a referral and follow-up system that is aided by recent computerized linkages between primary, secondary, and tertiary levels of care; training and developing health promoters and volunteers; and developing home- and community-based interventions (WHO Eastern Mediterranean Region, 2020).

According to 2019 health information, the total workforce across all sectors in Kuwait comprises 45,107 clinicians, healthcare personnel, and other para-medical staff. More than half (n=35,511; 78.7%) work in the MoH (MOH, 2019). Kuwaiti nationals represent 0.44 percent of all nurses, 17.4 percent of all dentists, and 10.9 percent of all physicians within the private health sector. In the public health sector (MoH), Kuwaiti nationals constitute 4.9 percent of all nurses, 73.6 percent of all dentists, and 41 percent of all physicians (MOH, 2019). The 2019 physicians and nursing density in Kuwait per 1,000 of the population are 2.7 and 6.9, respectively (MOH, 2019); although a steady increase from previous years, coverage and concentration rates based on population estimates are slightly less than other high-income nations. Thus, practical strategies to retain and attract more Kuwaitis into the medical workforce and field of healthcare are required for the overall sustainability of the national health system. It is also essential to provide further education opportunities and clinical training programs that aim to substitute the large expatriate workforce to meet the increasing healthcare needs of the public health system.

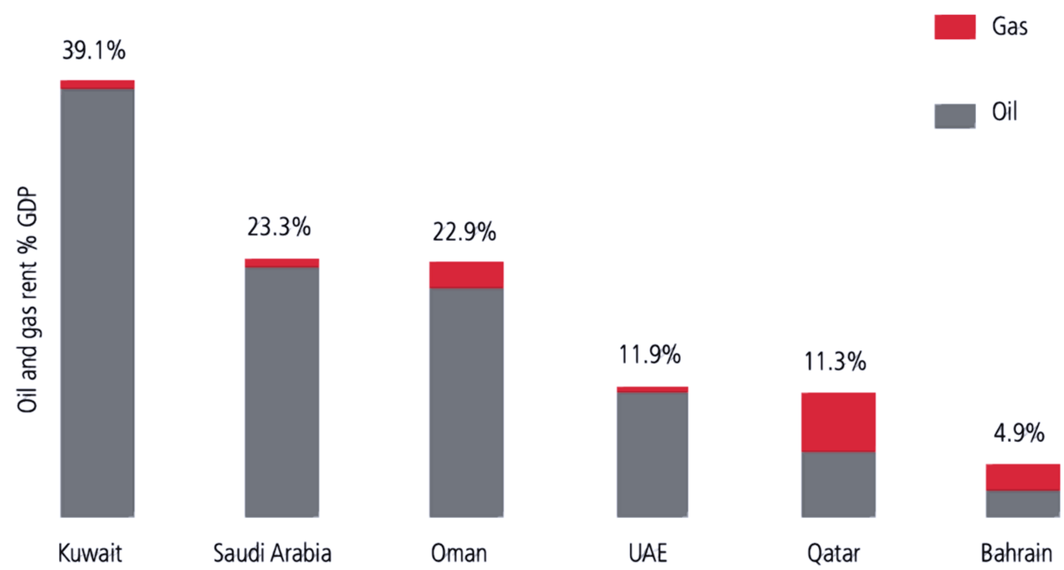
The Future of Kuwait's Health System

Strong healthcare systems are fundamental if we are to improve population health outcomes and accelerate progress towards SDGs of reducing maternal and child mortality, and combating HIV, malaria and other diseases. At a time when economic downturn, a new influenza pandemic, and climate change add to the challenges of meeting those goals, the need for robust health systems is more acute than ever. Kuwait's current health-care system is projected to confront a number of issues in the near future. With the country's reliance on oil revenues (Figure 2), the economic slowdown of global oil markets and drop in prices induced by the COVID-19 pandemic led to increased annual budget deficits, prompting the government to seek passage of a debt law that facilitates deficit spending with significantly less barriers. Such a strategy implies that the economic obstacles are mostly the result of unprecedent disease epidemics and emergencies that have temporarily lowered global oil consumption, nevertheless, in a world that realizes the environmental consequences of fossil fuels and hydrocarbons, the likelihood of unceasingly rising oil prices is not guaranteed. Kuwait may be unable to continue paying for what it wants with the assumption that there is always a future for oil in an era of heightened environmental consciousness. The burden of noncommunicable diseases, including cardiovascular disease, diabetes mellitus, and mental disorders are expected to rise further and the proportion of the Kuwaiti population over 60 years old is anticipated to reach 25% of the total population by 2050; implying dramatic increase in prevalence of NCDs is still yet to come (Behbehani, 2014). For instance, obesity rates are expected to reach exceedingly high levels by 2030; similarly, the population frequency of diabetes nationwide is prone to increase in response (Kilpi et al., 2013).

Unfortunately, however, Kuwait's current healthcare system – availability and distribution of essential medicines, health products and supply chains, detailed coordination of complex operation structural service delivery of reliable, accessible, quality care – is likely to encounter a number of easily avoidable issues in the near future if left unchecked. Instability of being dependent on the fluctuations of oil prices presents a certain degree of economic and development concerns (Figure 2). Kuwait's substantial reliance on oil proceeds for domestic government spending; meaning that early economic slowdown associated with stagnation of global markets due to the COVID-19 pandemic, along with low oil prices, has increased yearly budget deficits, prompting the government to seek passage of a debt legislation that facilitates deficit spending. This bid presupposes that the economic challenges are mostly the result of the pandemic temporarily lowering global oil consumption. However, the possibility of oil earnings continuing indefinitely is far from guaranteed in a well-informed society that recognizes the environmental consequences of hydrocarbon emissions. Kuwait may find itself unable to continue paying for what it wants with loans based on an optimistic future for petroleum production and oil exports in an era of heightened environmental consciousness. The global burden of non-communicable diseases, including cardiovascular illnesses, diabetes mellitus, and mental disorders, are projected to grow exponentially; particularly in the Middle East and North Africa (MENA) region. Kuwait's population over the age of 60 is predicted to reach 25 percent of the total population by 2050 (Behbehani, 2014); as a result, the prevalence of NCDs will grow dramatically. For example, obesity is anticipated to reach epidemic proportions by 2030 (Kilpi et al., 2013). Similarly, diabetes prevalence is anticipated to grow across the country.

Figure 2

Oil & Gas Dependency in Kuwait and the GCC, 2014–2016



Note. Adapted from data obtained from the Kuwait Central Statistical Bureau, National Accounts (at constant prices). Borrowed from Kuwait Health System Review, London School of Economics & Political Science (LSE Health), Kuwait Foundation for the Advancement of Science (2018).

It was estimated that from 2010 to 2030, there would be a 22 percent increase in the global cost of care for cardiovascular diseases (from $863 billion to $1053 billion); while global spending on diabetes is projected to increase from $500 billion in 2010 to $745 billion by 2030 (World Economic Forum, 2011). The international cost of mental health care was estimated to be $2.5 trillion in 2010 and is expected to rise to 6$ trillion in 2030 (World Economic Forum, 2011). It was documented that the cost of common NCDs for GCC countries is expected to increase from $36 billion in 2013 to $68 billion in 2022 if governments fail to implement measures to curb the prevalence of NCDs (Alshaikh et al., 2017). As mentioned above, the prevalence of diabetes and global health spending to treat it are expected to increase. The International Diabetes Federation predicts that the health expenditure due to diabetes for individuals aged 20-79 years in the Middle East and Northern Africa (MENA) region is going to increase from $13.6 billion in 2013 to $24.7 billion in 2035 (International Diabetes Federation, 2013).

Chapter Summary

Despite the government and community attempts to enhance public health awareness and education, the health burden continues to rise, hence increasing the demand for health financing. As practically all present health expenditures are paid by oil income, the state's ability to fulfill expanding demand will depend on raising oil revenues at the same rate, lowering spending in other sectors, restricting health service supply, or boosting the efficiency of health expenditures. Current research implies that oil income may be dropping, while health care expenditures are rising. In addition, the projections for oil prices in the next years do not indicate that income will be sufficient to cover the rising need for healthcare.

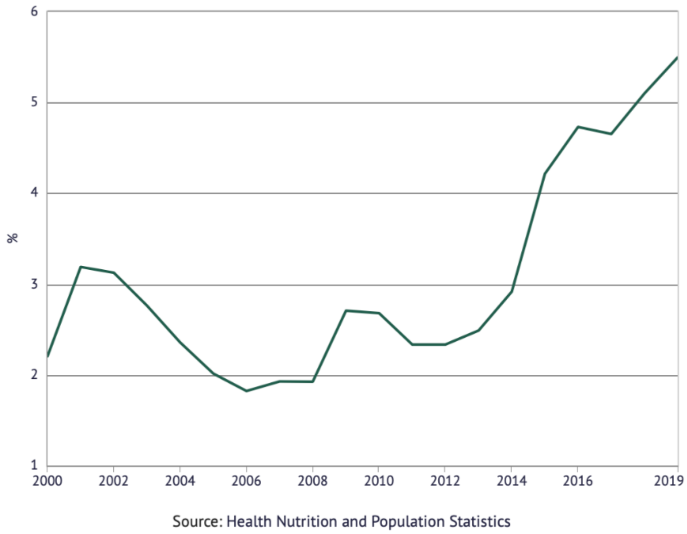
In relation to the growing demand for healthcare and increasing government expenditure, securing an efficient, equitable, and cost-effective healthcare system is both a national imperative and global responsibility. The United Nations (UN) have recognized the vital role of healthcare systems for the successful achievement of Universal Health Coverage (UHC) goals (WHO, 2019). The State of Kuwait joins several other nations that also experienced substantial population growth, increased life expectancy (aging population 65+), and the proliferation of lifestyle-related diseases (non-communicable diseases; NCDs). These combined set of circumstances have increased the demand for healthcare services at a time of scant health resource (Khoja et al., 2017; Ram, 2014).

When monitoring the health financing function, performance also has to be measured relative to monetary funding entering the public health system. Thus, we need to consider the resources potentially available to the system, the conditions that influence how difficult it might be to mobilize these resources, and the broader budget constraint faced by policymakers in the public health sector. In addition to more general macroeconomic data (i.e., GDP per capita), an additional indicator that tends to reveal more than just Kuwait's (or any given country's) health financing function are public sector expenditures as a share of gross domestic product (GDP); measuring the share of national income effectively captured and utilized by the public sector; in a sense, this represents the public sector's budget constraint when allocating resources between different public demands (WHO, 2003).

If we begin evaluating the effectiveness of the financing function or Kuwait's health financing policies, we can see that by 2019, the current health expenditure in Kuwait as percent of GDP was 5.5 percent; that corresponds to a 7.77 percent increase from the previous year in 2018 and maintains the positive percent change consistently found through the years – with the exception of the minor dip in 2017 that indicates a -1.64 percent reduction from 2016 – as notably illustrated in Figure 3 (The World Bank, 2019). The current health expenditure per capita (current US$) that same year in the country was at $1,758.67 in 2019, a modest percent change increase of 1.43 percent from 2018; nevertheless, the overall trend of the line graph suggests consistent increase prior to 2015, but continuing to climb again after 2015 with a positive percent change of almost 40 percent between 2015-2019 displayed in Figure 4 (MoH, 2020; World Development Indicators [WDI], 2019; Health Nutrition and Population Statistics [HNPS], 2019).

Figure 3

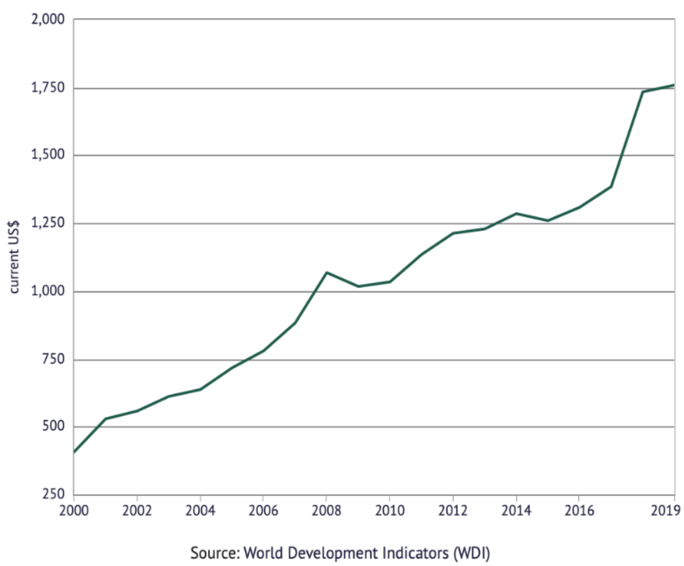
Kuwait - Current Health Expenditure (% of GDP)



DATE	VALUE	CHANGE, %
2019	5.50	7.77 %
2018	5.10	9.59 %
2017	4.65	-1.64 %
2016	4.73	12.24 %
2015	4.21	44.55 %
2014	2.92	17.21 %
2013	2.49	6.63 %
2012	2.33	0.00 %
2011	2.33	-12.91 %
2010	2.68	-1.02 %

Figure 4

Kuwait - Current Health Expenditure per Capita (Current US$)



DATE	VALUE	CHANGE, %
2019	1,758.67	1.43 %
2018	1,733.81	25.22 %
2017	1,384.58	5.85 %
2016	1,308.11	3.89 %
2015	1,259.18	-2.01 %
2014	1,285.01	4.58 %
2013	1,228.77	1.34 %
2012	1,212.57	6.89 %
2011	1,134.39	9.77 %
2010	1,033.38	1.65 %

Keeping the focus on the same years between 2015-2019, inclusively; public spending on health is remarkably high in comparison to other neighboring countries in the region, yet, noticeably unremarkable increases in hospital bed capital and nursing human resources essential to ensure an adequate ratio of beds-to-nurses or nurse per hospital bed (staffed beds) compared to the yearly increase of funds entering the system (The World Bank, 2019).

Thus, the empirical objectives of this study are to measure the technical, pure/managerial, and scale efficiencies of hospitals in the two health sectors in Kuwait: public vs. private health sectors. The ultimate goal is to evaluate changes in productivity, retrospectively and just before the onset of the COVID-19 pandemic, to highlight possible implications for government policy moving forward. If this study is able to successfully be used by the MoH for benchmarking purposes and applied to set individual hospital benchmarks of efficiency; this research project has met its primary goals.

Chapter 2

Health Services Research and Applied Econometrics: A Scoping Review of Health System Efficiency and Hospital Performance

This chapter introduces different econometric models and applications used in measuring organizational efficiency in order to lay the groundwork for the empirical research to follow. Chapter 2 is an exploratory precursor to the literature and systematic review in Chapter 3; it discusses the concepts of efficiency in healthcare promotion and the different frontier estimation techniques used to evaluate hospital performance and productivity. The first section of this chapter delves into the theoretical underpinnings of efficiency and production, as well as the framework of efficiency in the health system. Subsequent sections examine the methodology for evaluating efficiency of healthcare services and care delivery, and estimate the productivity of public health systems and hospital performance, including approaches most used in peer-reviewed hospital efficiency research. The third section concludes with knowledge gained, based on current evidence from existing primary studies, and how particular estimation techniques will be applied in this research to measure and improve hospital efficiency in the State of Kuwait.

Study Design

This chapter is an exploratory scoping review of the literature on hospital efficiency and its determinants. The review centered on ratio methods of efficiency analysis, data envelopment analysis (DEA), and stochastic frontier analysis (SFA), including relevant econometric statistical models such as Tobit regression, to assess sources and determinants of efficiency as well as factors of inefficiency.

As a precursor to Chapter 3, preliminary overview (Grant & Booth, 2009) was conducted in accordance with Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) to identify studies that provide assessments of efficiency in healthcare and hospital performance (Tricco et al., 2018). The review was designed to curate a snapshot of active methodologies regarding efficiency over the past 20 years in order to evaluate the current landscape. Therefore, inclusion criteria were unlimited to identifying literature that included methodologies examining efficiency performance of hospitals.

Search Strategy

Four (4) electronic databases were searched initially in December 2021, aiming to identify best practices of measuring efficiency in healthcare settings: PubMed/Medline, CINAHL, Embase, and Cochrane Library. An additional EconLit database is later searched in April 2022 for relevant economic research literature. A secondary search of the four databases was repeated in January 2022. Appropriate literature from the December 2021 and January 2022 searches were identified via citation sorting and other additional results from the economic literature search in April 2022 were included; checking reference lists of impactful publications added important papers of classic economic theories that built on concepts such as efficiency and are usually associated with the early days of this field. To encompass a wide range of the literature and reduce publication bias, secondary sources from the gray literature were searched via the citation indexes in Web of Science (or the Google Scholar search engine) by using keywords search options.

Theoretical Foundations

'Efficiency,' according to traditional economic theory, is the connection between one or more inputs (or ‘factors of production') and one or more outputs. However, measuring efficiency in the health sector is confounded by the fact that what matters most to 'consumers' (patients) are not the 'outputs' of healthcare (e.g., consultations with physicians or various surgical procedures/treatments), but instead the 'outcomes' of these activities (i.e., surviving and recovering from various health problems, and generally feeling better). While data on the outcomes of various health treatments are critical for assessing health system efficiency, they are typically less easily available than data on health system outputs (activities).

Furthermore, even when such data are available, assigning clear responsibility for the outcomes of various health interventions to the "producers" of these services (i.e., health professionals) is not always straightforward, as numerous factors other than the quality of care provided may influence the ultimate health outcomes for patients, including the inherent uncertainties associated with many health interventions, as well as individual patient characteristics and behaviors. In many nations, efficiency has proven to be the most difficult attribute of health system performance to quantify. As one prominent health economist put it, “the concept of ‘productivity’ or ‘efficiency’ is very simple in principle, but rather slippery to pin down in practice” (Evans, 2010, p. 78).

In non-parametric data envelopment analysis (DEA) models, such as the methodology of choice for this research, inefficient units are improved when the efficiency boundary is reached. The frontier boundary consists of units of efficiency ‘one’ (1). In general, there are two types of solutions for improving inefficient units and achieving efficiency: (i) decreasing inputs without reducing outputs until the unit reaches the border (performance improvement of input-oriented efficiency); and (ii) increasing outputs by reaching a unit on the efficiency boundary without attracting further inputs (performance improvement of output-oriented measurement) (Jeremic et al., 2012). For input-oriented DEA models, it is desired to establish a technical efficiency ratio that decreases inputs so that the unit remains within its efficiency frontier without affecting output. In contrast, the output-oriented technique attempts to estimate the ratio at which outputs should be increased so that the unit can reach the efficiency frontier without modifying inputs (Jeremic et al., 2012; Varabyova & Schreyögg, 2013).

Efficiency had been assessed in light of various concepts including technical-, scale-, and pure-efficiency with a primary focus on technical efficiency (TE) in the reviewed literature. Efficiency from an economic perspective measures how close a decision-making unit (DMU) gets to its production possibility frontier, composed of sets of points that optimally combine inputs in order to produce one unit of output (Kablan, 2010). Alternatively, efficiency is defined as the ability of a firm to derive maximum output given a set of input levels under certain conditions (Coelli, 2000). We can consider a firm being technically efficient if it produces a given set of outputs using the smallest possible amount of inputs. On the other hand, technical efficiency is the ability of the firm to maximize outputs from a given set of inputs and is associated with managerial decisions (Lovell, 1993). The technical efficiency (TE) scores can be decomposed into pure technical efficiency and scale efficiency to determine the main source of the technical efficiency. Scale efficiency refers to the relationship between the level of output and the average cost, therefore, it relates to the size of operation in the organization. For example, when the relationship between input and output is constant let's say, then the output changes proportionately with an increase or decrease in inputs and therefore, the organization is said to be scale efficient. Also, scale efficiency (S) is derived from the measures of technical efficiency (T) and pure TE efficiency (PT) as described by Banker et al. (1984) and shown below in Equation 1:

Equation 1

$$S = \frac{PT}{T}$$

Therefore, if the value of S=1, the firm is then said to be scale efficient; all values less than one (1) reflect scale *inefficiency* (Banker et al., 1984; Cooper et al., 2004).

Indeed, looking at the various forms in which efficiency has been studied shows that the concept of efficiency is a multi-faceted concept with several meanings, depending from which perspective it is regarded (Leibenstein, 1966). For instance, in the banking sector, Al-Muharrami et al. (2008) investigated the technical, or TE, pure TE, and scale efficiency, for Gulf Cooperation Council (GCC) banks for the period 1993 - 2002. Smaller banks were found to be overall technical efficient than bigger banks. Big banks were more successful in adopting best technology, while medium sized banks had successes in adopting optimal levels of output. Finally, Islamic banks were successful in both technology adoption and choosing optimal levels.

The hospital efficiency literature essentially can be classified according to different characteristics (e.g., methods of estimations, such as DEA and stochastic frontier analysis SFA, such as: number of production firms or decision-making units (DMUs) in the frontier (here, hospital DMUs or firms); number of input/output variables; estimation method (parametric SFA or non-parametric DEA linear programing); etc. (Varabyova & Muller, 2016; Kiadaliri et al., 2013; Alatawi et al., 2020). Other specifications of the DEA model were also considered following the reviewed literature; namely, the four main characteristics: (i) model type; (ii) return to scale; (iii) model orientation; and (iv) input-output combination (Cantor & Poh, 2018).

CCR (Charnes-Cooper-Rhodes) and BBC (Banker-Charnes-Cooper) are the model type classifications. These two models enable DMUs to quantify their relative efficiency by comparing the ratio that can be increased or lowered in all of their inputs (outputs) to their known outputs (inputs) according to technological constraints. The two types of returns to scale: constant return to scale (CRS) and variable return to scale (VRS). It is reasonable to assume that a given organization or unit of operation complies to a CSR or VRS, as its premise is based on the production function attribute. The orientation of the model can be input- or output-oriented. In an input-oriented approach, outputs are expected to be constant while inputs are decreased. The output-oriented perspective argues that inputs remain constant while outputs grow. The input and output combination refers to the multiple inputs and multiple outputs that are utilized in the production process (Cantor & Poh, 2018).

Productivity and Efficiency

In a broad sense, efficiency refers to the careful and diligent use of finite resources in order to maximize benefit at the lowest possible cost. This appears basic, yet several attempts to define efficiency have been attempted since the mid-twentieth century. Although the phrases productivity and efficiency are frequently used interchangeably in economic contexts, they are not synonymous (Jacobs et al., 2006). Productivity is defined as the ratio of the monetary worth of the outputs produced by an organization to the cost of the inputs used in the production process (Lovell, 1993). The ratio of two scalars (outputs to inputs) remains the productivity; consequently, the concept of productivity may encompass but is not limited to the concept of efficiency (Jacobs et al., 2006).

Efficiency can be described as the distance between the quantity of input and output, and the amount of input and output that defines a frontier, the best possible frontier for that entity

(Daraio & Simar, 2007). Lovell (1993) defines efficiency as the difference between observed and ideal values of a manufacturing unit's output and input. Alternatively, the ratio of observed to maximum possible output from a given input, or the ratio of observed to minimal possible input necessary to create the given output of production possibilities. Applying the virtual input-output method helps identify key input/output variables through virtual weights restrictions in data envelopment, a function done by the program operation being used in analysis; the higher the level of virtual input/output, the more important we expect that input/output is within the efficiency rating of the decision-making unit (DMU) concerned. Mathematically, efficiency can be represented as follows in Equation 2 below:

Equation 2

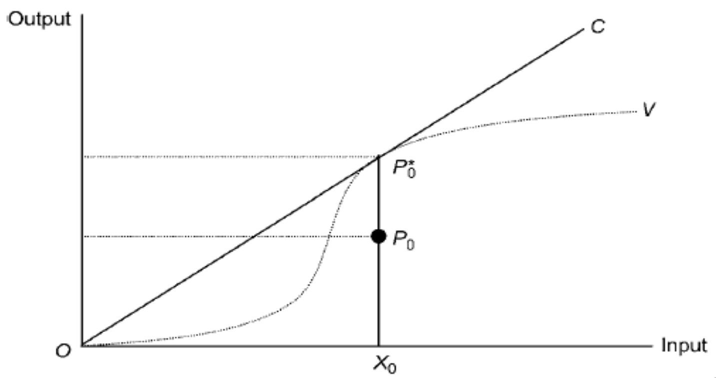
$$\theta_o = \frac{Virtual\ output_o}{Virtual\ input_o}, o \epsilon \left(1, 2, \ldots n\right\}$$

However, efficiency and productivity are complementary concepts. Efficiency metrics are more precise than productivity measures, as they require comparisons to the most efficient frontier, whereas productivity measures are primarily dependent on the output-to-input ratio (Daraio & Simar, 2007).

The fundamental concept of efficiency is illustrated in Figure 2 (adopted from Jacobs et al., 2006), which illustrates the straightforward situation of a single input and output. Under constant returns to scale, the OC line represents the efficient frontier. On this path, a technically efficient company would work. Any company that is inefficient will go below the OC line. For example, in an inefficient organization (P0), the ratio X0P0/X0P*0 indicates how distant it is from the production frontier, or how inefficient it is; hence, we can quantify its level of efficiency (Jacobs et al., 2006).

Figure 5

Efficiency in the Presence of Constant Returns to Scale



When many inputs and outputs are used, an organization's overall efficiency (eff_0) is equal to the ratio of the weighted sum of the outputs to the weighted sum of the inputs. Because the organization ($_0$) consumes a vector of M inputs X_0 and creates a vector of S outputs Y_0, its total efficiency is determined using the weight vectors U and V as shown in Equation 3 below:

Equation 3

$$eff_0 = \frac{\sum_{s=1}^{S} u_s \, y_{s0}}{\sum_{m=1}^{m} v_m \, x_{m0}}$$

Where Ys0 denotes the quantity of (s) output generated; U_s denotes the weight given to the (s) output; Xm0 denotes the quantity of (m) input consumed; and Vm denotes the weight given to the (m) input.

Efficiency Concepts

There are two types of efficiency in economics: allocative efficiency and technical efficiency. While technical efficiency is defined as the ratio between inputs and outputs, allocative efficiency is defined as allocating resources to provide the optimal mix of inputs and outputs while maximizing benefits (Yip & Hafez, 2015; Hollingsworth, 2008).

According to Leibenstein (1996), allocative efficiency occurs when a provider selects a combination of inputs in precise proportions to their prices; this enables the provider to provide the selected output with the lowest possible average costs; or, alternatively, when the provider selects an output mix that maximizes revenue at the given output prices (Blatnik et al., 2017). It is worth noting that allocative efficiency is not synonymous with fairness; no alternative resource allocation strategy can benefit at least one person without harming another; thus, an allocatively efficient scenario may be inequitable. Transitioning from an inequitable to an equitable resource allocation can also be allocatively inefficient.

Koopmans (1951) defined efficiency through the analysis of the production function, whereas Debreu (1951) established the coefficient of resource utilization measurement. Farrell (1957) defined technical efficiency as a relative concept, referring to the best-observed practice in a reference set or comparison group. Technical efficiency refers to the ability to generate a large number of outputs from a small number of inputs or to generate a specified number of outputs from a small number of inputs (Farrell, 1957; Hollingsworth, 2008). When a business is technically efficient, it operates at the frontier of its output. Productive efficiency is related to technical efficiency and economies of scale, which means that the more units produced, the cheaper the unit costs (Farrel, 1957; Suhartano, 2017).

Allocative and technical efficiency combine to form a unit of cost or economic efficiency, which is defined as the product of technical and allocative efficiency. Thus, cost efficiency can be attained only by utilizing the fewest possible inputs and integrating them in such a way that the desired output is produced at the lowest possible cost (Blatnik et al., 2017). Economic efficiency in healthcare refers to individual decisions between objectives and alternatives and the way by which they are attained, with the goal of maximizing the overall benefit from the healthcare facility's available resources. The approach for obtaining this efficiency is through the comparative valuation of the advantages and costs of various solutions (Afzali, & Mahmood, 2009; Fragkiadakis et al., 2016).

Efficiency in Healthcare

Healthcare Efficiency Analysis

Efficiency measurement in healthcare is a complex and difficult endeavor due to conceptual difficulties, many objectives, and measurement mistakes in the application (Jacobs et al., 2006). In 2000, the World Health Report dedicated a section to measuring health system efficiency; since then, efficiency analysis has been a focus of considerable research and international concern (WHO, 2010). Farrell (1957) pioneered the development of methods with a high level of analytical complexity that may be used to assess the productive efficiency of healthcare systems (Jacobs et al., 2006). Yip and Hafez (2015) examined the efficiency of healthcare services in ten different countries, focusing on the inefficiencies inherent in healthcare services and health policy, as well as the nations' experiences in overcoming these inefficiencies. They discovered that there were numerous interpretations of efficiency, prompting them to advocate the development of a framework for evaluating and measuring efficiency in order to meaningfully inform and impact policy (Yip & Hafez, 2015).

Hollingsworth (2003) summarized the advances made in the literature up to the year 2002. He reviewed 189 published research on efficiency variations and production functions in health care, almost half of which were conducted in the hospital sector, and the majority of which used data envelopment analysis (DEA) (Hollingsworth, 2003). Varabyova and Muller (2016) conducted a systematic review and meta-analysis of published studies on the efficiency of health care in Organization for Economic Cooperation and Development (OECD) member countries. Additionally, they conducted cross-country comparisons and evaluated the studies' quality, as well as the efficiency models' characteristics, methodological difficulties, and policy implications (Varabyova & Muller, 2016).

Kiadaliri et al. (2013) conducted a meta-analysis of 29 papers on efficiency evaluations in Iranian hospitals. DEA was used in all of the trials that were examined. They concluded that the research lacked methodological rigor, as evidenced by the low quality of the data, and presented recommendations for improvement to Iranian policymakers (Kiadaliri et al., 2013). DEA analysis was utilized in a previous efficiency study of Kuwait’s hospital industry, but was hampered by data inadequacies (Alsabah et al., 2019). The study examined Kuwait's health system and expressed worry about the difficulty of healthcare information systems in providing trustworthy data for accurately assessing efficiency. Due to its adaptability, the DEA was a widely utilized and successful approach for assessing the performance efficiency of hospitals and healthcare systems. As a result, this research employs the DEA framework for evaluating Kuwait's public hospitals.

Efficiency Evaluation of the Public Health Sector

Healthcare in the public sector has a number of obstacles that make assessing efficiency more challenging. One factor contributing to this complexity is the absence of competition in healthcare as the government maintains a monopoly in the public sector (Jacobs et al., 2006; Yip & Hafez, 2015). Because the public sector is owned by all citizens, we can estimate the costs of inputs such as equipment, personnel, infrastructure, and medications, but we cannot determine the value of output because no one pays for services directly (Czyzewski et al., 2016).

Efficiency in public health systems is determined by functions such as resource production, funding, system organization, and method of providing health services, all of which are influenced by the system's underlying institutional characteristics and evolution (Al-Hanawi et al., 2019). On the other hand, efficiency contributes to the health systems' ultimate goals, which are articulated in terms of health gains and equity in health, financial protection and equity in finance, and the health system's responsibility to meet the requirements of the population (Fried et al., 1993). In this context, efficiency is viewed as a necessary condition for achieving the strategy's objectives of universal access and coverage, whether in terms of appropriate utilization in relation to the population's health requirements, service quality, or universal financial protection (WHO, 2019; Fried et al., 1993).

In most economies, the government finances health services, including public hospitals, and is concerned with the quality and efficiency of those services. In the long run, the absence of control and evaluation of these two traits (quality and efficiency) in health services will indicate a decline in the state's ability to offer all social services (Al-Hanawi et al., 2019). On the other hand, quantifying abstract concepts such as the quality and efficiency of healthcare requires a quantitative operationalization that enables time and space comparisons and the identification of patterns that enable failures and/or successes to be identified (Al-Hanawi et al., 2019).

However, price is not the primary criterion for measuring the efficiency of healthcare services for a large number of public goods. This is due to the fact that they must be provided regardless of current prices (Almalki et al., 2011; Jacobs et al., 2006). The absence of profit in the public sector also eliminates the chance of institutions going bankrupt, as the funds are guaranteed by the state budget (Al-Hanawi et al., 2019). If funds are insufficient, the state debt will grow, but the system as a whole will not collapse. As a result, resource allocation in the public sector is frequently inefficient. Additionally, it has been argued that resources are not allocated where they would be most beneficial at any particular time (Le Grand & Robinson, 2017). Various non-economic factors, often of a qualitative nature, also influence the efficiency of the public sector (Kim & Wang, 2019). Examples include government decisions, public budget spending and legislation that need to be taken into account when measuring efficiency. These factors are taken into account in efficiency models in the competitive market, which inevitably is a subjective assessment (Kim & Wang, 2019).

Techniques for Evaluating Hospital Efficiency

Hospital care is a major component of the health system. It is significant on a social level since hospital treatment is reserved for the most serious health conditions and is typically the most expensive part of the health system due to the specialized and technologically advanced care offered (Alomran, 2019; Walston et al., 2008). Given the substantial amount of health resources dedicated to hospital finance, there is an increasing interest in determining the efficiency of hospitals, with the primary motivation being value for money. Hanson et al. (2002)

estimate that public hospitals use around 40percentof the entire health budget in Sub-Saharan African countries. In comparison, in the United Kingdom in 2012/2013, this sector accounted for over 44percentof total health spending (Kelly et al., 2016). Thus, because hospitals are significant consumers of health resources, their efficiency is crucial to the broader health system's efficiency (Hollingsworth, 2003). Additionally, the health sector's ongoing review of the efficiency of hospital care and its social and economic ramifications is critical (Hanson et al. 2002).

However, due to the range of purposes, objects of analysis, and contexts of application in healthcare, the idea of efficiency has been applied in a variety of ways and with some ambiguity. Indeed, the argument over health policies has been framed in some instances as a conflict between health equity and health efficiency objectives. This thesis seeks to distinguish various uses of the idea of technical efficiency in order to better comprehend efficiency in the context of public hospitals.

Empirical methodologies can be used to evaluate hospital efficiency, which requires the input-output ratio to be calculated. In healthcare, inputs include funding, capital (such as the number of beds), human resources (labor), physical infrastructure, medical equipment, and information systems (Jacobs et al., 2006; Yip & Hafez, 2015), all of which are quantifiable, while outputs used in hospitals efficiency studies were healthcare activities (e.g. number of outpatient and inpatient services, number of surgeries) and health outcomes (e.g., mortality rate and quality of life), which are not so easily quantifiable in monetary values. (Afzali, & Mahmood, 2009; Jacobs et al., 2006).

Numerous methods have been used to quantify hospital efficiency, most notably frontier analysis methods, which compare hospital performance to an estimated efficient frontier comprised of the best-performing hospitals, either using non-parametric data envelopment analysis (DEA) or parametric stochastic frontier analysis (SFA) (Jacobs et al. 2006; Hollingsworth, 2003). However, there are additional approaches for monitoring and optimizing healthcare efficiency. For example, Deprins et al. (1984) developed the Free Disposal Hull (FDH) estimator, which is a more general version of the DEA estimator that is based solely on the free disposability assumption; that is, if a specific pair of input and output is producible, any other pair of more input and less output is also producible. The Malmquist index, which is an extremely useful instrument for analyzing the evolution of public sector productivity over time (Coelli et al., 1998). Additionally, statisticians created multilevel (or hierarchical) models to explicitly reflect organizations' multidimensional nature (Hill & Goldstein, 1998).

Parametric approaches, such as SFA, assume a specific functional form for the production function, such as a Cobb-Douglas or Translog function. By contrast, procedures might be either statistical or non-statistical. Statistical approaches frequently involve assumptions about the stochastic nature of data, especially stochastic frontiers, which enable evaluation of statistical 'noise' as opposed to deterministic data. Non-statistical approaches, such as DEA, are typically non-parametric (and deterministic); whereas statistical methods, such as SFA, are typically parametric (and stochastic) (Jacobs, 2001; Barrow & Wagstaff, 1989).

Data Envelopment Analysis (DEA)

In general, efficiency measurement entails three things: identifying key model variables; formulating an efficiency measure that incorporates these variables; and obtaining data to describe these variables and calculate the efficiency measure. The first task requires a comprehension of the unit’s (hospital’s) production process, including its technological and behavioral aspects, as well as the factors impacting producers' (hospital workforce) capacity to perform. For the second task, the selection of an appropriate evaluation technique is based on its capability to generate robust and informative efficiency estimates, and to adapt to features of the production process analyzed. The third task requires the collection of well-defined and accurate data, consistent with the conceptual framework underpinning the efficiency measure. Health systems and healthcare have unique characteristics that complicate the numerous tasks of efficiency measurement in this sector. Several of these characteristics are indicative of the intangible nature of service production. Others are related more to the complex determinants of health needs, the relationship between service providers and recipients, and factors affecting the choice of care procedures.

For many years, data envelopment analysis (DEA) was the primary tool for assessing efficiency in healthcare and hospital efficiency in particular. DEA is an efficiency approach pioneered by Farrell (1957) and operationalized by Charnes et al. (1978) as linear programming estimators. DEA is a data-driven (non-parametric) technique, which means that the location of the efficiency frontier is chosen by the data, allowing for direct comparison of inputs and outputs without making statistical assumptions. The efficiency or maximum productivity curve is defined by DEA when the output-to-input ratio is ideal. It assumes that the realized values of inputs and outputs are known and aims to maximize the relative efficiency of each organization under review by determining replacement rates for inputs and outputs, as well as relative weights for inputs and outputs (Podinovski, 2016; Fried et al., 1993).

The organization or decision-making unit (DMU) that uses fewer inputs to produce the same number of outputs as others is regarded technically efficient, and thus establishes the efficiency frontier based on 'best-observed practice DMU' (Jacobs et al., 2006; Charnes et al., 1978). The efficiency frontier (border) encloses inefficient DMUs, and efficiency scores are determined relative to this frontier. In other words, the efficiency score of each DMU unit equals the distance between it and that border (Cooper et al., 2007; O'Neill et al., 2008). Due to numerous advantages over alternative methods, DEA has been the most widely utilized tool for assessing relative efficiency in hospitals. DEA is capable of managing a variety of inputs and outputs expressed in a variety of measurement units. Management has strong preferences about the relative importance of various factors in the model. No restrictions are imposed on the functional form relating inputs to outputs, as DEA (deterministic) does not require any specification of the underlying functional form that relates the inputs with the outputs. The differences in DMUs sizes can be dealt with by adopting models that provide variable returns to scale, without bias to small organizations. Also, more than one DMU can be classified as efficient, composing the frontier of relative efficiency and serving as a benchmark for the performance of other organizations (Charnes et al., 1994; Borisov et al., 2012).

On the other hand, DEA has some significant drawbacks (Charnes et al., 1994; Jacobs et al., 2006; Khezrimotlagh et al., 2019). The sample size is one of the disadvantages, although this can be increased by pooling and thus efficiency performance can be evaluated as a sample of hospital observations instead of individual hospital units. Nevertheless, proper statistical methods are required so that an even distribution of sample points can be observed and adjustments made when analyzing the efficiency of a pooled data sample in a single frontier, since size should not be retained as a continuous attribute. A large, homogeneous sample is required for DEA analysis. A greater number of DMUs is expected to increase the likelihood of finding units near the production frontier. Another issue is assessing factors that are unable to be pooled due to DEA's reliance on individual datasets. Similar difficulties arise when the data has correlating input and output. Additionally, DEA models do not account for any inadvertent mistake or deviation, as they make no allowance for noise or random error effects because the scores obtained from DEA and the corresponding envelopment surface are calculated rather than statistically evaluated (Charnes et al., 1994; Jacobs et al., 2006; Khezrimotlagh et al., 2019).

Bootstrapping DEA

Bootstrapping means using thousands of random selections of ‘pseudo samples’ from the observed sample. ‘Pseudo’ estimates can then be obtained from each of these samples, which form an empirical distribution of the estimators. Consequently, this distribution approximates the true sampling distribution (Assaf & Matawie, 2009). The bootstrapping approach is applied to correct the possible biased estimations in DEA-efficiency scores and to overcome the correlation problem of the efficiency scores. Furthermore, it used to provide consistent inferences in accounting for determinants of the DEA efficiency estimates (Assaf & Matawie, 2009).

Yet, due to the nature of DEA-efficiency scores (limited between 0 and 1), this imposes some complications on the bootstrapping process; which will lead to inconsistencies in the measures (Simar & Wilson, 1998). Subsequently, Simar and Wilson (1998; 2000) adopted a smoothed bootstrapping procedure to overcome this problem (based on density estimates of the sample). Still, there are more correlations expected between the input/output variables and the environmental variables in the DEA model. Therefore, Simar and Wilson (2007) developed a double bootstrapping procedure in the second-stage analysis to calculate the standard errors of the estimates (Simar & Wilson, 2007).

In general, data errors may bias deterministic efficiency measures as the technical efficiency of individual hospitals is measured relative to other hospitals. If data errors are distributed inconsistently across observations, relative rankings of hospitals in terms of efficiency will be affected, in addition to efficiency scores being biased (Burgess & Wilson, 1996). Tziogkidis (2012) mathematically defines bootstrap bias for “DMU A" as:

$$\widehat{bias}_{\mathrm{A}} = \overline{\hat{\theta}_A^b} - \hat{\theta}_{\mathrm{A}}$$

Note. Adapted from (Tziogkidis, 2012)

Where $\overline{\hat{\theta}_A^b}$ is the mean (or median) of the bootstrapped efficiency score of DMU A and $\hat{\theta}_{\mathrm{A}}$ is the ‘biased’ DEA efficiency score of DMU A. The success of this logic is based on the assumption that the distribution of the bootstrap bias is similar to that of the model, or DEA bias (Tziogkidis, 2012).

We decided to apply bootstrapping in our analysis mainly to construct confidence intervals or acceptance regions about $\hat{\theta}_{\mathrm{A}}$ (a region where the ‘true’ efficiency score θ_{A} lies). Hence, if the efficiency score of another DMU falls within the region of “DMU A” we could state that the two DMUs do not differ significantly in efficiency and this will be due to the implied sensitivity of efficiency scores introduced by the distribution of (in)efficiency (Simar & Wilson, 2007; Tziogkidis, 2012).

DEA Window Analysis or Window-DEA (WDEA) Efficiency Analysis

As DEA methods become more popular among researchers, perhaps the greatest rewards are the various extensions and types of DEA models currently available for every real-world situation or application imaginable (Liu et al., 2013a, 2013b). As more studies apply conventional DEA models, where frontier estimation and data assessments are cross-sectional analyses of homogeneous DMUs of large sample size; the performance of hospital units is evaluated by only one period of data and the effect of time variations is not considered. Issues such as these are now easily eliminated with methods such as extended DEA approaches employed by researchers for dynamic performance measurement (DPM) of hospital firms (Emrouznejad & Yang, 2018). Dynamic data envelopment analysis (DDEA), DEA-based productivity index (DBPI), and window data envelopment analysis (WDEA) are all among the main techniques used in DPM.

The DDEA approach calculates the interdependence between different periods. In other words, the DDEA method includes transition activities between periods and establishes the performance relationships of the hospital units over time horizon (Allen & Thanassoulis, 2004). The DBPI approach, for example, combines DEA methodology and productivity indices such as the Malmquist productivity index (MPI) or even Luenberger productivity index (LPI) to measure productivity changes of DMUs over two periods (Emrouznejad & Yang, 2018). The last approach in the DPM field is WDEA that is the result of merging DEA method and window analysis (WA) techniques to measure the efficiency of panel data (Halkos et al., 2014). Indeed, this window approach, first introduced by Charnes et al. (1985), is a useful and effective alternative that can describe the dynamic changes of efficiency in each individual DMU, comprehensively. The main advantage of the WDEA approach is its ability to describe the horizontal and vertical changes in the performance efficiency of hospital units. Most importantly, the WA methodology increases discrimination power by increasing the number of DMUs and thus tackling research issues when only a limited number of discrete production firms are available for sample analysis.

In effect, due to the drawback of DEA, where efficiency measures are defined relative to the best practice frontier of the sample under examination, such as the consistently repeated term ‘relative efficiency;’ consequently, DMUs deemed efficient are efficient only in relation to others in the particular sample (Sathye, 2003). Therefore, it is not meaningful in general to compare the scores between two different samples as all calculations are based on different best practice frontiers whose differences are not known. In essence, the basic idea of a DEA-Window Analysis is simply to consider each DMU as if it were a different unit in each of the reporting ‘window’ that span the whole period set (Charnes et al., 1985). With that, the performance of a DMU in a particular period is compared with its own performance in other periods as well as with the performance of other units. It’s important to mention, however, that within this perspective, a year-to-year comparison may be appealing, or usually two-years; the researcher will have to keep in mind that the approach implicitly assumes that there are no substantial technical changes over the entire time period. (i.e. the technological frontier is fixed, no changes expected in hospital units). Due to this assumption, this approach cannot always be considered valid, especially when long time periods are analyzed (3-5 years would not be ideal) since production conditions of units may have substantially altered between distant years.

Formulation of DEA Models

The DEA formulation, as created by Charnes, Cooper, and Rhodes (1978) and known as the CCR model, is presented below in Equation 4. DEA is a non-parametric, deterministic technique that calculates technical efficiency (TE) as the ratio of a weighted sum of outputs of a DMU divided by a weighted sum of its inputs. The linear programming is understood as:

Equation 4

$$Max \quad = \frac{\sum_{r=1}^{s} u_r\, y_{r0}}{\sum_{i=1}^{m} v_i\, x_{i0}}$$

$$Subjected\ to \quad \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{\sum_{i=1}^{m} v_i\, x_{ij}} \leq 1 \quad j = 1, 2, \ldots n$$

$$u_r \geq 0, v_i \geq 0 \qquad r = 1, \ldots\ldots, s, \qquad i = 1, \ldots\ldots, m$$

Adapted from Charnes et al. (1978).

Where,

n denotes the number of units capable of making decisions (DMUs)

m represents the number of inputs and s represents the number of outputs.

xij = the quantity of input i (i = 1,...., m) used by DMUj (j = 1,....., n); and

yrj = the quantity of output r (r = 1,..., s) produced by DMUj (j = 1,......, n);

ur = weight assigned to output (r = 1,..., s); and

vi= weights assigned to inputs (i = 1,..., m) are weights.

Constraints in the preceding model limit all efficiency scores to a maximum value of unity (value in the range from 0 to 1). The variables *ur* and *vi* are quantified in terms of the efficiency of DMUs, which is determined by solving the maximization problem. Therefore, it compares the performance of each DMU0 relative to that of all DMUs with j = 1,..., n. These same weights are attached to all DMUs (O'Neill et al., 2008).

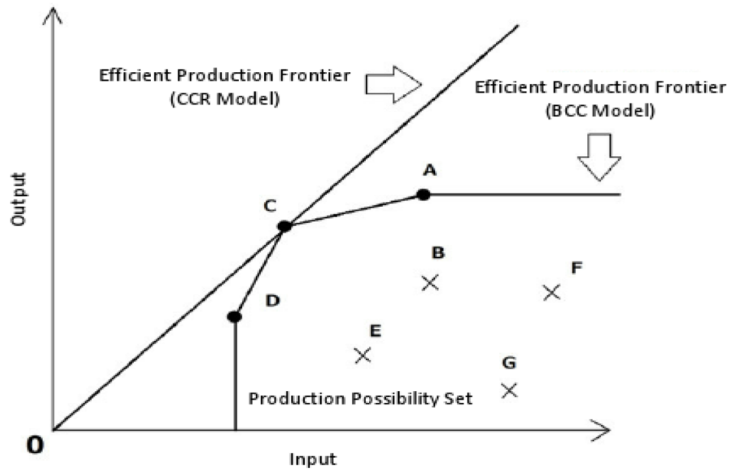
For those organizations (in the case of this research, hospital units) deemed inefficient, the development of performance targets presents an opportunity to improve contributions. It is applicable to a variety of orientations, allowing for the verification of an organization's efficiency evolution and the investigation of the causes that contributed to its growth or decline. It presents a multidimensional picture of efficiency, allowing for investigation of the aspects that most significantly contribute to its achievement, while also proving to be an easily interpretable indicator.

Constant and Variable Return to Scales

In 1978, Charnes, Cooper, and Rhodes established the DEA efficiency analysis under constant returns to scale (CRS) (CCR model). Banker, Charnes, and Cooper (BCC model) updated the CCR model in 1984. It is a more flexible model that considers variable return to scale (VRS) into account when calculating efficiency (see Figure 6 below) (Jacobs et al. 2006), which implies that the effective boundary will have a convex nature (Charnes et al., 1978; Banker et al., 1984). Thus, VRS may be acceptable in situations when not all DMUs can operate at an optimal scale (Cooper et al., 2007).

Figure 6

Both CCR and BCC Models



The returns to scale express how the quantity produced by an organization varies as the use of all the factors involved in the production process varies in the same proportion (Charnes et al., 1978). Banker calculated the Returns to Scale (RTS) by applying the multiplier model's optimal free variable value. The model is based on the notion of optimizing input and output weights in order to determine the efficiency unit's highest value (Banker et al., 1984). CRS occurs when all production components (inputs) are increased equally, resulting in an equal proportionate increase in production (output). Increasing returns to scale (IRS) means the increase in all production factors (inputs) resulted in more production (outputs). On the other hand, when an equal increase in all production factors lead to less production, that indicates a decreasing returns to scale (DRS) (Banker et al., 1984; Lovell, 1993). The technical properties of long-term production of an organization can show different types of returns to scale for different production ranges.

The decision to apply CRS or VRS in studies is critical and is contingent upon the analyst's grasp of the market restrictions confronting units in a given industry. If CRS is deployed in an incorrect manner, such as when all hospitals are operating at a suboptimal scale, estimations of technical efficiency will be confounded by scale efficiency effects. Numerous hospital efficiency studies used the VRS and CRS models to differentiate between "scale efficiency" and "pure technological efficiency." Scale efficiency can be determined by calculating the difference between two frontiers: CRS and VRS (O'Neill et al., 2008; Suhartano, 2017; Cooper, 2013).

Input and Output Orientations

DEA, in conjunction with the input orientation method, tries to minimize input amounts while maintaining the existing output level. This is accomplished by basing the reduction on the input requirements in use and efficient boundaries. That is, until the DMU reaches the frontier, the output level remains constant while the input quantities are reduced accordingly. This is the default orientation when the decision maker has control over the inputs but not the outcomes. For instance, public hospitals that are devoted to providing public services are interested in minimizing inputs. A hospital might reduce its reliance on doctors and nurses proportionately to the amount of treatment services it delivers, and move towards the frontier for being technically efficiency (Daraio & Simar, 2007; Jacobs et al., 2006). In contrast, output orientation analysis seeks to maximize output levels with the available input. This strategy maintains the integrity of the input bundle while increasing the output level until the frontier is reached. In practice, the most appropriate orientation metric would depend on whether input conservation or output expansion is the priority of the evaluation (Deprins et al., 1984; Daraio & Simar, 2007).

Analysis of Uncertainty in the Stochastic Frontier (SFA)

Aigner et al. (1977) proposed the stochastic frontier analysis (SFA) in order to extend the deterministic frontier and incorporate the production function's random error. As with the DEA approach, the SFA method use the distance function to determine a DMU's technical efficiency in comparison to the most efficient provider located on the frontier production or frontier cost function (Blatnik et al., 2017). In contrast to the non-parametric DEA, the SFA is a parametric method that assumes a specific functional form of the production function, such as a Cobb-Douglas or a Translog function. SFA is also a statistical method, in that it frequently makes assumptions about the stochastic nature of the data, such as stochastic frontiers, which allow for the assessment of statistical 'noise' in the data, in contrast to deterministic models such as DEA (Jacobs, 2001; Barrow & Wagstaff, 1989). As illustrated below, SFA follows the standard statistical procedure for specifying an econometric model:

Equation 5

$$y\mathrm{i} = a + bx\mathrm{i} + e\mathrm{i}$$

Adapted from Chen (2007).

Where,

y= the output;

i= the number of observations, i= 1,...;

a= constant;

x= the vector of explanatory variables;

b= the association between the dependent and explanatory variables; and

e = residual

The SFA offers a number of advantages when it comes to evaluating technical efficiency. A stochastic frontier incorporates sophisticated statistical tests to determine the validity of the model specifications. Additionally, SFA may distinguish between data uncertainty and pure inefficiency on the basis of efficiency levels (Chen, 2007). Lastly, the SFA can estimate cost-inefficiency in the technical inefficiency, as efficiency estimations are highly dependent on which output is selected for deflation (Rosko & Mutter, 2008).

Chapter Summary

Measuring efficiency is a cornerstone of the health system in terms of evaluating individual performance of production units such as healthcare facilities/centers and hospitals. It creates the conceptual framework for the allocation of resources within and between healthcare entities (Kontodimopoulos et al., 2006). Since the primary aim of health-related organization units is to boost performance and maximize 'healthy' outcomes, strategies to evaluate their performance and pinpoint factors in the health production function should be defined clearly (Cantor & Poh, 2018). Data envelopment analysis (DEA) has already become the standard method for measuring technical efficiency and is the preeminent tool for assessing the efficiency of public hospitals, according to a large number of systematic reviews (Hollingsworth, 2003; Hollingsworth, 2008; Alatawi et al., 2019). Data envelopment analysis is frequently utilized since no a priori characterization of the underlying functional form that links inputs and outputs is required. In addition, DEA's flexibility to combine various inputs and outputs in different units of analysis justifies its use (Jacobs et al., 2006; Hollingsworth, 2014). Using DEA methodology, we are able to empirically determine the operating entities' relative efficiency. These operating entities are also known as decision-making units (DMUs), and they are considered to consume equal inputs and generate equal outputs (Ramírez-Valdivia et al., 2015).

The prime objective of this chapter was to review the literature to determine how technical efficiency of hospitals in the State of Kuwait can be measured using two stage DEA. According to Farrell (1957), there are three distinct forms of efficiency, which involve technical, allocative, and economic efficiency. Technical efficiency is where an entity is able to produce greatest output from a predetermined set of inputs (easier explained as the maximization of the outputs for a combination of known input levels. Equally implying to also mean expanding the use of inputs for a certain level of output). The allocative efficiency refers to the ability of technically efficient firms to use inputs in ratio that reduce production costs for set input prices. Meanwhile, the combination of allocative efficiency and technical efficiency indicates the economic efficiency. So, when a firm is technically and allocatively efficient, it is considered economically efficient. Economic efficiency in its most basic form can be estimated as the ratio of the lowest possible costs and the actual identified costs for a firm (Farrell, 1957) as follows:

Equation 6

$$Efficiency = \frac{weighted\ sum\ of\ output}{weighted\ sum\ of\ input}$$

Adapted from Farrell (1957).

The economic theory of production has a simple principle: production entails the use of various types of services and products to generate output. In a production operation, these services and products relate to inputs that are turned to outputs (Hollingsworth & Peacock, 2008). Economists distinguish between three types of inputs, known as production factors, according to Hollingsworth and Peacock: labor, capital, and land. Whereas labor refers to human effort inputs, capital relates to structures, machinery, and plants. Land provides inputs from natural resources, enabling production to take place (Hollingsworth & Peacock, 2008). It's critical to know how much output can be generated from various input combinations. The probabilities are explained by the function of production, which is stated quantitatively by determining the range of technically feasible input mixtures in the process of making output (Hollingsworth & Peacock, 2008).

To estimate hospital efficiency, the outputs of the hospital must be determined. There are many feasible measurements of hospital outcomes for instance, number of cases treated, number of techniques performed, number of inpatient days, bed turnover and bed occupancy rate. The hospital objectives determine the output or combination of outputs which are used to evaluate hospital efficiency (Moshiri et al., 2010). The capability of DEA to cope with a variety of hospital activities which are carried out within the organization itself makes the DEA model a unique technique for measuring the technical efficiency of health facilities (Helal & Elimam, 2017). Moreover, the DEA can cope with multiple inputs and outputs, making it an attractive choice for measuring the efficiency of hospitals (Abou El-Seoud, 2013; Du et al., 2014).

Chapter 3

Implications of Model Choice on the Estimation of Efficient Frontiers: A Systematic Literature Review and Meta-Regression Analysis

Chapter 2 provided insight into the literature on efficiency analysis in healthcare and hospital settings; the preliminary overview of existing evidence and current research studies described in the previous chapter offers supporting details for the systematic review analysis in Chapter 3. From topic conception, the preparation format for this chapter was structured toward identifying relevant health research standards and appropriate guideline manuals for conducting a systematic review and meta-analysis. Based on disciplinary area, systematic review questions, and aims for a statistical analysis of the literature, the guideline standard followed in the undertaking of this systematic review and meta-regression analysis.

The scoping review conducted in the previous chapter is in accordance with best practice recommendations and an exploratory precursor of this chapter. For Chapter 3, we carry out a systematic review of the published research in hospital efficiency using frontier-based analysis, then extracted the study results for a meta-regression. This chapter examines the effect of modeling choices on technical efficiency scores within the econometric literature as well as the literature on operations and production management sciences. Building on critical concepts of efficiency analysis and diverse frontier estimation methods introduced in Chapter 2, the focuses here is on the significant considerations following the selection of non-parametric data envelopment analysis (DEA). Much greater importance should be placed on rationale for modeling choices of frontier estimation; the recurring theme of “based on previous studies” should not be the common practice for including input and output variables in DEA models. This chapter concludes with an empirical section containing a statistical summary of the literature on hospital efficiency frontier modeling and a discussion of the findings from the meta-regression analysis. Ultimately, the hope is to identify the critical factors of DEA model specifications or other unique study characteristics that influence efficiency scores and estimated hospital performance results.

Healthcare and Hospital Efficiency Literature

Frontier-based analytical techniques for measuring the relative efficiency of production firms or decision-making units (DMUs) have been widely applied in health services research to evaluate many different types of healthcare facilities, including nursing homes, hospitals, administrative health districts/regions, or private clinical practices. Parametric methods (stochastic frontier analysis; SFA) have gradually gained popularity over the years, while non-parametric methods (data envelopment analysis; DEA) have long been the dominant tool of choice in this body of literature (Burgess & Wilson, 1996; White & Ozcan, 1996; Chang, 1998). A majority of studies utilize efficiency estimates to shed light on policy issues such as ownership and organizational structure (please see McKay et al., 2002; Chang et al., 2004; Dervaux et al., 2004; Ferrier & Valdmanis, 2004; Barbetta et al., 2007; Lee et al., 2008). Therefore, this empirical review of the literature and meta-analysis regression is necessary to determine how best to model variables and capture measures of efficiency for addressing: (i) the first objective of this dissertation, which aims to evaluate the efficiency of Kuwait's Ministry of Health (MoH) public general/specialized hospitals over a five (5) year period (2015-2019); and (ii) the second objective of this dissertation that aims to conduct a comparative study of public and private hospital performance and evaluate inefficiency by ownership type and managerial differences (please refer to Chapter 1).

The efficiency literature widely acknowledges the influence of modeling choice on efficiency estimates. Due to data availability constraints, the sample size and variables utilized in the vast majority of studies cannot be controlled. However, the choice of analytical methods and model specifications can be adjusted to the research question to a greater extent (s). In order to protect the estimation accuracy, it is reasonable to explore the different model specifications and their outcomes. This is particularly important for studies with a policy design focus, as other health economists have emphasized in past studies (primarily, Newhouse, 1994; Parkin & Hollingsworth, 1997; Folland & Hofler, 2001; Jacobs, 2001; Street & Jacobs, 2002; Chen et al., 2005). If the estimated efficiency scores and hospital results aim to inform decision-makers on capacity utilization and health funding, those hospitals inaccurately found to be inefficient may receive fewer allocation of funds or required to reduce production to limit resource waste. If the issue at hand is a post-evaluation of a healthcare policy on hospital behavior, for example, a skewed measurement of efficiency would be a distortion of the policy’s true effects and misleading to evaluate actual policy's impacts.. Thus, data preparation and appropriate efficiency model choice are vital before carrying out any efficiency analysis studies in the healthcare field.

How to Improve Measuring Methods of Efficiency: Study Characteristics and Key Modeling Specifications

Variables

The first significant decision in modeling production technology relates to output and input choices. Inputs and outputs should be relevant and sufficient to capture the production process. In practice, problems with variable options come in the form of imperfect measures of inputs or outputs, incorrect aggregation, and omitted variables. Including irrelevant variables is also another issue (Worthington, 2004). However, in the hospital efficiency literature, it is far more often that a frontier model fails to capture all aspects of the healthcare service production than including an extraneous variable, mainly because of data deficiency.

Furthermore, it is suggested that excluding relevant variables is likely to be more damaging to frontier models than the inclusion of irrelevant variables (Smith, 1997). Although studies far too often do not have a choice over the quality of input and output data, it is worth emphasizing that findings based on rudimentary measures of inputs/outputs should be interpreted with caution. In many situations, omitted variables and aggregation are mainly attributed to different research questions or data availability, while in other cases are due to modeling choice. Its existence usually distorts findings.

Now, let us consider whether it is possible to predict the direction of impact on the average efficiency score by including or excluding a variable in our model? What considerations should be taken when deciding which hospital variables to include in the efficiency model and what to expect in terms of overestimating efficiency scores or underestimating efficiency scores based on variables selection alone? Technically, the inclusion of another variable in the estimated model will increase the dimensions of the frontier. That said, the addition of a variable may alter operating processes that move or change the shape or form of the production frontier; making it easier for firms to reach the boundary of relative efficiency. We know this from previous studies that suggest increasing frontier dimensions may produce higher mean efficiency scores (overestimated efficiency). However, the magnitude of this effect depends on the omitted variable's correlations with included variables. For example, if the extra variable is an input and is highly correlated to other input variables, the omission of the variable is unlikely to affect the results significantly. However, if the variable is not strongly correlated, the impact on mean efficiencies can be significant. This is a solid point of consideration when constructing models for hospital efficiency analysis.

One strong example found in the hospital efficiency literature is the study by Rosko and Chilingerian (1999), in which they added case-mix variables to a basic translog function and found the primary trans log case yielded lower efficiency scores compared to the one with case-mix variables. Nunamaker discussed the potential impact of dimensionality on efficiency scores (1985), where the author found that variable set expansion, either through adding new variables or even disaggregating existing variables, may produce an upward trend in mean efficiency scores (an important consideration when attempting to transform or decompose data measures originally reported as aggregate hospital variables). Then again, other studies (please see Tauer, 2001; Fre et al., 2004; Barnum & Gleason, 2005) also confirmed that aggregation of many outputs into fewer or one output introduces a downward bias on efficiency estimates, and the more outputs are aggregated, the greater the bias that may be expected. The modeling process alone is arguably the ultimate determining factor of whether the efficiency scores obtained from our analysis truly represent a hospital's efficiency.

Lastly, almost all studies cite some arrangement or rule of thumb when considering the number of input and output variables to include in the efficiency model as related to the sample size (number of DMUs or hospital observations). For example, Golany and Roll (1989) established a rule of thumb that the sample number of (hospital) units should be at least twice the number of inputs and outputs considered. Bowlin (1998) maintains a need to have three times the number of decision-making units (DMUs) as there are input and output variables. Finally, Dyson et al. (2001) recommend two times the product of the number of input and output variables. Therefore, with a three input and four output efficiency model, Golany and Roll (1989) suggest using a minimum of 14 DMUs [no. of hospitals $\geq 2 \times$ (total inputs + outputs)], while Bowlin (1998) insists on 21 DMUs [no. of hospitals $\geq 3 \times$ (total inputs + outputs)]. Dyson et al. (2001) remain steadfast; it should be at least 24. Consequently, given the different conventions of a sample size to input/output ratios, these numbers are treated as assumptions used by studies in the literature as average minimums for inclusion in any basic productivity model instead of standard principles of efficiency modeling, and thus will be among the study specifications included in the meta-regression analysis.

Sample Size

In our analysis, the sample size, also known as the number of (hospital) DMUs or observations, the opposite effect is generally observed. Fre et al. (2004) reminds us that non-parametric frontier estimators are biased and the degree of bias depends on specific sample properties, most importantly sample size and number of dimensions of the model (Fre et al., 2004). The increase in sample size will either push the production frontier up when new observations form part of the new frontier or do not change the boundary when new observations lie entirely under the existing border (Fre et al., 2004). Suppose we decide to include more hospitals to have a larger sample size, and these new observations form part of the new frontier. The (hospital) units once identified as efficient under the old border may now be considered inefficient. It is only when a new observation in our sample does not affect the position of the frontier (because it is either on or below the existing boundary) then it will not change the status of already identified efficient and inefficient units.

Therefore, considerations of the number of hospital units in an efficiency analysis indicate a point of depreciation. Increasing the sample size is unlikely to improve mean efficiency scores. Zhang & Bartels (1998) also noted this critical point when they investigated the effect of this bias by comparing the effect of sample size on the mean efficiency in DEA applied to electricity distribution in Australia, New Zealand, and Sweden; where they found a negative correlation between the estimated mean efficiency and the number of firms in the industry (Zhang & Bartels, 1998). The key takeaway is that the mean efficiency decreases quickly as the number of observations increases when the sample is relatively small. When sample sizes are large, the mean efficiency shows little change. Above a threshold, a mean efficiency seems to tend to be reasonably constant.

Orientation

The other important point of consideration in frontier modeling relates to orientation. Choice of input/output orientation is usually driven by the objective of production units under relevant production and management constraints. In our case for Kuwaiti public hospital efficiency, input orientation aimed at minimization of inputs for a given set of outputs seems reasonable. Arguments for using the input orientation include that hospitals have more control over inputs than outputs and it is interested in minimizing inputs or costs. If maximizing output (or outcome) is considered a relevant objective of a hospital, usually associated with private, for-profit hospitals, then an output orientation (output-oriented DEA frontier) may be warranted. Generally, in practice, the underlying assumption of input orientation in hospital efficiency studies is that of cost (input) minimizing behavior of hospitals. We assume this and justify it from the viewpoint of hospital managers, who are constantly under pressure to meet budget requirements. However, this assumption has received much criticism in the literature, especially from medical professionals who often argue that their objective is not minimizing cost but improving lives through the prevention and treatment of diseases.

Measuring efficiency changes in a healthcare system involves a comparison of the amount of outputs produced by the healthcare system and the amount of inputs used to produce those outputs over time. The choice of inputs and outputs used in this study was guided equally by both previous studies on the performance of public hospitals as well as by availability of MoH hospital data. Generally, in the literature on hospital performance, the set of inputs typically includes the numbers of physicians, nurses, allied health professionals, and hospital beds, along with operational expenses (Alatawi et al., 2020; Alsabah et al., 2019). In some studies, a distinction was made between specialist and general physicians. The set of outputs generally includes the numbers of inpatient visits, outpatient visits, surgical procedures, laboratory tests, radiology films, and patients; bed turnover rate (BTR); bed occupancy rates (BOR); and average length of stay (ALoS) (Ravaghi et al., 2019). Some studies adjusted for the case-mix and complexity of surgical procedures (Silwal & Ashton, 2017). Among the limitations identified in this dissertation, and further discussed in following chapters, is the lack of quality indicator data (i.e., specific dead versus alive hospital discharges for mortality as a measure of quality) or existing case-mix variables for hospitals in Kuwait due to no standardized system to classify hospital cases (i.e., diagnosis-related groups, or DRGs).

For our analysis of public MoH hospitals, we used hospital beds as well as full-time number of physicians and nurses as inputs, while outputs include total number of inpatients discharges (adjusted for non-surgical treatments and surgical interventions performed) as well as total visits (both outpatient and emergency visits). The comparative study of public versus private general hospitals was able to include total number of surgical operations performed as outputs since all general hospitals in our sample perform both emergency and inpatient surgical interventions.

We apply input-oriented models in our initial analysis and output orientation in the latter. In this case, orientation must be considered carefully since it has a particular effect on the efficiency score. Suppose the sample in the analysis contains mainly small and few large hospitals; which is the case in our public versus private comparative study. In that case, it is expected that most hospitals are operating in the increasing returns to scale region, and therefore an input-oriented DEA approach would produce a higher efficiency level for small hospitals; consequently, higher mean efficiency. The reverse applies to samples with mainly large hospitals. A sample with a balanced mix of hospital size is likely to generate a similar mean efficiency score under either output or input orientations. It is noted that this issue only applies to variable returns to scale (VRS) frontier. In the constant returns to scale (CRS), output and input orientations produce identical technical efficiency (Coelli et al., 2005). This consideration indicates that adjustments should be made in terms of the total number of hospital beds (hospital size) to control for higher exaggerated efficiency estimates in a sample of small, medium, and large hospital sizes.

Returns to Scale

In economics, returns to scale describe what happens to long-run returns as the scale of production increases when all input levels, including physical capital usage, are variable (able to be set by the firm). The concept of returns to scale arises in the context of a firm's production function and relates to whether production units are of the optimal size or not. This is one of the famous research questions in efficiency analysis. Some production technologies possess the property of constant returns to scale (CRS), and the production size does not matter. Others (the majority) do not. This raises the question of how returns to scale should be modeled. CRS assumption is appropriate when all hospitals operate at the optimal scale (i.e., productivity is scale-dependent). However, imperfect competition, government regulations, valid social objectives, and financial and labor constraints may cause the hospital to not operate at the optimal scale (Coelli et al., 2005).

In this case, if we impose CRS in the model, efficiency estimates will be significantly biased. This bias is generally more severe than in the case where VRS is assumed for a CRS technology (Burgess & Wilson, 1996). Moreover, Webster et al. (1998) suggest that imposing CRS will vastly underestimate efficiency, whereby Smith (1997) implies this inappropriate use of returns to scale assumption is particularly damaging when the sample size is small. Table 3 summarizes this section on the expected relationships between efficiency scores and choice of model specifications based on the literature outlined above. The following section statistically evaluates differences in study characteristics, model specifications, and reported efficiency scores in a reviewed study sample.

Table 3

Some Expected Impacts of Modeling Choices on Mean Efficiency Estimates

Factors that push mean efficiency upwards	The factor with an ambiguous impact on mean efficiency	Factors that push mean efficiency downwards
Number of variables	Orientation	Sample size
Pooled panel data		Constant returns to scale (CRS)

Systematic Review and Meta-Regression Analysis

Data and Methodology

In virtually every case where statistics is applied in the analysis of data samples extracted from reviewed papers, much attention is placed on the preparation of the final dataset analyzed.

Common summary measures like the sample mean or the sample standard deviation are included as descriptive statistics later in the chapter, the focus was spent more on measures of differences in the study variables being analyzed, including heteroskedasticity or variability (variance), effect size based on mean comparison, and overall prevalence of outliers in study sample. Therefore, priority was given to the construction of the meta-dataset and declaring the meta-analysis regression (meta-regression) in Stata 16.1 software package, which is used to perform the meta-regression analysis on study-level summary data.

The systematic search of the literature is also a critical component of the systematic review process that involves a methodical search strategy. When done correctly, it should produce a transparent report of study identification and leave readers clear about what was done to identify studies. The same information retrieval approach conducted previously in Chapter 2 is applied to our literature search strategy, using the initial 'hits' or returns from the many databases searched in December 2021 and again in January 2022 (setting notifications was considered unnecessary). A third and final search was conducted in March 2022 and began to review scholarly peer-reviewed studies following specific, pre-determined inclusion/exclusion criteria. Primary studies from all three search events were sorted according to keyword usage in the title or abstract with choice words including the terms: "efficiency," "hospital," "healthcare facility," "health center," "data envelopment analysis," "DEA," "productivity," "performance," "technical efficiency," "pure efficiency," "CCR model," and "BCC model."

Electronic databases were systematically searched for a total coverage period of four months and an average of every 1-2 months. The search strategy mainly includes the hospital efficiency literature, but also extended to the applied econometrics literature and papers in leading general interest journals of the economics profession or peer-reviewed statistics articles and econometric methods publications (i.e., *American Economic Review*, etc.). The databases searched include MEDLINE (via PubMed), Embase, Cochrane Library, and EconLit; the stated review objective and search aim were to identify standards or best practices for measuring hospital efficiency and performance estimates using DEA techniques.

A consistent search algorithm was used again to search titles/abstracts [tiab] in the literature and ensure a wide array of studies are screened: (("efficiency" OR "performance" OR "inefficiency" OR "data envelopment analysis" OR "DEA" OR "stochastic frontier" OR "SFA" OR "parametric" OR "non-parametric")) AND (("hospitals" OR "health facilities" OR "healthcare" OR "health care")). All relevant studies identified through literature database searches compiled from December 2021, January 2022, and March 2022 were imported into EndNote 20.2 citation manager after checking reference lists for additional studies or missed information and before screening for eligibility. Supporting secondary sources and other academic papers further extended to results from the gray literature by a manual search of citation indexes, such as Web of Science (or the search engine, Google Scholar), using the same query/keywords to reduce publication bias.

The review protocol and search strategy aligned with the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) reporting guideline for systematic literature reviews and was also compliant with the most recent PRISMA 2020 Statement, an updated guideline for reporting systematic reviews (Page et al., 2021). This current study review protocol is preregistered on the Open Science Forum (OSF) and materials for the working project is registered in OSF open-ended registration for public consumption and freedom of information sharing (Registration DOI: 10.17605/OSF.IO/K8T2F); work is licensed under the Creative

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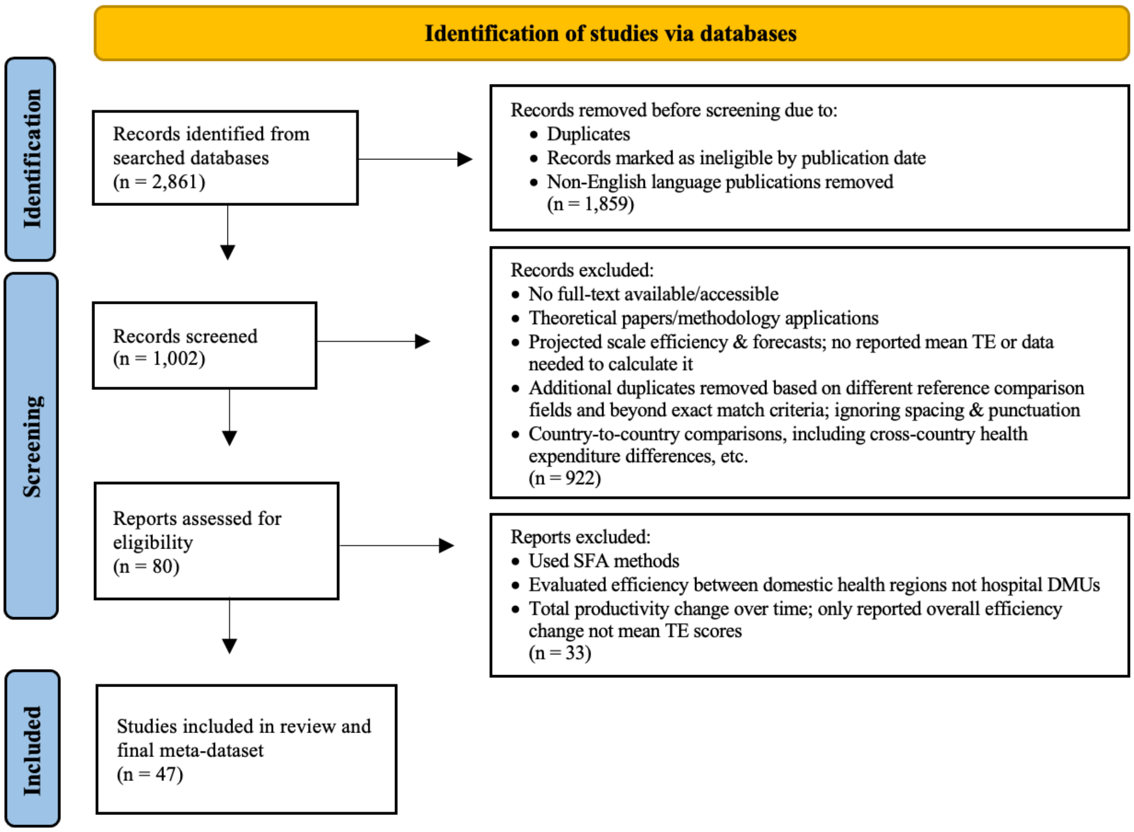
The de-duplication and preparation of references for screening is done with EndNote 20.2 as described in the comprehensive manual for evidence synthesis endorsed by the Joanna Briggs Institute (JBI) at the University of Adelaide (Moola et al., 2020). The procedural guidance for the two-stage screening of database search results imported into EndNote citation manager software included; preparing references for screening per our pre-defined review plan or developed protocol, performing custom sorting of all references in our library, undertaking the duplicates removal process, evaluating eligibility criteria (inclusion/exclusion), and finally, preparing the total number of reference results from the searched databases for final reporting. The complete EndNote library was exported to a data file reader before imported into Stata 16.1 meta-analysis panel and declared. Other JBI review manual recommendations used, such as preparation (or 'scoping') exercise undertaken before the actual systematic review and critical appraisal checklist for quality assessment of reviewed studies, are compatible with PRISMA protocol and supported and approved by the international scientific committee (Peters et al., 2020).

Approximately 2,861 primary studies on efficiency analysis in healthcare were identified via the searched databases (the search for primary literature usually is orientated towards achieving high sensitivity). Elimination of duplicates, as well as any research papers dated before 2002 (over 20 years old) and not published in English, identified 1,002 articles for screening; broader exclusion criteria include studies not reporting weighted average technical efficiency scores (or no data given for readers to calculate), no full-text available or accessible, DMUs other than hospitals (i.e., cross-country health system comparisons, health districts/regions, etc.), literature reviews and all different types of study analyses (graduate thesis, dissertations, etc.), studies using cost function to estimate cost-effectiveness and productivity along with efficiency measures, and any hospital efficiency study using parametric stochastic frontier analysis (SFA) and not non-parametric data envelopment analysis (DEA) as the primary technique of frontier estimation. Working papers were removed if no recent versions or updates were found, and the work is yet to be published five (5) years later.

Finally, studies on allocative efficiency or equity and other healthcare services (such as physician burnout, primary health clinics, diagnostic labs, nursing homes, etc.) were removed from the list. Eighty full-text primary studies were assessed for eligibility, and 47 peer-reviewed articles were included in the review. The below PRISMA Flow Diagram depicting the flow of information through the different phases of the literature search and review is shown in Figure 7.

Figure 7

PRISMA 2020 Flow Diagram of Search Process in Systematic Review



Note. A newly updated PRISMA 2020 flow diagram for systematic reviews was adapted for searches of databases and registers. The borrowed template was provided by Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372,* n71. https://doi.org/10.1136/bmj.n71

The screening of identified articles and the eligibility assessment process included critical appraisal tools to assist in evaluating the trustworthiness, quality, relevance, and results of published papers. Articles were essentially assessed for statistical rigor and authority in terms of the research question(s) and study objectives, as well as other characteristics or qualities, such as units of analysis (DMUs), country/region, publication year, model specifications, and efficiency results and findings – among other exogenous variables that were included in the meta-regression based on approaches and model specifications in the primary studies, such as cross-section versus panel data and sample heterogeneity. The majority of the relevant primary studies identified were journal publications. Studies using any of the different forms or extensions of DEA methods (two-staged Tobit, two-staged Malmquist Productivity Index, bootstrap DEA, dynamic network DEA, etc.) are enough to warrant their inclusion, as long as the technical efficiency scores were clearly reported or data were available to calculate a weighted average efficiency. The final meta-dataset consisted of 47 peer-reviewed studies from 27 countries and published within the past two decades with a median publication year of 2015; the sample size ranged from five (5) DMUs to 1,259 (hospital) observations. The number of input/output variables was among the model specifications recorded, ownership and hospital type(s) heterogeneity, and model orientation choice and returns to scale assumption. A summary of the different efficiency frontier characteristics in DEA studies of hospital efficiency is shown in Table 4.

Table 4

Characteristics of Reviewed Hospital Efficiency Studies using DEA

Article No.	Study	Publication Year	Country	Sample Size	No. of Inputs	No. of Outputs	Orientation	Return to Scale	Hospital Type
1	Stefko et al.	2018	Slovakia	8	3	2	Output-oriented	VRS & CRS	Regional public healthcare facilities
2	Cheng et al.	2015	China	114	3	2	Input-oriented	VRS & CRS	County hospitals
3	Lin et al.	2021	Taiwan	19	5	6	Input-oriented	VRS & CRS	MoH tertiary hospitals
4	Torabipour et al.	2014	Iran	12	3	3	Input-oriented	VRS	University teaching & non-teaching hospitals
5	Jehu-Appiah et al.	2014	Ghana	128	4	4	Output-oriented	VRS	Mixed-ownership district hospitals

6	Ahmed et al.	2019	Bangladesh	62	2	3	Input-oriented	VRS & CRS	Public district hospitals
7	Campanella et al.	2017	Italy	50	3	3	Input-oriented	CRS	Public hospital trusts
8	Kalhor et al.	2016	Iran	54	4	4	Input-oriented	VRS	General hospitals
9	Jat & Sebastian	2013	India	40	3	8	Input-oriented	VRS	District hospitals
10	Yusefzadeh et al.	2013	Iran	23	3	2	Input-oriented	VRS	Public hospitals
11	Masiye	2007	Zambia	30	4	4	Input-oriented	VRS	Public hospitals
12	Dash et al.	2010	India	29	4	5	Input-oriented	VRS	District hospitals
13	Shahhosseini et al.	2011	Iran	12	4	5	Input-oriented	VRS & CRS	Provincial hospitals
14	Farzianpour et al.	2012	Iran	16	3	3	Input- and output-oriented	VRS & CRS	University teaching hospitals
15	Li & Dong	2015	China	14	2	2	Output-oriented	CRS	Public hospitals
16	Medarevic & Vukovic	2021	Serbia	39	3	2	Input-oriented	VRS & CRS	Public general hospitals
17	Xu et al.	2015	China	51	4	3	Input-oriented	CRS	Provincial tertiary hospitals
18	Lobo et al.	2016	Brazil	31	3	1	Output-oriented	VRS	University teaching hospitals
19	Mujasi et al.	2016	Uganda	18	2	2	Output-oriented	VRS	District hospitals
20	Flokou et al.	2017	Greece	73	3	3	Input-oriented	VRS & CRS	Public hospitals
21	Jia & Yuan et al.	2017	China	5	2	3	Output-oriented	VRS	Public hospitals
22	Li et al.	2017	China	12	4	3	Input-oriented	VRS & CRS	Public hospitals
23	Giancotti et al.	2018	Italy	41	2	3	Input-oriented	VRS & CRS	Public hospitals
24	Alsabah et al.	2019	Kuwait	15	4	2	Input-oriented	VRS	MoH hospitals
25	Franco Miguel et al.	2019	Spain	25	3	4	Input-oriented	CRS	Mixed-managed public-private hospitals
26	Alatawi et al.	2020	Saudi Arabia	91	4	6	Input-oriented	VRS & CRS	MoH hospitals
27	Hofmarcher et al.	2002	Australia	93	4	2	Input-oriented	VRS	Provincial hospitals
28	Ramanathan	2005	Oman	20	3	3	Input-oriented	VRS & CRS	MoH & public regional hospitals: university teaching hospital, police hospital

29	Mahate & Hamidi	2016	UAE	96	6	3	Output-oriented	VRS & CRS	Private & government hospitals
30	Mogha et al.	2012	India	55	3	1	Output-oriented	VRS & CRS	Private hospitals
31	Sultan & Crispim	2016	Jordan	27	4	3	Input-oriented	VRS & CRS	MoH public hospitals
32	Kontodimopoulos et al.	2006	Greece	17	3	2	Input-oriented	CRS	Rural small-scaled hospitals
33	Wei et al.	2011	Taiwan	21	2	3	Input-oriented	CRS	Public & private medical centers
34	Vitikainen et al.	2009	Finland	40	1	2	Input-oriented	VRS & CRS	Public acute care hospitals
35	Puenpatom & Rosenman	2008	Thailand	92	5	5	Input-oriented	VRS	Provincial public hospitals
36	Prior	2006	Spain	29	4	5	Output-oriented	CRS	Public healthcare network hospitals
37	Butler & Li	2015	United States	57	4	4	Input-oriented	VRS	Rural state hospitals
38	Mitropoulos et al.	2015	Greece	117	4	2	Output-oriented	VRS	Public hospitals
39	Mitropoulos et al.	2013	Greece	96	4	5	Input-oriented	VRS & CRS	MoH public general hospitals
40	Mehrtak et al.	2014	Iran	18	4	3	Input-oriented	VRS	Provincial general hospitals
41	Linh Pham	2011	Vietnam	101	2	3	Input-oriented	VRS	MoH hospitals
42	Lindlbauer et al.	2016	Germany	749	7	1	Input-oriented	VRS	Mixed ownership acute care hospitals
43	Lee et al.	2008	Korea	106	3	2	Input-oriented	CRS	Mixed-ownership acute care hospitals
44	Khushalani & Ozcan	2017	United States	1259	3	4	Input-oriented	CRS	General medical-surgical hospitals
45	Kawaguchi et al.	2014	Japan	112	10	4	Input-oriented	VRS & CRS	Municipal hospitals
46	Friesner et al.	2008	United States	80	3	4	Input-oriented	VRS & CRS	General, mixed-ownership acute-care hospitals
47	Abo El-Seoud	2013	Saudi Arabia	20	4	4	Input- and output-oriented	VRS & CRS	Privately-managed public hospitals

The final meta-dataset contained a total of 4,217 hospitals (pooled sample size) spanning 19 years (2002-2021); categorized according to frontier-based study characteristics, DEA model specifications, and estimated mean technical efficiency (MTE). Also, studies using panel data that were already pooled and reported MTE as weighted averages from across the study period, their sample size, therefore, included the number of "observations" accounted for over the years and not necessarily individual numbers of hospital units. Reported efficiency scores were assessed in light of the different estimates or measures of efficiency, including overall technical efficiency, pure technical efficiency, and scale efficiency, with a primary focus on technical efficiency (TE) scores of the reviewed studies. Since TE is provided by the CRS model while also capturing both pure technical efficiency (PTE) and scale efficiency (SE), whereas the VRS returns to scale model captures PTE devoid of SE effects, studies typically will apply the most relevant model best suited to address research questions and provide the efficiency score of interest; both models can also be pursued in a given study according to research objectives.

Nonetheless, the average TE score being evaluated and recorded for each reviewed study refers explicitly to the CCR (CRS) technical efficiency model as described by Charnes, Cooper, and Rhodes (1978) and based on the extended BCC (VRS) pure technical efficiency model developed by Banker, Charnes, and Cooper (1984) shown in Equation 3.1 (Charnes et al., 1978; Banker et al., 1984). This formula illustrates the fundamentals of CCR and BCC models that follow the assumptions of CRS and VRS technology; whereby the CRS score can be further decomposed into a VRS score and an estimate of scale efficiency, or more often in practice, the scale efficiency (SE) is determined as a quotient (or as a fraction or a ratio in the case of proper division) when dividing technical efficiency (TE) by pure technical efficiency (PTE), or the dividend TE / PTE the divisor (please see Chapter 2):

*CRS score = VRS score * Scale efficiency*

*TE = PTE * SE*

As for the choice of input- or output- orientation, only two studies decided on a mixed-orientation approach (i.e., both input- and output-oriented models), in which output orientation was used for sensitivity analysis (Abo El-Seoud, 2013; Farzianpour et al., 2012). A clear majority of studies had selected the input-oriented approach (74.5%) based on the argument that hospitals (especially government or state-funded public hospitals) cannot choose their output level, which depends on the demand for health services. Hospitals then try to conserve inputs, which makes input (or cost) minimization a reasonable assumption for DEA estimation. Some countries have different methods of financing health service providers. Instead of payment based on cost history or per diem, reimbursement for hospitals is based on output volume and sector average cost with a cap (global budget). The assumption of maximizing output level, given the amount of health resources available, has been chosen in those studies to reflect this change. Overall, the distribution of studies using CRS versus VRS assumptions to estimate efficiency scores is unevenly spread out, where the highest proportion of studies favored utilizing a combination of both VRS & CRS models (42.6%), followed by the VRS model only (38.3%) and lastly the CRS model only (19.1%). Technical efficiency (TE) scores, classified by model orientation and returns to scale (under CRS and VRS technologies), are presented in Table 5.

Table 5

Technical Efficiency Estimates by Choice of Returns to Scale and Model Orientation of Studies

	Technical Efficiency (TE) Scores

DEA Model Specifications	Mean	Std. Dev.	Median	Min	Max
Input-oriented (n=35)	0.810	0.1046	0.8154	0.52	0.989
Output-oriented (n=10)	0.748	0.1373	0.7716	0.476	0.96
Mixed orientation (n=2)	0.902	0.079	0.902	0.846	0.958
CRS (n=9)	0.8007	0.1256	0.8	0.52	0.96
VRS (n=18)	0.7947	0.1187	0.8045	0.584	0.989
VRS & CRS (n=20)	0.8069	0.1105	0.8027	0.476	0.96

Note. TE scores are shown on a 0-1 scale. Model orientation (input- and output-oriented) and returns to scale (VRS and CRS) are not restricted to one model choice or a specific approach in frontier analysis. Technical efficiency scores are grouped by the selection of returns to scale (RTS) orientation choice due to this very fact; please see meta-regression results and interpretation for more information.

The number of variables contains all inputs and outputs included in the model (dimension). In general, the number of input/output variables included in the model depends on the sample size; the rule of thumb believed is 2 or 3 times the sum of input/output variables should be less than the sample size (number of hospital observations). The sample size is generally the number of individual hospitals included in the primary study. In effect, we can assume a larger sample size and lower number of input and output variables in a study will be associated with lower efficiency scores since not enough variables are accounted for; however, with proper weighted adjustments to hospital data and suitable model choices, there may not be any such constraints besides the restrictions of the number of variables used in modeling analysis for small sample size studies. Table 6 below shows some descriptive statistics of model specifications recorded from the reviewed studies.

Table 6

Descriptive Statistics of Prominent Study Features

	Sample Size	No. of Inputs	No. of Outputs
Mean	89.72	3.55	3.26
Median	40	3	3
Min	5	1	1
Max	1259	10	8

The most common inputs were capital-based (number of hospital beds, etc.) and labor-based variables (counts of human resources and hospital workforce; i.e., number of different specialists, clinicians, allied health professionals, other medical and non-medical staff). Several output variables were centered around healthcare activities and direct patient services (i.e., number of outpatient visits, discharges, and inpatient services received). The pooled estimate of mean TE was 0.803 (±0.114). This suggests that hospitals could improve their performance by about 19.7 percent.

Although addressed briefly earlier, there is a need to repeat a few points here since it is one of the difficulties in developing an efficiency model and preparing the data. Besides managerial reasoning for selecting input and output factors, the computational and data aspects of this selection process are unclear among all 47 reviewed studies. Typically, the choice and the number of inputs and outputs and the (hospital) DMUs determine how good of a discrimination exists between efficient and inefficient units. There are two conflicting considerations when evaluating the sample size. One consideration is to include as many DMUs as possible because, with a larger population, there is a greater probability of capturing high-performance units that would determine the efficient frontier and improve discriminatory power (Contreras, 2020). However, the other conflicting consideration with a large sample size is that the homogeneity of the dataset may decrease, meaning that some exogenous impacts beyond our control have the potential to affect the final results (Golany & Roll, 1989).

Another interesting trend emerged when we compared technical efficiency TE scores reported from high-income versus lower to upper-middle-income economies and hospital efficiency studies from developed versus developing countries in Table 7 below. The reported scores in the reviewed studies tell us that, on average, hospitals in developing countries are much less efficient than those of the developed world, with around 22.2 percent versus 16.6percentinefficiency. This observation is recognized but difficult to verify. The story changes after the mean technical efficiency TE estimates are adjusted by country income levels, introducing high-income nations classified as developing or emerging markets (Gulf Arab states). The difference is now not so far behind between high-income and lower to upper-middle-income countries, with only a 3.2 percentage point difference being observed.

The hypothesis is that this significant change is primarily a consequence of developing country studies having access to datasets with sample sizes and variables that are smaller relative to developed country studies; suggesting that developing country studies construct DEA efficiency models based on the availability of observations and hospital-level data and not based on reliability or accuracy considerations. The comparison after adjusting for development or holding development constant while only considering income level has shifted the efficiency studies from the high-income Gulf Cooperation Council (GCC) member states into a group with the majority developed European Organization for Economic Cooperation and Development (OECD) member countries that were previously analyzed separately based on development; this directly points to the weakness in regional study methodology. However, it must be emphasized that comparisons of mean efficiencies across countries (or across any groups) can be misleading unless a single reference frontier is used.

Table 7

Hospital Technical Efficiency in High-Income and Developed Countries

Technical efficiency TE score	Developed countries	Developing countries	High-income economies	Lower to upper-middle-income economies
Mean	0.834	0.778	0.817	0.785
Median	0.855	0.79	0.846	0.79
Std. Dev.	0.108	0.114	0.124	0.104
Min	0.52	0.476	0.476	0.584
Max	0.96	0.989	0.96	0.989

Note. Income level determined by GNI per capita (calculated using the Atlas method) definition from World Bank; country development index based on World Trade Organization (WTO) classification threshold. High-income economies are not necessarily developed countries.

Lastly, although less than a handful of publications allude to the unique concept touched on briefly by some, the theory that the construction of the DEA efficiency model is less about the number of variables included but rather the broad range of input/output variables accounted for in the efficiency frontier analysis is interesting. The logic for this focus on the scope of coverage is based on the theoretical foundations of non-parametric methods introduced by Worthington (2004); the argument is that hospitals are complex organizations of production and should not be treated like other frontier firms in an industry. Thus, attempts are made to ensure those hospital variables used in efficiency models closely mirror the resource intensity of procedures in healthcare delivery units (Worthington, 2004). But at what cost? This raises the issue concerning the aggregation of variables. Constraints on degrees of freedom and zero (0) values in some variables (not missing data) usually lead to aggregation of variables. In most studies, the leading human resources of two primary labor categories of doctors and nurses are produced by aggregating many sub-categories of very different skill levels, ranging from junior trainees to specialists or directors of nursing, without much weight adjustments. Aggregation of administrative, allied health professionals, and other non-medical staff or hospital workforce is another common practice (Alatawi et al., 2020; Alsabah et al., 2019; Li & Dong, 2015; Ramanathan, 2005).

On the output side, episodes and procedures in healthcare usually differ from one patient to the other, and aggregation is generally required to reduce the number of outputs. Since the development of case-mix systems that consider the differences in resource consumption for various types of treatments, studies have been using case-mix information to aggregate outputs, often from more than several hundred output categories, into one or maybe two outputs. Many other analyses, most notable studies from developing countries, including high-income countries in the Arabian Gulf, struggle with data deficiency or limited data availability and often use raw counts (or unweighted aggregation) of the total number of inpatient and outpatient events of services. This, unsurprisingly, can potentially lead to significantly biased results when certain units provide more complex services than accounted for in the model (Ramanathan, 2005; Mahate & Hamidi, 2016; Alsabah et al., 2019; Alatawi et al., 2020).

Statistical Summary

Univariate and Multivariate Analyses

This section discusses the two main types of univariate and multivariate data analyses employed in our empirical literature evaluation. The practical application of multivariate statistics to a particular problem usually requires several types of univariate and multivariate analyses to fully understand the relationships between variables and their relevance to the issue being studied. That said, additional calculations in the analysis, such as estimating weighted averages of pooled TE scores from panel data studies or using simple hypothesis testing like the independent-samples t-test to compare estimated mean TE, among some others, are not detailed in the methodology but mentioned if applied to estimates or displayed in final results. In the univariate analysis, mean TE estimates were compared using Wilcoxon's rank-sum test. Also known as the Mann-Whitney two-sample statistic, this non-parametric analysis applies to unmatched data and was used to test the hypothesis of whether two independent samples are likely to derive from the same population with the same distribution (i.e., if the two populations have the same shape) (Wilcoxon, 1945; Mann & Whitney, 1947). We follow the majority of the literature in naming these tests for Wilcoxon, Mann, and Whitney; but other researchers also contributed independently to developing this test, and credit is due to Festinger (1946), Whitfield (1947), Haldane and Smith (1947), and Van der Reyden (1952) as well.

As for the multivariate statistical analysis, the dependent variable is the mean efficiency score expressed as a percentage with average TE values now on a scale between 0 and 100. The transformation of efficiency estimates to percentages has no real impact on results and is simply for ease of interpretation. Other considerations in the meta-regression analysis included explanatory variables, such as the dimension regressor, which we expect to positively impact efficiency estimates, while the sample size is the opposite. Their effects are likely to be non-linear and diminishing when the dimension and the sample size increase. Among the many functional forms that appear to suit this expectation (quadratic, translog, etc.), the linear-log model, as indicated by R-squared and adjusted R-squared, proved more effective in capturing the positive and diminishing marginal impact on efficiency estimates we expect as the dimension (number of inputs and outputs) increases and the marginal effect eventually turns negative.

Furthermore, the linear-log mathematical model takes the form of a function whose logarithm equals a linear combination of the parameters of the model, which makes it possible to perform multivariate linear regressions (see Jandaghi et al., 2010; Worthington, 2004; O'Neill et al., 2008; Hussey et al., 2009); therefore, it was chosen as an ideal candidate for the meta-regression of the reviewed literature. Exogenous variables included in the meta-regression were chosen based on approaches and model specifications in the primary studies, including dimension variables of the frontier model (consisting of inputs, outputs, and control variables like case-mix), sample size, dummy variables to capture the type of data used (cross-section versus pooled panel data) as well as heterogeneity in the sample (lack of homogeneity in terms of hospital type, activity, and ownership), orientation (input versus output), and other explanatory variables such as model specifications (CRS versus VRS technologies) and accessibility factors that may impact the availability of reliable data (developed versus developing countries). Explanatory variables used to explain efficiency (in the one-stage or two-stage estimation approaches) were not included in the count because they do not alter the dimensions of the production space. Again, studies that pool the panel data to construct one frontier instead of estimating a separate boundary for each year will be considered as having a sample size based on the total number of observations that is usually equal to the number of individual hospitals multiplied by the number of years for a balanced panel.

Our primary aim is to examine the consistency of efficiency estimates and the effect of model selection on the final technical efficiency score. According to the literature, the number of input and output variables (dimension) in our analysis is expected to have a positive impact on efficiency estimates, whereas the sample size is the opposite (please see Table 3 above); their effects are likely to be non-linear and diminishing when the sample size and the model dimension increase (Jacobs et al., 2006; Kiadaliri et al., 2013). Also, larger sample sizes and lower numbers of input and output variables included in frontier models are associated with lower efficiency scores (Kibambe & Kocht, 2007). As such, conducting a rigorous systematic literature review followed by a meta-regression is crucial to statistically identify the significant factor(s) of influence in DEA models and average hospital efficiency scores using a diverse dataset of reviewed studies. Variables included in the analysis were chosen based on study approaches and model specifications expected to impact estimated mean efficiency. Table 8 shows Wilcoxon's rank-sum test of average TE scores by variables used in the analysis and variable subgroups falling above or below the median; power calculation for the rank-sum test via Monte Carlo simulations was also performed.

Essentially, as the non-parametric version of the two-sample t-test in which we compare two groups of continuous outcomes or measures, the power of the Wilcoxon Mann-Whitney rank-sum test is formulated using the Monte Carlo approach described by Mollan et al. (2020); defining $P(X<Y) \equiv p$ as a measure of effect size, where X and Y denote random observations from two distributions that we hypothesize to be equal under the null. This approach is feasible even without background data and approximations are shown to be accurate regardless of sample size; performing well in many small sample scenarios (Mollan et al., 2020; Montoya, 2022).

That said, the two-sample Wilcoxon rank-sum (Mann-Whitney) is used to test the following null hypothesis:

$$Ho: mean\ efficiency\ (variable\ subgroup = 0) = mean\ efficiency\ (variable\ subgroup = 1)$$

Additionally, the following probability estimation of observations above and below the median measures effect size, and whether the first group is larger in efficiency than the second group below the median attempts to test the following null hypothesis:

$$Ho : P\left(mean\ efficiency\ (variab\ subgroup = 0) > mean\ efficiency\ (variable\ subgroup = 1)\right)$$

Table 8

Rank-Sum Mean Technical Efficiency Estimates by Variables in the Analysis and by Median Value

Variable	N	Mean TE (Std. Dev.)	P-Value
No. of hospitals			0.120
≤ 40	25	82.82 (±10.51)	
> 40	22	77.45 (±12.05)	
Orientation			0.259
Input	37	81.534 (±10.462)	
Output	10	81.18 (±10.19)	
No. of input & output variables			0.360
≤ 6	23	79.32 (±11.38)	
> 6	24	81.25 (±11.70)	
Data sample			0.116
Panel	20	83.58 (±9.53)	
Cross-section	27	77.88 (±12.32)	
Returns to scale			0.607
CRS	29	80.83 (±11.38)	
VRS	18	79.47 (±11.87)	
Homogeneity			0.264
Yes	23	79.54 (±9.52)	
No	24	81.05 (±13.22)	
Country development status			0.077
Developed economies	19	83.44 (±10.84)	
Developing/emerging economies	28	78.18 (±11.57)	
Sample size/ dimension ratio			0.083

< 3	7	87.26 (±6.76)	
≥ 3	40	79.09 (±11.73)	
Overall total	47	80.30 (±11.4)	--

Eight (8) variables are specified to capture the various frontier efficiency model options discussed above. Most studies incorporate around three (3) to four (4) input and output variables; notable exceptions include Kawaguchi et al. (2014) with ten input variables, Jat & Sebastian (2013) using eight (8) output variables, Khushalani & Ozcan (2017) analyzing a sample size of 1,259 observations, and Farzianpour et al. (2012) as well as Abo El-Seoud (2013) applying a mixed-orientation model (both input- and output-oriented approach). Detailed variable descriptions are presented in Table 9.

Table 9

Regression Variables and Definitions

Variable Name	Label	Variable Definition
TE	Technical efficiency score	Reported average technical efficiency scores (0-100 scale)
SIZE	Number of observations	Number of (hospital) observations included in the reviewed studies
DIMENSION	Number of variables	Total number of inputs, outputs, & control variables included in the frontier model (this does not include control variables in second stage analyses)
INPUT_ORT	Orientation dummy	Dummy 0/1 variable takes value of 1 if input-oriented (including if mixed input- output- orientation), and 0 otherwise (output-oriented only)
CRS	Returns to scale	Returns to scale can either be variable or constant returns to scale; dummy variable takes value of 1 if CRS (including both CRS & VRS mix), and 0 otherwise (VRS only)

PANEL	Pooled panel data	This attempts to capture any effects of using pooled panel data instead of cross-sectional data for efficiency frontier construction; dummy variable takes value of 1 if pooled panel data study, and 0 otherwise
HOMOGENEITY	Sample homogeneity in (hospital) ownership status	Efficiency frontier units must be comparable & adjusted for heterogeneity; this dummy variable takes value of 1 if same ownership type in sample, and 0 otherwise
DEVELOPED	Efficiency studies using (hospital) data and/or published from industrialized countries with economically developed markets NOT BASED ON HIGH-INCOME	Dummy 0/1 variable takes value of 1 if classified "developed" by WTO (more advanced post-industrial economies with advanced technological infrastructure & high quality of life), and 0 otherwise *If no data available, IMF reference of $20,000 in 2021 USD nominal GDP per capita used

The dependent variable in the meta-regression is the reported average TE score on a continuous scale of 0-100. Apart from the two variables of sample size and dimension of input/output variables, the rest are dummies that explain different methodological choices. Heterogeneity in sample observations in terms of hospital type, ownership, activities, and level of care, among others, has been associated with higher efficiency scores if no adjustments are applied to homogenize hospital units (Hollingsworth, 2008). Hospital ownership type is included as an additional explanatory variable since failure in accounting for heterogeneity across units of a frontier can affect estimated efficiency scores (Kirigia et al., 2004; Harrison & Ogniewski, 2005).

Lastly, many studies estimate frontier models using panel data in a cross-sectional manner (i.e., they pool the panel to construct one frontier instead of estimating a separate boundary for each year). It is expected that a pooled panel sample has more minor variation than a cross-sectional sample because one hospital will be observed more than once; thus, variation from year to year is expected to be smaller than the variation between different hospitals (McDonald, 2009; Hoff, 2007). This can potentially produce higher average efficiency scores (see Table 3.1). Therefore, a dummy variable is included in our regression to capture any differences and account for the type of data used (cross-sectional versus pooled panel data).

Table 10 contains some descriptive statistics of the dependent and explanatory variables. Pooled mean TE was 80.30 (±11.4), with the highest being 98.9 and the lowest 47.6. Interestingly, this considerable variation in efficiency scores comes from studies in the Middle East with similar variable measures being used to estimate the frontier, as well as hospital activity data included in the analysis; yet, the model specifications clarify the distinction: (i) heterogeneity in type of hospital, ownership status, and hospital activities (sample included both teaching and non-teaching hospitals; teaching and research activities of University hospitals were not accounted for and other general differences in ownership and hospital management were poorly handled), pooled panel data, input-oriented, VRS, 3 inputs (dimension), 12 hospitals (size) = 98.9 average TE score; and (ii) heterogeneity in hospital ownership status (sample included both private and government hospitals; differences were unadjusted but instead hospitals were grouped by ownership type and analyzed separately then merged unweighted efficiency frontiers for comparison), cross-sectional, output-oriented, VRS & CRS, 6 inputs (dimension), 96 hospitals (size) = 47.6 average TE score (Torabipour et al., 2014; Mahate & Hamidi, 2016).

This is a striking example of how the choice of models, input/output variables, and quality control adjustments can significantly alter efficiency estimates and study robustness; which leads one to question the degree to which this type of performance indicator can influence policy and if indeed basic measures are done correctly, what can be drawn from hospital efficiency studies?

Table 10

Descriptive Statistics of Modeling Choices in Estimating Production-Possibility Frontier

Variable	Mean	Median	Std. Dev.	Min	Max
TE	80.30	80	11.41	47.60	98.90
SIZE	89.723	40	205.046	5	1,259
DIMENSION	6.809	6	2.223	3	14
INPUT_ORT	0.787	1	0.414	0	1
CRS	0.617	1	0.491	0	1
PANEL	0.426	0	0.410	0	1
HOMOGENEITY	0.489	0	0.505	0	1
DEVELOPED	0.404	0	0.496	0	1

Note. Efficiency scores (TE) are shown on a 0-100 percentage scale, similar to how mean TE estimates were applied in the meta-regression and analyzed as dependent variables.

The choice of functional form is driven by the possible impacts of the two continuous variables, dimension and sample size. Dimension is expected to positively affect efficiency estimates, while the sample size is the opposite. Their effects are likely to be non-linear and diminishing when the dimension and the sample size increase. The functional form that appears to suit this expectation is the linear-log model. Described by Uberti (2017), this log-transformed model is used in the following estimation with the below specifications:

$$\text{MTE} = \beta o + \beta 1 \ln(Size) + \beta 2 \ln(Dimension) + \beta 3(Input - oriented) + \beta 4(CRS) + \beta 5(Panel) + \beta 6(Homogeneity) + \beta 7(Development)$$

Where MTE is mean technical efficiency TE. The marginal effect of dimension on efficiency estimates is expressed by the partial derivative or differential below (Uberti, 2017):

$$\frac{\partial MTE}{\partial Dimension} = \beta 1 \frac{1}{Dimension}$$

And the marginal effect of sample size on efficiency as well is:

$$\frac{\partial MTE}{\partial Size} = \beta 2 \frac{1}{Size}$$

Consequently, when dimension increases, a positive $\beta 1$ will ensure the marginal effect approaching zero but not turning negative. The opposite happens to size; a negative value of $\beta 2$ allows the marginal effect of size on efficiency to approach zero from below as sizes increases (Kiadaliri et al., 2013; Orendi, 2008).

Ordinary least squares (OLS), a type of linear least squares method for estimating the unknown parameters in a linear regression model, was used for this model since ordinary least squares regression is considered a consistent enough estimator (Kieschnick & McCullough, 2003). That said, it is not necessary for us to use Tobit or limited dependent variable procedures, which are usually used when the dependent variable is bounded; there is no mean efficiency of 0 or 1 (or 100 in the case of percentage scale) in the meta-data, therefore, Tobit estimates are exactly identical to their OLS counterparts. Meta-regression was analyzed in Stata/SE 16.1 (StataCorp LLC, College Station, TX) and a correlation matrix identified absence of multicollinearity between the independent variables. The regression results are displayed in the following table below.

Table 11

Results of Meta-Regression Analysis

Variables	Coef. (Std. Err.)
Ln (SIZE)	-4.072562 *** (1.573681) P < 0.003
Ln (DIMENSION)	6.798539 ** (1.186624) P < 0.023
INPUT_ORT	5.278795 (3.780669) P < 0.557
CRS	-0.9297522 * (3.164268) P < 0.098
PANEL	4.573849 * (1.127381) P < 0.082
HOMOGENEITY	-1.058234 ** (1.203779) P < 0.044
DEVELOPMENT	7.999337 ** (3.421742) P < 0.038
Constant	89.03749 *** (6.434255) P < 0.000
F-statistics	3.5657
R-squared	0.3902
Adjusted R-squared	0.3615

Note. * p < 0.1, ** p < 0.05, *** p < 0.01.

Discussion and Interpretation of Results

The estimated coefficient for SIZE, capturing the effect of sample size on mean efficiency, is negative while that for DIMENSION, the regressor that represents the influence of the number of input and output variables on efficiency, is positive. Both sample size and dimension are significant at the 1% and 5% level, respectively, and in line with expectations according to the reviewed literature. The negative sign of the coefficient for SIZE indicates that, holding everything else constant or all other variables equal, increasing the number of hospital observations will yield a lower mean technical efficiency score. For example, when evaluated at the median sample size of 40 hospital observations, the marginal effect of SIZE is -0.102; however, the marginal effect is larger at smaller sample sizes. Upon evaluating a sample size of 30 hospital observations, the marginal effect now becomes -0.136; looking at a sample size of 20, for instance, the marginal effect is larger at -0.204, suggesting that the addition of observations could lead to a reduction in mean efficiency.

The effect of DIMENSION on average efficiency score is more substantial. The marginal effect is 1.133 when evaluated at the sample median of 6 variables. However, as the number of variables decreases the marginal effect is larger. For example, a value of 3 variables results in a marginal effect of 2.266, suggesting that the addition of extra variables could lead to an increase in mean efficiency. These larger effects at low SIZE and DIMENSION values seem to statistically show relevant DEA assumptions cited in the literature. Based on the meta-regression analysis, it is clearer that as the number of variables included in the frontier model increases, the average efficiency predictions drop pretty rapidly when the sample size is fairly small. Zhang and Bartels (1998) also arrived at the similar conclusion on the sample size effect, further showing how inclusion of an extra variable into a model with more than 10 (hospital) observations does not alter the average efficiency score very much. They observed that when sample size was large, the mean technical efficiency shows little change and the mean efficiency seems to remain constant after a threshold. Therefore, correcting for sample size has a major impact on the assessment of average efficiency estimates (Zhang & Bartels, 1998).

As expected, although significant only at the 10% level, the coefficient for PANEL variable produces a positive sign, suggesting the use of pooled panel tends to produce higher average efficiency scores of 4.57 percentage points. A possible explanation for this is because a single hospital is observed more than once in a pooled panel, and therefore any variation from year to year is expected to be smaller than variations between different hospitals when cross-sectional data analysis is used. This can potentially produce higher average efficiency scores. The lesson learned from this is to ensure that separate production frontiers are created for each year in a cross-sectional manner instead of pooling the entire panel data into a single efficiency frontier and analyzing hospitals at yearly cross-sections. Another variable identified as barely statistically significant at the 10% level is the estimated coefficient for CRS, which displays a negative and $p<0.1$ coefficient effect on the mean efficiency score. The magnitude of the CRS coefficient implies that choosing a CRS technology over a VRS returns to scale will reduce the mean efficiency estimate by approximately one (1) percentage point. To be honest, the "oomph" of the CRS coefficient, without confusing it with merely statistical significance, fails to deliver. Of course, readers are left to draw their own conclusions.

While heterogeneity is assumed to be associated with higher efficiency scores or exaggerated efficiency estimates (Ozcan, 2008; Hussey et al., 2009), only heterogeneity in hospital type and ownership status was statistically significant. As the regression suggests, maintaining homogeneity (uniform hospital sample) is expected to reduce overestimated efficiency scores seen in heterogenous data analysis by reducing the mean efficiency by about one (1) percentage point as compared to non-homogenous hospital samples. Lastly, data analysis studies from developed countries are statistically significant and reported an average of about eight percentage points higher efficiency scores than data analysis studies from developing/emerging countries. For several reasons, the main findings suggest that developing countries suffer from weak studies due to aggregation of input categories, no adjustment for differences in case-mix and quality of care between hospitals, small sample size, little adjustment for heterogeneity in hospital sample, and no attempt to evaluate the misspecification in applied models. This raises issues of validity, usefulness, and generalizability of studies from the developing world.

Perhaps the region with the highest concentration of poorly handled data and low-quality DEA methodology is, much unfortunately, the Middle East. It should be noted, however, that each study from the region did, in fact, state one of the study limitations to be the availability of data (Torabipour et al., 2014; Kalhor et al., 2016; Yusefzadeh et al., 2013; Alsabah et al., 2019; Alatawi et al., 2020; Mehrtak et al., 2014). The lack of prioritizing standards of regular data collection or health information storage management is the main explanation for such poor studies with understandably no effect on health policy-making due to validity and reliability concerns following significant methodological deficiencies. Indeed, the words of Hollingworth (2003) seem to ring true in this case regarding the nature of reviewed efficiency studies from the Middle East, which are structured more like "have frontier analysis software – will analyze" approaches rather than anything else.

Chapter Summary

The next chapter will discuss the research methodology and apply the proper adjustments and model considerations gleaned from the findings of this meta-regression analysis, especially for the robustness of statistical methods. Indeed, the knowledge gained from this systematic review and meta-regression of existing studies found a substantial amount of fundamental econometric methodologies absent from about 46.8 percent (22 articles, including all 12 Middle Eastern studies in our sample) of reviewed papers. In some cases, the wrong variables have been included, for example (which is to say errors in the specification have weakened the efficiency conclusions); authors ignored some tiny coefficients because less attention is given to size compared to statistical significance (which must be noted as different than economic significance). Several instances were observed on how this dismissal of size in preference for p-values of statistical significance has inflated the performance reputation of many hospitals and led to misguided policy recommendations proposed by researchers based on their interpretation of results.

This chapter has demonstrated the consequences of ignoring what scientists from Edgeworth (1881) to Goldberger (1991) have been saying: science is about magnitudes. In fact, rarely was the magnitude of the sampling error considered in any of the papers, even when it was clearly a statistical issue in the study. Significance testing alone had no theoretical justification either; most papers mentioned slacks or possible input reductions based on current output levels using a test of statistical significance and seem to have mistaken a statistically significant finding in the results for an economically significant one. Severe consequences emerge when studies facing statistical issues in their analysis follow their results with more policy recommendations that go on to address improving cost-efficiency and health spending reform.

A difference actually can, in fact, be significant for science or policy but not necessarily statistically significant if we consider clinical measures of effect; for example, one can only imagine the amount of type I and type II errors committed otherwise. Lastly, the other noted observation was in the differentiation of ‘fit’ from ‘importance’ in DEA modeling, and univariate assessment causing false hypotheses to be accepted and true hypotheses to be rejected. Overall, these abovementioned key considerations and takeaways are vital in the preparation of data and variable selection and input-output combinations prior to running a frontier-based efficiency analysis.

Chapter 4

Evaluating Hospital Performance for Potential Efficiency Drivers in Kuwait's Public Health System and Potential Efficiency Effects by Ownership Models: Application of Data Envelopment Analysis and Tobit Regression

In this chapter, we first analyze the performance change of Ministry of Health (MoH) general and specialty public hospitals in Kuwait over a five-year period between 2015 and 2019 to identify the contextual factors that drive public health system inefficiency using a two-staged data envelopment analysis (DEA) technique. The second-stage Tobit regression is applied to investigate any potential external effects influencing the average technical efficiency scores of MoH hospitals, such as environmental or institutional factors, that may explain possible determinants of systemic public health inefficiency and low performance in government healthcare facilities. Additionally, possible savings (slack-analysis), effective utilization of health resources, and suggestions to improve performance of MoH hospitals are assessed.

A comparative study ensues to evaluate the efficiency of public and private general hospitals in Kuwait is conducted during the census year 2019-2020 (variables covering March/April 2019 through the first quarter of March/April 2020); focusing on the census year leading up to the onset of the COVID-19 pandemic to investigate hospital performance status just before demands on the health system hit an all-time high. The differences between hospitals can be understood further by subsequently analyzing the features of organizations and their geographic environment in view of ownership and management type. With the participation of private hospitals in the health system and its growing market size, improving hospital efficiency becomes more important while better understanding the influence of ownership on technical efficiency, productivity, and overall performance is needed more than ever.

Evaluating Relative Efficiency Among MoH Public Hospitals and Comparing Productivity of Private-Public General Hospitals in Kuwait

As seen in Chapter 3, evaluating hospital efficiency requires a large and complex DEA model. In order to produce DEA efficiency scores that can be relied on and used by managers and policymakers, the models need to capture the complexity of the service unit studied, while the inputs and outputs need to reflect the key resources used and services provided. Although this condition may be obvious, many studies fail to meet it but still consider their research results worthy enough to pioneer policy change and health reform. Research implementing DEA or other forms of frontier-based methodology comparing hospital efficiency, while using unrefined, poorly handled data in their estimation models of unit production, cannot generate evidence-based insights to inform health decisionmakers nor provide any valid information for hospital managers to improve service performance and delivery of care. Unfortunately, this may be one of the reasons DEA efficiency studies and research findings have not had reported impact on policymakers or management of healthcare organizations in the Middle East as much as one would hope or expect to see.

The purpose of this dissertation is not to inform policy directly; despite transformation of data and variable adjustments, several limitations linger, however, the rigor of the study is able to serve as a reference in hospital management and robust enough to guide the way public health decisions are made in Kuwait. Now we begin to discuss the methods that were implemented for assessing the efficiency and productivity of decision-making units (DMUs) using data envelopment analysis (DEA) techniques. This chapter unfolds by providing a brief background on different hospital settings, organizational specifications, and source of sample data;

subsequently, we describe existing performance measures, descriptive statistics of hospital-level variables used, and data availability and limitations; we show the data preparation process for DEA modeling and include the rationale for any transformations made where certain characteristics of data may not be acceptable for the execution of hospital efficiency analysis before showing results of our analysis.

As mentioned above, we recognize the need to implement data adjustments or ratio transformations that can account for existing internal and external factors such as sample size, hospital type and complexity of activities (minimizing level of care heterogeneity), as well as population characteristics in the catchment area that can influence hospital efficiency. Therefore, in an effort to avoid confounding by these basic factors, the stratification of the sample of MoH public hospitals into more homogeneous subgroups is crucial. Accordingly, hospitals are categorized based on size (i.e., total number of beds; also known as bed capacity), complexity of services (proxied by treatment focus or area of care), and other features of healthcare delivery.

Hospital Setting: The Case of Kuwait

In the broadest sense, a healthcare system compromises the financer, the consumer, and the provider (Varabyova & Müller, 2016). The Kuwait Ministry of Health (MoH) is the main healthcare financier and provider in the State of Kuwait, where the private sector represents a much smaller share of the healthcare market size that remains under public sector control through government provision of health services (MoH, 2017). An assessment of Kuwait hospital market competition indicates the market has been dominated by the private sector in terms of revenues, however, in terms of annual outpatient visits and inpatient services provided over a single year, public hospitals have consistently recorded much larger numbers than private hospitals. Table 12 displays the total number of outpatients and total number of admissions reported in 2017, which are stratified by health sector and proxied by total number of discharges in 2017 to represent the inpatient admission values shown below.

Table 12

Total Patient Flow in Public and Private Health Sectors in Kuwait, 2017

By Number of Patients		2017 (N)	2017 (%)
Outpatient		**6,082,898**	94.2%
	Public	*3,235,403*	
	Private	*2,847,495*	
Admitted/Inpatients		**352,823**	5.8%
	Public	*256,258*	
	Private	*96,565*	
Total		**6,435,721**	**100.0%**

Note. Number of outpatients in the public sector is recorded from 18 MoH facilities: 6 general hospitals and 12 specialty hospitals (a new public specialized hospital is introduced in 2017); no data available yet for number of inpatients/discharges for this new public specialized hospital so it is not included in the public sector inpatient estimate.

For example, considering total bed capacity in 2017, estimates of the major and leading private secondary hospitals show the private sector holding approximately 1,100 of hospital beds (not including private primary clinics/polyclinics and private diagnostic imaging) as seen in Table 13; in comparison, the public sector accounted for around 7,176 of hospital beds (not including primary healthcare and MoH primary health centers, PHCs) as depicted in Table 14 as well.

Table 13

Private Health Sector Bed Strength and Individual Private Hospital Bed Capacity, 2017

By Number of Beds in Private Hospitals	2017 (N)	2017 (%)
Al Salam International Hospital	185	16.8%
International Clinic	140	12.7%
Hadi Clinic	135	12.3%

Dar Al Shifa	133	12.1%
Al Seef Hospital	120	10.9%
Taiba Hospital	110	10.0%
New Mowasat Hospital	100	9.1%
Aliya International Hospital	70	6.4%
Others	107	9.7%
Total	**1,100**	**100.0%**

Note: Others include private Jarallah German Specialized Clinic, Royale Hayat Hospital, Al Rashid Hospital, Sidra Hospital, and Alorf Hospital. Obtained values of these 13 private facilities were estimated by decomposing private sector aggregates in 2017 MoH Health Data Bulletin (no information on private sector hospital type/level of care or number of private facilities included in calculating the private sector variable; notice is given when aggregate variable includes private clinics). Final numbers were cross-referenced with hospital websites/other secondary sources available to support estimated values; these decomposed values were then used later to draw data from other hospital variables stratified from recently reported private sector aggregates.

Table 14

MoH Health Sector Bed Strength and Individual Public General/Specialized Hospital Bed Capacity, 2017

By Number of Beds in Public Hospitals	2017 (N)	2017 (%)
Al-Farwaniya	868	12.1%
Psychiatric Hospital/ Kuwait Center for Mental Health	828	11.5%
Al-Adan	826	11.5%
Al-Jahra	759	10.6%
Mubarak Al -Kabeer	724	10.1%
Maternity	448	6.2%
Al-Sabah	441	6.1%
Al-Razi	438	6.1%
Al-Amiri	414	5.8%
Ibn-Sina	355	4.9%
Chest Diseases	326	4.5%
Kuwait Cancer Control Center	199	2.8%
Infectious Diseases	173	2.4%
Others	377	5.3%
Total	**7,176**	**100.0%**

Note: Others include MoH specialty hospital aggregates of: Physical Medicine & Rehabilitation Facility, Allergy & Respiratory Center, Palliative Care Center, Sabah Al-Ahmad Urology Center, and Hospital National Bank of Kuwait – Zain Hospital (inpatient bed size less than 100 and/or total hospital bed strength with all clinical bed units unknown).

If we now consider the number of hospital beds as capital and proxies for hospital size, looking at hospital beds in Kuwait in 2017, including inpatient beds available in public, private, general, and specialized hospitals and rehabilitation centers, in most cases beds for both acute and chronic care are included; how does Kuwait compare to neighboring countries and others in the region? By aggregation and weighted average, the bed strength of the Kuwaiti health system is strong when observed in a regional context. As illustrated in Figure 8, Kuwait boasts a weighted average of 2.04 hospital beds per 1,000 people across all sectors and levels of care in 2017; slightly under the Kingdom of Saudi Arabia (KSA) with 2.24 hospital beds per 1,000 people, Lebanon with 2.73 hospital beds per 1,000 people, and Turkey with 2.81 hospital beds per 1,000 people. Nevertheless, a higher bed capacity than more populated neighboring countries, such as Iraq with 1.32, United Arab Emirates (UAE) with 1.38, Oman with 1.47, Jordan with 1.47, Iran with 1.56, and Egypt with 1.43 hospital beds per 1,000 people; smaller and less populated neighboring states are compared, with Qatar at 1.25 hospital beds per 1,000 people and Bahrain at 1.74 hospital beds per 1,000 people (WHO, 2017; Databank, 2018).

Figure 8

Regional Hospital Bed Number (per 1,000 people) in Relation to Kuwait, 2017

Another consideration is the fact that Kuwait's MoH aims to distribute healthcare effectively, with high quality and productivity; its hospitals are non-profit, public health organizations funded by the Kuwaiti Government and the Ministry is the responsible body for managing financial and human resources, infrastructure, facilities, and health information systems. Additionally, Kuwait's MoH also leads, organizes, supervises, and manages the activities of providing healthcare services, disease prevention, and health promotion. Furthermore, it establishes the roles and regulations as well as developing and implementing the health plan and policies. All these activities are carried out and coordinated across five decentralized MoH health regions; each of which offers a public general hospital providing full outpatient services and 24-hour emergency services as well as 94 primary care institutions spread out among areas of the country.

Dispersal of hospitals is actually effective, we see a fairly even distribution as aimed by the Ministry despite the concentration of the majority of hospitals in 2017 against each of the six governorates of Kuwait suggests prevalence is highest in Al Asimah (Capital) Governorate, which can indicate low equity and access for a large portion of the population. Nevertheless, the high numbers in Capital Governorate compared to other locations that is captured in Table 15 are mainly due to clustered MoH specialized hospitals. However, clustering of specialized facilities in the Sabah Health Region at Shuwaikh Medical Zone in Kuwait City is not necessarily problematic (Figure 9); tertiary hospitals are usually by referrals from primary/secondary general hospitals (we emphasize *usually* since specialized tertiary care access *should* be through a referral system; it must be noted that this is not necessarily the reality on the ground), therefore, general hospitals need to be meeting health needs of the population in different regions and the distribution suggests they do.

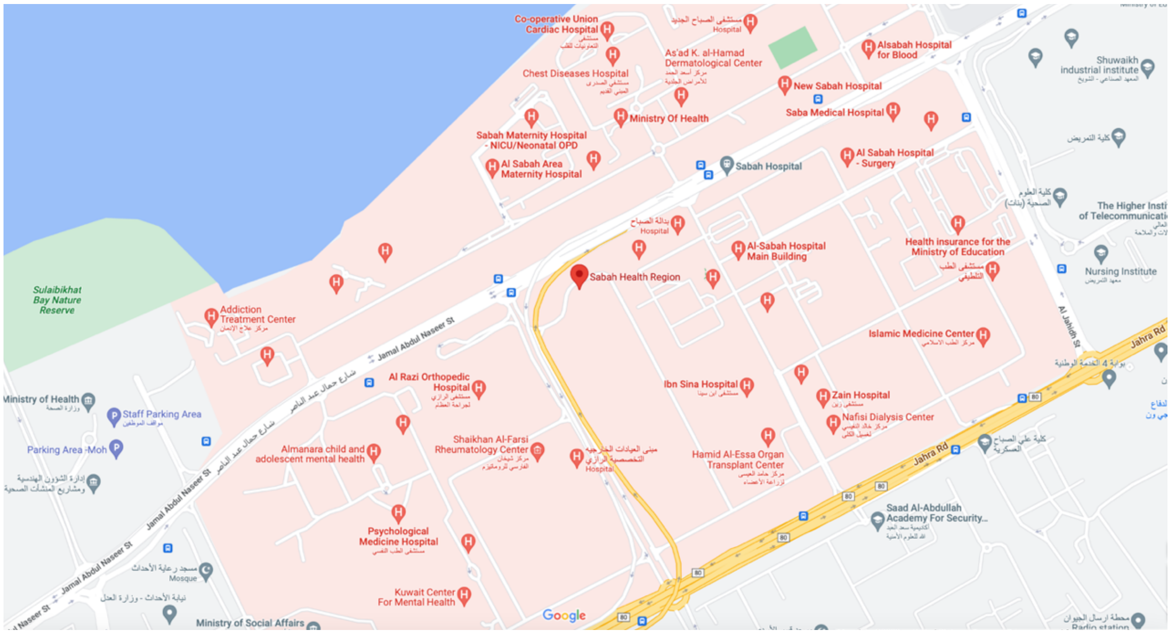
Table 15

Concentration of Secondary & Tertiary Facilities and Distribution of Private and Public Specialty & General Hospitals Across Kuwait, 2017

By Region	By Hospital Type	2017 (N)	2017 (%)
Al Asimah (Capital)	Private = 3 Public general = 2 Public specialty = 12	17	54.8%
Hawalli Governorate	Private = 7 Public general = 1	8	25.8%
Al Ahmadi	Public general = 1 Private = 1	2	6.5%
Al Jahra Governorate	Public general = 1 Private = 1	2	6.5%
Al Farwaniya	Public general	1	3.2%
Mubarak Al-Kabeer	Private	1	3.2%
Total	**N/A**	**31**	**100.0%**

Figure 9

Clustering of MoH Specialized Tertiary Hospitals in Sabah Health Region at Shuwaikh Medical Zone in Kuwait City, Al Asimah (Capital) Governorate, 2017



Note. Local concentration (red area) of public specialty facilities in Kuwait City.

Nurses and midwives in the private sector do not have the same number of beds distributed per nurse as seen in the public sector, therefore, the argument is that nurses and midwives are not spread too thinly for safe care compared to their counterparts in the public health sector. The accepted international benchmark of 60 staff for 140 bed hospital, or under 0.5 staff per bed, may be the potential efficiency driver missing from Kuwait's MoH expansion and reform arsenal as 'mega-projects' add more hospital beds but staffing and human resources struggle to keep up (World Bank, 1993). This alone may suggest that maintaining appropriate staffing levels and ensuring safe nurse-to-patient ratios not only contributes to higher patient satisfaction, but allows for closer monitoring of patient symptoms that lead to decreased readmissions and better care quality standards; directly improving hospital efficiency and cost-effectiveness (Velenyi, 2007). The question now becomes whether the much higher government spending in MoH hospitals, compared to domestic private healthcare, is being utilized efficiently with optimal scale production?

Table 16

Allocation of Government Funds and Ministry of Health Budget

Indicator	2015	2016	2017	2018	2019
Domestic general government health expenditure (% of current health expenditure)	84.86	85.316	85.71	88.198	86.96
Domestic private health expenditure (% of current health expenditure)	15.14	14.68	14.29	11.80	13.04
Domestic general government health expenditure (% of GDP)	3.58	4.04	3.989	4.497	4.78
Domestic general government health expenditure (% of general government expenditure)	6.57	7.51	7.76	9.11	8.93
Domestic general government health expenditure per capita (current US$)	1068.53	1116.03	1186.71	1529.19	1529.36
Domestic private health expenditure per capita (current US$)	190.65	192.08	197.87	204.62	229.31
Public sector nurses and midwives (per 1,000 people)	5	5.2	5.2	4.9	4.9
Private sector nurses and midwives (per 1,000 people)	1.5	1.3	1.5	1.8	1.9
Total country nurses and midwives (per 1,000 people)	6.61	6.52	6.74	6.73	6.82
Public sector hospital beds (per 1,000 people)	1.7	1.6	1.6	1.6	1.8
Private sector hospital beds (per 1,000 people)	0.3	0.3	0.3	0.3	0.3
Total country hospital beds (per 1,000 people)	2.04	1.9	1.9	1.9	2.11

Note. Total country rates of hospital beds per 1,000 people, as well as total country rates of nurses and midwives per 1,000 people, are national rates, whereby the MoH tends to calculate as a compilation of total public and private sector data and not including the oil sector (which was operating a single large private, general secondary hospital during 2015-2019 timeframe).

Source of Sample Data

A panel for this dissertation containing the data needed for the study (hospital inputs as well as outputs) was drawn from Kuwait's Ministry of Health (MoH) Annual

Health Bulletin, which provides publicly available, albeit limited, retrospective statistics on the main secondary and tertiary public government hospitals in the country. Each year, the National Center for Health Informatics at the MoH collects hospital-level data and other health indicators and reports them to the Central Statistical Bureau (CSB), a government agency that sorts reported data from all ministerial sectors and across all public institutions in Kuwait and officially releases national information and annual statistical data every December. Therefore, hospital data in each panel was cross-referenced and supported by the Kuwait Annual Statistical Abstract published by CSB for 2014/2015 through 2019/2020. A dataset was assembled and a common set of input and output indicators was constructed to support the estimation of DEA models. Input as well as output data were gathered for fifteen MoH hospitals (six public general hospitals and nine public specialized hospitals) that were operating at the beginning of 2015 and through the five-year period till 2019.

Two specialized hospitals, Psychiatric/Mental Health Facility and Palliative Care Center, were dropped due to their difference in activities and overall purpose. In an attempt to limit heterogeneity, the aim of palliative care services as well as psychiatric care is focused on long-term care, hence, measuring efficiency performance by means of output production levels relative to other hospitals in our sample will skew efficiency scores. The potential gains from using panel data to measure technical efficiency appear to be quite large. A pooled sample, whenever possible, especially with a small DMU sample size such as in our case, obviously contains more information about a particular DMU than does a cross-sectional analysis. The study concentrates on the periods between 2015 and 2019 because this period yields a balanced panel.

Supplementary data on annual population statistics and demographic changes in the catchment area are matched to governorate-level or city-level information of hospital locations whenever possible using the Kuwait Public Authority for Civil Information (PACI) geographical information database. The reference period covers the census year 2015-2019 for a total observation window of five consecutive years. Additional supporting data was obtained through further secondary sources, including policy or legislative papers pertaining to Kuwait's health system and other country profile reports published by international organizations and non-profits. as well as other forms of published material that can provide details on the different changes over the years in Kuwait's MoH hospitals, public health sector reforms in general, and changes in financial and managerial regulation of hospitals in particular. In some cases, further information was gathered by directly contacting individual hospitals whenever possible; other attempts of data collection were through hospital websites (where existing), news aggregators (usually website that aggregates global news from various sources), official press releases, open data sources, and publicly-available quality control reports.

As empirically confirmed by the meta-regression in Chapter 3, implementation of non-parametric-based efficiency estimates (DEA efficiency measures) demands limited heterogeneity among the efficiency reference sets selected and necessitates a homogeneous sample of DMUs that reflect comparable hospitals (i.e., all hospitals in the group are believed to share similar ownership status, location, level of care, etc.). Therefore, the DEA dataset must contain comparable hospital units that use similar inputs to produce similar outputs and share similar mission or purpose. Efficiency literature argues that the hospitals under evaluation should be of the same type and provide the same health services and activities because inclusion of divergent specialized versus general units in the same sample would confound the results since frontier techniques are susceptible to outliers; unless these differences are addressed (Varabyova & Muller, 2016; Hollingsworth, 2008).

Two distinct datasets have been developed. The first data set contains input and output variables that are utilized to calculate the 2015-2019 efficiency scores of six public general hospitals and nine specialized hospitals; also other institutional indicators used to examine the effect of external factors on hospital efficiency, including environmental, demographic, and socioeconomic aspects of the catchment population. In this thesis, we recognize the data limitations both as deficient in terms of missing or unavailable values as well as not necessarily reliable due to simple human errors, nevertheless, we have used what data was available and applied relevant adjustments to be able to estimate efficiency as accurately as possible. The public hospitals in our sample are defined as those that are government-owned; operated by or affiliated with the Ministry of Health (MoH). The second dataset is for the 2019-2020 comparative study of efficient productivity in six public general hospitals and six private general hospitals in Kuwait. Here, private hospitals are defined as privately-owned, for-profit facilities to be examined against their public MoH hospital counterparts in view of ownership.

Because efficiency analysis requires a homogeneous (comparative) sample of units that employ comparable inputs (health resources) to produce comparable outputs (health services and activities), adjustments are made in both datasets (MoH public general/specialized hospitals & public-private general hospitals) to reduce heterogeneity and account for differences in hospital type, level of care, main activities, complexity of health interventions, etc.

Knowledge Gap

Governments conduct efficiency assessments of the national health system to ensure that public funds are effectively utilized and facilitate the process of meeting the UHC goals (WHO, 2019). Efficiency evaluation is carried out under many concepts, such as technical, allocative, cost, and overall efficiency; of course, the most familiar by now as we push through be among those, the technical efficiency approach is most commonly used (Jacobs et al., 2006). The latter is based on Farrell's theory (1957), which introduced a measure of technical efficiency based on the relative notion of comparing the inputs and outputs of set entities, or decision-making units (DMUs) (Farrell, 1957).

The efficiency of Kuwait's public health system is based mainly on the performance of all operating MoH hospitals from 2015-2019, thus capturing each public, government-funded hospital that is among the principal consumers of public health resources. Counting the costs through yearly government health expenditure and the budget of the MoH as a percentage of the government's budget warrants a full efficiency evaluation in the public provision of care, followed by the identification of potential factors shaping efficiency in hospital delivery, optimization of resource utilization, and reduction of waste and hospital system leakages. In general, there is a scarcity of empirical studies on the efficiency of Kuwait's public health system based on: (i) the performance of its own MoH public hospitals and their change in optimal production levels over 5 years; (ii) the productivity of MoH public hospitals when compared against similar secondary private sector hospitals; and (iii) overall impacts of hospital ownership models on efficiency in the context of private, for-profit general hospitals in Kuwait having significantly higher technical efficiency scores, whereas technical efficiency scores in MoH public general hospitals impacted in view of ownership.

Data Adjustments, Manipulations, and Transformations

Two primary implications emerge with result to variable selection within the DEA model. First, prior DEA studies have generally advocated identification and measurement of those dimensions, or input and output variables, deemed 'most relevant' for a particular set of decision-making units (DMUs) (Nunamaker, 1985; Hadad et al., 2013; Kohl et al., 2019). The importance of a particular variable to the DEA results is established via a panel of experts, prior statistical work, the researcher's knowledge of the decision environment or a combination of the three approaches. Moreover, consideration of some reduced variable set is considered appropriate if the selected variables are 'broadly representative' of the omitted factors (Charnes et al., 1981; Cooper et al., 2004); implying that variables which are highly correlated with existing model variables can be omitted from further analysis without significantly impacting the DEA efficiency result. Here, since data deficiency presents a major limitation that threatens to weaken the analysis, some transformations need to be done to the current available raw values of our hospital-level variables via weighted adjustments and normalized distribution before any attempts are made to construct the estimation model for the efficiency frontier. Thus, this section begins with data preparation followed by model testing, then, based on different statistical evaluations of input/output combinations, the choice of DEA model for estimating hospital efficiency will be analyzed against the boundaries of the production frontier.

Public General/Specialty Hospitals: MoH 2015-2019 Panel Data Preparation

Hospital efficiency studies frequently use outpatient events such as the number of outpatient visits and/or emergency attendances. Some studies have indicated that these outputs are assumed to be homogeneous and consequently do not need to be further grouped (Magnusen, 1996). This assumption, however, may stem from the fact that relatively little work has been done on classifying non-inpatient services compared with the detailed efforts made to categorize inpatient activities. Some researchers attempted to respond to this deficiency at a time before the Health Care Financing Administration's (HCFA) development of an outpatient classification system in 1990; known as Ambulatory Patient Groups (APGs), this patient classification system helped explain both the resource amount and type used in an ambulatory visit. The earliest proposal, and most sensible and sound, came from Banker et al. (1989), in which they introduced feasible adjustments to raw counts of outpatient visits that reflect differences in resource utilization between surgical and non-surgical interventions by considering the following basic formula (Banker et al., 1989; Cooper et al., 2004):

$$Adjusted\ outpatient\ visits = nonsurgical\ outpatient\ visits + 2(surgical\ outpatient\ vists)$$

Note. The multiplication by two (2) indicates the assumption of at least double the resources used in surgical compared to non-surgical treatment interventions.

The above formula may be an applicable transformation in our first dataset of 2015-2019 MoH public general/specialized hospital panel data, where, noticeably, specialized hospitals often lack some types of secondary services offered in general hospitals, such as Emergency Departments and causality operations or surgical interventions; some tertiary, specialty hospitals (i.e., Psychiatric Hospital/ Kuwait Center for Mental Health and Palliative Care Center) focus on the long-time care of patients within a highly specialized setting and more concentrated tertiary-level consultants and nurses, hence were excluded. Such hospitals, if included even with adjustments applied, will appear inefficient as discharges is considered among the important output variables of efficient patient flow and hospital performance (Kiadaliri et al., 2013; Hollingsworth, 2008; Pelone et al., 2015).

Again, due to data limitations, a fair amount of creativity is needed to capture more information from the given set of available hospital variables. Using the above formula by Banker et al. (1989), the adjustments will be made for discharges based on non-surgical interventions of inpatient treatments and those discharges that involved surgical interventions of treatment, not including casualty operations, with the following formula:

$$Adjusted\ discharges = nonsurgical\ inpatient\ treatments + 2(surgical\ inpatient\ treatments)$$

Note. Adapted from original Banker et al. (1989) formula for adjusted outpatient visits.

Table 17 below displays the adjustments applied to the output variable for our MoH public hospitals DEA model.

Table 17

Adjusted Discharges According to Inpatient Surgical Vs. Non-Surgical Interventions for Fifteen General/Specialty Public Hospitals by Year

		Original discharges (raw counts)	**Total surgical treatments (not casualty)**	**Total non-surgical treatments**	**New discharges (adjusted)**
2015	Mean	15322.73	4883.80	10696.07	20463.67
	Std. Dev	14501.42	4448.43	11059.23	18220.00
	Min	296	0	296	296
	Max	44429	12625	31804	57054
2016	Mean	16155.53	6339.17	11084.20	21226.87
	Std. Dev	15271.60	4169.28	11854.10	19157.70
	Min	97	433	97	97
	Max	46357	12070	34287	58427
2017	Mean	15427.27	6131.33	10522.20	20332.33
	Std. Dev	14806.35	4069.60	11501.26	18576.65
	Min	111	593	111	111
	Max	44600	12186	33438	55762
2018	Mean	16109.67	6000.83	11417.27	21018.60
	Std. Dev	15110.25	4060.03	11711.12	18787.62
	Min	251	547	78	251
	Max	45319	11898	33421	57217
2019	Mean	14799.13	6221.75	10547.93	20502.73
	Std. Dev	14508.43	4290.32	10459.16	18116.69
	Min	251	676	233	251
	Max	45319	12937	32382	58256

Similarly, the complexity of the services offered by hospitals is another factor that can influence their performance. One aspect of complexity is the number and type of specialties. Moreover, the existence of a psychiatric hospital, for example, can affect some service utilization variables such as average length of stay (ALOS) and bed turnover rate (BTR). In general, there are different ways of adjusting for these differences in general/specialized hospitals. The selection of an appropriate data transformation strongly depends on the complex service or operational factor a hospital performs that weigh heavily towards its output production. For instance, classification of MoH hospital service demands and performance can be evaluated according to the availability of an emergency department; whereby we see that all six general hospitals have emergency visits data while only four out of nine specialized hospitals have emergency visit data (the five that do not have EDs are: Physical Medicine & Rehab Facility; Chest Disease Hospital; Kuwait Cancer Control Center 'KCCC'; Allergy & Respiratory Center; and Sabah Al-Ahmad Urology Center). This is different than the previous surgical and non-surgical treatment interventions discussed earlier, some of these facilities carry out complex surgeries and even non-surgical interventions that still consume high levels of hospital resources (i.e., chemotherapy, radiotherapy, dialysis, etc.), however, in this case, we are only addressing the existence of a 24-hour Emergency Department that accepts emergency patient visits.

Following the hospital efficiency studies conducted by Cheng et al. (2015), Li et al. (2014), and Tlotlego et al. (2010) that attempted to account for the differences of emergency visits, or lack thereof, among hospital samples; we adjust our second output variable 'outpatient visits' so that this output is now represented by the number of outpatient *and* emergency visits. Thus, accounting for the additional complexity of emergency visits and emergency services offered by 10 out of the 15 hospitals on top of the outpatient visits offered by all 15 hospitals as shown.

Table 18

Output Adjusted to Reflect the Number of Total Visits

Year	Outpatient visits	Emergency visits	Total visits

2015	3017689	3634709	6652398
2016	3054623	3592909	6647532
2017	3103337	3505728	6609065
2018	2839389	3510380	6349769
2019	3019688	3563148	6582836

Public-Private General Hospitals: 2019-2020 Data Preparation

For the public-private comparative study, private general hospitals were selected for inclusion in our 2019-2020 productivity analysis by stratifying available private facilities into four groups according to hospital size (proxied by their bed capacity) due to the large variation in bed numbers between public and private sector hospitals. Although hospital size categorizations used in previous studies usually consider small hospitals (100 to 200 beds), lower-medium hospitals (200 to 299 beds), upper-medium hospitals (300 to 499 beds), and large-size hospitals (500 or more beds) (Gok & Sezen, 2013); bed capacity here was stratified based on hospital bed numbers relative to existing ranges (minimum and maximum, upper and lower limits) in the context of Kuwait in Table 19.

Table 19

Segregation of Private Hospitals

Bed Size	Category of Hospital
>200 beds	Private Large Hospital
100-200 beds	Private Medium Hospital
<100 beds	Private Small Hospital

It is worth mentioning that none of the private sector general hospitals surpassed 200 beds (although several facilities were undergoing planned expansions), therefore, all six private medium hospitals were included in the analysis along with the six public general hospitals from our previous MoH panel data for a total of 12 hospitals in 2019-2020. As an additional step to ensure the variations in hospital beds are balanced, we used *staffed beds* as inputs (see analysis in next section).

Two-Staged Data Envelopment Analysis (DEA)

Data Envelopment Analysis (DEA) is a non-parametric approach that is based on linear programming as provided in previous chapters. It was developed for calculating the relative efficiencies of a set of comparable entities, called Decision Making Units (DMUs), which evaluated as the ratio of the total weighted output to the total weighted input (Cooper et al., 2007; Hollingsworth, 2014). In DEA, each hospital is compared against the estimated efficient frontier, which comprises the most efficient hospitals (Hussey et al., 2009; Kiadaliri et al., 2013).

Based on Farrell's thesis, several DEA models have been built to analyze technological efficiency. The CCR model created by Charnes, Cooper, and Rhodes (1978) is the most well-known of the DEA models; it posits that production has constant returns to scale (CRS). In addition, the BCC model established by Banker, Charnes, and Cooper (1984) under the assumption of variable returns to scale (VRS) has been utilized frequently (Jacobs et al., 2006; Hollingsworth, 2003). The selection of the CCR or BCC model depends on the context of the examined problem (i.e., the technology linking the inputs and outputs in the transformation process) (Jacobs et al., 2006).

In general, the CCR model stipulates that the efficiency frontier has a constant slope (CRS), which means that every change in inputs results in an equal change in outputs (Cooper et al., 2007). When machines are included in the production process, constant returns to scale (CRS) may be implemented, which generally translates to a doubling of production outputs for each doubling of inputs. When employees (healthcare workers) participate in the process, however, it is unrealistic to expect them to maintain a steady pace. Regardless, it is suggested when DEA analysis is conducted from the decision-maker perspective that aims to measure efficiency regardless of any managerial factors (Gok & Sezen, 2013).

Since the CRS does not distinguish between scale and pure (managerial) technical efficiency, the CCR efficiency assessment may be impacted if the DMUs are not operating on the optimal scale size (Chuang et al., 2011). If the efficiency analysis is conducted from a management perspective, a BCC technology assumption will be better suitable for determining if the scale of operations or the provider's practice affects productivity (Gok & Sezen, 2013; Gok & Altindag, 2015). Scale efficiency is defined as the ratio of CRS to VRS efficiency scores and indicates if the DMU is operating on the optimal scale size (Hollingsworth, 2003; Varabyova & Müller, 2016). Nonetheless, the efficiency of DMUs can be thoroughly examined utilizing both CRS and VRS assumptions for more realistic changes in the production process and real-world implications (Jacobs et al., 2006; Cooper et al., 2007). Other systematic reviews have revealed comparable results when both CRS and VRS assumptions were used in efficiency measures. (Varabyova & Müller, 2016; Pelone et al., 2015).

Input orientation (i.e., minimization of inputs with a specified amount of outputs) and output orientation (i.e., inputs are held constant and outputs are increased proportionally) are rationally the most frequently utilized orientations in DEA analysis (Cooper et al., 2007). Previous empirical studies have argued that hospitals have relatively little control over their outputs (such as expanding surgical procedures or diagnostic tests), but greater control over their inputs (such as medical devices) due to their social obligation to provide medical care through public hospitals in general (Chuang et al., 2011). Consequently, the majority of research use input orientation to evaluate the efficiency of hospitals (Varabyova & Müller, 2016; Pelone et al., 2015; O'Neill et al., 2008). The output orientation that we use for our public-private analysis in our other comparative study was adopted in response to a specific health-related period at the time (one year prior to the onset of the COVID-19 pandemic) in order to evaluate the productivity of healthcare provision in both the public and private sectors just prior to the global spread of the coronavirus and weakening of several health systems. However, the purpose of this research is to determine the optimal levels of health resources without compromising the quality of health services provided by public hospitals. In this approach, we provide policymakers with information regarding prospective hospital savings.

Input and Output Variables

The choice of the sample size, number of inputs as well as the number of outputs was guided by the 'rule of thumb' proposed by Banker and Morey (1989), in which $n \geq 3(m + s)$, and where: n is the number of DMUs included in the sample; m is the number of inputs; and s is the number of outputs included in the analysis. The rule captures two issues, sample size and number of factors [(m + s)]. However, Pedraja-Chaparro et al. (1999) note that the rule ignores two other issues, the distribution of efficiencies as well as the covariance structure of factors. Nevertheless, we still use the 'rule of thumb' as a guide in the absence of any a priori view on the number of factors. We selected the hospital outputs that depend on the selected inputs, which cover a wide range of health services and health resources used by public hospitals. Notably, three inputs and two outputs were chosen based on the availability of the data in the Kuwaiti MoH context and previous conducted modeling trials.

For the 2015-2019 MoH panel data of 15 public hospital units (DMUs), the inputs include: (i) the number of hospital beds; (ii) the number of full-time physicians; and (iii) the number of full-time nurses and midwives. The output variables chosen in this analysis were: (i) total visits (outpatient and emergency visits, accounting for hospitals with Emergency Departments); and (ii) discharges (adjusted for inpatient surgical interventions performed in addition to any non-surgical inpatient treatments).

For the public-private comparative study of 12 total DMUs, the inputs include: (i) total number of full-time physicians; (ii) hospital beds; and (iii) hospital beds. The output variables in this analysis were: (i) total discharged patients (number of patients receiving inpatient medical care annually as an indicator of productive patient flow); and (ii) the total number of surgical procedures performed over one year. Due to many factors, namely a limited sample size among several others; double bootstrapping will be applied in the first-stage DEA analysis (bootstrapped-DEA efficiency estimations with approximately 1,000-2,000 iterations) but no additional repetitions in the following second-stage Tobit regression.

External Factors

After DEA analysis, we assessed the variation in the efficiency levels of hospitals and to what degree the differences in the efficiency scores can be explained by the observed external factors (demand factors), such as health status and demographic characteristics of the populations in the catchment area in each hospital. Thus, we examined the factors that influence healthcare utilization concerning the demographic structure of the population variables in the catchment area of each hospital governorate that predict the efficiency scores.

However, the external variables (i.e., environmental and institutional factors) not included in the efficiency model need to be accounted for in an additional analysis since different factors may be contributing to inefficiency. The potentially contributing factors are often included in a second stage DEA study to identify possible barriers to efficiency and their impact on inefficient hospitals (Cordero et al., 2015). The external variables have been selected based on literature review of the efficiency analysis of public/government hospitals and the effect of these variables on the production of healthcare services (Cordero et al., 2015; Cheng et al., 2015). Factors that affect the efficiency of public hospitals are classified as institutional (i.e., physician per nurse ratio, hospital size proxied by bed capacity or number of beds), environmental factors (i.e., demographics of population in the catchment area including under five population and elderly population, percent of females and non-Kuwaitis), and health status (i.e., cases of under one-year old deaths, number of external causes of morbidity and mortality) (Cheng et al., 2015; Cordero et al., 2015).

The following environmental and demographic factors were selected for the second-stage Tobit regression in our first MoH DEA analysis of public hospital efficiency: (i) population number in the hospital catchment area (registered residents in selected hospital governorate); (ii) percentage of non-Kuwaiti population (expats need either health insurance or pay minimal fees for service); (iii) percentage of non-Kuwaiti population (free public services for nationals may translate into more healthcare consumption); (iv) percentage of females and percentage of males (different health risks in each gender); (v) proportion of 0-5 years old children and proportion of the elderly population 65 years old and older (vulnerable populations); (vi) number of under one year-old deaths; (vii) number of external causes of morbidity and mortality in catchment area; (viii) hospital bed size dummy variable (hospital beds >372 median bed size = 1, hospital beds <372 = 0); (ix) nurses per hospital bed ratio (nurse staffed beds); and (x) ratio of physician-to-nurses. All data were collected for the 2015-2019 observation period.

The following external factors were selected for the second-stage Tobit regression in our second public-private DEA analysis comparing efficiency and productivity changes in view of ownership: (i) population number in the hospital catchment area (registered residents in selected hospital governorate); (ii) percentage of non-Kuwaiti population (use of private hospitals are expected to be higher for expats); (iii) ratio of hospital patients-to-physicians; (iv) nurse-to-bed ratio (nurse staffed beds); and (v) hospital ownership type dummy variable (based on public/government ownership model reference group = 1, private/for-profit ownership model = 0). All data were collected for 2019-2020 census year.

Results

Evaluating Efficiency in MoH Public Hospitals: First-Stage DEA Application

Descriptive statistics of all the input and output variables of the 15 MoH general/specialty hospitals during 2015-2019 are presented in Table 20 below. The average hospital size over the five-year period is 404 beds, with a range between 27 to 864 beds. Physicians per hospital ranged from 13 to 997, with an overall average of 363 full-time physicians. Nursing staff per hospital ranged from 48 and 2,160, maintaining an average of 943 full-time nurses. As for the outputs, the five-year average of adjusted discharges (adjusted for surgical interventions and non-surgical inpatient treatments) is 18,479, ranging from 106 and 57,343 discharges. Likewise, the outpatient and emergency visits (accounting for hospital ED services where available) upheld a five-year average of 390,898, with a range between 1,168 to 1,523,679 visits.

Table 20

Descriptive Statistics of Inputs and Outputs of MoH Public Hospitals

		INPUTS			OUTPUTS	
		Beds	Physicians	Nurses	Adj. discharges	Total visits
2015	Mean	406	369	981	20464	443493
	Std. dev.	279	315	721	18220	471193
	Median	722	620	1125	21446	298612
	Min.	36	31	51	296	2529
	Max.	869	843	2097	57054	1556494
2016	Mean	410	387	1025	21227	443169
	Std. dev.	575	633	1051	19454	472266
	Median	828	678	1296	21612	323898

	Min.	36	31	49	97	3064
	Max.	868	909	2186	58427	1580132
2017	Mean	413	404	1028	20332	440604
	Std. dev.	278	362	760	18577	466554
	Median	414	274	908	17685	331636
	Min.	36	32	48	111	3081
	Max.	868	1013	2211	55762	1536849
2018	Mean	410	421	1022	21019	423318
	Std. dev.	278	373	735	18788	455835
	Median	372	273	924	21801	306516
	Min.	36	33	45	251	2300
	Max.	868	1057	2187	57217	1491520
2019	Mean	410	429	969	20503	438856
	Std. dev.	274	403	720	18117	461980
	Median	362	264	860	19968	323744
	Min.	36	31	46	251	2919
	Max.	849	1163	2118	58256	1453402
Average	**Mean**	410	402	1005	20709	437888
	Std. dev.	337	417	797	18631	465566
	Median	540	422	1023	20502	316881
	Min.	36	32	48	201	2779
	Max.	864	997	2160	57343	1523679

Note. Adj. = adjusted.

Meanwhile, the pooled descriptive statistics for our select environmental factors of 2015-2019 MoH public hospitals are presented in Table 21. The average population of the catchment areas of the 15 hospitals over five years is 662,642 (Std. dev.180,277) with a range of 531,342 to 1,206,377 across five out of six Kuwaiti governorates between 2015 and 2019.

Table 21

Descriptive Statistics of Environmental Factors

Variable	Mean	Max.	Min.
Kuwaitis (%)	40.73	46.86	19.44
Population of catchment area (n)	662642.4	1206377	531342
External causes of morbidity & mortality (n)	12.56	20	4
<1 year old deaths (n)	31.08	169	17
Females (%)	42.40	45.59	28.17
Non-Kuwaitis (%)	59.27	80.56	53.14
Children <5 years (%)	6.40	9.05	5.01
Elderly ≥65 years (%)	3.133	4.154	1.442
Ratio of physicians-to-nurses (ROPTN)	0.383	0.73	0.23
Nurse per bed ratio	2.245	3.884	0.844
Males (%)	57.60	71.83	54.41
Bed capacity (>372 = 1)	37	869	372

Note. The bed capacity cutoff of 372 is based on median of hospital beds in our sample to evaluate whether hospital size is a factor of efficiency.

Peter Drucker, often touted as the "Father of Modern Management," famously said: "Efficiency is doing things right; effectiveness is doing the right things" (Drucker, 1976, p. 6). Guided by that definition and with that distinction in mind, we conducted the first-stage, input-oriented efficiency analysis for 2015-2019 MoH hospitals to identify the facilities that were doing things right and evaluate exogenous variables affecting inefficient hospitals from doings things right; Table 22 shows the results of the DEA models for individual hospitals, including summary statistics of the pooled average technical (CRS and VRS) efficiency and scale (SE) efficiency scores, as well as the returns to operation scale (increasing or decreasing returns to scale).

Pooling our sample at the end yielded the maximum sample size; creating a balanced panel structure of N = 15 individual MoH hospitals, T = 5-year period between 2015 and 2019, and observations (n) in the dataset being n = N×T for a final total of 75 observations that can evaluate overall efficiency change in 2015-2019. Our focus on determining technical inefficiency (CRS scores < 1) implies that the producer (hospital) is not achieving a maximum output from a given input combination. It is as if workers or machines were misused, not working at full capacity, or perhaps not cooperating well. This first-stage DEA identifies the technically inefficient firm (hospital) that falls off its frontier.

Table 22

Technical Efficiency Scores and Returns to Scale of MoH Public Hospitals in Kuwait

	CRS technical efficiency	VRS technical efficiency	Scale efficiency	RTS	Hospital type
		2015			
Al-Adan	1.00	1.00	1.00	CRS	General
Al-Amiri	0.78	0.80	0.98	IRS	General
Al-Farwaniya	1.00	1.00	1.00	CRS	General
Al-Jahra	1.00	1.00	1.00	CRS	General
Al-Sabah	0.98	1.00	0.98	IRS	General
Mubarak Al-Kabir	0.80	0.81	0.98	DRS	General
Al-Razi	0.70	0.70	1.00	IRS	Specialized
Physical Med. & Rehab Facility	1.00	1.00	1.00	CRS	Specialized

Maternity Hospital	0.99	1.00	0.99	DRS	Specialized
Chest Diseases Hospital	0.52	0.57	0.92	IRS	Specialized
Infectious Disease Facility	0.33	0.56	0.59	IRS	Specialized
Ibn Sina Hospital	1.00	1.00	1.00	CRS	Specialized
Kuwait Cancer Control Center	0.45	0.55	0.81	IRS	Specialized
Allergy & Respiratory Center	1.00	1.00	1.00	CRS	Specialized
Sabah Al-Ahmad Urology Center	0.50	1.00	0.50	IRS	Specialized
Average	**0.80**	**0.87**	**0.92**	**-----**	**-----**
			2016		
Al-Adan Hospital	1.00	1.00	1.00	CRS	General
Al-Amiri Hospital	0.85	0.88	0.96	IRS	General
Al-Farwaniya Hospital	1.00	1.00	1.00	CRS	General
Al -Jahra Hospital	1.00	1.00	1.00	CRS	General
Al-Sabah Hospital	0.98	1.00	0.98	IRS	General
Mubarak Al-Kabir Hospital	0.78	0.78	1.00	IRS	General
Al-Razi Hospital	0.64	0.64	1.00	DRS	Specialized
Physical Med. & Rehab Facility	1.00	1.00	1.00	CRS	Specialized

Maternity Hospital	1.00	1.00	1.00	CRS	Specialized
Chest Diseases Hospital	0.46	0.50	0.91	IRS	Specialized
Infectious Disease Facility	0.30	0.53	0.56	IRS	Specialized
Ibn Sina Hospital	1.00	1.00	1.00	CRS	Specialized
Kuwait Cancer Control Center	0.37	0.47	0.78	IRS	Specialized
Allergy & Respiratory Center	1.00	1.00	1.00	CRS	Specialized
Sabah Al-Ahmad Urology Center	0.47	1.00	0.47	IRS	Specialized
Average	**0.79**	**0.85**	**0.91**	**-----**	**-----**
2017					
Al-Adan Hospital	1.00	1.00	1.00	CRS	General
Al-Amiri Hospital	0.68	0.71	0.96	IRS	General
Al-Farwaniya Hospital	1.00	1.00	1.00	CRS	General
Al -Jahra Hospital	1.00	1.00	1.00	CRS	General
Al-Sabah Hospital	1.00	1.00	1.00	CRS	General
Mubarak Al-Kabir Hospital	0.75	0.75	1.00	IRS	General
Al-Razi Hospital	0.68	0.70	0.97	DRS	Specialized

Physical Med. & Rehab Facility	1.00	1.00	1.00	CRS	Specialized
Maternity Hospital	1.00	1.00	1.00	CRS	Specialized
Chest Diseases Hospital	0.47	0.52	0.91	IRS	Specialized
Infectious Disease Facility	0.42	0.63	0.67	IRS	Specialized
Ibn Sina Hospital	1.00	1.00	1.00	CRS	Specialized
Kuwait Cancer Control Center	0.37	0.46	0.80	IRS	Specialized
Allergy & Respiratory Center	1.00	1.00	1.00	CRS	Specialized
Sabah Al-Ahmad Urology Center	0.62	1.00	0.62	IRS	Specialized
Average	**0.80**	**0.85**	**0.93**	**-----**	**-----**
			2018		
Al-Adan Hospital	1.00	1.00	1.00	CRS	General
Al-Amiri Hospital	0.76	0.77	0.98	IRS	General
Al-Farwaniya Hospital	1.00	1.00	1.00	CRS	General
Al -Jahra Hospital	1.00	1.00	1.00	CRS	General
Al-Sabah Hospital	1.00	1.00	1.00	CRS	General
Mubarak Al-Kabir Hospital	0.77	0.77	0.99	IRS	General

Al-Razi Hospital	0.69	0.72	0.96	IRS	Specialized
Physical Med. & Rehab Facility	1.00	1.00	1.00	CRS	Specialized
Maternity Hospital	1.00	1.00	1.00	CRS	Specialized
Chest Diseases Hospital	0.53	0.57	0.92	IRS	Specialized
Infectious Disease Facility	0.44	0.73	0.60	IRS	Specialized
Ibn Sina Hospital	0.86	0.88	0.98	IRS	Specialized
Kuwait Cancer Control Center	0.36	0.45	0.81	IRS	Specialized
Allergy & Respiratory Center	1.00	1.00	1.00	CRS	Specialized
Sabah Al-Ahmad Urology Center	0.46	1.00	0.46	IRS	Specialized
Average	**0.791**	**0.860**	**0.914**	**-----**	**-----**
			2019		
Al-Adan Hospital	1.00	1.00	1.00	CRS	General
Al-Amiri Hospital	0.66	0.68	0.97	IRS	General
Al-Farwaniya Hospital	1.00	1.00	1.00	CRS	General
Al -Jahra Hospital	1.00	1.00	1.00	CRS	General
Al-Sabah Hospital	0.89	0.92	0.97	IRS	General

Mubarak Al-Kabir Hospital	0.72	0.73	0.98	DRS	General
Al-Razi Hospital	0.84	0.87	0.97	DRS	Specialized
Physical Med. & Rehab Facility	1.00	1.00	1.00	CRS	Specialized
Maternity Hospital	1.00	1.00	1.00	CRS	Specialized
Chest Diseases Hospital	0.45	0.49	0.92	IRS	Specialized
Infectious Disease Facility	0.28	0.56	0.50	IRS	Specialized
Ibn Sina Hospital	1.00	1.00	1.00	CRS	Specialized
Kuwait Cancer Control Center	0.35	0.43	0.82	IRS	Specialized
Allergy & Respiratory Center	1.00	1.00	1.00	CRS	Specialized
Sabah Al-Ahmad Urology Center	0.57	1.00	0.57	IRS	Specialized
Average	**0.78**	**0.84**	**0.91**	**-----**	**-----**

Pooled 2015-2019 sample (N=75 observations)					
	CRS technical efficiency	**VRS technical efficiency**	**Scale efficiency**	**IRS [N (%)]**	**DRS [N (%)]**
Mean	0.79	0.85	0.92		
Std. dev.	0.01	0.01	0.01	34 (45.3%)	6 (8%)
Min.	0.78	0.84	0.91		
No. of fully efficient scores	35 (46.7%)	43 (57.3%)	35 (46.7%)		

Note. RTS, returns to scale; CRS, constant returns to scale; VRS, variable returns to scale; DRS, decreasing returns to scale; IRS, increasing returns to scale.

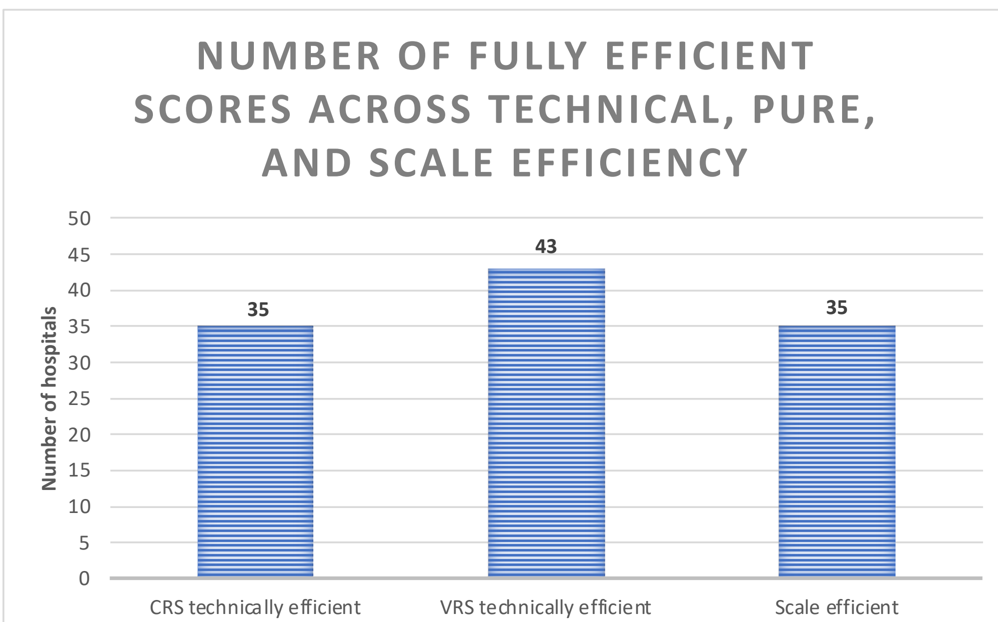
Technical efficiency (CRS score) can be decomposed into two parts, one due to scale efficiency and the other due to pure technical efficiency (VRS score) (Contreras, 2020). Therefore, when mentioning pure technical efficiency, we are referring to a firm's (hospital's) ability to avoid waste by producing as much output as input usage allows, or by using as little input as output production allows. On the other hand, scale efficiency (SE) refers to the hospital's ability to work (produce) at its optimal scale (Contreras, 2020).

In interpreting our analysis in Table 22, we see the pooled average technical efficiency (CRS score) for MOH hospitals over the five-year period between 2015 and 2019 is 0.79, that is an overall efficiency of 79 percent with a standard deviation (Std. dev.) of 0.01; indicating that without changing current production and keeping efficiency levels as is, Kuwait's public hospitals could still decrease usage of all their inputs by 21 percent on average without any compromised reduction in service provision. Also in Table 22, the MoH 2015-2019 pooled average pure technical efficiency (VRS score) is 0.85, or simply 85 percent with a Std. dev. of 0.01, implying that if they run efficiently, the hospitals should decrease 15 percent of inputs for the same volume of outputs.

Annual, cross-sectional evaluations in Table 22 for 2015, 2016, 2017, 2018, and 2019 reveal 6 (40%), 7 (46.6%), 8 (53.3%), 7 (46.6%), and 7 (46.6%) hospitals, respectively, out of 15 hospitals per panel-year were defined as technically efficient. This essentially means that those same technical efficiency levels per panel-year could have still decreased the hospitals' use of all inputs on a yearly basis by 60%, 53.4%, 46.7%, 53.4% and 53.4%, respectively, while continuing to meet identical levels of healthcare delivery. As for pure technical efficiency in Table 22 for 2015, 2016, 2017, 2018, and 2019; 9 (60%), 9 (60%), 9 (60%), 8 (53.3%), and 8 (53.3%) hospitals, respectively, operated at the best efficiency levels with a VRS score of 1.000. These findings indicate further missed opportunities for decreasing annual input resources of up to 40%, 40%, 40%, 46.7%, and 46.7% by simply operating efficiently. The pooled distribution of hospital observations across technical, pure technical, and scale efficiency scores is shown in Figure 10.

Figure 10

Distribution of Hospital Observations Across Efficiency Scores of Technical (CRS), Pure Technical (VRS), and Scale Efficiencies for 2015-2019



Note. VRS technical efficiency (TE) is also known as pure TE or pure/managerial TE. Pooled hospital observations N=75, CRS technically efficient observations = 35, VRS technically efficient observations = 43, and scale efficient observations = 35.

We noticed from Table 22 and Figure 10 that the lowest reported efficiency score is 0.28 (28%) by the Infectious Disease Center in 2019 as it was undergoing organizational changes but remained operational for valid efficiency measurement (its overall efficiency never exceeded 44 percent throughout the five years); however, Figure 10 shows 35 out of 75 hospital observations (46.7%) pooled for 2015-2019 were both technically and scale efficient, which indicates these hospitals utilize their inputs optimally. We also notice from Table 22 that average pure technical efficiency (managerial efficiency) and scale efficiency scores were not identical, with 0.85 and 0.92, respectively. Since management (managerial) efficiency refers to using correct and optimal methods for management; it is important to measure management's ability to save inputs to produce a certain amount of outputs, or to produce more outputs given a set of inputs, because it is associated with managerial decisions or bad managerial practices (Contreras, 2020). Strategic hospital decisions are controlled by administrative rules and hospital directors or managers in Kuwait's public hospitals are mostly appointed by the MoH; without well-designed mechanisms, rules and regulations. Therefore, as indicated by Li et al. (2014), the lack of clearly defined rights and responsibility increases their subjectivity in decision-making, which would decrease the quality of management practices and further influence pure technical efficiency (Li et al., 2014).

Lastly, with regards to returns to scale in Table 22 – other than the facilities operating under CRS – 45.3 percent of hospital observations in our pooled 2015-2019 dataset operated under increasing returns to scale (IRS) and 8 percent under decreasing returns to scale (DRS). Hospitals that were operating on either IRS or DRS need to adjust their capacity to operate on their optimal scale size (i.e., at the CRS, which would be required to achieve technical efficiency and operate at their most productive size). As dimensions under the *variable* return to scale (VRS) assumption and not constant return to scale, IRS means 1 percent increase in inputs will be followed by more than 1 percent increase in outputs, while DRS means 1 percent increase in inputs will result in less than 1 percent increase in outputs (Cheng et al., 2015). Consequently, the 44 observed hospitals showing IRS suggests these facilities should *expand* their scale to become scale efficient, while the other 6 observed hospitals with DRS means they should scale *down* to become scale efficient.

Below, Table 23 teases out the same hospitals each year to illustrate the changes in technical efficiency across the five-year observation period.

Table 23

Technical Efficiency Changes of Hospitals Annually Over Five Years

Hospital DMU	2015 CRS (VRS)	2016 CRS (VRS)	2017 CRS (VRS)	2018 CRS (VRS)	2019 CRS (VRS)
Al-Adan	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)
Al-Amiri	0.78 (0.79)	0.85 (0.88)	0.68 (0.713)	0.76 (0.774)	0.66 (0.677)
Al-Farwaniya	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)
Al-Jahra	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)
Al-Sabah	0.98 (1.00)	0.977 (1.00)	1.00 (1.00)	1.00 (1.00)	0.892 (0.915)
Mubarak Al-Kabir	0.795 (0.808)	0.78 (0.778)	0.748 (0.75)	0.767 (0.77)	0.723 (0.735)
Al-Razi	0.699 (0.610)	0.64 (0.644)	0.677 (0.698)	0.69 (0.715)	0.84 (0.866)

Physical Med. & Rehab Facility	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)
Maternity Hospital	0.99 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)
Chest Diseases Hospital	0.523 (0.567)	0.46 (0.503)	0.47 (0.515)	0.53 (0.57)	0.45 (0.49)
Infectious Disease Facility	0.33 (0.557)	0.30 (0.531)	0.42 (0.631)	0.44 (0.73)	0.277 (0.557)
Ibn Sina Hospital	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	0.86 (0.883)	1.00 (1.00)
Kuwait Cancer Control Center	0.45 (0.553)	0.37 (0.473)	0.37 (0.458)	0.36 (0.45)	0.35 (0.427)
Allergy & Respiratory Center	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)	1.00 (1.00)
Sabah Al-Ahmad Urology Center	0.50 (1.00)	0.47 (1.00)	0.62 (1.00)	0.46 (1.00)	0.575 (1.00)
Overall Count	**6 (9)**	**7 (9)**	**8 (9)**	**7 (8)**	**7 (8)**

According to Table 22, overall, 43 observations (57.3%) reported efficient scores in VRS (pure efficiency) while 35 (46.67%) hospital observations were efficient on the scale; thus, suggesting that almost 53.33 percent of observed hospitals should explore their optimum operation scale since they failed to meet optimal performance levels. Looking at hospital DMUs cross-sectionally between 2015 and 2019 in Table 23, we see Ibn Sina specialized hospital, for instance, achieving perfect technical (CRS) and pure technical (VRS) efficiency each year, except for in 2018, where it was found to be 86 percent technically efficient with a VRS score of 88 percent before coming back to full efficiency again in 2019. This example of technical efficiency change in Ibn Sina for the year 2018 and its recovery from that one-year dip in 2019 can be explained by looking at the decomposed values of pure technical change (whether hospital managers have improved using resources) or scale efficiency change (whether the hospital has moved to an optimal scale relative to the frontier).

We then conducted a DEA sensitivity analysis by removing variables one at a time in order to determine the robustness of the efficiency scores obtained by our model (Jahanshahloo et al., 2011). In essence, the sensitivity analysis found under Appendix B is used to assess how sensitive the values and efficiency scores of the DMUs are to the numerical observations; basically, we are trying to evaluate if using different input and output variables changes the DMUs' efficiency scores. The changes observed in the efficiency scores of each hospital in the sensitivity analysis validated our current DEA model with the selected variables; allowing us to move forward with our constructed frontier estimation model, or input/output combination.

We further considered evaluating observation efficiency scores according to hospital type (secondary general hospital vs. tertiary specialized hospitals) in Table 24, then based on hospital size (bed capacity size) in Table 25; noticing an interesting trend (graphic visualizations of efficiency trends provided in Appendix B). For Table 24, general hospitals in the public sector from 2015 to 2019 seem to have achieved the highest average technical efficiency (TE) score of 0.91 (Std. dev. 0.12), followed by the specialized hospitals with an average TE score of 0.71 (Std. dev. 0.28). The minimum technical efficiency value, or lowest CRS score, among general hospitals is 0.66 (Al-Amiri Hospital in 2019) while the minimum among the nine specialty hospitals over the five-year period is 0.28 (Infectious Disease Facility in 2019). Furthermore, the percentage of efficient general hospitals (56.7%) account for more than half of the observations in the stratum, while the proportion of efficient specialized hospitals constitute just under half of the decision-making units (DMUs) observed in the sample (40%). Lastly in Table 24, general hospitals reported a relatively higher VRS (pure technical efficiency) score of 0.92. Even in terms of average scale efficiency scores, we see that general hospitals (SE = 0.99) were essentially operating better in terms of scale size (but not yet optimally) compared to the specialized tertiary hospitals. It is noteworthy to remember that due to the nature of activities in specialty hospitals, we may need a new scale specific to these hospitals to accurately measure whether they are operating at optimal levels.

Table 24

Pooled MoH Technical Efficiency Scores and Returns to Scale in 2015-2019, Stratified by Public Hospital Type

<table>
<tr><th></th><th></th><th>CRS technical efficiency</th><th>VRS technical efficiency</th><th>Scale efficiency SE</th><th>IRS [N (%)]</th><th>DRS [N (%)]</th></tr>
<tr><td rowspan="5">General</td><td colspan="6">Pooled 2015-2019 General Hospital Sample (N=30)</td></tr>
<tr><td>Mean</td><td>0.913</td><td>0.92</td><td>0.99</td><td rowspan="4">11 (36.7%)</td><td rowspan="4">2 (6.7%)</td></tr>
<tr><td>Std. dev.</td><td>0.12</td><td>0.11</td><td>0.012</td></tr>
<tr><td>Min.</td><td>0.66</td><td>0.68</td><td>0.96</td></tr>
<tr><td>No. of fully efficient observation scores</td><td>17 (56.7%)</td><td>19 (63.3%)</td><td>17 (56.7%)</td></tr>
<tr><td rowspan="5">Specialty</td><td colspan="6">Pooled 2015-2019 Specialized Hospital Sample (N=45)</td></tr>
<tr><td>Mean</td><td>0.71</td><td>0.81</td><td>0.87</td><td rowspan="4">23 (51.1%)</td><td rowspan="4">4 (8.89%)</td></tr>
<tr><td>Std. dev.</td><td>0.28</td><td>0.22</td><td>0.18</td></tr>
<tr><td>Min.</td><td>0.28</td><td>0.43</td><td>0.46</td></tr>
<tr><td>No. of fully efficient observation scores</td><td>18 (40%)</td><td>24 (53.3%)</td><td>20 (44.4%)</td></tr>
</table>

Note. RTS, returns to scale; CRS, constant returns to scale; VRS, variable returns to scale; DRS, decreasing returns to scale; IRS, increasing returns to scale; SE, scale efficiency.

In an effort to evaluate efficiency differences between hospital observations based on hospital size (proxied by number of beds), Table 25 presents the 2015-2019 pooled efficiency scores of MoH general and specialized hospitals from a capacity perspective. Most notable in Table 25 is that small hospitals (< 100 beds) are higher in average technical efficiency (both CRS and VRS scores) than both categories of medium-sized hospitals (100-499 beds); whereas only the mean VRS score is higher compared to large hospitals (≥ 500 beds), while average CRS technical efficiency remains lower.

Table 25 below displays the efficiency values for each hospital observation by bed size, where hospitals classified as small in size (< 100 beds) show an average technical efficiency score of 0.84 (Std. dev. 0.24); the pooled observations for small hospitals include three specialized hospitals, in which two-thirds of hospitals between 2015 and 2019 were technically efficient on the scale. Still following Table 25, average technical efficiency of low- to medium sized hospitals is 0.37 (Std. dev. 0.06); including pooled observations of two specialized hospitals that remained technically and scale inefficient all through 2015-2019. Despite upper-medium sized hospital observations (two general and four specialized hospitals) reporting, in comparison, higher average efficiency of 0.81 (Std. dev. 0.20); a third were efficient between 2015-2019, while 66.6 percent of observations reported inefficiencies. Finally, Table 25 shows four of the six public general hospitals with 500 or more hospital beds and classified as large in size. The average technical efficiency of large hospital-sized observations in 2015-2019 was 0.94 (Std. dev. 0.11), where 75 percent of large general hospital observations were fully efficient and one large general hospital DMU did not reach full technical efficiency throughout the five-year observation period.

Table 25

Pooled MoH Technical Efficiency Scores and Returns to Scale in 2015-2019, Stratified by Bed Capacity

	CRS technical efficiency	VRS technical efficiency	Scale efficiency SE	General hospitals DMUs [N (%)]	Specialty hospitals DMUs [N (%)]
2015-2019 Large size public hospitals ≥ 500 beds (n=20 observations)					
Mean	0.941	0.942	0.998	4 (100%)	0 (0%)
Std. dev.	0.106	0.104	0.006		
Min.	0.72	0.73	0.98		
Fully efficient observations	15	15	17		
2015-2019 Upper-medium size public hospitals 300-499 beds (n=30 observations)					
Mean	0.814	0.831	0.974	2 (33.3%)	4 (66.6%)
Std. dev.	0.195	0.183	0.030		
Min.	0.45	0.49	0.91		
Fully efficient observations	10	13	12		
2015-2019 Lower-medium size public hospitals 100-299 beds (n=10 observations)					
Mean	0.367	0.537	0.694	0 (0%)	2 (100%)
Std. dev.	0.057	0.092	0.123		
Min.	0.28	0.43	0.5		
Fully efficient observations	0	0	0		
2015-2019 Small size public hospitals < 100 beds (n=15 observations)					
Mean	0.841	1.000	0.841	0 (0%)	3 (100%)
Std. dev.	0.235	0.000	0.235		
Min.	0.46	1	0.46		
Fully efficient observations	10	15	10		

Note. RTS, returns to scale; CRS, constant returns to scale; VRS, variable returns to scale; SE, scale efficiency.

Our performance analysis also identified the slacks, which were either excess input utilization or shortages of output production. Slacks represent only the leftover portions of inefficiencies; after proportional reductions in inputs or increases in outputs, if a DMU cannot reach the efficiency frontier (to its efficient target), slacks are needed to push the DMU to the frontier (target) (Zyphur et al., 2018). Therefore, inefficiently used inputs or not sufficiently produced outputs could be determined by healthcare management. In general, we should consider decision-making units (DMUs) truly efficient when our DEA score equals one (1) and all slacks are zero (0). If only the first condition is satisfied, then, as we have been doing above, the DMU (hospital unit) is called efficient in terms of 'technical' efficiency; only when both conditions are satisfied, we would then say the DMU is efficient in terms of 'strong' efficiency (Coelli et al., 2005).

The following data in Table 26 reveals the pooled average amount of slack over a five-year period in hospitals that were inefficient (<0.1, or under 100% efficiency). These are the values of the variables corresponding to the slack variables in the envelopment model. The variables show the scope for improving input and output values after the changes in input and output levels corresponding to the optimal value of the objective function. The findings combine the slack for all inefficient (TE scores <1) MoH public hospitals, stratified by inputs and outputs; Table 26 also demonstrates the average percent change (slacks) in the number of inputs or outputs required in order to eliminate the inefficiencies and achieve target levels. The actual and target values of inputs and outputs, as well as the percentage of change in each hospital, are provided in more details in Appendix B. Nevertheless, we recognize that DEA results, in general, should be interpreted with much caution to avoid giving wrong signals and providing inappropriate recommendations.

Table 26

Evaluation of Pooled Slacks in Inefficient MoH Public Hospitals in Kuwait

INPUT SLACKS	Mean difference of values from targets	Std. dev.	Percent change to target
Hospital Beds	67.10	77.76	-16.37
Physicians	75.71	124.83	-18.83
Nurses	169.23	212.93	-16.84
OUTPUT SLACKS			
Outpatient & Emergency Visits	4955.39	30509.59	1.13

Note. No slacks were reported for the discharges output in any of the inefficient hospitals. This analysis used Performance Improvement Management Software (PIM-DEA) by Emrouznejad & Thanassoulis (2015).

The amount of slack for each hospital per panel-year between 2015 and 2019, and the actual and target values of inputs and outputs as well as the percent change in each hospital, are all provided in Appendix B. For targets, we look at the individual DMUs and their targets which would allow them to gain full efficiency. Other details such as the efficient refrents (benchmarks) for each of the individual DMUs are also available under Appendix B to allow readers to see which hospitals can be used as role models for an *inefficient* DMU or hospital. For example, under Appendix B, we see Al-Amiri Hospital in 2015 had Al-Adan Hospital and Farwaniya Hospital as efficient referents (peers); indicating the performance of Al-Amiri inferior relative to those of Al-Adan and Farwaniya in 2015 and it would be useful for Al-Amiri to relate to those hospitals as role models of efficiency. For 2017, Al-Amiri was matched with Al-Sabah Hospital and

Farwaniya Hospital as efficient referents (peers), thus suggesting, based on Al-Amiri Hospital's performance in 2017, it would have benefitted from relating to those hospitals as role models for achieving efficiency.

Additionally, we attempted to improve the accuracy of our DEA analysis even more by applying non-parametric bootstrapped-DEA methodology to the technical efficiency scores in order to obtain the bias corrected estimates and the 95% confidence intervals of efficiency scores shown in Table 27. As cited in Chapter 2, the bootstrap concept or technique is based on a procedure of drawing with replacement from a sample; mimicking the data generating process of the underlying true model and in essence producing multiple estimates that we can use for statistical inference (Tziogkidis, 2012). Since one of the disadvantages of DEA is that statistical inference is very difficult to be applied on DEA scores, bootstrapping DEA efficiency values allows us to extract the sensitivity of efficiency scores which results from the distribution of (in)efficiency in the sample. Ideally, the sample of estimates would be as large as possible given the time resources, with hundreds or thousands of repeats. As displayed in Table 27, we applied 2,000 iterations to our sample as described by Simar and Wilson (1998) for bootstrapping, in which a smoothed distribution of efficiency scores is drawn from instead of the actual distribution. We would like to avoid delving deeper into the technical details of the method since it is fairly established and beyond the scope of this chapter; however, further details and analysis on this topic can be found in the papers of Simar and Wilson (1998, 2000, 2007) as well as their book chapters (Simar & Wilson, 2004; 2008).

Table 27

Data Envelopment Analysis (DEA) Bootstrapping Approach

	Hospital DMU	Sample TE	Bootstrap mean	Bootstrap median	95% Confidence Interval (CI)		Bootstrap bias
					Bootstrap lower bound	Bootstrap upper bound	
2015							
	Al-Adan Hospital	100	100	100	100	100	0
	Al-Amiri Hospital	78.02	63.46	62.72	56.05	79.48	-14.56
	Al-Farwaniya Hospital	100	100	100	100	100	0
	Al -Jahra Hospital	100	100	100	100	100	0
	Al-Sabah Hospital	98.25	96.52	96.5	96.5	100	-1.73
	Mubarak Al-Kabir Hospital	79.54	65.34	63.77	59.07	81.4	-14.2
	Al-Razi Hospital	69.93	52.39	52.7	39.86	72.14	-17.54
	Physical Med. & Rehab Facility	100	100	100	100	100	0
	Maternity Hospital	99.21	98.41	98.41	98.41	100	-0.8
	Chest Diseases Hospital	52.31	39.24	39.96	20.15	53.45	-13.07
	Infectious Disease Facility	32.98	22.65	23.47	8.15	33.81	-10.33
	Ibn Sina Hospital	100	100	100	100	100	0
	Kuwait Cancer Control Center	44.88	36.19	36.89	24.33	45.84	-8.69

	Allergy & Respiratory Center	100	100	100	100	100	0
	Sabah Al-Ahmad Urology Center	49.74	39.81	40.93	23.09	50.35	-9.93
2016							
	Al-Adan Hospital	100	100	100	100	100	0
	Al-Amiri Hospital	84.98	76.87	77.49	69.97	85.38	-8.11
	Al-Farwaniya Hospital	100	100	100	100	100	0
	Al -Jahra Hospital	100	100	100	100	100	0
	Al-Sabah Hospital	97.67	95.43	95.34	95.34	98.5	-2.24
	Mubarak Al-Kabir Hospital	77.66	67.2	68.07	55.31	78.33	-10.46
	Al-Razi Hospital	64.15	54.15	55.21	38.25	64.75	-10
	Physical Med. & Rehab Facility	100	100	100	100	100	0
	Maternity Hospital	100	100	100	100	100	0
	Chest Diseases Hospital	45.66	39.25	40.48	27.95	46.15	-6.41
	Infectious Disease Facility	29.63	23.97	25.4	12.91	29.94	-5.66
	Ibn Sina Hospital	100	100	100	100	100	0
	Kuwait Cancer Control Center	37.1	32.98	33.45	26.74	37.46	-4.12
	Allergy & Respiratory Center	100	100	100	100	100	0

	Sabah Al-Ahmad Urology Center	47.08	40.68	41.62	29.14	47.34	-6.4
2017							
	Al-Adan Hospital	100	100	100	100	100	0
	Al-Amiri Hospital	68.21	56.89	58.03	40.27	69.19	-11.32
	Al-Farwaniya Hospital	100	100	100	100	100	0
	Al -Jahra Hospital	100	100	100	100	100	0
	Al-Sabah Hospital	100	100	100	100	100	0
	Mubarak Al-Kabir Hospital	74.84	62.45	62.56	49.67	75.56	-12.39
	Al-Razi Hospital	67.7	55.36	56.65	35.95	68.52	-12.34
	Physical Med. & Rehab Facility	100	100	100	100	100	0
	Maternity Hospital	100	100	100	100	100	0
	Chest Diseases Hospital	47.04	38.95	39.94	24.88	47.77	-8.09
	Infectious Disease Facility	42.46	33.84	35.25	17.37	42.88	-8.62
	Ibn Sina Hospital	100	100	100	100	100	0
	Kuwait Cancer Control Center	36.77	31.79	32.11	24.38	37.09	-4.98
	Allergy & Respiratory Center	100	100	100	100	100	0

	Sabah Al-Ahmad Urology Center	62.27	54.02	55.62	38.51	62.64	-8.25
2018							
	Al-Adan Hospital	100	100	100	100	100	0
	Al-Amiri Hospital	76.29	63.28	63.5	52.58	77.52	-13.01
	Al-Farwaniya Hospital	100	100	100	100	100	0
	Al -Jahra Hospital	100	100	100	100	100	0
	Al-Sabah Hospital	100	100	100	100	100	0
	Mubarak Al-Kabir Hospital	76.68	63.05	63.18	53.36	78.06	-13.63
	Al-Razi Hospital	68.76	52.62	53.35	37.51	69.68	-16.14
	Physical Med. & Rehab Facility	100	100	100	100	100	0
	Maternity Hospital	100	100	100	100	100	0
	Chest Diseases Hospital	52.63	40.5	41.63	22.7	53.21	-12.13
	Infectious Disease Facility	43.78	35.65	36.18	24.38	44.43	-8.13
	Ibn Sina Hospital	86.47	75.12	72.94	72.94	88.3	-11.35
	Kuwait Cancer Control Center	23.49	18.77	19.06	12.05	23.83	-4.72
	Allergy & Respiratory Center	100	100	100	100	100	0

	Sabah Al-Ahmad Urology Center	45.64	35.69	36.07	22.28	46.09	-9.95
2019							
	Al-Adan Hospital	100	100	100	100	100	0
	Al-Amiri Hospital	65.74	51.23	52.05	32.41	66.86	-14.51
	Al-Farwaniya Hospital	100	100	100	100	100	0
	Al -Jahra Hospital	100	100	100	100	100	0
	Al-Sabah Hospital	89.16	79.49	78.31	78.31	91.37	-9.67
	Mubarak Al-Kabir Hospital	72.25	56.14	56.58	44.5	74.14	-16.11
	Al-Razi Hospital	83.98	70.27	67.97	67.97	85.83	-13.71
	Physical Med. & Rehab Facility	100	100	100	100	100	0
	Maternity Hospital	100	100	100	100	100	0
	Chest Diseases Hospital	45.11	31.55	33.23	9.87	46.21	-13.56
	Infectious Disease Facility	27.69	21.15	21.9	11.6	28.3	-6.54
	Ibn Sina Hospital	100	100	100	100	100	0
	Kuwait Cancer Control Center	35	27.31	27.85	17.12	35.78	-7.69
	Allergy & Respiratory Center	100	100	100	100	100	0
	Sabah Al-Ahmad Urology Center	57.46	43.81	45.66	20.89	58.09	-13.65

Pooled Average	**Mean**	79.18	73.91	74.16	67.90	79.68	-5.26
	Std. dev.	24.82	28.81	28.44	35.11	24.60	5.79
	Median	97.67	95.43	95.34	95.34	98.5	-2.24

Note. Values shown in percentages. DEA-bootstrapping analysis was based on the non-parametric bootstrap-DEA application introduced by Simar & Wilson (1998) and provided through the . `simarwilson` command in Stata with a standard number of 1,000 iterations (Simar & Wilson, 2007). TE, technical efficiency score, referring to the sample DEA estimated efficiency score assumed to be the 'biased' DEA efficiency score of the corresponding hospital DMUs.

Table 27 reveals that the majority of MoH public hospitals, 58.82 percent on average, were operating on sub-optimal scale; where 64.71 percent inefficiency was calculated in 2015, 58.82 percent inefficiency was recorded in 2016, 52.94 percent in 2017, 58.82 percent in 2018, and 58.82 percent in 2019, indicating that 2015 was the least efficient year for MoH public hospitals with 35.29 percent efficiency, whereas 2017 demonstrated the greatest efficiency in the public sector with 47.06 percent of hospitals operating efficiently on the scale.

Beyond just the construction of confidence intervals and accounting for DEA efficiency score bias, bootstrapping helped us overcome the correlation problem of DEA-efficiency scores; furthermore, as a powerful tool in statistics, bootstrapping helped provide consistent inferences in explaining the determinants of Kuwait's public health system efficiency (given our small sample size and the non-parametric nature of DEA) and discussing MoH's delivery of care in the subsequent concluding chapter. Table 28 provides the adjusted efficiency means obtained from bootstrapped-DEA scores compared to original DEA averages.

Table 28

Mean Sample CRS Technical Efficiency Scores and Mean Adjusted Bootstrapped-DEA Efficiency Scores by Hospital Type

	Public Hospital Type	Mean	
		TE	Bootstrap-Adjusted TE
2015	**General**	92.64	87.55
	Specialized	72.12	65.41
	Annual average	80.32	74.27
2016	**General**	93.39	89.92
	Specialized	69.29	65.67
	Annual average	78.93	75.37
2017	**General**	90.51	86.56
	Specialized	72.92	68.22
	Annual average	79.95	75.55
2018	**General**	92.16	87.72
	Specialized	68.97	62.04
	Annual average	78.25	72.312
2019	**General**	87.86	81.14
	Specialized	72.14	66.01
	Annual average	78.43	72.06

Determinants of Inefficiency in MoH Public Hospitals: Second-Stage Tobit Regression

The Tobit regression (a censored regression model in econometric analysis) was used to relate technical efficiency scores to the external variables as well as some organizational factors of hospitals that may help explain potential unobservable forces behind optimum performance. After using the TE equation shown in Equation 7, adapted from Kirigia et al. (2002), to obtain our input-oriented CRS scores for each hospital in the first-stage DEA; we included our explanatory variables from Table 21 in our Tobit regression model that follows in order to identify which factor(s) influence technical efficiency.

Equation 7

DEA weights model, input-oriented CRS

$$
\begin{aligned}
&\mathrm{Eff} = \underset{u_r,\, v_i}{\mathrm{Max}} \textstyle\sum_r u_r y_{r j_0} \\
&s.t. \\
&\qquad \textstyle\sum_r u_r y_{rj} - \sum_i v_i x_{ij} \leq 0; \quad \forall j \\
&\qquad \textstyle\sum_i v_i x_{i j_0} = 1 \\
&\qquad u_r, v_i \geq 0; \qquad\qquad\qquad \forall r, \forall i.
\end{aligned}
$$

Note. Adapted from Ahmadkiadaliri et al. (2011) as depicted by Ketabi, 2011.

Where,

Yrj is the amount of output r produced by hospital j ,

xij is the amount of input i used by hospital j ,

ur is the weight given to output r , (r = 1…, t and t is the number of outputs)

vi is the weight given to input i , (i = 1…, m and m is the number of inputs)

n is the number of hospitals,

j0 is the hospital under assessment.

MoH Hospitals Tobit Regression Model

Technical efficiency (TE) = β0 +β1(Bed capacity > 372 hospital beds) +β2(Catchment population) +β3(External causes of morbidity/mortality) +β4(<1 year old deaths)

$+\beta5(Females) +\beta6(non\text{-}Kuwaitis) +\beta7(Children< 5\ population) +\beta8(Elderly >64\ population) +\beta9(Ratio\ of\ physicians\text{-}to\text{-}nurses) +\beta10(Nurses\ per\ bed\ ratio) +\varepsilon$

Explanatory variables were chosen based on: (i) data availability; and (ii) most likely mediating factors (institutional and environmental) that may influence the production process in hospitals and potentially drive (in)efficiency. The results of our Tobit model are displayed in Table 29 where standard errors were adjusted for clustered observations.

Table 29

Second-Stage Tobit Regression Analysis

Explanatory variables	Tobit regression Coefficient	Bootstrap-adjusted Tobit regression coefficient
Bed capacity dummy variable (hospital beds >327 = 1)	0.263***	0.263***
Population of catchment area (n)	- 0.00000159***	- 0.00000159***
External causes of morbidity & mortality in catchment (n)	-0.0584*	-0.0584
<1 year old deaths in catchment (n)	0.04891**	0.04891
Females (%)	-0.0965**	-0.0965*
Non-Kuwaitis (%)	-0.2083***	-0.2083**
Children <5 years (%)	-3.632	-3.632
Elderly ≥65 years (%)	-21.107*	-21.107*
Ratio of physicians-to-nurses (ROPTN)	0.482**	0.482**
Nurses per bed ratio	-0.0024*	-0.0024
_Constant	2.906***	2.906***
Wald chi2(10)	43.35	
Prob > chi2	0.0000***	
Log pseudolikelihood	-4.986	

Note. *P ≤0.10, 10% level of significance. **P ≤0.05, 5% level of significance. ***P ≤0.01, 1% level of significance. Std. err. = Standard error. 95% CI = 95% Confidence Interval. Standard errors are adjusted for clustered observations.

The regression results in Table 29 show that hospital size based on bed capacity >372 hospital beds ($p < 0.01$), under one year-old mortality ($p < 0.05$), and ratio of physicians-to-nurses ($p < 0.01$) are all positively related with the CRS technical efficiency scores of hospital observations with a 1% level of significance; meaning that larger hospital size (higher number of hospital beds), higher proportion of under one year-old mortality in the catchment area, and higher ratios of physician per nurse are associated with higher technically efficient hospital performance. Since under one year-old mortality lost significance when regressed on bootstrap-adjusted CRS technical efficiency scores ($p < 0.447$), we accept the bootstrap-adjusted estimate and consider this variable to be a weak correlate of hospital efficiency once adjusted for bias. As for the population number of catchment area ($p < 0.01$), we see a negative association with the hospital CRS technical efficiency scores at the 1% level of significance. The coefficient amount for the population number in the catchment area as an environmental factor correlating to hospital efficiency is $-1.59\text{x}10^{-06}$, or - 0.00000159; although statistically significant, it is immaterial.

Assessing the Productive Efficiency of Public Versus Private Delivery of Care: First-Stage DEA Application

This second retrospective data analysis is a comparative study evaluating efficient productivity differences between public and private general hospitals in Kuwait during 2019-2020. Efficiency in productivity means that the aim of our DEA estimation model is to calculate the production efficiency of firms (hospitals units or DMUs) in the frontier by looking at output maximization while holding input levels constant (output-orientation). This makes the assessment an analysis of hospital productivity and performance efficiency in using given inputs to produce the most or highest levels of outputs.

After stratifying private hospitals according to bed size (number of beds as a proxy for hospital size), we included the largest (100-200 beds) private, medium sized for-profit secondary general hospitals to analyze against our much larger public MoH general hospitals. After mapping service availability of all hospitals in our sample in order to ensure each delivered similar levels of care, no other adjustments were needed and we conducted our first-stage DEA calculations on a sample of 12 general hospitals in Kuwait, six from the public sector and six from the private sector, distributed across all six governorates in the State of Kuwait (Figure 11).

Figure 11

Governorate Distribution of Public and Private Hospitals in Kuwait, 2019-2020

Descriptive statistics of all the input and output model variables used to fit the frontier estimation for our 12 public and private general hospitals are presented in Table 30. Physicians per hospital in the private sector ranged from 11 to 228, with an overall average of 120 full-time physicians. As for private sector nurses, staffing ranged from 72 and 451, maintaining an average of approximately 255 nursing workforce. As for the outputs, average annual discharges among the six private general hospital is 11,652 whereas we see in public general hospital for that same year an average of 36,337 discharges. Likewise, surgical procedures or operations performed per year in the public sector averaged at about 7,539 procedures annually, while the average in the private sector comes to 5,362 operations over one calendar year. Finally, we excluded casualty operations/emergency department values from the surgical procedures variable for a more even playing field as signs of confounding during input/output frontier modeling indicated some bias in public general hospitals (MoH emergency medicine/ambulance services hold an 80-90 percent majority share of the country's ambulatory care).

Table 30

Descriptive Statistics of Inputs and Outputs of Public-Private Hospitals in Kuwait 2019/2020

		INPUTS			OUTPUTS	
		Beds	**Nurses**	**Physicians**	**Surgical Procedures**	**Discharges**
Public	**Mean**	694	1724.17	852.67	7539.33	36336.5
	Std. dev.	206.95	329.54	274.52	4291.70	9846.57
	Median	744	1680.5	857.5	7152	33414.5
	Min.	418	1394	486	2589	23796
	Max.	955	2118	1153	12937	50523
Private	**Mean**	133.17	255.17	126.5	5362	11652.17
	Std. dev.	28.84	144.7	71.88	1966.88	5393.51
	Median	125	283	193.88	5215.5	9769.5
	Min.	112	72	50	2159	7049
	Max.	189	451	228	7500	21978
Sample Average	**Mean**	413.58	989.67	489.59	6450.67	23994.33
	Std. dev.	216.46	487.97	173.2	3129.29	7620.04
	Median	374.76	860.28	525.69	6183.75	21592
	Min.	265	760.78	268	2374	15422.5
	Max.	82	1284.5	690.5	10218.5	36250.5

Table 31 displays the correlation coefficients of input and output variables. We can see positive correlations between the inputs and outputs, satisfying the isotonicity property that an output does not decrease with increase in the input (Thanassoulis & Allen, 1998). The correlation coefficient between inputs and outputs ranged from 0.1608 to 0.9580 and the correlations are all statistically significant at least at the 10% significance level (p <0.1). Therefore, following Lee and Seo (2017), the selected inputs and outputs were not functional for analysis and further data transformation or manipulation is not required, such as variable reduction or dimension reduction techniques (Lee & Seo, 2017).

Table 31

Spearman's Rank Correlation Matrix of Inputs and Outputs

	Bed No.	**Physicians**	**Nurses**	**Annual surgeries**	**Annual inpatient discharges (admission proxy)**
Bed No.	1.0000				
Physicians	0.2028***	1.0000			
Nurses	0.9091***	0.9580*	1.0000		
Annual surgeries	0.6434**	0.1608 **	0.5105**	1.0000	
Annual inpatient discharges (admissions proxy)	0.7762***	0.2867*	0.9021*	0.3357**	1.0000

Note. *** Indicates significance level α = 0.01. ** Indicates significance level α = 0.05. * Indicates significance level α = 0.1.

Table 32 below shows the pooled descriptive statistics for our select environmental and organizational explanatory variables of inefficiency in public and private general hospitals during the census year 2019/2020. The average population of the catchment areas of the 12 hospitals is 808,734 with a standard deviation (Std. dev.) of 262,949 as well as a range of 287,372 to 1,182,528 across all six governorates of Kuwait.

Table 32

Descriptive Statistics of Environmental Factors

Variable	Mean	Std. dev.	Median	Min.	Max.
Population of catchment area (n)	808734.33	262949.19	971,645	287,372	1,182,528
Non-Kuwaitis (%)	65.59	13.29	75	40	80
Ratio of patients-to-physicians	0.46	0.14	0.489	0.153	0.671
Hospital ownership type dummy variable (1= MoH public, 0= private)	0.5	0.522	1	0	1
Nurse to bed ratio	2.236	0.7908	2.41	0.533	3.35

For our efficiency analysis, we assumed an output-oriented model with variable returns to scale (VRS) technology to estimate the production efficiency for each hospital using DEA. We decided to adopt the alternative extended model proposed by Banker, Charnes, and Cooper (1984) for estimating technical and scale inefficiencies (BCC model) under the VRS assumption, which, in practice, is based on the understanding that not all hospitals are operating at an optimal scale (Banker et al., 1984). In general, there are important economies and diseconomies of scale, our reasoning, or rationale, is that a hospital may be too large for the volume of activities it is conducting and therefore may experience *diseconomies of scale*; on the other hand, we also acknowledge that a hospital may be too small for its level of operation and thus may experience *economies of scale* (see Worthington, 2004; Masiye, 2007; Younsi, 2014; Zheng et al., 2018; Yang et al., 2021).

Due to their different production behaviors, it was expected that the input-oriented approach would favor public hospitals, while the output-oriented approach would favor private hospitals (Yin et al., 2021). However, this expectation does not imply that the efficiency scores of public hospitals are expected to be higher under the input-oriented model than under the output-oriented model. It also does not necessarily imply that public hospitals should be ranked higher than private hospitals under the input-oriented model, while the rankings should reverse under the output-oriented model (Varabyova & Schreyögg, 2013). Rather, the effect of the model orientation is shown in the margin of difference between the public and private efficiency scores: under the output-oriented model, private hospitals are more efficient than public hospitals by 8.9 percent, yet this difference narrows to 7.7 percent under the input-oriented model in the context of Kuwait.

Although the DEA model is relatively simple to estimate efficiency scores, it has several limitations, regardless of the objective pursued. In the simple search for the most efficient units, or the projections towards the frontier, we must show that the estimator of the efficiency measure is biased from its own construction. In order to avoid the problems related to the serial correlation, we used the Simar and Wilson (2007) procedure to correct the bias in the estimated efficiency score, while estimating the confidence intervals (Simar & Wilson, 2007). In Table 33, we show the results of the output-oriented DEA model and bootstrapped-DEA efficiency scores with 2,000 repetitions for individual hospitals.

Table 33

Efficiency Scores and Returns to Scale of MoH Public Hospitals and Private, For-Profit Hospitals in Kuwait, 2019

						95% CI		
DMU	**Facility type**	**VRS score**	**Scale**	**RTS**	**Mean bootstrap-adjusted VRS score**	**Bootstrap lower bound**	**Bootstrap upper bound**	**Bootstrap bias**
Taiba Hospital	Private general hospital	1	1	DRS	1	1	1	0
New Mowasat Hospital	Private general hospital	1	1	DRS	1	1	1	0
Mubarak Al-Kabir Hospital	Public generate hospital	0.618	0.363	DRS	0.594	0.535	0.6198	-2.42
Hadi Clinic	Private general hospital	1	1	CRS	1	1	1	0
Dar Al Shifa hospital	Private general hospital	1	1	DRS	1	1	1	0
Al-Sabah Hospital	Public generate hospital	0.835	0.629	DRS	0.798	0.671	0.837	-3.74
Al-Jahra Hospital	Public generate hospital	1	0.571	CRS	1	1	1	0
Al-Amiri Hospital	Public generate hospital	0.905	0.5097	DRS	0.878	0.809	0.906	-2.64
Al Seef Hospital, Salmiya	Private general hospital	0.809	0.980	DRS	0.772	0.650	0.8098	-3.67
Al Salam International Hospital	Private general hospital	0.961	0.780	DRS	0.937	0.922	0.963	-2.42
Al Farwaniya Hospital	Public generate hospital	0.933	0.302	DRS	0.904	0.866	0.934	-2.84
Al Adan Hospital	Public generate hospital	1	0.379	DRS	1	1	1	0
Overall Average	______	0.9217	0.709	_____	0.907	0.871	0.922	-1.478

Note. VRS, variable returns to scale (pure technical efficiency). RTS, returns to scale. DRS, decreasing returns to scale. CRS, constant returns to scale. 95% CI, 95% Confidence Interval.

Based on Table 33, the rankings did not change substantially after bootstrapping, however, overall pure technical efficiency scores were generally reduced. According to the bootstrapped mean scores in Table 33, the average VRS technical efficiency for the entire sample now stands at 0.907 (90.7%); meaning that, from the same input levels, these hospitals could potentially increase their outputs by 9.3 percent to reach the relative maximum efficiency level. In addition, no hospital, after bootstrap was applied, lost its previous efficiency status and scored under a bootstrapped value of 1. The average scores for the initial BCC model, also in Table 33, was 0.9217 (92.17%), resulting in a 50 percent split of fully efficient public and private general hospitals in Kuwait during the production year of 2019/2020. Figure 12 illustrates this productivity by health sector.

Figure 12

Visual Comparison of Production Efficiency and Output Maximization in Public-Private General Hospitals in Kuwait, 2019

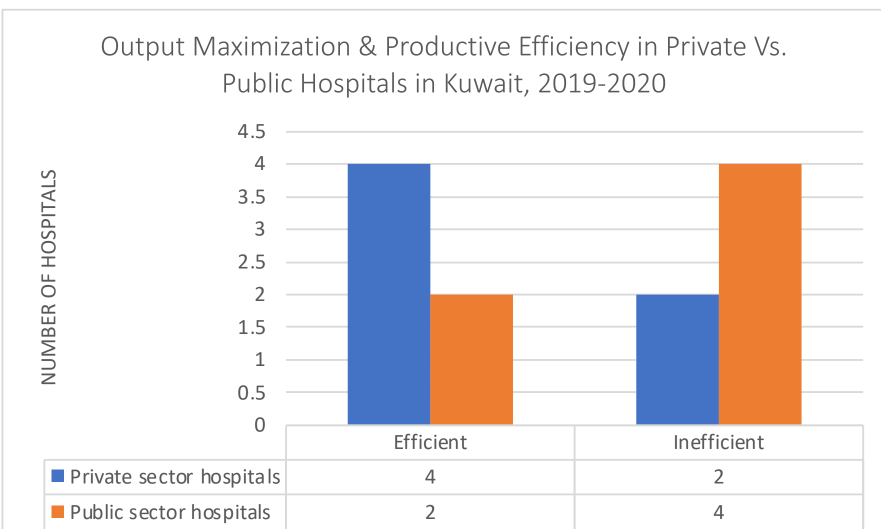


Table 34 collects the descriptive statistics both for the original and the bootstrap-corrected efficiency, for the different inefficient hospitals and for the overall health sectors. Like Simar and Wilson (1998), corrected efficiency estimates were obtained using 2,000 repetitions (bootstrap iterations) (Simar & Wilson, 1998, 2003, 2007).

Table 34

Descriptive Statistics of BCC Output Model and VRS Scores, Original and Adjusted Efficiency by Health Sector

		Original Efficiency	Adjusted Efficiency
Inefficient private hospitals (n=2)	Mean	88.47	85.425
	Std. dev	10.78	11.66
	Min	80.85	77.18
	Max	96.09	93.67
All private hospitals (n=6)	Mean	96.16	95.14
	Std. dev	7.66	9.16
	Min	80.85	77.18
	Max	100	100
Inefficient public hospitals (n=4)	Mean	82.275	79.365
	Std. dev	14.23	14.05
	Min	61.84	59.42
	Max	93.28	90.44
All public hospitals (n=6)	Mean	88.18	86.24
	Std. dev	14.33	15.23
	Min	61.84	59.42
	Max	100	100

Computationally, the technical efficiency scores relate to the distance of a hospital's current production point from its respective benchmarking frontier. Indeed, each public hospital does, in fact, 'produce' higher numbers of patient discharges and inpatient surgical procedures than private hospitals; however, for this output-oriented model, the efficiency scores measure the volume of output that a hospital is currently producing, relative to the maximum volume it could potentially produce from its current inputs. That said, we must always consider how public hospitals, in general, enjoy a much larger clinical workforce, much more hospital beds per 1,000 population, and much higher health expenditures compared to private hospitals, thus, those vast input levels that enter the public hospital's production process are included to assess how much more outputs they could have cranked out basically, relative to what or how much resources were being put in. For example, in terms of Mubarak Al-Kabeer Hospital with a bootstrap-corrected, output-oriented efficiency score of 0.5942 suggests that this MoH public general hospital in 2019-2020 was producing 59.42 percent of its full output potential. This would be interpreted to mean that Mubarak Al-Kabeer Hospital was producing at 40.58 percent below its maximum capacity, or that it has the potential to increase its current output level by 40.58 percent without needing to increase its resources.

We used the Mann–Whitney, or Wilcoxon nonparametric test, in order to observe any differences in the efficiency scores between the models before and after the bias correction and to determine whether the bias adjustment helped us improve our results. We recorded a Z statistic value of -21.12 ($p < 0.01$, p-value = 0.0014), therefore, we rejected the null hypothesis of equality between the efficiency scores and adjusted efficiency score. The results show that bootstrapped efficiency scores are always lower than those of the original efficiency, as the latter do not take into account the sampling ‘noise’. Therefore, analysis based on the conventional DEA model can lead to erroneous conclusions by ignoring the bias inherent in the DEA procedure (Simar & Wilson, 2000).

To test the robustness of DEA results, we conducted a sensitivity analysis by omitting an input or an output and then studying the results. The score and the biased-adjusted score for each model are calculated and the mean of the scores obtained are shown in Table 35. We can verify that changes in efficiency are observed for all input and output removals from the BCC model, confirming each variable’s contribution to the efficiency frontier estimation. Total full-time physicians seemed to be the variables that had the least influence on the level of efficiency. The variable with the greatest effect was hospital beds, since it constituted the most important input in this type of scale efficiency. Nevertheless, overall, the different models validated the conclusions of the original DEA model.

Table 35

Means Original and Adjusted VRS Efficiency, BCC Model with and Without Each Input and Output Variable

Mean	BCC model	BCC without total hospital beds input	BCC without physician input	BCC without total nurses’ inputs	BCC without discharges output	BCC without surgeries performed output
Original efficiency	92.17	88.04	92.17	91.51	72.99	82.49
Adjusted efficiency	90.693	85.48	90.75	89.87	67.53	79.39

Finally, additional details such as the efficient refrents (benchmarks) for each of the individual DMUs are available in Appendix B; allowing readers to observe which hospitals can be paired and used as 'role models' for inefficient DMUs for benchmarking purposes.

The Effects of Hospital Ownership on Optimal Production Performance: Second-Stage Tobit Regression

We went on to analyze the impact of the context variables on hospital management carried out by public MoH ownership and private, for-profit ownership models in each healthcare facility; measured through the bootstrap-adjusted technical efficiency levels we computed above. Again, DEA is a highly convenient and popular non-parametric approach to examine performance and productivity in healthcare; however, it could not provide statistical information such as confidence intervals on the estimated efficiency scores and we applied bootstrapping to disentangle noise and bias from the DEA efficiency scores and accordingly provide confidence intervals for estimated hospital efficiency. Lothgren and Tambour (1999) argued that by using bootstrap, one can resample the observed sample to be an approximation of the population; simply put, the efficiency scores observed from DEA are only a sample of the population (of the efficiency scores) and therefore our first bootstrapped-DEA application provided better estimators of the efficiency scores but an additional round of strapping permits valid inferences as well in statistical regressions. We further went on to apply additional bootstrap iterations to our second-stage Tobit regression analysis so that parameters could be estimated in 32 bootstrap replicates ('double-bootstrapping'; see Simar & Wilson, 200, 2007, 2013).

The public-private Tobit regression model is shown below, followed by the coefficient results of the bootstrap truncated regression with robust standard errors adjusted for clustered observations and presented in Table 36.

Public-Private Tobit Regression Model

Technical efficiency = $\beta 0$ +$\beta 1$(Population in catchment area) +$\beta 2$(non-Kuwaitis) +$\beta 3$(ownership type dummy variable; public/MoH ownership model = 1) +$\beta 4$(Ratio of patients-to-physicians) +$\beta 5$(Nurse to beds ratio) +ε

Table 36

Second-Stage Tobit Regression Analysis of Factors of Inefficiency in Public and Private Hospitals in Kuwait, 2019/2020

Explanatory Variables	Bootstrapped-Tobit Coefficient
Population of catchment area (n)	$1.06\text{x}10^{-6}$ *
Non-Kuwaitis (%)	-0.0752
Ratio of patients-to-physician	-0.2081**
Nurse to beds ratio (Staffed beds)	0.017**
Ownership type (MoH/public)	-0.1918***
_Constant	1.563***
Wald chi2(5)	6.81
Prob > chi2	0.0000***

Note. Standard errors are adjusted for clustered observations.

In Table 36, the variables reported as negative values suggest they affect hospital efficiency negatively (negative correlation). The Tobit regression indicates that when the ratio of patients-to-physicians decreases 20.8 percent, the efficiency scores would increase to 100%, meaning ratio of patients-to-physicians can negatively and significantly drive inefficiency. However, the nurse-to-bed ratio in Table 4.21 shows an increase of 1.7 percent would increase efficiency output to 100%; thus, is a favorable indicator to make a hospital perform productively. Lastly, ownership type and its several influences on hospital management is empirically shown in Table 36 to impact efficiency and possibly drive inefficiency in DMU operations, production process, and output maximization and productivity.

Coefficients from Tobit regressions with dummy variables are not readily interpretable as effect sizes. Interpretation of these coefficients are able to assess the negative or positive sign of the coefficient and whether it is statistically significant or not. Considering the number of efficient hospitals in each sector, it is possible to draw conclusions from ownership coefficient values. Looking at MoH-operated and government-owned hospitals dummy variables in Table 36, public government ownership negatively affects hospital efficiency by at least 19.2 percent, while private ownership is suggested to be positively associated with hospital efficiency. We interpret this negative dummy variable coefficient as a problem of hospital management, lack of organizational leadership, poor governance, and resource allocation and priority settings. This failure is a call for action, Kuwait's MoH requires a more responsive system of governance and management before attempting another hospital expansion project, which, according to DEA performance trends, will likely operate at an average of 78 percent efficiency.

Finally, we looked at potential output improvements, or output increases expected for each public and private hospital with current input levels if hospitals were to operate as efficiently as their peers. Most noteworthy is that in order to reduce the amount of leakages due to inefficiency for census year 2019/2020 in Kuwait, the largest output increases are to be made in the public sector with a pooled average of approximately 436 percent compared to 60 percent in the private sector. In other words, these are the potential gains that should be reaped by the health sector at no extra cost if inefficient hospitals were to operate productively. Further details are outlined in Appendix B.

Chapter Summary

In addition to the determinants of efficiency, additional evaluation and research is required in the technical and allocative efficiency spheres to generate evidence-based knowledge on the causes of inefficiency and challenges in healthcare products in the public sector and to guide potential reforms of health policies and objectives for public hospitals in the State of Kuwait.

Overall, research on ownership and comprehension of organizational decision-making and market-level dynamics can lead to a better knowledge of the institutional environment in which provider performance is affected by ownership. It will help identify which institutional reforms could improve performance, based on best practices. The following chapter concludes the dissertation research with a discussion analyzing the above findings and exploring the different stories behind the decimal points.

Chapter 5

Anatomy of Public Health Efficiency in Kuwait: Discussion and Conclusions

With healthcare forming an increasing share of Kuwait's GDP, government health expenditure has heightening concerns with fiscal sustainability and productivity in the public sector. In the allocation of government funds for goods and services, societies spending more on healthcare, in effect, opt to invest in human capital in the form of health, where health status influences labor inputs and contributes to production of goods and economic growth. Thus, health spending must be viewed, at least in part, as an *investment* rather than expense such that a high return on investment suggests investment's gains compare favorably to its cost.

This dissertation begins with a theoretic analysis of the inherent challenges in measuring health system efficiency. If we consider the non-market context of public healthcare delivery, it is difficult to offer the necessary incentives for productivity improvement. On the one hand, one would believe it fairly simple for policymakers to design more efficient health systems and for hospital management to push efficiency within such systems. However, the obstacles involved are not theoretical, but rather practical, such as whether inputs and outputs are measured correctly and whether the right incentives are in place to ensure managers can achieve efficiencies once identified (Cullen & Ergas, 2014). The empirical investigation first estimate the 2015-2019 efficiency of public healthcare services in MoH hospitals in the State of Kuwait in terms of outputs; the analysis then turns to the drivers of inefficiency in health, as an understanding of these drivers and the types of inefficiencies that arise in health is essential to the development of measures of productivity and efficiency that will actually assist managers and policymakers in identifying and rectifying inefficiencies. In addition, we assessed possible managerial impacts of hospital inefficiency by comparing efficient production (productivity) in Kuwait's public versus private sectors in view of ownership differences.

This final chapter addresses the findings and limits of our research; discusses policy implications and provides policy recommendations to enhance performance efficiency in the Kuwaiti public health system and the MoH's delivery of care.

This dissertation was able to successfully address the following:

1. Were hospitals producing the maximum outputs with the available inputs over the 2015-2019 census year?
2. Could hospitals have reduced current or available inputs while still producing the same levels of outputs during that same five-year period?
3. If recognized *inefficient* hospitals were performing *efficiently*, how much more outputs should they have produced? How much less inputs would they have needed to consume?
4. Were MoH public hospitals operating at optimal scale? Were MoH hospital performance on the efficiency scale comparable between public general and public specialized hospitals?
5. What was the trend of hospital productivity?
6. What percentage of observed productivity changes can be attributed to environmental factors? Driven by hospital ownership type? Impacted by hospital management and organizational governance determined by ownership models for the census year 2019/2020?

Addressing Research Findings

This dissertation employs a wide range of hospital efficiency indicators to provide empirical evidence on the relative efficiency of MoH public hospitals in Kuwait for the years 2015-2019, inclusively. Using robust methodologies, we revealed consistent results indicating the same directions of the effects of several variables on measures of efficiency. The empirical findings in the chapters included the measurement of efficiency levels and the analysis of factors determining efficiency and potential institutional drivers of inefficiency; as well as a comparative analysis of public versus private general hospitals to determine whether one sector truly outperforms the other on the basis of ownership variance and to better understand potential barriers to efficiency in light of operational managerial differences that come with ownership models of hospital care.

Lastly, recommendations for improvements are discussed centered on these findings. Our analysis included 15 MoH public hospitals – six general and nine specialized – operating consistently from 2015 to 2019, not missing any variables over the five-year period and not considered facilities of long-term care activities. The public hospitals in our sample are distributed across five out of six administrative governorates of Kuwait, indicating that this research is representative of Kuwait's MoH public health system. This dissertation is, to the best of our knowledge, the first to employ national health datasets from Kuwait between the years 2015 and 2019, inclusively; incorporating a wide range of hospital characteristics using robust statistical tools to determine the efficiency changes of public hospitals over this five-year timeframe.

Estimating Efficiency and Productivity: Data Envelopment Analysis

The actions towards efficiency in resource utilization would contribute to the ongoing global challenge of achieving universal health coverage (UHC), as declared in target 3.8 of the Sustainable Development Goals (SDGs) by the United Nations (UN, 2015). Our current research appears to be useful for addressing both the national interest of the Kuwaiti public health system as well as the global mission of UHC. Such findings would also be helpful for high-income Gulf nations, and if anything, encourages more investment and prioritization of data collection tools in the Middle East and North Africa (MENA) region as a whole. Our comprehensive systematic literature review and meta-regression analysis of hospital efficiency studies (Chapter 3) yielded valuable evidence for the development of a clear conceptual framework from which to approach the measurement of efficiency using DEA methodology and that which we applied to our empirical investigations. In general, the number of efficiency studies from the Arabian Gulf was limited; particularly considering hospital efficiency studies from the State of Kuwait.

Furthermore, in Chapter 3, we noticed that studies from the MENA region have considerable deficiencies in terms of quality and reliability, as well as methodological applications compared to relevant studies from other regions of the world. Our systematic literature review clearly demonstrates a need for further research into the performance of the public health sector in order to determine the (in)efficiency of government facilities in delivering care and to assist policymakers in identifying appropriate indicator data and methodological approaches to measure and evaluate efficiency. The meta-regression analysis in Chapter 3 indicates that the methodologies, technological assumptions, model orientation, and hospital variables utilized in DEA for the estimation of the efficiency frontier have major effects on efficiency analysis.

Data envelopment analysis (DEA) is a widely applicable method for assessing efficiency in healthcare because it does not require prior specification of the underlying functional form and can include multiple input and output variables in various assessment units (Hollingsworth, 2003; O'Neill et al., 2008). Consequently, DEA was the approach of choice for Chapter 4’s empirical efficiency analysis. This research constructs empirical benchmarks based on Kuwaiti MoH hospital efficiency analysis using input orientation and public-private general hospital productive efficiency using output orientation. In addition, since we assumed the position that MoH hospitals may have more control over the inputs than the outputs, the input orientation analysis was determined more appropriate in the context of public hospital efficiency analysis based on previous international studies (Cooper et al., 2007; Chuang et al., 2011; O'Neill et al., 2008); whereas the opposite is true for private hospitals.

The specific objectives of this dissertation, overall, were met since we were able to: (i) estimate the relative technical and scale efficiency of MoH general and specialty hospitals in Kuwait in 2015-2019, inclusively, as well as relative managerial (‘pure') technical efficiency and productivity in private vs. public general hospitals in Kuwait for the census year 2019/2020; (ii) estimate the magnitude of output increases and/or input reductions that would have been needed to make relatively inequitable hospitals more equitable (slacks and input/output targets); and (iii) use Tobit regression as a means to identify potential environmental and institutional factors of efficiency, as well as estimate the impact of ownership, governance, and management on health sector efficiency and productivity.

Empirical Evaluation of MoH Public Hospitals and Efficiency Analysis

The relative efficiency of MoH public hospitals in Kuwait between 2015 and 2019 revealed that the majority of hospitals were technically inefficient in Chapter 4; the bulk of inefficiency was mostly attributable to specialized hospitals over the five-year period as displayed in Table 24. When further stratified by hospital size (bed capacity) in Table 25, large MoH general hospitals (≥ 500 beds) seem to be more technically and scale efficient (94 percent), while small MoH specialized hospitals (< 100 beds) show higher technical CRS (84 percent) and VRS (100 percent) efficiency than upper- to lower- medium sized hospitals (100-499 beds) with 81 percent and 37 percent technical efficiency, respectively; indicating potential for capital input reduction of hospital bed numbers as a means to improve efficiency and diseconomies of scale in the *inefficient* lower-medium sized Infectious Disease Facility and Kuwait Cancer Control Center specialized hospitals (100-299 beds) as well as observations in the *inefficient* upper-medium sized Al-Amiri general, Al-Sabah general in 2019, Al-Razi specialized, Maternity specialized in 2015, Ibn Sina specialized in 2018, and Chest Diseases specialized hospitals (given their current levels of outputs if they are to be held constant).

The pooled average efficiency of MoH hospitals from 2015-2019 was 79.18 percent as indicated in Table 27; where the bootstrap-adjusted efficiency score was 73.91 percent (95% confidence interval: 67.90 – 79.68 percent), indicating that the 15 hospitals evaluated could have decreased health resources by 26.09 percent without compromising health service delivery. Overall, MoH general hospitals were more efficient than specialized hospitals, with a five-year bootstrap-adjusted TE average of 86.58 percent compared to 65.47 percent for MoH specialized hospitals (Table 28).

Interesting findings, to name a few, were in Table 22, where we see specialized hospitals, such as Ibn Sina, achieving perfect technical (CRS), pure technical (VRS), and scale efficiency scores each year except for in 2018, where it was found to be 86 percent technically efficient with a VRS score of 88 percent and a SE score of 98 percent before jumping back to full efficiency again in 2019. Again, in Table 22 – further detailed in Table 23 – the same is seen for the Maternity specialized hospital as well, where the hospital begins with 99 percent technical efficiency, a VRS score of 100 percent, and a SE score of 99 percent in 2015, however, achieves full efficiency throughout the remaining four years from 2016-2019.

The improvement of the Maternity hospital from a one-year low of marginally under 1.00 technical efficiency in 2015 (0.99 average TE, but 0.9841 bootstrap-adjusted mean TE shown in Table 27) and the technical efficiency change of Ibn Sina in 2018 (before recovering in 2019), can generally be explained by looking at the decomposed values of pure technical change (whether hospital managers have improved using resources) or scale efficiency change (whether the hospital has moved to an optimal scale relative to the frontier). Scale efficiency is caused either by (i) changes in the shape of the technology; (ii) change in the location of the hospital in the input/output space from one year to the next; or a combination of both (i) and (ii) (Hollingsworth, 2008). However, in the case of Ibn Sina, for example, its 2018 decline of pure TE (VRS score) to 0.88, compared to a SE score of 0.98, can be implied that the 2018 dip in technical efficiency may be attributed to poor hospital governance and management and was most likely a result of the change in the pure technical efficiency of that year that is usually caused by a movement of the hospital relative to the existing technology (under managerial control). As a matter of fact, we noted the Maternity hospital, for instance, was indeed undergoing managerial changes in 2014-2015 and Ibn Sina was also found to be undergoing the same alterations in management throughout 2018 (Kuwait MOH Annual Health Bulletin, 2014/2015, 2017/2018).

Another observation was in the case of pooled slacks in MoH public hospitals for 2015-2019. Table 26 shows that for inputs, the values indicate an excess of hospital beds to be the capital input variable linked to inefficiencies in *inefficient* (< 1 TE) public hospitals. This is not a surprising result, if one considers the potential inefficiency and excessive costs that excess bed capacity can generate and during periods where their effective occupancy is too low; it then becomes a viable option to reduce, or move away, from increasing bed numbers as a method of addressing efficiency and focus instead on optimizing the use of existing hospital beds as a better method for improving efficiency of operations and enhancing overall cost-effectiveness.

According to our findings in Table 26, a feasible average reduction in the number of beds for *inefficient* hospitals is approximately 16 percent of the current bed capacity (compared to quantities of input/output statistics). If we look at other significant slack among *inefficient* hospitals, our human resources input variables in Table 26 and further detailed in Appendix B show that physician numbers are close behind with an excess utilization of about 19 percent. A surplus of nurses in *inefficient* hospitals is also an important source of inefficiency that should be reduced by an average of approximately 17 percent.

In addition to input reductions, output slacks in Table 26 indicate that the average number of hospital services in *inefficient* hospitals need to be increased in order to meet targets (should inefficient hospitals opt to keep inputs constant instead, without any reductions in their consumption levels), where the average number of outpatient and emergency visits (total visits) could be further increased by 1.13 percent to meet the target efficiency. Again, this is all based on economies of scale and centered around current levels of production. It is noteworthy to remember that these slacks are associated with pooled *inefficient* hospitals for 2015-2019, whereby giving them the option of reducing capital (beds) or human capital (physicians/nurses) based on maintaining their current levels of outputs; or increase their total visits outputs services (outpatient & emergency visits) if input levels are to be kept constant.

Prior work also supports these results. In similar context, Gok and Sezen (2011) looked at Turkish hospitals and determined that one crucial way to increase the efficiency of the Turkish public or state hospitals is by decreasing investments in the health field and/or increasing the production factors, such as the existing beds or physicians (Gok & Sezen, 2011). Moreover, the argument that high investments in equipment (technology) and resources are required to treat patients can breed hospitals' inefficiency (Rezapour et al., 2011). A noteworthy consideration is the absence of any slack in annual patient discharges in the inefficient hospitals; implying that no further increases in adjusted discharge numbers (proxied by inpatient admissions) are needed at this time to reach efficiency targets. Therefore, Kuwait's public health system should start planning different ways to deliver healthcare services to a growing pool of patients through the effective utilization of existing resources.

The findings in Chapter 4 further propose adjustments to production capacity by downsizing the hospitals operating on DRS and reallocating their resources to the hospitals on IRS, as reflected by our scale analysis in Table 27 (Gok & Sezen, 2013). In addition, according to our Tobit regression in Table 29 (where standard errors were adjusted for clustered observations), the institutional factor of physician-to-nurse ratio appears to be positively correlated with hospital efficiency with a statistically significant bootstrap-adjusted coefficient of 0.482 ($p < 0.01$), while the environmental factor measuring the percent of non-Kuwaitis in the catchment area was found to be negatively associated with efficiency with a statistically significant coefficient of -0.2083 ($p < 0.01$); overall suggesting the misallocation of health workers as a potential impediment to full efficiency in MoH hospitals and advising decisionmakers they may need to redeploy their labor forces for effective utilization of medical capacity as well as provide higher additional facilities in areas with higher rates of expatriate populations in light of the legal conditions and regulations in Kuwait. These results also suggest, until Pareto optimality is reached (where technical efficiency is 1 and slacks are zero), any potential reallocation of resources must not compromise patients' current access to public hospitals. The findings of Chapter 4 may assist *inefficient* public hospitals in benchmarking their care delivery system and overall performance in comparison to *efficient* hospitals with comparable capacities with the aid of efficiency peer data provided in Appendix B.

Before beginning the process of health resource redistribution, any relocation of resources from inefficient to efficient hospitals must be based on regular discussions with health officials, hospital management, and MoH decisionmakers. The fundamental objective of this approach should be to increase the usage of health resources, while ensuring that such efforts do not negatively impact the delivery of healthcare services to the catchment population. Overall, the results of our MoH public hospital analysis imply that hospital efficiency and resource allocation policies and plans should be revised to account for the demographic diversity of catchment populations (i.e., population density and service utilization in catchment area). In order to promote efficient and equitable health services in the State of Kuwait, policymakers should pay additional attention to ensuring the correct allocation mechanisms of health resources and expanding the utilization of health services among target populations.

Public Vs. Private Sector Performance Measures and Productivity Outcomes

For our comparative study conducted for the census year 2019/2020 between the two largest health sectors in the country (the public and private delivery of care), this is the first of its kind to examine the production efficiency of private versus public general hospitals in Kuwait, in light of ownership differences; where the potential impact that governance may have on hospital performance and what this would mean for the future of the Kuwaiti public health system was explored. Using an output-oriented analysis of pure efficiency (VRS score) to assess productivity based on different ownership models in public versus private hospitals, we find ownership to be a potential driver of efficiency and the associated managerial practices in private hospitals to be among the institutional factors influencing greater output production compared to public hospitals.

The comparative study of public-private health sector productivity filled in knowledge gaps and enhanced our understanding of hospital efficiency and determinants of *inefficiency* by examining key ownership differences between public and private hospitals; addressing how hospital management, governance, and organizational leadership translate into hospital performance, productivity, and overall output production efficiency. Despite much smaller bed capacity and hospital size, much less general government health expenditure in the domestic private healthcare sector, and a fraction of the exponentially growing MoH clinical workforce, Table 33 (illustrated graphically in Figure 12) indicates that 66.7 percent of private, medium-sized (100-200 beds), general hospitals in Kuwait are able to operate efficiently using current levels of inputs to maximize their total level of production outputs without consuming any additional resources. In comparison, 33.3 percent, or a third of Kuwait's public MoH general hospitals during the 2019/2020 census year, were able to achieve efficiency. The two public hospitals that were found to be efficient, according to Table 33, were Al-Adan Hospital and Al-Jahra Hospital; these public general hospitals are the same facilities that recently completed extensive 'mega' expansion projects around that time and have been suggested (post-construction) to be capable of providing tertiary level of care – though remain secondary acute care providers.

Additionally, Table 34 indicates that the average efficiency score of *inefficient* private hospitals (n=2, VRS score <1) was 85.43 percent, while the overall mean efficiency of all six private general hospitals in our sample was 95.14 percent. For public general hospitals, we see that the average efficiency score of *inefficient* MoH general hospitals (n=4, VRS score <1) was 79.37 percent, with an overall mean efficiency for all six public general hospitals at 86.24 percent. When assessing the ultimate question of ownership type in hospital performance and considering impacts of managerial differences in governance on efficiency scores, our bootstrapped Tobit regression analysis (with standard errors adjusted for clustering in Table 36) reveals that our reference ownership type (public/MoH =1) is negatively associated with efficiency; with a statistically significant coefficient of -0.1918 ($p < 0.01$). Other institutional factors include patient-to-physician ratio and nurses per hospital bed, where we see a high ratio of the former to be negatively correlated with efficiency at a statistically significant coefficient value of -0.2081 ($p < 0.05$), and a low ratio of the latter to be positively associated with efficiency with a statistically significant coefficient value of 0.017 ($p < 0.05$).

These findings on public versus private efficiency in Kuwait are extremely informative, especially since it explores the notion of health sector productivity differences in the Kuwait context. There are numerous research studies exploring the effects of hospital ownership on technical efficiency, with DEA being the most well-known and commonly used non-parametric methodology. Reviewing 317 published studies, Hollingsworth concluded that public hospitals in Europe and the United States might provide medical services more efficiently than private hospitals (Hollingsworth, 2008). Using meta-analytic approaches, Shen et al. (2007) verified the impact of hospital ownership on efficiency, but they were unable to conclude that private hospitals operated more efficiently.

Ozcan et al. (1992) and Burgess and Wilson (1996) concluded, using DEA, that public hospitals were more efficient than private hospitals and that there was a difference in efficiency between private, for-profit and public, non-profit hospitals. However, according to Brown (2003), private hospitals are more efficient than public government hospitals. Later, Tiemann and Schreyogg (2012) found that the efficiency of public hospitals in Germany increased by 2.9 to 4.9 percent following privatization, however, Helimig and Lapsley (2001) discovered that public, welfare hospitals were more efficient than private, for-profit hospitals. Therefore, empirical research conducted across the globe have yet to establish a consensus on the efficiency of hospitals with diverse ownership status. Impact of ownership on efficiency findings are exclusive to Kuwait and shed extremely important light on what the private sector does right in terms of maximization of outputs while keeping inputs constant; and what the public sector can take away from these important results, if anything, is the concept of hospital management and the power of strong leadership governance in hospital settings that efficiently allocate health resources.

Although future studies should investigate how hospital ownership models and other aspects of hospital market composition affect healthcare productivity, and focus on whether for-profit hospitals have important spillover benefits for healthcare productivity; we were able to show, for the first time through this dissertation, that Kuwait's private, for-profit hospitals in the 2019/2020 census year were more productive based on hospital ownership status, leading to improvements in management efficiency gains. Also, that barriers to hospital efficiency in public hospitals include ineffective management, perhaps a lack of strategic planning and goals and weak administrative leadership, when compared with output-oriented private hospital VRS ('pure' technical efficiency) scores. Since previous, albeit limited, studies on hospital technical efficiency in Arab Gulf states focused on input-oriented, CRS scores of public hospitals due to the slow development of private hospitals in the region, this is the only study that explores the impact of hospital ownership on efficiency. Several non-MENA regional studies speculate that private, for-profit hospitals entering the market would compete with established public hospitals, which will drive public hospitals to change their behavior and improve efficiency by offering higher physician salaries and acquiring the latest high-tech medical equipment. However, there has been no empirical comparisons of efficiency and productivity between public and private hospitals in Kuwait; especially when considering the rapid development of the private sector in the region over the past two decades, there is a dire need to further understand performance differences between the two ownership models and evaluate determinants of inefficiency beyond the simple external, environmental factors of the catchment area.

Study Limitations

Finding data for trend analysis of hospital efficiency in Kuwait presented numerous obstacles for this doctoral research. For example, we had to limit our comparative analysis of public-private efficiency and productivity to a single census year (2019-2020) because of available aggregate variables and data sources lacking the necessary details for manual stratification of private sector aggregates from the prior census periods (namely 2018 and the first quarter, Q1, of 2019), which hampered the implementation of productivity change estimates using the Malmquist productivity index. Also, for our output variables, there was insufficient data on the severity of cases, the case mix, or even the quality of services.

Therefore, attempts to utilize the mortality rate as a proxy for service quality proved futile; the lack of available data on individual hospital discharges (dead vs. alive) was an additional limitation. Indeed, availability of quality variables would enhance future analyses for more robust findings that can be used to develop evidence-based healthy policy decisions with better accuracy and higher significance. Possible suggestions include the adoption of a standard classification system, such as diagnosis-related groups (DRGs), and implementation of better data collection tools altogether. Another limitation that led us to divert from our other aim to evaluate allocative and economic efficiency was the lack of hospital cost and input price data in national datasets, or any possible way to de-aggregate fiscal data variables when referencing national accounts reported by the Kuwait Ministry of Finance (MoF). Consequently, the objective of this study was the evaluation of the technical efficiency of public hospitals to relate MoH hospital performance with public health system efficiency.

The lack of consistent electronic information system usage in all MoH public hospitals was possibly the most data-limiting factor in this study and will undoubtedly pose a significant barrier for future healthcare efficiency studies in Kuwait. Another consideration was that although 'on paper' patients should be referred to tertiary specialty hospitals either by secondary general hospitals or more ideally through primary health centers (PHCs) as gateways into the public health system, with the absence of a referral system linking service providers, it was virtually impossible to accurately determine the population number of catchment areas and we instead opted for figures of catchment areas associated with hospital governorate locations and population reported yearly in relative health regions. Therefore, improvements to the health referral system are essential for optimizing patient health records. In addition, the absence of numerous hospital-level variables for DEA and second-stage Tobit regression led to the elimination of three private hospitals from our comparative study as well as one new MoH public specialty hospital as a direct result of unspecified, missing data values in private sector aggregate variables and inconsistent, poor data collection techniques for reliable values of newer MoH public hospitals. Thus, the construction of a health information system is essential for optimizing hospital records before any recommendation can be made for future research or direction in hospital efficiency analysis in the State of Kuwait.

Two-staged DEA analysis was conducted, comparable to techniques applied in a number of previous publications aiming to evaluate hospital efficiency as well as determinants of inefficiency. Furthermore, bootstrapping DEA was additionally used to provide bias-corrected estimates and 95% confidence intervals for efficiency scores. Although bootstrapping with replacement (sample size of five DMUs for the public-private comparative study; while sample size of six hospital units for our MoH efficiency analysis) was not required, given we had conducted several sensitivity analyses and diagnostic tests (including sensitivity analysis for DEA, multicollinearity, heteroskedasticity, etc.; none of which revealed any major potential bias exceeding $\pm$ 2), we nevertheless performed bootstrapped-DEA with 2,000 iterations as described by Simar and Wilson (1998, 2003, 2007) to ensure robust and accurate results, in the case of the State of Kuwait, that can prove more reliable based on stringent statistical methods used.

When considering the degree to which this evidence-based analysis supports our claim about the effect of exogenous variables (institutional and environmental factors) on hospital efficiency, within the context of Kuwait, we cannot rule out alternative explanations for our findings (i.e., sources of systematic error or bias) despite the application of standard statistical procedures. Still, the stringency and robustness of our analysis minimizes, to the extent possible, bias of observed values in our statistical sample from their ‘true value’ of performance efficiency scores not necessarily observable; thus, establishing internal validity. Finally, the extent to which our efficiency results can justify conclusions about other contexts of hospital efficiency is limited; efficiency values and driving factors of inefficiency are in the context of Kuwait’s MoH public general/specialized hospitals between 2015 and 2019, inclusively, as well as private, for-profit hospitals during the 2019/202 census year, therefore, external validity of this study and its generalizability is contextual and may be restricted by health system and region.

Policy Implications and Recommendations

On the basis of our research in MoH hospital efficiency in Kuwait from 2015 to 2019 and the productivity of general hospitals in the Kuwaiti public and private sectors during the 2019-2020 census year, the following recommendations are made with policymakers – especially officials in Kuwait's Ministry of Health – in mind. The goal is for the implementation of more evidence-based health policies that are backed by rigorous empirical research and well-established scientific practices; enhancing government hospital performance and thereby the efficiency of the Kuwaiti public health system as well as regaining public trust in the public health sector and boosting political will for future healthcare reform:

Recommendation 1

Based on findings from our MoH study that assesses relative efficiency of general and specialized public hospitals in Kuwait over a five-year period, decisionmakers should first develop stringent standard procedures for the efficient use of hospital resources and their reallocation within the public health system.

Recommendation 2

The prospective reallocation of hospital beds and human resources (general clinical staffing, ratio of physicians-to-patients, nurses per hospital bed ratios) based on efficiency findings necessitates downsizing hospitals operating under decreasing return to scale (DRS) and the reallocation of those resources to hospitals operating under increasing return to scale (IRS); of course, this should be done without jeopardizing current healthcare access.

Recommendation 3

According to productivity measures of public general hospitals compared to private general hospitals, in view of ownership models which impacts mission and hospital goals, as well as management focus (private, for-profit priorities versus public, non-income oriented, public welfare priorities), pure technical efficiency (VRS scores) and scale efficiency (SE) of private hospitals were found to be higher than those of public hospitals. Nevertheless, it is *very* important to note that our findings show that the pure technical efficiency of public hospitals became lower than that of private hospitals, while the matched scale efficiency of public hospitals remained higher than private hospitals. Therefore, the ownership of hospitals could affect the hospital's pure technical efficiency, indicating that private hospitals had better management standards and incorporate scale.

Recommendation 4

Since the influencing factors for public hospitals and private hospitals differ; our policy recommendations for public hospitals is based on the fact that their management model can be properly adjusted to improve management standards, including reasonable structures of doctors and nurses staffing levels, as well as appropriate reduction of hospital beds to keep up with hospital human resources that can staff them. For private hospitals, operating scales should be expanded via proper restructuring, mergers and acquisitions, as they should pay special attention to the fact that pure technical efficiency (VRS scores) does not mean technical performance efficiency (CRS scores) and that better management contributed to higher managerial efficiency and thus productive efficiency (output production maximization).

Recommendation 5

Indeed, policymakers should create competitive eligibility criteria for hiring MoH hospital administrators based on qualifications and relevant past experiences as well as management credentials. Otherwise, current public hospital administrators should be provided with suitable management training, and kept under more stringent MoH monitoring; to which management should be held accountable for efficiency levels, wastage, and output shortages.

Recommendation 6

To optimize the usage of health resources, policymakers should stress building the concept of operational efficiency and hospital performance among clinicians and managers.

Recommendation 7

Policymakers must encourage greater autonomy and flexibility for MoH hospital administrators over general managerial tasks, redistribution and purchase of health resources, as well as in the care delivery process and routine healthcare service operations.

Recommendation 8

In reference to our findings on health system leakage and allocative inefficiency (slacks), it is required to reassign personnel from *inefficient* hospitals to *efficient* ones, in accordance with the applicable legislative framework and Kuwait's MoH regulations for the efficient utilization of medical capacity.

Recommendation 9

Among their many important duties and responsibilities, policymakers have an obligation to both plan and implement training programs aimed at enhancing hospital performance and quality of services provided by public health workers.

Recommendation 10

In order to retain current health workforce numbers and reduce turnover rates in the MoH public sector (given that the public health system depends on a non-Kuwaiti majority workforce), policymakers must consider improvement of working conditions and the flexibility of employment contracts; including fair compensation packages and promotions, and rewards and recognition based on merits. More importantly, the priority should be given to enhancing medical education in the country and attracting more Kuwaiti citizens to the clinical fields to contribute to the nation's public health system.

Beyond Efficiency: Future Research and Other Priority-Setting Criteria in Health

The empirical research conducted in this dissertation has contributed to the formulation of new questions about our current understanding of public health system efficiency and government hospital performance in Kuwait. Through this research study, we uncovered a variety of unreliable health information and annual datasets that provide insufficient data on a myriad of hospital operations, service production, quality treatment, and health profiles.

Consequently, stakeholders must first collect and process high-quality data to enhance Kuwait's public hospital databases. Valid and reliable data should include all levels of service provision and capture the health demand, pattern of activities, severity of cases, and quality of healthcare, all of which are essential steps for hospital service monitoring. The establishment of an integrated hospital information systems, containing patient information, medical history and clinical cases, services delivered, and treatment methods based on diagnosis, as well as the utilization of health resources, is the responsibility of key stakeholders.

Such a comprehensive, linked hospital information system would contribute to improvements in patient safety and the efficient utilization of health services, as well as prove useful in gaining an understanding of the production mechanisms involved in public hospitals by extracting knowledge from the diverse experiences of health facilities in order to make improvements. By highlighting the flaws in the healthcare production process, these improvements would increase future research into hospital efficiency in the State of Kuwait. In addition, it directs policymakers and decisionmakers towards other potential improvements as well (Hollingsworth, 2003).

Further research should be conducted so that we can better comprehend the healthcare production process in Kuwait's MoH hospitals and its efficiency at the national and region level compared to neighboring countries in the Gulf Cooperation Council (GCC). Regarding sample units, future research could be implemented using PHCs or even other quasi-governmental, private hospitals under different ministerial ownership, such as the Kuwait Oil Company's (KOC) Al Ahmadi Hospital operated by the oil sector, or the Military's Jaber Al-Ahmed Armed Forces Hospital operating under Kuwait Ministry of Defense ownership. These investigations would provide more valuable information to help further explain the varying levels of performance within (departmental differences) or between hospitals, thereby yielding more recommendations for enhancing hospital efficiency.

Subsequently, it is necessary to undertake additional technical, allocative, and cost-effectiveness (economic efficiency) analysis of public hospitals and to exchange these assessments between researchers, clinicians, and Kuwait MoH policymakers. Thus, the aim is creating a comprehensive picture of the efficiency status, identifying performance deficiencies, and determining the optimal allocation of health resources. This will contribute to the development of evidence-based policies and future strategic planning for Kuwait's public health system.

Numerous high-income, developing markets in the Arabian Gulf, such as the case in the State of Kuwait, are oil-dependent economies since oil revenues account for the majority of exports and government income. The recent decline in global oil prices as a result of the COVID-19 pandemic has affected governmental provision of social services; especially public delivery of care. Reliance on vacillating oil prices is unsustainable in the long term; the ageing of the population, the implications of that ageing for health expenditure together with the dominant role played by the public sector in the financing and delivery of healthcare services has seen a particular focus on productivity in the health sector. Indeed, this study proves that an unsustainable and fragmented health system is one of the biggest threats to Kuwait's productivity and long-term prosperity.

In response to these issues, the MoH must consider perhaps running a series of roundtable talks on efficiency and productivity enhancement pathways in health. That is not to dispute the generally acceptable proposition that increases in technical efficiency are a component of productivity growth. Rather, the point is that Kuwait's policymakers need to pay particular attention to the factors that encourage or impede the development of new ways of doing things and the reallocation of resources from more to less productive uses. Moreover, the evidence of high spending and allocative and productive inefficiency in the Kuwaiti public health system suggest the scope to get better value for money. The focus should be on efficiency in order to maximize outputs based on given sets of resources, or reducing existing levels of inputs should outputs be kept constant.

Lastly, however, it is the researcher's belief that efficiency challenges must not be addressed as technical and measuring issues, but as fundamental management objectives. For considerable efficiency benefits to be accomplished, one must make difficult and unpalatable decisions. Perhaps most importantly, efficiency improvement must never be viewed as a one-time 'purge' of existing inefficiencies. There may be a compelling reason for a particular structural change, as indicated in this research; yet this should not disguise the need to instill and *continually* enforce a culture of ongoing efficiency improvement at all levels of Kuwait's health system. Without such a culture, we feel that the only result will be a change from one level of static productivity to another. Each ineffective healthcare facility is inefficient in its own way, and each efficient healthcare facility is efficient in the same manner. Therefore, it is essential to identify specific difficulties at all levels of the delivery of healthcare services (a top-down approach;

starting with public hospital governance) and to develop localized solutions that overcome specific constraints.

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Appendices

Appendix A: New York Medical College (NYMC) IRB Exemption of Research Protocol # 15157

NYMC IRB | IRB Review Not Required

To: AlJawhara AlSabah
From: Carla Charles, BS, CCRC, Director, Human Subjects Administration
Subject: Protocol #15157
Date: 06/09/2022

The protocol **15157 High Spending, Poor Productivity Gains! Assessing Public Health System (In)Efficiency and Hospital Performance in the State of Kuwait: Would More Private Delivery Improve Healthcare?** has been reviewed by the IRB Chair or Designee and found not to require further IRB review or oversight because this protocol does not meet the definition of human subjects research according to the Federal Regulations at 45 CFR 46.

This determination applies only to the activities described in the Mentor IRB submission and does not apply should any changes be made. If changes are being considered and there are questions about whether IRB review is needed, please contact the IRB Office to discuss those changes. You may be asked to submit a new application for determination.

This determination does not constitute or guarantee institutional approval and/or support. Investigators and study team members must comply with all applicable federal, state, and local laws, as well as NYMC Policies and Procedures, which may include obtaining approval for your activities from other individuals or entities.

Please contact the IRB with questions.

Carla Charles
Director, Human Subjects Administration
New York Medical College
40 Sunshine Cottage Rd.
Valhalla, NY 10595
(914) 594-2590
www.nymc.edu

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Appendix B: Additional Analyses and Material From Chapter 4

Appendix Table B.1

Actual and Target Values of Inefficient Hospitals to Render Efficient, Plus the Amount of Change in Each Hospital for MoH Hospitals in 2015-2019

DMU	Beds Value	Beds Target	Beds Gain(%)	Physicians Value	Physicians Target	Physicians Gain(%)	Nurses Value	Nurses Target	Nurses Gain(%)
2015									
Al-Adan Hospital	826	826	0	838	838	0	2086	2086	0
Al-Amiri Hospital	417	325.36	-21.98	689	325.81	-52.71	1486	810.88	-45.43
Al-Farwaniya Hospital	869	869	0	843	843	0	2097	2097	0
Al -Jahra Hospital	757	757	0	580	580	0	1883	1883	0
Al-Sabah Hospital	433	425.43	-1.75	498	430.29	-13.6	1450	1071.06	-26.13
Mubarak Al-Kabir Hospital	731	581.4	-20.46	837	447.65	-46.52	1442	1146.9	-20.46
Al-Razi Hospital	361	252.44	-30.07	259	181.12	-30.07	764	534.26	-30.07
Physical Med. & Rehab Facility	75	75	0	34	34	0	132	132	0
Maternity Hospital	458	454.36	-0.79	278	270.59	-2.66	945	937.5	-0.79
Chest Diseases Hospital	326	170.53	-47.69	203	106.19	-47.69	761	356.97	-53.09

Infectious Disease Facility	173	26.86	-84.47	41	13.52	-67.02	180	50.68	-71.85
Ibn Sina Hospital	358	358	0	199	199	0	723	723	0
Kuwait Cancer Control Center	199	89.31	-55.12	174	78.09	-55.12	638	211.74	-66.81
Allergy & Respiratory Center	36	36	0	34	34	0	51	51	0
Sabah Al-Ahmad Urology Center	74	20.44	-72.37	31	11.36	-63.34	83	41.29	-50.26
2016									
Al-Adan Hospital	826	826	0	909	909	0	2179	2179	0
Al-Amiri Hospital	414	351.83	-15.02	689	383.32	-44.37	1527	920.14	-39.74
Al-Farwaniya Hospital	868	868	0	905	905	0	2186	2186	0
Al -Jahra Hospital	759	759	0	600	600	0	1955	1955	0
Al-Sabah Hospital	441	430.73	-2.33	499	469.12	-5.99	1485	1126.15	-24.16
Mubarak Al-Kabir Hospital	724	501.1	-30.79	909	481.22	-47.06	1575	1223.09	-22.34
Al-Razi Hospital	438	264.55	-39.6	264	169.36	-35.85	882	565.81	-35.85
Physical Med. & Rehab Facility	69	69	0	33	33	0	137	137	0
Maternity Hospital	448	448	0	270	270	0	958	958	0

Chest Diseases Hospital	326	148.84	-54.34	217	99.07	-54.34	776	325.66	-58.03
Infectious Disease Facility	173	22.72	-86.87	42	12.44	-70.37	178	46.6	-73.82
Ibn Sina Hospital	355	355	0	210	210	0	743	743	0
Kuwait Cancer Control Center	199	73.82	-62.9	191	70.85	-62.9	656	183.93	-71.96
Allergy & Respiratory Center	36	36	0	33	33	0	49	49	0
Sabah Al-Ahmad Urology Center	74	18.28	-75.3	31	11.01	-64.47	83	39.08	-52.92
2017									
Al-Adan Hospital	826	826	0	990	990	0	2211	2211	0
Al-Amiri Hospital	414	282.41	-31.79	686	330.89	-51.76	1513	791.02	-47.72
Al-Farwaniya Hospital	868	868	0	1013	1013	0	2191	2191	0
Al -Jahra Hospital	765	765	0	616	616	0	1952	1952	0
Al-Sabah Hospital	426	426	0	504	504	0	1483	1483	0
Mubarak Al-Kabir Hospital	725	484.33	-33.2	942	542.89	-42.37	1611	1205.61	-25.16
Al-Razi Hospital	465	295.02	-36.55	274	185.51	-32.3	908	614.74	-32.3
Physical Med. & Rehab Facility	69	69	0	37	37	0	132	132	0

Maternity Hospital	453	453	0	279	279	0	957	957	0
Chest Diseases Hospital	323	151.93	-52.96	210	98.78	-52.96	774	337.16	-56.44
Infectious Disease Facility	173	33.27	-80.77	44	18.68	-57.54	173	66.67	-61.46
Ibn Sina Hospital	355	355	0	207	207	0	739	739	0
Kuwait Cancer Control Center	199	73.16	-63.23	193	70.96	-63.23	649	217.35	-66.51
Allergy & Respiratory Center	36	36	0	33	33	0	48	48	0
Sabah Al-Ahmad Urology Center	96	23.88	-75.13	32	14.7	-54.05	81	50.44	-37.73
2018									
Al-Adan Hospital	826	826	0	1049	1049	0	2187	2187	0
Al-Amiri Hospital	428	326.51	-23.71	694	413.91	-40.36	1468	1119.91	-23.71
Al-Farwaniya Hospital	868	868	0	1057	1057	0	2117	2117	0
Al -Jahra Hospital	765	765	0	588	588	0	1900	1900	0
Al-Sabah Hospital	372	372	0	478	478	0	1445	1445	0
Mubarak Al-Kabir Hospital	726	484.64	-33.25	970	555.38	-42.74	1512	1159.42	-23.32
Al-Razi Hospital	465	243.68	-47.6	269	184.95	-31.24	886	598.94	-32.4

Physical Med. & Rehab Facility	71	71	0	33	33	0	129	129	0
Maternity Hospital	453	453	0	273	273	0	924	924	0
Chest Diseases Hospital	323	163.13	-49.49	199	104.74	-47.37	753	349.95	-53.53
Infectious Disease Facility	173	30.51	-82.37	48	21.01	-56.22	166	69.25	-58.28
Ibn Sina Hospital	355	306.97	-13.53	402	347.61	-13.53	1079	933.02	-13.53
Kuwait Cancer Control Center	199	46.75	-76.51	186	43.7	-76.51	639	137.2	-78.53
Allergy & Respiratory Center	36	36	0	33	33	0	45	45	0
Sabah Al-Ahmad Urology Center	87	18.57	-78.65	34	11.19	-67.08	83	37.88	-54.36
2019									
Al-Adan Hospital	810	810	0	1107	1107	0	2118	2118	0
Al-Amiri Hospital	478	314.25	-34.26	702	429.99	-38.75	1400	793.92	-43.29
Al-Farwaniya Hospital	849	849	0	1163	1163	0	2072	2072	0
Al -Jahra Hospital	785	785	0	655	655	0	1837	1837	0
Al-Sabah Hospital	362	322.74	-10.84	486	433.3	-10.84	1394	811.77	-41.77
Mubarak Al-Kabir Hospital	718	518.77	-27.75	1013	532.66	-47.42	1524	1101.11	-27.75

Al-Razi Hospital	467	372.6	-20.22	264	221.72	-16.02	860	722.27	-16.02
Physical Med. & Rehab Facility	71	71	0	31	31	0	127	127	0
Maternity Hospital	406	406	0	273	273	0	890	890	0
Chest Diseases Hospital	327	147.52	-54.89	212	95.64	-54.89	718	303.99	-57.66
Infectious Disease Facility	173	19.08	-88.97	53	14.67	-72.31	152	42.09	-72.31
Ibn Sina Hospital	355	355	0	219	219	0	690	690	0
Kuwait Cancer Control Center	218	76.31	-65	197	68.96	-65	626	167.92	-73.18
Allergy & Respiratory Center	36	36	0	33	33	0	46	46	0
Sabah Al-Ahmad Urology Center	96	24.54	-74.44	34	15.14	-55.48	83	47.69	-42.54

DMU	Discharges Value	Discharges Target	Discharges Gain(%)	Outpatient & Emergency Visits Value	Outpatient & Emergency Visits Target	Outpatient & Emergency Visits Gain(%)
2015						
Al-Adan Hospital	57054	57054	0	992226	992226	0
Al-Amiri Hospital	21085	21085	0	447497	447497	0
Al-Farwaniya Hospital	47465	47465	0	1556494	1556494	0

Al -Jahra Hospital	42673	42673	0	1109410	1109410	0
Al-Sabah Hospital	28958	28958	0	528486	528486	0
Mubarak Al-Kabir Hospital	27172	27172	0	830618	830618	0
Al-Razi Hospital	13865	13865	0	315264	315264	0
Physical Med. & Rehab Facility	296	296	0	143658	143658	0
Maternity Hospital	27768	27768	0	132653	393002.98	196.26
Chest Diseases Hospital	10510	10510	0	111469	151220.64	35.66
Infectious Disease Facility	846	846	0	37251	37251	0
Ibn Sina Hospital	21609	21609	0	298251	298251	0
Kuwait Cancer Control Center	5931	5931	0	70209	97234.26	38.49
Allergy & Respiratory Center	489	489	0	76383	76383	0
Sabah Al-Ahmad Urology Center	1234	1234	0	2529	17031.87	573.46
2016						
Al-Adan Hospital	58427	58427	0	931711	931711	0
Al-Amiri Hospital	24099	24099	0	443200	443200	0

Al-Farwaniya Hospital	51178	51178	0	1580132	1580132	0
Al -Jahra Hospital	43306	43306	0	1107771	1107771	0
Al-Sabah Hospital	29471	29471	0	544480	544480	0
Mubarak Al-Kabir Hospital	29614	29614	0	835770	835770	0
Al-Razi Hospital	14032	14032	0	323484	323484	0
Physical Med. & Rehab Facility	293	293	0	139862	139862	0
Maternity Hospital	29931	29931	0	119978	119978	0
Chest Diseases Hospital	9606	9606	0	99258	99258	0
Infectious Disease Facility	870	870	0	31503	31503	0
Ibn Sina Hospital	21198	21198	0	349417	349417	0
Kuwait Cancer Control Center	5060	5060	0	73707	73707	0
Allergy & Respiratory Center	97	97	0	64195	64195	0
Sabah Al-Ahmad Urology Center	1221	1221	0	3064	4894.36	59.74
2017						
Al-Adan Hospital	55762	55762	0	966069	966069	0

Al-Amiri Hospital	17685	17685	0	445203	445203	0
Al-Farwaniya Hospital	51403	51403	0	1536849	1536849	0
Al -Jahra Hospital	41302	41302	0	1123456	1123456	0
Al-Sabah Hospital	30239	30239	0	468373	468373	0
Mubarak Al-Kabir Hospital	28701	28701	0	825533	825533	0
Al-Razi Hospital	13597	13597	0	370501	370501	0
Physical Med. & Rehab Facility	293	293	0	132049	132049	0
Maternity Hospital	27834	27834	0	133423	133423	0
Chest Diseases Hospital	9334	9334	0	103830	103830	0
Infectious Disease Facility	1134	1134	0	46149	46149	0
Ibn Sina Hospital	21199	21199	0	331636	331636	0
Kuwait Cancer Control Center	4924	4924	0	62428	62428	0
Allergy & Respiratory Center	111	111	0	60485	60485	0
Sabah Al-Ahmad Urology Center	1467	1467	0	3081	7032.1	128.24
2018						

Al-Adan Hospital	57217	57217	0	848683	848683	0
Al-Amiri Hospital	23739	23739	0	418685	418685	0
Al-Farwaniya Hospital	51328	51328	0	1491520	1491520	0
Al -Jahra Hospital	42571	42571	0	1195594	1195594	0
Al-Sabah Hospital	28997	28997	0	432631	432631	0
Mubarak Al-Kabir Hospital	28883	28883	0	757168	757168	0
Al-Razi Hospital	13666	13666	0	364129	364129	0
Physical Med. & Rehab Facility	260	260	0	105314	105314	0
Maternity Hospital	28588	28588	0	172818	172818	0
Chest Diseases Hospital	10006	10006	0	108006	108006	0
Infectious Disease Facility	1807	1807	0	30346	30346	0
Ibn Sina Hospital	21801	21801	0	306516	306516	0
Kuwait Cancer Control Center	2993	2993	0	62032	62032	0
Allergy & Respiratory Center	251	251	0	54027	54027	0

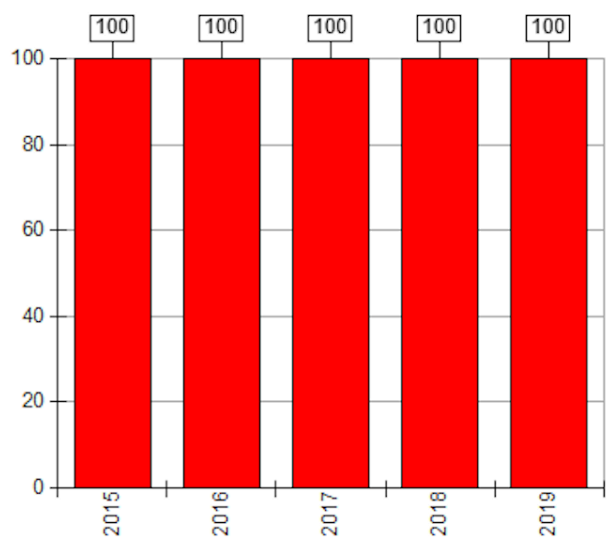
Sabah Al-Ahmad Urology Center	1172	1172	0	2300	7084.89	208.04
			2019			
Al-Adan Hospital	58256	58256	0	928840	928840	0
Al-Amiri Hospital	19968	19968	0	450474	450474	0
Al-Farwaniya Hospital	47039	47039	0	1453402	1453402	0
Al -Jahra Hospital	40929	40929	0	1271090	1271090	0
Al-Sabah Hospital	20263	20263	0	467831	467831	0
Mubarak Al-Kabir Hospital	27946	27946	0	733795	733795	0
Al-Razi Hospital	19242	19242	0	396231	396231	0
Physical Med. & Rehab Facility	260	260	0	102381	102381	0
Maternity Hospital	28715	28715	0	178122	178122	0
Chest Diseases Hospital	9943	9943	0	103615	103615	0
Infectious Disease Facility	1056	1056	0	26844	26844	0
Ibn Sina Hospital	22931	22931	0	323744	323744	0
Kuwait Cancer Control Center	5142	5142	0	76479	76479	0

Allergy & Respirator y Center	251	251	0	67069	67069	0
Sabah Al-Ahmad Urology Center	1585	1585	0	2919	22377.32	666.61

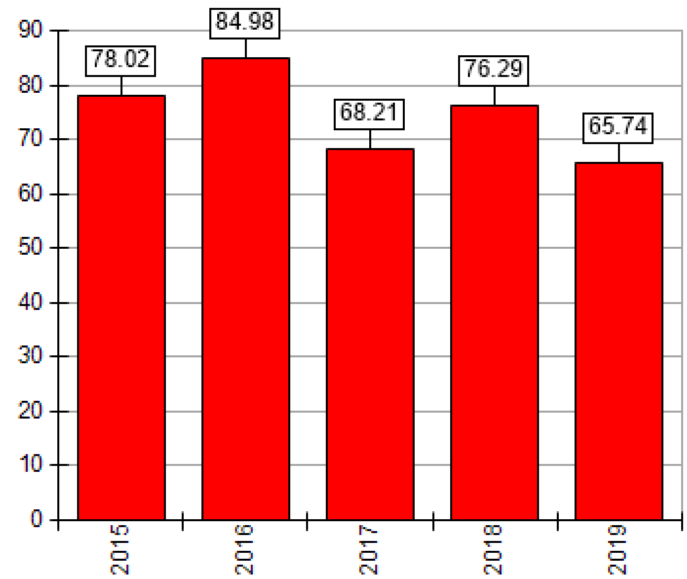
Appendix Table B.2

Technical Efficiency Trend for MoH Public Hospitals From 2015 to 2019

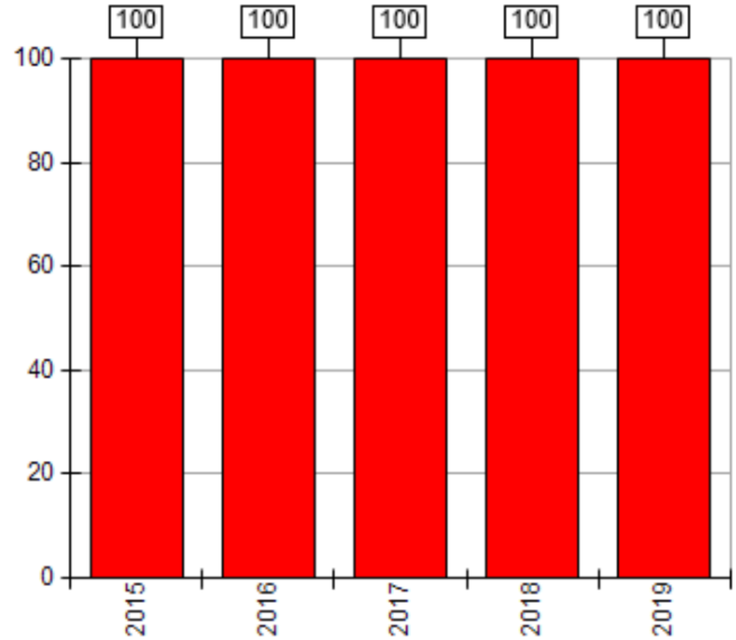
DMU 1: Al-Adan Hospital (General)



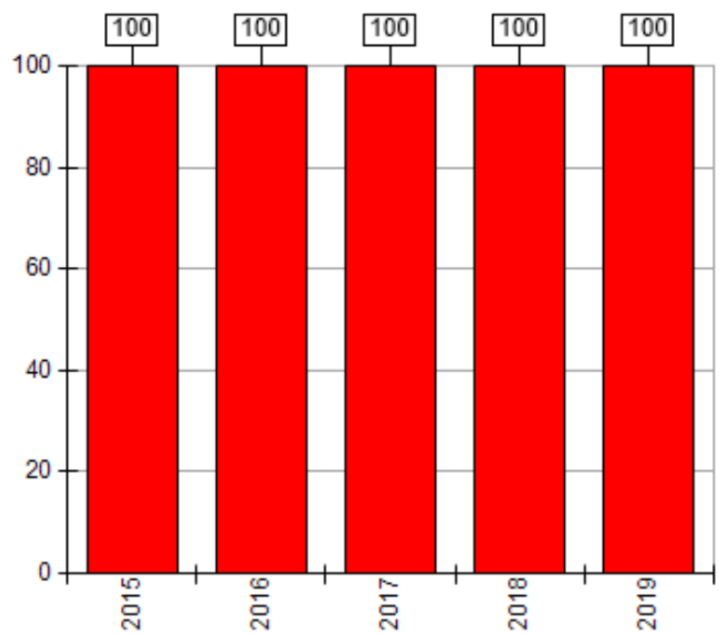
DMU 2: Al-Amiri Hospital (General)



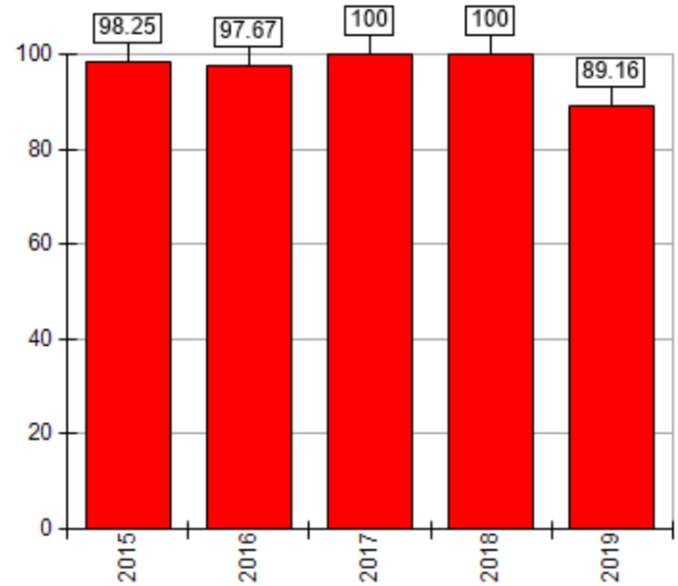
DMU 3: Al-Farwaniya Hospital (General)



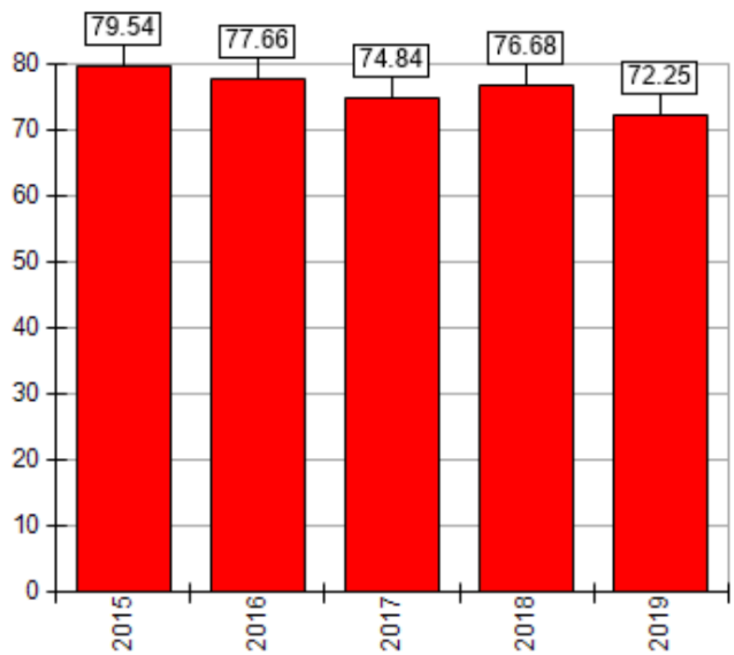
DMU 4: Al-Jahra Hospital (General)



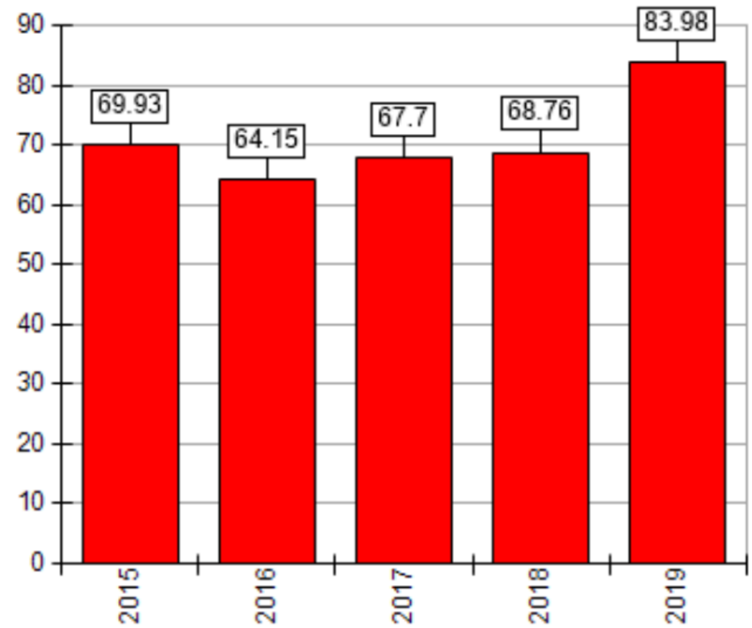
DMU 5: Al-Sabah Hospital (General)



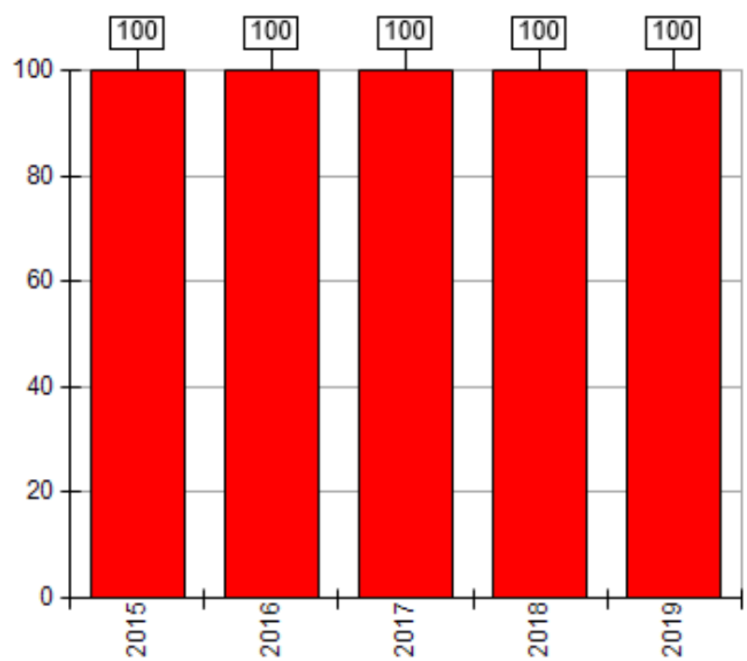
DMU 6: Mubarak Al-Kabir Hospital (General)



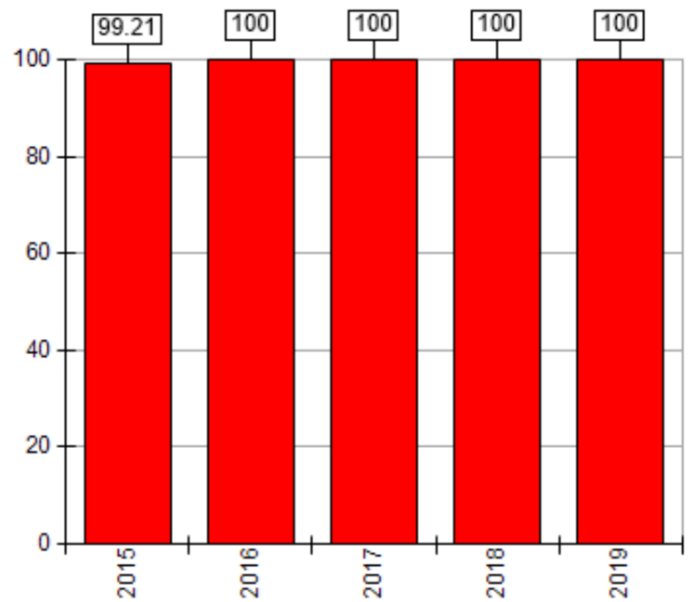
DMU 7: Al-Razi Hospital (Specialized)



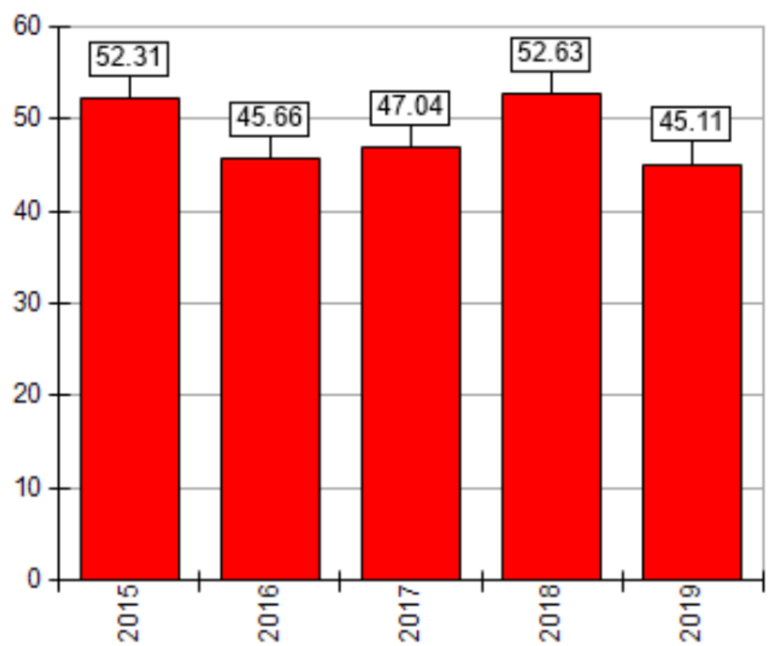
DMU 8: Physical Med. & Rehab Facility (Specialized)



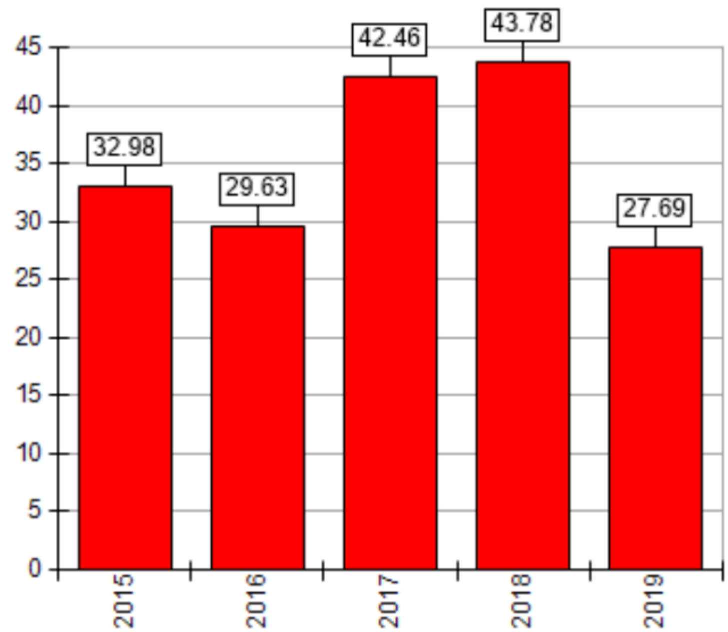
DMU 9: Maternity Hospital (Specialized)



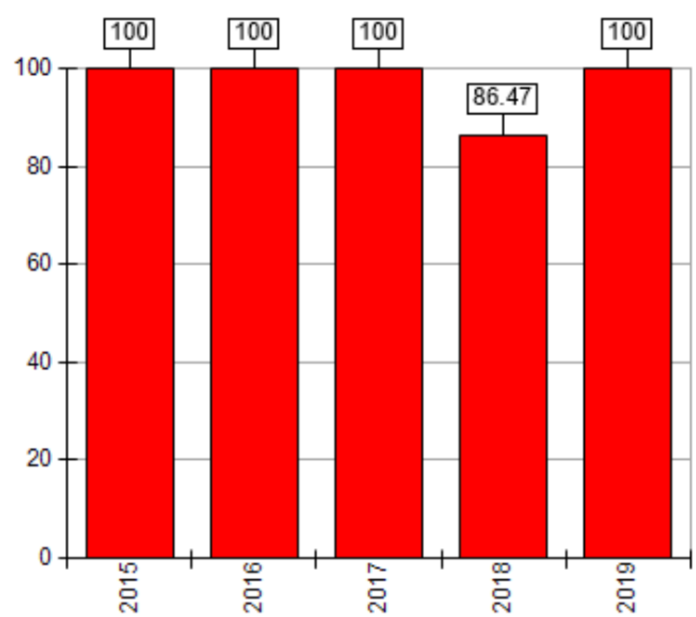
DMU 10: Chest Diseases Hospital (Specialized)



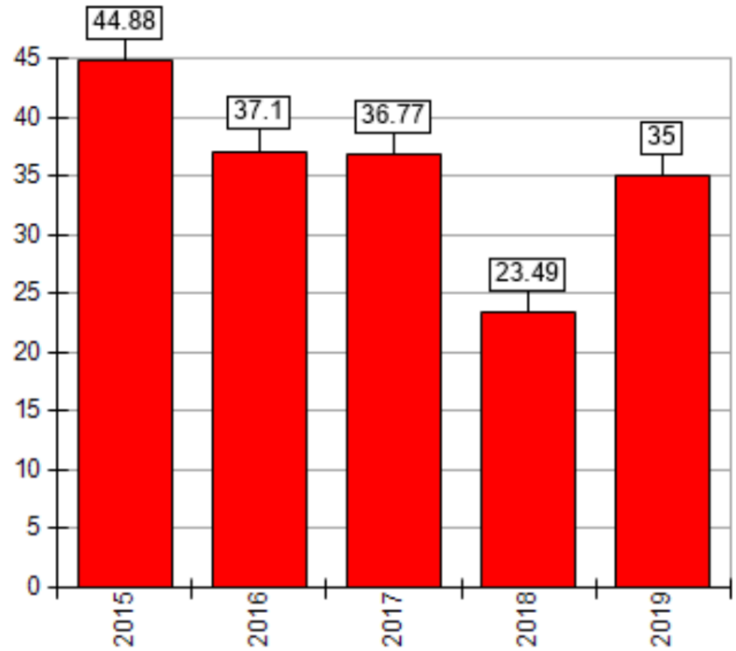
DMU 11: Infectious Disease Facility (Specialized)



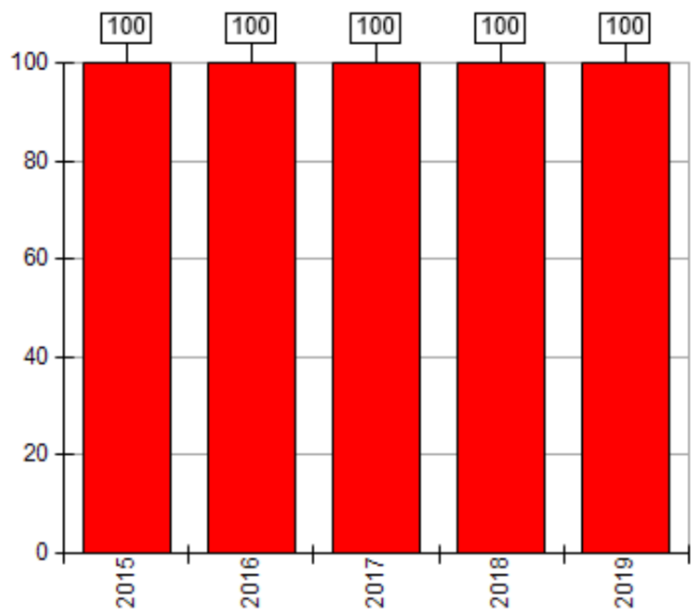
DMU 12: Ibn Sina Hospital (Specialized)



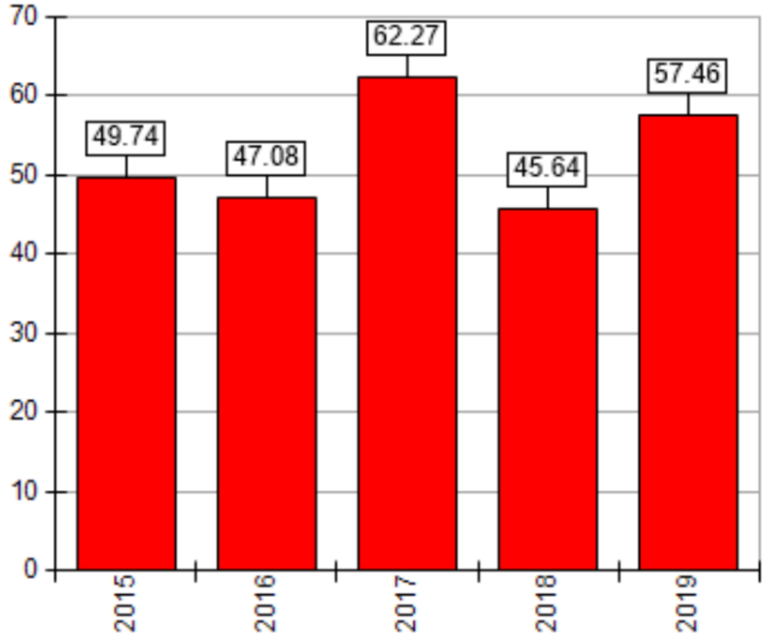
DMU 13: Kuwait Cancer Control Center (Specialized)



DMU 14: Allergy & Respiratory Center (Specialized)



DMU 15: Sabah Al-Ahmad Urology Center (Specialized)



Appendix Table B.3

Sensitivity Analysis of MoH Public Hospitals, CRS Efficiency Means and CCR Model With and Without Each Input and Output Variable for 2015-2019

	CCR MODEL WITHOUT BEDS INPUT				
Hospital DMUs	Efficiency Year 2015	Efficiency Year 2016	Efficiency Year 2017	Efficiency Year 2018	Efficiency Year 2019
Al-Adan Hospital	96.39	93.63	90.23	93.47	85.8
Al-Amiri Hospital	52.71	56.92	46.81	59.53	50.2
Al-Farwaniya Hospital	97.13	100	100	100	91.37
Al -Jahra Hospital	95.53	93.62	94.6	100	100
Al-Sabah Hospital	71.24	71.67	71.07	73.74	54.62
Mubarak Al-Kabir Hospital	78.76	77.66	74.84	76.68	68.65
Al-Razi Hospital	69.09	64.15	67.7	68.76	83.98
Physical Med. & Rehab Facility	100	100	100	100	100
Maternity Hospital	98.31	100	100	100	100
Chest Diseases Hospital	47.68	41.92	43.4	52.63	44.7

Infectious Disease Facility	32.98	29.63	42.46	43.78	27.69
Ibn Sina Hospital	100	100	100	71.78	100
Kuwait Cancer Control Center	31.39	26.68	26.35	19.94	25.5
Allergy & Respiratory Center	100	100	100	100	100
Sabah Al-Ahmad Urology Center	49.74	47.08	62.27	45.64	57.46

	CCR MODEL WITHOUT PHYSICIAN INPUT				
Hospital DMUs	Efficiency Year 2015	Efficiency Year 2016	Efficiency Year 2017	Efficiency Year 2018	Efficiency Year 2019
Al-Adan Hospital	100	100	100	100	100
Al-Amiri Hospital	78.02	84.98	68.21	76.29	65.74
Al-Farwaniya Hospital	100	100	100	100	100
Al -Jahra Hospital	93.68	91.06	88.81	92.85	97.53
Al-Sabah Hospital	98.25	97.67	100	100	88.91
Mubarak Al-Kabir Hospital	79.54	77.66	74.84	76.68	72.25
Al-Razi Hospital	69.59	61.33	61.67	62.17	76.4
Physical Med. & Rehab Facility	90.28	100	100	92.45	77.4
Maternity Hospital	99.21	100	100	100	100
Chest Diseases Hospital	49.01	43.01	44.81	47.02	44.03
Infectious Disease Facility	22.79	22.79	33.3	39.72	25.66
Ibn Sina Hospital	100	100	100	85.27	100
Kuwait Cancer Control Center	43.15	35.95	35.33	21.82	32.8
Allergy & Respiratory Center	100	100	100	100	100
Sabah Al-Ahmad Urology Center	49.74	47.08	62.27	45.64	57.46

	CCR MODEL WITHOUT NURSES INPUT				
Hospital DMUs	Efficiency Year 2015	Efficiency Year 2016	Efficiency Year 2017	Efficiency Year 2018	Efficiency Year 2019
Al-Adan Hospital	100	100	97.51	89.3	100
Al-Amiri Hospital	78.02	84.98	68.21	75.51	65.74
Al-Farwaniya Hospital	100	100	100	100	100
Al -Jahra Hospital	100	100	100	100	100
Al-Sabah Hospital	98.25	97.67	100	100	89.16
Mubarak Al-Kabir Hospital	66	67.32	65.98	64.01	65.24

Al-Razi Hospital	66.8	61.96	64.88	68.76	83.24
Physical Med. & Rehab Facility	100	100	100	100	100
Maternity Hospital	98.85	100	100	100	100
Chest Diseases Hospital	52.31	45.66	47.04	52.63	45.11
Infectious Disease Facility	32.98	29.63	42.46	43.78	25.53
Ibn Sina Hospital	100	100	100	82.94	100
Kuwait Cancer Control Center	44.88	37.1	36.77	23.49	35
Allergy & Respiratory Center	100	87.97	87.79	92.39	100
Sabah Al-Ahmad Urology Center	36.66	35.53	44.76	32.92	44.32

	CCR MODEL WITHOUT TOTAL VISITS OUTPUTS (OUTPATIENTS & EMERGENCY)				
Hospital DMUs	Efficiency Year 2015	Efficiency Year 2016	Efficiency Year 2017	Efficiency Year 2018	Efficiency Year 2019
Al-Adan Hospital	100	100	100	100	100
Al-Amiri Hospital	73.2	82.29	60.18	74.19	58.08
Al-Farwaniya Hospital	81.35	84.48	89.91	88.06	77.57
Al -Jahra Hospital	87.59	83.55	83.64	83.45	73.43
Al-Sabah Hospital	96.82	94.48	100	100	77.87
Mubarak Al-Kabir Hospital	63.05	60.96	63.22	62.61	56.4
Al-Razi Hospital	61.92	50.92	51.49	49.85	69.3
Physical Med. & Rehab Facility	8.02	8.01	7.74	7.52	7.97
Maternity Hospital	99.21	100	100	100	100
Chest Diseases Hospital	52.31	43.78	46.59	48.86	44.59
Infectious Disease Facility	19	18.69	25.17	35.95	20.9
Ibn Sina Hospital	100	91.32	100	85.76	100
Kuwait Cancer Control Center	44.88	36.52	36.71	21.39	33.16
Allergy & Respiratory Center	32.08	6.34	7.95	18.03	16.42

Sabah Al-Ahmad Urology Center	49.74	47.08	62.27	45.64	57.46

	CCR MODEL WITHOUT ADJUSTED DISCHARGE OUTPUTS				
Hospital DMUs	Efficiency Year 2015	Efficiency Year 2016	Efficiency Year 2017	Efficiency Year 2018	Efficiency Year 2019
Al-Adan Hospital	56.62	55.65	61.11	59.79	61.55
Al-Amiri Hospital	50.58	52.81	56.19	56.93	50.59
Al-Farwaniya Hospital	84.42	89.81	92.52	100	91.89
Al -Jahra Hospital	71.6	72	76.74	99.03	90.42
Al-Sabah Hospital	57.52	60.91	57.45	67.68	69.37
Mubarak Al-Kabir Hospital	53.55	56.95	59.5	63.09	54.86
Al-Razi Hospital	43.1	36.44	41.63	51.58	54.57
Physical Med. & Rehab Facility	100	100	100	100	100
Maternity Hospital	14.63	13.21	15.39	24.99	26.61
Chest Diseases Hospital	17.21	15.02	16.8	21.85	19.47
Infectious Disease Facility	21.5	17.7	29.39	21.68	18.59
Ibn Sina Hospital	42.54	48.56	48.81	51.04	56.99
Kuwait Cancer Control Center	16.86	18.27	16.39	19.12	18.95
Allergy & Respiratory Center	100	100	100	100	100
Sabah Al-Ahmad Urology Center	2.53	3.33	3.54	2.95	3.4

Appendix Table B.4

Inefficient MoH Hospitals with Their Peers (Benchmarking) by Year

	Year 2015					
DMU	**Al-Adan Hospital**	**Al-Farwaniya Hospital**	**Al -Jahra Hospital**	**Physical Med. & Rehab Facility**	**Ibn Sina Hospital**	**Allergy & Respiratory Center**
(Frequencies)	6	5	1	3	8	3
Al-Adan Hospital	True	False	False	False	False	False

Al-Amiri Hospital	True	True	False	False	False	False
Al-Farwaniya Hospital	False	True	False	False	False	False
Al -Jahra Hospital	False	False	True	False	False	False
Al-Sabah Hospital	True	True	False	False	False	False
Mubarak Al-Kabir Hospital	False	True	False	False	True	True
Al-Razi Hospital	False	True	False	True	True	True
Physical Med. & Rehab Facility	False	False	False	True	False	False
Maternity Hospital	True	False	False	False	True	False
Chest Diseases Hospital	True	False	False	False	True	False
Infectious Disease Facility	False	False	False	True	True	False
Ibn Sina Hospital	False	False	False	False	True	False
Kuwait Cancer Control Center	True	False	False	False	True	False
Allergy & Respiratory Center	False	False	False	False	False	True
Sabah Al-Ahmad Urology Center	False	False	False	False	True	False

Note. ‘True’ indicates a matched hospital efficiency peer. ‘False’ indicates not a match efficiency benchmark.

	Year 2016						
DMU	**Al-Adan Hospital**	**Al-Farwaniya Hospital**	**Al -Jahra Hospital**	**Physical Med. & Rehab Facility**	**Maternity Hospital**	**Ibn Sina Hospital**	**Allergy & Respiratory Center**
(Frequencies)	5	5	1	3	4	6	1
Al-Adan Hospital	True	False	False	False	False	False	False

Al-Amiri Hospital	True	True	False	False	False	False	False
Al-Farwaniya Hospital	False	True	False	False	False	False	False
Al -Jahra Hospital	False	False	True	False	False	False	False
Al-Sabah Hospital	True	True	False	False	False	False	False
Mubarak Al-Kabir Hospital	False	True	False	False	False	True	False
Al-Razi Hospital	False	True	False	True	False	True	False
Physical Med. & Rehab Facility	False	False	False	True	False	False	False
Maternity Hospital	False	False	False	False	True	False	False
Chest Diseases Hospital	True	False	False	False	True	True	False
Infectious Disease Facility	False	False	False	True	False	True	False
Ibn Sina Hospital	False	False	False	False	False	True	False
Kuwait Cancer Control Center	True	False	False	False	True	True	False
Allergy & Respiratory Center	False	False	False	False	False	False	True
Sabah Al-Ahmad Urology Center	False	False	False	False	True	False	False

Note. 'True' indicates a matched hospital efficiency peer. 'False' indicates not a match efficiency benchmark.

	2017							
DMU	**Al-Adan Hospital**	**Al-Farwaniya Hospital**	**Al -Jahra Hospital**	**Al-Sabah Hospital**	**Physical Med. & Rehab Facility**	**Maternity Hospital**	**Ibn Sina Hospital**	**Allergy & Respiratory Center**
(Frequencies)	1	4	1	4	3	4	6	1
Al-Adan Hospital	True	False	False	False	False	False	False	False
Al-Amiri Hospital	False	True	False	True	False	False	False	False
Al-Farwaniya Hospital	False	True	False	False	False	False	False	False
Al -Jahra Hospital	False	False	True	False	False	False	False	False
Al-Sabah Hospital	False	False	False	True	False	False	False	False
Mubarak Al-Kabir Hospital	False	True	False	False	False	False	True	False
Al-Razi Hospital	False	True	False	False	True	False	True	False
Physical Med. & Rehab Facility	False	False	False	False	True	False	False	False
Maternity Hospital	False	False	False	False	False	True	False	False
Chest Diseases Hospital	False	False	False	True	False	True	True	False
Infectious Disease Facility	False	False	False	False	True	False	True	False
Ibn Sina Hospital	False	False	False	False	False	False	True	False

Kuwait Cancer Control Center	False	False	False	True	False	True	True	False
Allergy & Respiratory Center	False	False	False	False	False	False	False	True
Sabah Al-Ahmad Urology Center	False	False	False	False	False	True	False	False

Note. 'True' indicates a matched hospital efficiency peer. 'False' indicates not a match efficiency benchmark.

	2018						
DMU	**Al-Adan Hospital**	**Al-Farwaniya Hospital**	**Al -Jahra Hospital**	**Al-Sabah Hospital**	**Physical Med. & Rehab Facility**	**Maternity Hospital**	**Allergy & Respiratory Center**
(Frequencies)	3	3	6	4	1	8	1
Al-Adan Hospital	True	False	False	False	False	False	False
Al-Amiri Hospital	True	True	False	True	False	False	False
Al-Farwaniya Hospital	False	True	False	False	False	False	False
Al -Jahra Hospital	False	False	True	False	False	False	False
Al-Sabah Hospital	False	False	False	True	False	False	False
Mubarak Al-Kabir Hospital	False	True	False	False	False	True	False
Al-Razi Hospital	False	False	True	False	False	True	False
Physical Med. & Rehab Facility	False	False	False	False	True	False	False
Maternity Hospital	False	False	False	False	False	True	False
Chest Diseases Hospital	False	False	True	False	False	True	False

Infectious Disease Facility	False	False	True	False	False	True	False
Ibn Sina Hospital	True	False	True	True	False	True	False
Kuwait Cancer Control Center	False	False	True	True	False	True	False
Allergy & Respiratory Center	False	False	False	False	False	False	True
Sabah Al-Ahmad Urology Center	False	False	False	False	False	True	False

Note. 'True' indicates a matched hospital efficiency peer. 'False' indicates not a match efficiency benchmark.

	Year 2019						
DMU	**Al-Adan Hospital**	**Al-Farwaniya Hospital**	**Al -Jahra Hospital**	**Physical Med. & Rehab Facility**	**Maternity Hospital**	**Kuwait Cancer Control Center**	**Sabah Al-Ahmad Urology Center**
(Frequencies)	5	4	5	2	2	7	3
Al-Adan Hospital	True	False	False	False	False	False	False
Al-Amiri Hospital	True	True	False	False	False	False	False
Al-Farwaniya Hospital	False	True	False	False	False	False	False
Al -Jahra Hospital	False	False	True	False	False	False	False
Al-Sabah Hospital	True	True	True	False	False	False	False
Mubarak Al-Kabir Hospital	False	True	False	False	False	True	True
Al-Razi Hospital	False	False	True	True	False	True	False
Physical Med. & Rehab Facility	False	False	False	True	False	False	False

Maternity Hospital	False	False	False	False	True	False	False
Chest Diseases Hospital	True	False	False	False	True	True	False
Infectious Disease Facility	False	False	True	False	False	True	True
Ibn Sina Hospital	False	False	False	False	False	True	False
Kuwait Cancer Control Center	True	False	True	False	False	True	False
Allergy & Respiratory Center	False	False	False	False	False	False	True
Sabah Al-Ahmad Urology Center	False	False	False	False	False	True	False

Note. 'True' indicates a matched hospital efficiency peer. 'False' indicates not a match efficiency benchmark.

Appendix Table B.5

Actual and Target Values of Inefficient Hospitals to Render Efficient, Plus the Amount of Change in Each Hospital for Public-Private Sector in 2019-2020

DMUs	Beds Value	Beds Target	Beds Gain(%)	Physicians Value	Physicians Target	Physicians Gain(%)	Nurses Value	Nurses Target	Nurses Gain(%)
Taiba hospital	113	113	0	114	114	0	300	300	0
New Mowasat	112	112	0	50	50	0	102	102	0
Mubarak	731	597.9	-18.21	1013	779.56	-23.04	1524	1524	0
Hadi	135	135	0	50	50	0	72	72	0
Dar il Shifa	130	130	0	228	228	0	340	340	0
Al-Sabah	477	477	0	486	464.31	-4.46	1394	1168.48	-16.18
Jahra	757	757	0	655	655	0	1837	1837	0
Al-Amiri	418	418	0	702	424.13	-39.58	1400	1027.62	-26.6

Al Seef	120	120	0	130	69.23	-46.75	266	119.81	-54.96
Al Salam	189	189	0	187	132.6	-29.09	451	231.89	-48.58
Farwaniya	955	810.46	-15.13	1153	1083.24	-6.05	2072	2072	0
Al-Adan	826	826	0	1107	1107	0	2118	2118	0

DMUs	Surgery Value	Surgery Target	Surgery Gain(%)	Discharges Value	Discharges Target	Discharges Gain(%)
Taiba hospital	2159	2159	0	12671	12671	0
New Mowasat	5303	5303	0	10341	10341	0
Mubarak	6150	9945.22	61.71	23796	38480.72	61.71
Hadi	7370	7370	0	7049	7049	0
Dar il Shifa	5128	5128	0	21978	21978	0
Al-Sabah	3455	6802.68	96.89	31552	37775.63	19.72
Jahra	8154	8154	0	50523	50523	0
Al-Amiri	2589	6517.93	151.75	31741	35089.58	10.55
Al Seef	4712	5828.3	23.69	8676	10731.39	23.69
Al Salam	7500	7805.05	4.07	9198	10039.71	9.15
Farwaniya	11951	12811.84	7.2	35088	44458.58	26.71
Al-Adan	12937	12937	0	45319	45319	0

Appendix Table B.6

Inefficient Public and Private General Hospitals with Their Peers (Benchmarking) From Kuwait Public Vs. Private Sectors in 2019

DMU	Taiba	New Mowasat	Hadi	Dar il Shifa	Jahra	Al Adan
(Frequencies)	1	2	4	5	4	4
Taiba	True	False	False	False	False	False
New Mowasat	False	True	False	False	False	False
Mubarak	False	False	False	True	True	True
Hadi	False	False	True	False	False	False
Dar il Shifa	False	False	False	True	False	False
Al Sabah	False	False	False	True	True	False
Jahra	False	False	False	False	True	False

Amiri	False	False	False	True	True	False
Al Seef	False	True	True	True	False	False
Al Salam	False	False	True	False	False	True
Farwaniya	False	False	True	False	False	True
Al Adan	False	False	False	False	False	True

Note. ‘True’ indicates a matched hospital efficiency peer. ‘False’ indicates not a match efficiency benchmark.