DEA Methodologies for Assessing the Efficiency Profiles of Commercial Banks under Heterogeneity Conditions

María Skarleth Atenea Carrales Escobedo

A thesis submitted in fulfilment of the requirement for the degree of Doctor of Philosophy

The University of Edinburgh

2019

ABSTRACT

Since the publication of the seminal paper by Charnes, Cooper and Rhodes in 1978, where the conventional CCR model of Data Envelopment Analysis (DEA) has been proposed, DEA as a field has substantially evolved both methodologically and in terms of applications. So far, efficiency and productivity studies in the banking sector proved to be amongst the most popular application areas. The popularity of DEA in this field, amongst others, is due to its unique features such as its non-parametric nature, it benchmarks against the best practice performers rather than the average performers. It allows one to identify targets for improvement; it does not need any functional specification of the relationship between inputs and outputs, and provides a variety of efficiency measures most suitable for a variety of applications. Moreover, it provides a wide range of models to perform analyses at the aggregate level and the detailed level. In addition, DEA models allow one to perform both Static and Dynamic analyses.

In this thesis, DEA is used to assess the efficiency profiles of commercial banks under heterogeneity conditions. First, a new DEA-based analysis framework with a regression-based feedback mechanism is proposed to deal with the particular features of the UK banking sector, where regression analysis provides DEA with feedback that informs about the relevance of the inputs and the outputs chosen by the analyst. Unlike previous studies, the DEA models used within the proposed framework could use both inputs and outputs, only inputs, or only outputs, which proved necessary with UK data. Second, to the best of our knowledge, no attempt has been made to investigate the relative efficiency of operating environments of banks. This thesis aims at filling this gap by analysing the efficiency of HSBC in different operating environments or countries over time. The choice of a single bank; namely, HSBC, is motivated by isolating the operating environment effect on efficiency

and thus avoiding any bias that would result from the relative efficiency of different banks within the same operating environment. From a methodological perspective, this analysis is performed using a variety of framework; namely, A four-stage analysis is performed with Static black box SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM DEA frameworks. Overall, this thesis contributes to both the DEA field, through its methodological contributions, and the banking sector, through its application of the methodological contributions in assessing banks' efficiency profiles.

LAY SUMMARY

Data Envelopment Analysis is a methodology used for measuring the efficiency of similar decision-making units (DMUs) in transforming inputs into outputs. In DEA, homogeneity is a fundamental assumption. It is assumed that all the DMUs under assessment have access to the same resources and that the outputs produced have the same characteristics (quality). However, the DMUs, inputs and outputs, and the environment are most of the time non-homogeneous.

Those issues have motivated to design a series of models to deal with those pitfalls in DEA. In this thesis, commercial banks have been used to explore the impact of the misspecification and heterogeneity in the assessment of the efficiency scores.

In the banking literature, objectives can be reflected in the type of assessment perspective, which drives the choices of inputs and outputs driven by a certain approach. Therefore, this thesis first presents an extensive literature survey of variables (inputs, outputs, dependent variables, explanatory variables) used in the relevant literature, and propose a classification of measures used in DEA works that can be translated to current and accessible data.

That summary of variables can be used for the analyst in choosing the relevant inputs and outputs for the analysis. One of the advantages of DEA is that is unit invariant, it obtains an efficient frontier from a set of observations without assuming any relationship between "inputs" and "outputs", however, it can also be a drawback because the variables selected by the analyst could have omitted relevant variables. Therefore, the selection of inputs and outputs has to be methodical and specific to the environment. As a second contribution, this thesis presents a regression-based feedback mechanism to assist in the selection of inputs and outputs for assessing the of the UK banking sector.

Finally, heterogeneity in DEA analysis can be also found in the environment, especially when assessing a multi-country DMUs. This thesis is concerned in specific to the operating environment of banks. The third contribution of this thesis lays in investigating the relative efficiency of operating environments of banks by analysing the efficiency of HSBC in different countries, and its effect in commercial banks under heterogeneity conditions.

Overall this thesis proposes modelling frameworks to correct the heterogeneity of environment and variables selection affecting the assessment of efficiency profiles of commercial banks using a variety of DEA models.

To my inspiring Mum

To my accomplice Husband

To my beloved Grandparents

ACKNOWLEDGEMENT

This thesis is the result of a long process that would not be possible without the support of my family, friends and colleagues.

Firstly I want to express my sincere gratitude to my supervisor, Professor Jamal Ouenniche. Thanks for your guidance, teaching, professional advice, time and friendship. For seeing in me the potential as a student but also as a collaborator, and for offered me diverse opportunities to develop my academic skills and enrich my academic experience.

Special thanks to my husband for supporting me and follow me on this journey. For always giving me the last push when I was hesitating, your trust makes me stronger. Your presence and funny conversations help me to overcome the rainy and cold days. You are my friend, colleague and accomplice in life.

To my Mum, thank you for your love, which is the power that makes my goals look reachable. For giving me advice in the most crucial times. For helping me being me and for trusting my decisions; but most importantly, for making me feel at home with your voice and your contagious smile.

To my Grand Mum for being an example of a life full of values and for giving me the best practical life advice. To my Grand Father, thank you for believing in me and for always made me feel special, even in your last moments; you are and will be always in my heart.

Finally, I want to thank the Mexican National Council of Science and Technology (CONACYT) for providing me with the awarded scholarship to study the PhD.

DECLARATION

I declare that the content of this thesis is my own work.

Signed:

Skarleth Carrales

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

INTRODUCTION

1.1 PRELIMINARIES

This section presents the motivations for this thesis, followed by a general introduction of the banking sector and the banking efficiency. Finally, the structure of the rest of the chapter is presented.

1.1.1 *Motivations*

1.1.1.1 Banking Sector

The banking sector plays a crucial socio-economic role at the regional, national and international levels. Banks are at the heart of financial systems in that they act as financial intermediaries; to be more specific, they borrow money by accepting deposits and issuing debt securities, and lend money both directly to their customers and indirectly through capital markets by investing in debt securities. Banks play an important role in the money supply and the efficient allocation of financial resources in an economy. Banks make profits in exchange for their services including risk management. Nowadays, banks have a diversified portfolio of activities that range from personal, corporate and investment banking to trading of currency, commodities, and financial securities on stock markets. Because of the crucial importance of banking systems to the economy and the financial risks they face, banks are required to comply with both national and international regulations, and their performance is constantly monitored by both regulatory bodies and investors. Poor performance often leads to distress which might lead to bankruptcy under some circumstances along with substantial financial, economic and social undesirable consequences.

Therefore, due to its vital role in a country's economic development and as the principal source of financial intermediation, it is important to evaluate their performance and efficiency. The necessity of having a reliable model that can assess the efficiency profile of banks is crucial for decision-makers such as stockholders, investors, depositors, governments and bank managers.

1.1.1.2 Commercial Banks

Banks contribute to enhance economic activities by transactions, acquisition and financing. There are different types of banks, Geoffrey Crowther (2011) classified them according to the basis of their functions (e.g. central, federal, national, commercial, industrial, exchange, and savings), investment (e.g. mortgage, micro-finance), ownership (e.g. public, corporative, private), domicile (e.g. domestic, foreign), and status (e.g. scheduled, non-schedule).

Some other types of banks have been created for specific reasons and each of them has its regulations such as the Islam Banks, Internet Banks, Ethical Banks, etc. It is important to mention that Banks can be classified at least in two of the basis mentioned before, for example, there are Saving Banks which are domestic and also private.

This thesis is concerned in assessing Commercial Banks, where most people do their banking activities by making deposits and receiving different types of loans and financial basic products. In other words, commercial banks are credit institutions authorized to receive funds from the public, mainly deposits (saving account deposits, recurring account deposits, and fixed deposits), which are the largest source of funds, and to grant credits to borrowers, known as loans, which are the primary use of their funds and the principal way in which they earn income. Therefore, commercial banks make money from their main core banking service as an intermediary by providing loans and earning interest income from those loans, because the interest rate paid by the banks on money they borrow is less than the rate charged on the money they lend.

1.1.1.3 Banking Efficiency

Evaluating the performance of commercial banks has been and will be the subject of interest for the economy in general for several reasons. The role of banks as intermediaries is crucial, they can manage savings, diversify risk and, encourage investment by helping to improve the productivity of the resources invested.

Banks have many areas where the efficiency can be impacted, according to Fethi and Pasiouras's survey (2010), there are 7 main topics of interest for researchers in banking issues.

- *Determinants of efficiency*: The factors that influence the efficiency of banks.
- *Stock returns and efficiency*: The relationship between stock returns and publicly available information.
- *Bank ownership*: The efficiency of banks across different ownership types.
- *Corporative events and efficiency*: Mergers and acquisition such as bankruptcy.
- *Regulatory reform/liberalization and efficiency*: The impact of regulatory reform and liberalization initiatives on bank efficiency and productivity.
- *Comparison of alternative frontier techniques*.
- *The efficiency of bank branches*: Focus on the efficiency of bank branches for the predominantly transaction-based.

In this thesis, the topic of study is focused on the *Determinants of efficiency* by controlling for heterogeneity and Comparison of alternative frontier techniques using a variety of models.

There is a considerable number of researchers that have attempted to examine the efficiency of banks by using different methodologies either parametric or non-parametric techniques. One of the most used methods to measure the performance and efficiency of banks is Data Envelopment Analysis (DEA), regarded as an indispensable tool to several studies aimed at evaluating efficiency. Since1978 and until 2010, according to Liu's et al. (2013) survey, the banking sector occupies in fact, the first place in the rank of studies where DEA is applied. Between 1978 and 2010, 3,134 papers have been published of which 323 are focused on the Banking sector, followed by Health care with 271, Agriculture and farm with 258, Transportation with 249, and Education with 184.

The efficiency in banks can be defined as the optimal use of resources for the production of banking services, which is associated with the proximity between the level of productivity, defined by the technical relationship between the resources used and the goods produced or financial services obtained from a particular entity and the maximum achievable in complex and highly competitive situations.

Therefore, the more efficient a bank is, the resources used to achieve its goals and objectives are better managed. The main objective is to do more with less, which involves the optimization of processes, the success of the investment decision either in the short and long term and, other key factors for the operation.

1.1.1.4 DEA in the banking sector

DEA began as a new Management Science tool for technical-efficiency analysis of DMUs, since the published paper wrote by Charnes, Cooper and Rhodes in 1978, considered as the most influential DEA paper, "Measuring the efficiency of decision-making units", several researchers have followed this study as the main path in the development of DEA. It was not until Since Sherman and Gold (1985) that the first bank study using DEA was published, proving the popularity of this application, nowadays, banking sector performance is the first place in the ranking of studies that use DEA.

DEA is a data-driven, non-parametric, frontier-based methodology originally designed for the evaluation of the relative performance of a set of entities commonly referred to as decision-making units (DMUs). Within a DEA framework, benchmarking is done with respect to the best or the worst peers rather than the average performers, which is the case for other methodologies such as stochastic frontier analysis. DEA has witnessed growing popularity amongst academics and practitioners, as suggested by the relatively large number of both methodological and application-oriented publications.

In banking studies, DEA typically addresses two types of problems, namely, performance evaluation problems and risk assessment problems. Concerning performance evaluation problems, the DEA literature on banking can be further divided into two categories depending on whether one is concerned with assessing the relative performance of banks or the relative performance of the branches of a given bank. As to risk assessment problems in the banking sector, the DEA literature could also be further divided into several categories depending on whether one is concerned with distress and bankruptcy of banks, or distress and default of a bank's customers.

In this thesis, the focus is on assessing the relative performance of commercial banks.

1.1.1.5 Heterogeneity

DEA measures the relative efficiency of a group of similar entities in transforming selected inputs into outputs. These entities, known as DMUs, are assumed homogenous. In DEA the homogeneity of the DMUs is a fundamental assumption. However, the DMUs are most of the time non-homogeneous for different factors. There is evidence that DMUs within a group of evaluation always present heterogeneity characteristics. The objectives of the DMUs can differ and therefore the use of the resources that are also assumed to be available in the same level under the “same environment” is unrealistic.

Heterogeneity in DMUS is not a new issue, several researchers have presented options to deal with the inconsistencies that heterogeneity causes (Castelli, Pesenti et al. 2001, Haas and Murphy 2003, Saen, Memariani et al. 2005, Samoilenko and Osei-Bryson 2008, Chen, Lee et al. 2017). Heterogeneity can be found not only in the DMUs, but also in the environment/contextual variables (Fried, Schmidt et al. 1999, Lozano-Vivas, Pastor et al. 2002, Drake, Hall et al. 2006, Tao 2013, Wanke and Barros 2014), and in the scales (Samoilenko and Osei-Bryson 2010).

In banking literature, due to homogeneity assumption, the tendency is to decide first which type of bank to assess according to its nature/function (e.g. central bank, commercial banks, saving Banks). If two or more different types of banks are assessed under the same analysis, the homogeneity assumption would be violated and therefore the efficiency scores obtained from that analysis would be inappropriate. Then within the chosen bank, the DMUs can be group according to factors such as ownership (e.g. public or cooperative), location (e.g. domestic or foreign), size (e.g. big, medium, small), and market condition.

This thesis proposes a series of a systematic method to deal with heterogeneity in the set of inputs and outputs used for the analysis and the effect that the operating environment has over the efficiency evaluation to provide fairness in the evaluation of DMU that most of the times are mistaken with management inefficiency.

1.1.2 Structure

The rest of this chapter is structured as follows:

Section 1.2 presents the general DEA models used in this thesis. These models are: CCR model (Input-oriented & Output oriented), BCC model (Input-oriented and Output-oriented), BCC without explicit inputs or outputs, SBM model (Input-oriented, Output-oriented and, Non-oriented), Network SBM model (Input-oriented, Output-oriented and, Non-oriented), Dynamic SBM model (Input-oriented, Output-oriented and, Non-oriented) and, Dynamic-Network SBM model (Input-oriented, Output-oriented and, Non-oriented).

Section 1.3 presents a comprehensive literature review of the paths followed on banking DEA, in particular, SBM models. Additionally, this section outlines the research gaps in the literature where this thesis fill.

Section 1.4 summarises the content of this thesis, highlights contributions of this work, and presents respective contributions for each of the following chapters.

Section 1.5 discusses future research directions. In particular heterogeneity in network models and other types of heterogeneity that DMUs presents.

Section 1.6 presents general conclusions.

1.2 MODELLING BACKGROUND

This section first discusses DEA as a methodology in section 1.2.1. Section 1.2.2 introduces the orientation perspective in DEA models. The rest of the sections presents the general modelling framework. Static model CCR and BCC are presented in section 1.2.3, Static SBM model in section 1.2.4, Dynamic model in section 1.2.5, Network model in section 1.2.6 and finally Dynamic-Network model in section 1.2.7.

1.2.1 DEA

Data Envelopment Analysis (DEA) is a data-oriented approach and a non-parametric data analytic technique for measuring efficiency. It obtains an efficient frontier from a set of observations without assuming any relationship between "inputs" and "outputs". It is ultimately an alternative to parametric methods to extract information from a set of observations and benchmarking against such frontier. It also seeks to optimize the efficiency of each unit tested, in this case, commercial banks in order to create an efficient frontier.

Another definition made by Charnes described DEA as a "mathematical programming model applied to observational data that provides a new way of obtaining empirical estimates of relations – such as the production functions and/or efficient production possibility surfaces – that are cornerstones of modern economics." In other words, this technique measures the relative efficiency of a group of decision-making units known as DMUs where multiple inputs are processed to generate multiple outputs.

In DEA the measures/metrics are classified as Inputs and Outputs. An important feature of DEA is its capability to provide efficiency scores, while taking account of both multiple common inputs and common multiple outputs, without assuming any relationship between them.

The inputs are the resources used to produce the outputs. The outputs are the products and/or services produced by the units. The inputs and outputs used in DEA define the basis to be used for assessing the units concerned, and so they must be determined with great care.

Some advantages of DEA are that it offers an alternative to the problem of weighting the partial indicators, allowing the search for a balance between objective and subjective elements that seem relevant. Also, it does not require that all units grant the same importance to the same partial indicator. It uses simple data which is not necessary to define and assumes that all Decision Making Units (DMU's) have the same possibilities of production.

DEA is very popular among researchers because it has proved to be an effective approach for measuring the performance of decision making units. DEA has been developed with the passing of the years, and recent studies have used these developments with some other models and techniques, creating hybrids methods to counteract the disadvantage of DEA. This thesis also used DEA in combination with other methods.

1.2.2 Orientations

To select the orientation of the model necessary and relevant. Therefore, the selection of the orientation of the model depends on the objective of the evaluation. There are three types of orientations, described as follows:

Input-oriented: To minimize the inputs at the same time that we are producing at least the same output level given

Output-oriented: To maximize the outputs at the same time that we are using no more than the inputs observed.

Non-oriented: To reduce at the same time inputs and increase outputs. In this type of orientation, we assume that managers can control the inputs and outputs and thus change them simultaneously.

The orientation is an important factor to measure the banking efficiency, this will also determine the type of measure to choose. According to Fethi and Pasiouras survey (2010), in banking studies, the orientation picked up to estimate the efficiency is by far the input-oriented approach. This orientation is popular in banking studies because "bank managers have higher control over inputs (e.g. personnel, expenses) rather than outputs (e.g. loans, income, etc.)".

The orientation of the analysis is a decision that the decision-maker should take into consideration depending on the main objective of the DMU. In this thesis, two or more orientations have been analysed in each chapter in order to give a bigger picture to the reader and see the differences in efficiency evaluation accordingly to the orientation.

1.2.3 Basic Data

For all the Variable Return to Scale (VRS) and Slack Based Measured DEA models presented in this thesis, the efficiency is measured on a scale of 0 to 1. The efficiency score is defined by θ for input-oriented models, *Ţ* for output-oriented models and ρ for non-oriented models.

Let:

n = the numbers of DMUs

m = the numbers of inputs

s = the numbers of outputs

j = DMUs

k = Division

λ = the intensity vector.

S^-= Input slack vector

S^+ = Output slack vector

Denote input *i* of DMU*j* by *xij (i*=1,…,*m*; *j*=1,…,*n)*

Denote *output r* of DMU*j* and *yrj (r* =1,…, *s*; *j*=1,…,*n)*

The input and output vectors for DMU*k* (*k*=1,…,*n*) are defined as:

x*k* = (*x*1*h*,…,*xmk)*

yk = (*y*1*h*,…,*ysk).*

The input and output matrices are defined as:

X= (*xij) (i*=1,…,*m*; *j*=1,…,*n)*

Y= (*yrj) (r* =1,…, *s*; *j*=1,…,*n)*

We assume X> 0 and Y> 0

When θ = 1 and S^-= 0 and S^+= 0 the DMU is considered as strongly efficient. When θ = 1 and S^-≠ 0 and S^+≠ 0 the DMU is considered as weakly efficient. And when θ < 1 the DMU is considered as inefficient.

1.2.4 Static CCR and BCC models

In the static models, the main idea is to use DEA as a tool to measure the efficiency of a DMU as a whole unit, without considering its internal structure, therefore the process between the inputs and the outputs is known as the black box. See figure 1.1

Figure 1.1 Black box

Two basic models can be implemented in DEA, the CCR model (1978) and the BCC model (1984), which are the most used among the studies in Commercial banks. The CCR model yields an objective evaluation of overall efficiency and results in a piecewise linear, constant returns-to-scale (CRS) envelopment surface. Whereas the BCC model estimates pure technical efficiency at the given scale of operation and yields in a piecewise linear, variable returns-to-scale (VRS) envelopment surface. Another difference between these models is that the CCR model identifies the sources and estimates the amounts of thus-identified inefficiencies and the BCC model Identifies whether increasing decreasing or constant returns to scale possibilities are presented for further exploitation.

In 1984, Banker, Charnes, and Cooper developed the BCC model in the publication “Some models for estimating technical and scale inefficiency in data envelopment analysis”. This model estimates the Pure Technical Efficiency of DMUs and Assume a Variable Return to Scale and do and take into account the efficiency frontier, therefore this model can handle negative data. Mehdi Toloo and Soroosh Nalchigar (2009) suggest that “CCR models are a specific type of BCC models” because “identifies whether a DMU is operating in increasing, decreasing or constant returns to scale”.

According to the nature of the data (positive or negative), one can determine which assumption to choose between CRS or VRS. According to Fethi and Pasiouras survey (2010), in recent papers, most of the times when DMUs are measured using the VRS assumption is because firms are operating far from the optimal scale. And when the opposite happens, CRS is used to evaluate the DMUs. On account of banking failure will use negative data, the assumption to use in this research is Variable Return to Scale.

The Objective functions and Constraints of the Static CCR and BCC models are presented below. Note that Chapter 3 also uses the BCC Model without explicit inputs and outputs. These models are presented in Chapter 3.

Table 1.1 Static* CCR and BCC Models*: The Generic Formulation

Formulation: Objective	Description
θ_k	θ_k is to be minimised or maximised depending on whether the analysis is input-oriented or output-oriented
Formulation: Constraints	Description
$\sum_{j=1}^{n} \lambda_j x_{i,j} \leq \theta_k \cdot x_{i,k}, i = 1, \dots, m$ OR $\sum_{j=1}^{n} \lambda_j x_{i,j} \leq x_{i,k}, i = 1, \dots, m$	For each input i $(i = 1, \dots, m)$, the amount used by DMU_k's "ideal" benchmark; i.e., its projection on the efficiency frontier, should at most be equal to the amount used by DMU_k adjusted for the degree of technical efficiency of DMU_k or not depending on whether the analysis is input-oriented or not
$\sum_{j=1}^{n} \lambda_j y_{r,j} \geq \theta_k \cdot y_{r,k}, r = 1, \dots, s$ OR $\sum_{j=1}^{n} \lambda_j y_{r,j} \geq y_{r,k}, r = 1, \dots, s$	For each output r $(r = 1, \dots, s)$, the amount produced by DMU_k's "ideal" benchmark; i.e., its projection on the efficiency frontier, should be at least as large as the amount produced by DMU_k adjusted for the degree of technical efficiency of DMU_k or not depending on whether the analysis is output-oriented or not
$\sum_{j=1}^{n} \lambda_j = 1$	The technology is required to be convex in BCC models. This constraint is relaxed in CCR models.

$\lambda_j \geq 0, j = 1, \ldots, n$ θ_k unrestricted	Other requirements including non-negativity

1.2.5 SBM model

Slack-based-measure (SBM) was first proposed by Kaoru Tone in 2001. This measure of efficiency deal with the “input excess and the outputs shortfalls” of the DMUs and takes into account slacks. Also “is determined only by consulting the reference-set of the DMU and is not affected by statics over the whole data set.” “It is unit invariant and monotone decreasing with respect to input excess and output shortfall. Furthermore, this measure is determined only by consulting the reference-set of the DMU and is not affected by statistics over the whole data set” (Tone 2001).

SBM can be compared with the additive model (Charnes 1985) due that also deals with the input excesses and output shortfalls, but the difference is that the SBM does not have a scalar measure, which means that it does not have a ratio efficiency per se. According to Tone (2001), a DMU is SBM-efficient if and only if is CCR-efficient and vice versa.

Other variants of slack-based-measure have been developed, one of them can be seen in Tone (2001) where slack-based measure with super-efficiency is applied in six power plants, basically, this model tries to "discriminate between the efficient status DMUs". Another one is the "network slack-based-measure non-oriented under variable return to scale", developed in the paper of Kao (2013). This model can decompose the system to identify the principal factors that improve the performance of the DMUs.

SBM has been presented also in models that are not static. That is the case of Network SBM model (Tone and Tsutsui, 2009), Dynamic SBM model (Tone and Tsutsui, 2010) and Dynamic Network DEA (Tone and Tsutsui, 2014), discussed in the next sections.

The Objective functions and Constraints of the Static VRS SBM models are presented below. Note that one contribution of this thesis (Chapter 3) is the SBM Model without explicit outputs. This model is presented in Chapter 3 together with the SBM model without explicit inputs.

Table 1.2 Static SBM Models: The Generic Formulation

Formulation: Objective	Description
$\rho_k = \left(1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{i,k}^{-}}{x_{i,k}}\right) \Big/ \left(1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_{r,k}^{+}}{y_{r,k}}\right)$ OR $\rho_k = 1 - \frac{1}{m}\sum_{i=1}^{m}\frac{s_{i,k}^{-}}{x_{i,k}}$ OR $\rho_k = 1 \Big/ \left(1 + \frac{1}{s}\sum_{r=1}^{s}\frac{s_{r,k}^{+}}{y_{r,k}}\right)$	One of these ρ_k formulations is to be minimised depending on whether the analysis is non-oriented, input-oriented, or output-oriented
Formulation: Constraints	Description
$\sum_{j=1}^{n}\lambda_j x_{i,j} + s_{i,k}^{-} = x_{i,k}, i = 1, \dots, m$	For each input i $(i = 1, \dots, m)$, the amount used by DMU_k's "ideal" benchmark; i.e., its projection on the efficiency frontier, should at most be equal to the amount used by DMU_k

$\sum_{j=1}^{n} \lambda_j y_{r,j} - s_{r,k}^{+} = y_{r,k}, r = 1, \dots, s$	For each output r $(r = 1, \dots, s)$, the amount produced by DMU_k's "ideal" benchmark; i.e., its projection on the efficiency frontier, should be at least as large as the amount produced by DMU_k
$\sum_{j=1}^{n} \lambda_j = 1$	This constraint requires the technology to be convex; however, it could be relaxed.
$\lambda_j \geq 0, j = 1, \dots, n$ $s_{i,k}^{-} \geq 0, i = 1, \dots, m$ $s_{r,k}^{+} \geq 0, r = 1, \dots, s$	Non-negativity requirements

1.2.6 Network, Dynamic and Dynamic-Network models

In Liu et al. survey (2016) the principal research path for Network DEA, Dynamic DEA Dynamic-Network, and SBM is defined as a same group of study, arguing that these DEA models are "conceptually associated with each other"

Network model.

One of the most criticized characteristics of the basic DEA model is that the internal structure is not taking into account. Most of the times the production system is conformed of many interrelated processes. To know this internal process is very helpful to understand the transformation of the inputs and therefore to have the possibility to improve the performance by focusing on the specific element of the Decision Making Units (DMUs).

Network DEA was first introduced by Fare and Grosskopf (1996) in the book "Intertemporal Production Frontier: With Dynamic DEA" where the static network models are introduced allowing to "go inside the black box of technology and explicitly consider intermediate products". The idea of a network model was employed to provide a general structure to derivate dynamic models.

Network DEA is very popular within DEA researchers because it is used as a technique to measure the efficiency of systems with a network structure and takes into account the internal structure that is connected with links. The Network Structure of the Network model will depend on the structure of the DMU and the process. Chiang Kao (2014) and Castelli et al. (2010), both agree in the classification of Network structures as follows: Basic two-stage structure/ two subunits, General two-stage structure/ More sub-processes, Series structure/ Series system, Parallel structure, Mixed structure, Hierarchical structure, Dynamic structure and Multi-stage DMUs.

The main differences between these structures depend on how the inputs supply the process, in which stage they do it, and how many times an input can be used. For example in the basic two-stage structure, which is the simplest one, the inputs used in the first stage, produce outputs which are used as inputs in the second stage to produce the final outputs.

Regarding series structure, the processes are connected in sequence using the same logic of inputs and outputs of the two-stage structures. On the contrary, in the parallel structures, the processes operate independently. However is very similar to the multistage period system, but this structure needs all the inputs and the outputs of every period to be the same. The Mixed structure is a mix of series and parallel. The Hierarchical structure is very close to the parallel one, but in this, the levels and the interaction between these are needed (headquarters and subordinate).

The general Network structure can be exemplified in the following diagram (Figure 1.2)

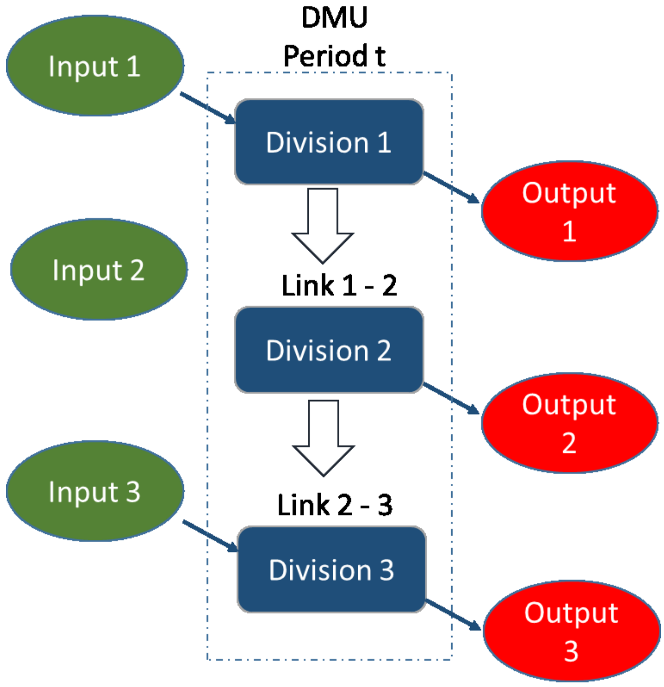


Figure 1.2 Network structure

Additionally to the notation introduced in section 1.2.3, The Network SBM model uses free link ℓ ($\ell = 1, \ldots, L_{k,\mathrm{h}}^{\mathrm{Free}}$) between Division k and Division h of DMU_{j_0} or/and fixed link ℓ ($\ell = 1, \ldots, L_{k,\mathrm{h}}^{Fix}$) between Division k and Division h of DMU_{j_0}.

The Objective functions and Constraints of the Network SBM models are presented below.

Table 1.3 Network DEA Models: The Generic Formulation

Formulation: Objective	Description
$\theta_{j_0} = \sum_{k=1}^{K} w^k \theta_k$; $\theta_k = 1 - \frac{1}{m_k}\left(\sum_{i=1}^{m_k} \frac{s_{i,j_0}^{k-}}{x_{i,j_0}^{k}}\right)$	Input-Oriented SBM Objective: weighted average of input-oriented divisional efficiencies, θ_ks, of DMU_{j_0} – also referred to as input-oriented overall efficiency θ_{j_0} of DMU_{j_0}, where w^ks are

	divisional weights and are supplied exogenously according to their importance and satisfy the conditions: $\sum_{k=1}^{K} w^k = 1$.
$\tau_{j_0} = \sum_{k=1}^{K} w^k \tau_k$; $\tau_k = \frac{1}{1+\frac{1}{s_k}\left(\sum_{r=1}^{s_k}\frac{s_{r,j_0}^{k+}}{y_{r,j_0}^{k}}\right)}$	Output-Oriented SBM Objective: weighted average of output-oriented divisional efficiencies, τ_ks, of DMU_{j_0} – also referred to as output-oriented overall efficiency τ_{j_0} of DMU_{j_0}, where w^ks are divisional weights and are supplied exogenously according to their importance and satisfy the conditions: $\sum_{k=1}^{K} w^k = 1$.
$\rho_{j_0} = \sum_{k=1}^{K} w^k \rho_k$; $\rho_k = \frac{1-\frac{1}{m_k}\left(\sum_{i=1}^{m_k}\frac{s_{i,j_0}^{k-}}{x_{i,j_0}^{k}}\right)}{1+\frac{1}{s_k}\left(\sum_{r=1}^{s_k}\frac{s_{r,j_0}^{k+}}{y_{r,j_0}^{k}}\right)}$	Non-Oriented SBM Objective: weighted average of non-oriented divisional efficiencies, ρ_ks, of DMU_{j_0} – also referred to as non-oriented overall efficiency $\rho_{j_0}$of DMU_{j_0}, where w^ks are divisional weights and are supplied exogenously according to their importance and satisfy the conditions: $\sum_{k=1}^{K} w^k = 1$.
Formulation: Constraints	Description
$\sum_{j=1}^{n} \lambda_j^k x_{i,j}^k + s_{i,j}^{k-} = x_{i,j_0}^k$; $\forall j_0, k, i$ $\Leftrightarrow$ $\sum_{j=1}^{n} \lambda_j^k x_{i,j}^k \leq x_{i,j_0}^k$; $\forall j_0, k, i$	For each division k ($k = 1, \ldots, K$) of each DMU_{j_0} ($j_0 = 1, \ldots, n$), the amount of *input* i ($i = 1, \ldots, m_k$) used by its “ideal” benchmark; i.e., its projection on the efficient frontier, should at most be equal to the amount used by $division_{j_0}^k$;

$\sum_{j=1}^{n} \lambda_j^k y_{r,j}^k - s_{r,j}^{k+} = y_{r,j_0}^k;\ \forall j_0, k, r$ $\Leftrightarrow$ $\sum_{j=1}^{n} \lambda_j^k y_{r,j}^k \geq y_{r,j_0}^k; \forall j_0, k, r$	For each division k ($k = 1, \dots, K$) of each DMU_{j_0} ($j_0 = 1, \dots, n$), the amount of *output* r ($r = 1, \dots, s_k$) produced by its "ideal" benchmark should be at least as large as the amount produced by $division_{j_0}^k$;
$\sum_{j=1}^{n} \lambda_j^k z_{k,h,j}^{\ell\, Free} = \sum_{j=1}^{n} \lambda_j^h z_{k,h,j}^{\ell\, Free}$; $\forall j_0, (k,h), \ell$ Notice that this constraint could be decomposed as follows: $\sum_{j=1}^{n} \lambda_j^k z_{k,h,j}^{\ell\, Free} \geq z_{k,h,j_0}^{\ell\, Free}; \forall j_0, (k,h), \ell$ (flow as output from division k) OR $\sum_{j=1}^{n} \lambda_j^k z_{k,h,j}^{\ell\, Free} - s_{k,h,j}^{\ell\, Free+} = z_{k,h,j_0}^{\ell\, Free}; \forall j_0, (k,h), \ell$ AND $\sum_{j=1}^{n} \lambda_j^h z_{k,h,j}^{\ell\, Free} \leq z_{k,h,j_0}^{\ell\, Free}; \forall j_0, (k,h), \ell$ (flow as input to division h) OR	For each free link ℓ ($\ell = 1, \dots, L_{k,\mathrm{h}}^{\mathrm{Free}}$) between Division k and Division h of DMU_{j_0}, the amount of free/discretionary flow carried by its "ideal" benchmark (i.e., its projection on the efficient frontier) – whether considered as output from division k or as input to division h - should be equal to the amount carried by free link ℓ; which implies that $z_{k,h,j_0}^{\ell\, Free}$ is free to manage, as $z_{k,h,j_0}^{\ell\, Free} \leq \sum_{j=1}^{n} \lambda_j^k z_{k,h,j}^{\ell\, Free}$ and $z_{k,h,j_0}^{\ell\, Free} \geq \sum_{j=1}^{n} \lambda_j^h z_{k,h,j}^{\ell\, Free}$ imply their equality. These type of constraints are often referred to as global balance equations for intermediate products in that they require that the amounts of an intermediate product produced and used by different processes do match. In sum, these constraints ensure continuity between inputs and outputs

$\sum_{j=1}^{n} \lambda_j^h z_{k,h,j}^{\ell\, Free} + s_{k,h,j}^{\ell\, Free-} = z_{k,h,j_0}^{\ell\, Free}; \forall j_0, (k,h), \ell$	
$\sum_{j=1}^{n} \lambda_j^k z_{k,h,j}^{\ell\, Fix} = z_{k,h,j_0}^{\ell\, Fix}; \forall j_0, (k,h), \ell$ (flow as output from division k) AND $\sum_{j=1}^{n} \lambda_j^h z_{k,h,j}^{\ell\, Fix} = z_{k,h,j_0}^{\ell\, Fix}; \forall j_0, (k,h), \ell$ (flow as input to division h)	For each fixed link ℓ ($\ell = 1, \dots, L_{k,\mathrm{h}}^{Fix}$) between Division k and Division h of DMU_{j_0}, the amount of fixed/non-discretionary flow carried by its "ideal" benchmark (i.e., its projection on the efficient frontier) – whether considered as output from division k or as input to division h - should be equal to the amount carried by fixed link ℓ. This type of constraints are also referred to as global balance equations for intermediate products
$\sum_{j=1}^{n} \lambda_j^k = 1;\ \forall k$	For each division k ($k = 1, \dots, K$), the technology is required to be convex;
$\lambda_j^k \geq 0;\ \forall j, k$ $s_{i,j}^{k-}; \forall i, k, j$ $s_{r,j}^{k+}; \forall r, k, j$ $s_{k,h,j}^{\ell\, Free+}; \forall j, (k,h), \ell$ $s_{k,h,j}^{\ell\, Free-}; \forall j, (k,h), \ell$	Non-negativity requirements

Dynamic model.

Another type of structure is the Dynamic, this structure uses carryovers as intermediate products, where the period is repeated, and it means that the inputs, outputs and carryovers are the same every period. The structure of the period can be any of the structures mentioned above. According to Tone and Tsutsui (2010) "What distinguish dynamic DEA from the ordinary DEA is the existence of carry-overs that connect two consecutive terms".

The Dynamic structure can be exemplified in the following diagram (Figure 1.3).

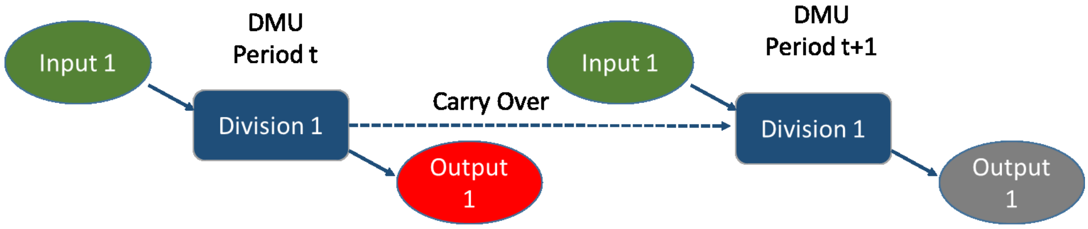


Figure 1.3 Dynamic structure

Additionally to the notation introduced in section 1.2.3, The Dynamic SBM model uses carry-overs, which are variables that take into account a positive or negative factor in the previous period. Tone and Tsutsui (2010) described four types of carryovers 1) Desirable (good) links e.g. retained earnings and net earned, 2) Undesirable (bad) link e.g. loss carried forward, bad debt and dead stock, 3) Discretionary (free) link are those that the DMU can handle freely and, 4) Non,-discretionary (fixed) link are those beyond the control of DMU. Also takes into consideration time t $(t = 1, \ldots, T)$.

The Objective functions and Constraints of the Dynamic SBM models are presented below.

Table 1.4 Dynamic DEA Models: The Generic Formulation

Formulation: Objective	**Description**
$\theta_k = \frac{1}{T}\sum_{t=1}^{T} w^t \theta_k^t$	Technical efficiency θ_k, where w^t is period t weight and is supplied exogenously according to its importance and satisfies the condition: $\sum_{t=1}^{T} w^t = T$.
$min\ \theta_k = \frac{1}{T}\sum_{t=1}^{T} w^t \theta_k^t$; $\theta_k^t = 1 - \frac{1}{m+b}\left(\sum_{i=1}^{m} \frac{w_i^- s_{i,t}^-}{x_{i,k,t}} + \sum_{i=1}^{b} \frac{s_{i,t}^{Bad-}}{z_{i,k,t}^{Bad}}\right)$	Input-Oriented SBM; i.e., weighted average of period or term efficiencies, θ_k^ts, over the assessment horizon T – also referred to as input-oriented overall efficiency θ_k, where w^t and w_i^- are period t and input i weights, respectively, and are supplied exogenously according to their importance and satisfy the conditions: $\sum_{t=1}^{T} w^t = T$ and $\sum_{i=1}^{m} w_i^- = m$.
$max\ \frac{1}{\tau_k} = \frac{1}{T}\sum_{t=1}^{T} w^t \frac{1}{\tau_k^t}$; $\frac{1}{\tau_k^t} = 1 + \frac{1}{s+g}\left(\sum_{r=1}^{s} \frac{w_r^+ s_{r,t}^+}{y_{r,k,t}} + \sum_{i=1}^{g} \frac{s_{i,t}^{Good+}}{z_{i,k,t}^{Good}}\right)$	Output-Oriented SBM; i.e., weighted average of period or term efficiencies, τ_k^ts, over the assessment horizon T – also referred to as output-oriented overall efficiency τ_k, where w^t and w_r^- are period t and output r weights, respectively, and are supplied exogenously according to their importance and satisfy the conditions: $\sum_{t=1}^{T} w^t = T$ and $\sum_{r=1}^{s} w_r^- = s$.

$min\ \rho_k = \frac{1}{T}\sum_{t=1}^{T} w^t \rho_k^t;$ $\rho_k^t =$ $\frac{1-\frac{1}{m+b}\left(\sum_{i=1}^{m}\frac{w_i^- s_{i,t}^-}{x_{i,k,t}}+\sum_{i=1}^{b}\frac{s_{i,t}^{Bad-}}{z_{i,k,t}^{Bad}}\right)}{1+\frac{1}{s+g}\left(\sum_{r=1}^{s}\frac{w_r^+ s_{r,t}^+}{y_{r,k,t}}+\sum_{i=1}^{g}\frac{s_{i,t}^{Good+}}{z_{i,k,t}^{Good}}\right)}$	Non-Oriented SBM; i.e., weighted average of period or term efficiencies, ρ_k^ts, over the assessment horizon T – also referred to as non-oriented overall efficiency ρ_k
Formulation: Constraints	**Description**
$\sum_{j=1}^{n}\lambda_j^t x_{i,j,t} \le \theta_k^t(F^t)\cdot x_{i,k,t};\ \forall i,t$ $\Leftrightarrow$ $\sum_{j=1}^{n}\lambda_j^t x_{i,j,t} + s_{i,t}^- = \theta_k^t(F^t)\cdot x_{i,k,t};\ \forall i,t$ OR $\sum_{j=1}^{n}\lambda_j^t x_{i,j,t} \le x_{i,k,t};\ \forall i,t$ $\Leftrightarrow$ $\sum_{j=1}^{n}\lambda_j^t x_{i,j,t} + s_{i,t}^- = x_{i,k,t};\ \forall i,t$	In each period t $(t = 1, \dots, T)$, the amount of variable input i $(i = 1, \dots, m)$ used by DMU_k's "ideal" benchmark; i.e., its projection on the efficient frontier of period t, say F^t, should at most be equal to the amount used by DMU_k whether revised (i.e., amount of variable input i adjusted for the degree of technical efficiency of DMU_k) or not depending on the specific formulation under consideration;
$\sum_{j=1}^{n}\lambda_j^t y_{r,j,t} \ge \theta_k^t(F^t)\cdot y_{r,k,t};\ \forall r,t$ $\Leftrightarrow$	In each period t $(t = 1, \dots, T)$, the amount of variable output r $(r = 1, \dots, s)$ produced by DMU_k's "ideal" benchmark should be at least as large as the amount produced by DMU_k whether revised or not depending

$\sum_{j=1}^{n}\lambda_j^t y_{r,j,t} - s_{r,t}^{+} = \theta_k^t(F^t) \cdot y_{r,k,t};\ \forall r,t$ OR $\sum_{j=1}^{n}\lambda_j^t y_{r,j,t} \geq y_{r,k,t};\ \forall r,t$ $\Leftrightarrow$ $\sum_{j=1}^{n}\lambda_j^t y_{r,j,t} - s_{r,t}^{+} = y_{r,k,t};\ \forall r,t$	on the specific formulation under consideration;
$\sum_{j=1}^{n}\lambda_j^t x_{i,j,t}^{Fix} = x_{i,k,t}^{Fix};\ \forall i,t$	In each period t ($t = 1, \dots, T$), the amount of fixed input i ($i = 1, \dots, m'$) used by DMU_k's "ideal" benchmark; i.e., its projection on the efficient frontier of period t, should be equal to the amount used by DMU_k;
$\sum_{j=1}^{n}\lambda_j^t y_{r,j,t}^{Fix} = y_{r,k,t}^{Fix};\ \forall r,t$	In each period t ($t = 1, \dots, T$), the amount of fixed output r ($r = 1, \dots, s$) produced by DMU_k's "ideal" benchmark should be equal to the amount produced by DMU_k;
$\sum_{j=1}^{n}\lambda_j^t z_{i,j,t}^{Good} \geq z_{i,k,t}^{Good};\ \forall i,t$ $\Leftrightarrow$ $\sum_{j=1}^{n}\lambda_j^t z_{i,j,t}^{Good} - s_{i,t}^{Good+} = z_{i,k,t}^{Good};\ \forall i,t$	In each period t ($t = 1, \dots, T$), the amount of good/desirable activity i ($i = 1, \dots, g$) carried over to the next period by DMU_k's "ideal" benchmark; i.e., its projection on the efficient frontier of period t, should at least

	be equal to the amount carried over by DMU_k;
$\sum_{j=1}^{n} \lambda_j^t z_{i,j,t}^{Bad} \leq z_{i,k,t}^{Bad}$; $\forall i, t$ $\Leftrightarrow$ $\sum_{j=1}^{n} \lambda_j^t z_{i,j,t}^{Bad} + s_{i,t}^{Bad-} = z_{i,k,t}^{Bad}$; $\forall i, t$	In each period t $(t = 1, \dots, T)$, the amount of bad/undesirable activity i $(i = 1, \dots, b)$ carried over to the next period by DMU_k's "ideal" benchmark; i.e., its projection on the efficient frontier of period t, should at most be equal to the amount carried over by DMU_k;
$\sum_{j=1}^{n} \lambda_j^t z_{i,j,t}^{Free} \leq z_{i,k,t}^{Free}$; $\forall i, t$ $\Leftrightarrow$ $\sum_{j=1}^{n} \lambda_j^t z_{i,j,t}^{Free} + s_{i,t}^{Free-} = z_{i,k,t}^{Free}$; $\forall i, t$	In each period t $(t = 1, \dots, T)$, the amount of free/discretionary activity i $(i = 1, \dots, f)$ carried over to the next period by DMU_k's "ideal" benchmark; i.e., its projection on the efficient frontier of period t, should at most be equal to the amount carried over by DMU_k;
$\sum_{j=1}^{n} \lambda_j^t z_{i,j,t}^{Fix} = z_{i,k,t}^{Fix}$; $\forall i, t$	In each period t $(t = 1, \dots, T)$, the amount of fixed/non-discretionary activity i $(i = 1, \dots, f')$ carried over to the next period by DMU_k's "ideal" benchmark; i.e., its projection on the efficient frontier of period t, should be equal to the amount carried over by DMU_k;
$\sum_{j=1}^{n} \lambda_j^t z_{i,j,t}^{\alpha} = \sum_{j=1}^{n} \lambda_j^{t+1} z_{i,j,t}^{\alpha}$;	Inter-temporal dependencies are taken account of through carry-overs from one

$\forall i, t = 1, \dots, T-1,$ $\alpha = Good, Bad, Free, Fix$	period to the next, where the projection on the efficient frontier of period t of the total amount of an activity, say i, carried over from period t ($t = 1, \dots, T-1$) to period $t + 1$ should be equal to its projection on the efficient frontier of period $t + 1$;
$\sum_{j=1}^{n} \lambda_j^t = 1;\ \forall t$	In each period t ($t = 1, \dots, T$), the technology is required to be convex;
$\lambda_j^t \geq 0;\ \forall j, t$ $s_{i,t}^{-} \geq 0; \forall i, t$ $s_{r,t}^{+} \geq 0; \forall r, t$ $s_{i,t}^{Good+} \geq 0; \forall i, t$ $s_{i,t}^{Bad-} \geq 0; \forall i, t$ $s_{i,t}^{Free-} \geq 0; \forall i, t$	Non-negativity requirements

Dynamic Network

According to Tone and Tsutsui (2010) "The dynamic DEA models have close connections with the network DEA models". In this sense, the Dynamic Network model then, is a mix between Network and Dynamic, as shown in the next figure (Figure 1.4).

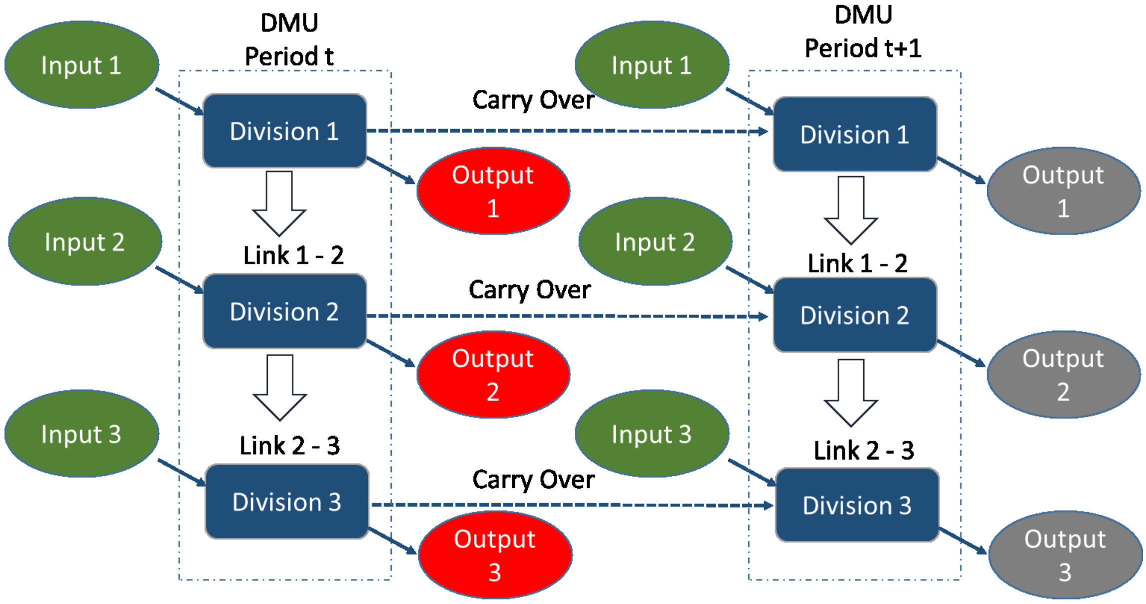
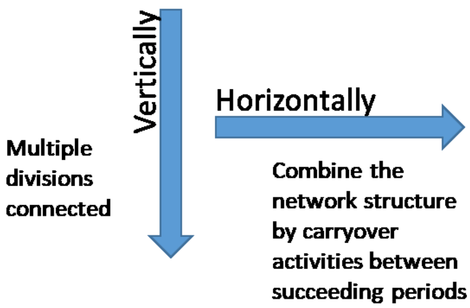


Figure 1.4 Dynamic-Network structure

In other words

Take into account the internal structure of a system and use the **links** as variables

Take into account the multiple-period to evaluate the performance from a long-term perspective using **carry-over** as variables



- ✓ Evaluate the Overall efficiency over the entire observed period
- ✓ ... Dynamic change of period efficiency
- ✓ ... Dynamic change of divisional efficiency

1.2.7 Other DEA models

With the passing of the years, DEA has been developed and becoming a "body of concepts and methodologies that have now been incorporated in a collection of models" (Cooper et al. 1994). These developments have emerged by the necessity of covering certain areas that the usual DEA method do not cover by itself. We can see a sample of the developed models In Cook and Seaford's survey (2009), shown in Table 1.5

- **DEA usual definition**
  - CRS (1978)
  - VRS (1985)
  - Additive Model
  - Slacks-based measures 2001
  - Russell measure
  - Non-radial models
  - Alternative views
  - Least distance projections
  - Invariance to Data alterations
- **Multilevel models**
  - Multi stage serial models
    - Network DEA 1996
    - Supply chains
  - Multicomponent parallel models
  - Hierarchical nested models
- **Multiplier restrictions**
  - Absolute multiplier restrictions
  - Cone ratio restrictions
  - Assurance regions
  - Facet models
- **Special considerations regarding the status of variables**
  - Non-discretionary variables
  - Non-controllable variables
  - Categorical variables
  - Ordinal variables data
  - Modelling undesirable factors
  - Flexible measure- Classifying inputs and outputs
- **Data variation**
  - Sensitivity analysis
    - Problem size issues
    - Direct data perturbations
    - Indirect data perturbation
    - Supper-efficiency
  - Data uncertainty and profitability-based models
  - Time series data- Window analysis
  - Time series data- The Malmquist index
  - Stochastic data-statistical inference

Table 1.5 DEA models

The choice of a particular DEA model should be determined by what are we interested to look for, therefore the type of information we are going to use, the source of the inputs, the structure, the process and others should be considered.

1.3 LITERATURE SURVEY

Research papers on efficiency assessment in banking could be classified into several categories depending on one's choice of the classification criterion. A literature review of DEA models and contributions has been done differently for each chapter in the thesis. Therefore, the remainder of this chapter is organized as follows. Section 1.3.1 presents the classification criteria for chapter 2. Section 1.3.2 presents three criteria to classify the literature of chapter 3 on static DEA analyses; namely, type of analysis, type of approach, and country of focus. Finally, section 1.3.2 presents three classification criteria that clearly shows the position of the contribution of chapter 4: namely single country analyses vs. cross-country analyses, analyses without environmental variables vs. analyses with environmental variables, and single-stage analyses vs. multi-stage analyses.

The detailed references of each classification can be found in the literature review part of each paper (Chapter 2, 3 and 4). Note that the process described in 1.3.1 was used for the rest of the chapters (3 and 4). The studies where classified accordingly once the paper was read. This practice led to classify one paper in more than one classification, making easier to find the scope and contribution of this thesis.

The rest of the DEA methodologies used in this thesis (chapter 4) such as Network, Dynamic, and Dynamic-Network, were selected similarly. Specific surveys regarding these methods have been published. Note that Network SBM model was first introduced in 2009, followed by Dynamic SBM model in 2010, and Dynamic-Network published in 2014. The number of papers reviewed for these models was smaller than the one performed for the static black-box model.

1.3.1 Chapter 2

This chapter presents a literature review of DEA studies that presents particular characteristics with a focus on static DEA models. The objective of this survey is to classify the literature by empirical motivation and variable selection. Therefore, the literature surveyed most be rich and varied.

There are several survey publications in DEA, table # presents the surveys used for the preliminary selection of papers (see table 1.6).

Table 1.6 DEA Surveys

Authors	Tittle	Year
Lawrence M. Seiford	Data Envelopment Analysis: The Evolution of the State of the Art (1978-1995)	1996
Allen N. Berger and David B. Humphrey	Efficiency of financial institutions: International survey and directions for future research	1997
Lawrence M. Seiford	A bibliography for Data Envelopment Analysis	1997
John Ashton and Philip Hardwick	Estimating Inefficiencies in Banking: A Survey	2000
Ali Emrouznejad, Barnett R. Parker, and Gabriel Tavares	Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA	2008
Wade D. Cook,*, Larry M. Seiford	Data envelopment analysis (DEA) Thirty years on	2009
Meryem Duygun Fethi, and Fotios Pasiouras	Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey	2010
Necmi K. Avkiran a, and Barnett R. Parker	Pushing the DEA research envelope	2010
John S.Liu, LouisY.Y.Lu, Wen-MinLu, and BruceJ.Y.Lin	A survey of DEA applications	2013
John S.Liu, LouisY.Y.Lu, Wen-MinLu, and BruceJ.Y.Lin	Data envelopment analysis 1978–2010: A citation-based literature survey	2013
Georgios I. Farantos	The Data Envelopment Analysis Method and the influence of a phenomenon in organizational Efficiency: A literature review and the Data Envelopment Contrast Analysis new application	2015

John S.Liu, LouisY.Y.Lu, and Wen-MinLu	Research fronts in data envelopment analysis	2016
Ali Emrouznejad and Guo-Liang Yang	A survey and analysis of the first 40 years of scholarly literature in DEA: 1978 - 2016	2017

However, the main surveys used for the cross-referencing technique were Liu et al, (2013) and Liu et al, (2016) and Ali et al, (2017). These surveys used methods such as directional network and network clustering. In banking literature, the key route paper for application is Sherman and Gold 1995, however this paper asses banking branches. For our specific case, the first paper in assessing the relevant efficiency of commercial banks is Rangan et al, (1988).

From the collection of this survey, a first filter where performed. In this first filter, all the studies most have the following characteristics:

- Application studies.
- Assessing commercial banks without considering studies assessing branches.
- Using exclusively static DEA models.

Once identified the studies with those characteristics, a selection of the most referred papers was done. The final selection of papers was related to the contribution to the chapter concerning variety and content.

A selection of 21 papers was obtained and was chronologically order to reflect the development of DEA in banking applications with static models. The details of these papers and its classification of their empirical investigations can be seen in chapter 2.

1.3.2 Chapter 3

In this chapter, we use three criteria to classify the literature on static DEA analyses as shown in figure #. The decision for this classification is based on the research questions which are focused on the whole UK commercial banking system. Although the UK banking system is relatively big compared to the banking systems of other countries, and has the largest banking sector on a residency basis compared to US, Japan and the ten largest EU Economies and nearly 1/5 of the global banking activity is booked in here, DEA studies focused on the UK banking system are quite scarce. Four papers were found that focuses on the UK (Drake 2001; Webb 2003; Webb et al. 2010; Tanna et al. 2011). Unlike those studies that only asses the biggest commercial banks, this research is focused on the whole UK commercial banking system. Therefore, this research can be situated under the category of static DEA models to assess the technical efficiency of commercial banks in a single-stage analysis, focused on a single country under the intermediation approach.

Concerning to variable selection in DEA, the literature could be divided into four categories (see figure 1.5):

- *Judgmental Screening*: e.g. Fuzzy Delphi Method.
- *Statistical Tests*: e.g. Bootstrapping.
- *Dimensionality Reduction Techniques* e.g. Principal Component Analysis.
- *Variable Reduction Techniques*: e.g. Correlation Analysis and Variants, Copula, Efficiency Contribution Measure, Stepwise Procedures, Akaike's Information Criterion rule, Directional Technology Distance Function, Regression Analysis, Decision Tree Analysis, and Genetic Algorithms.

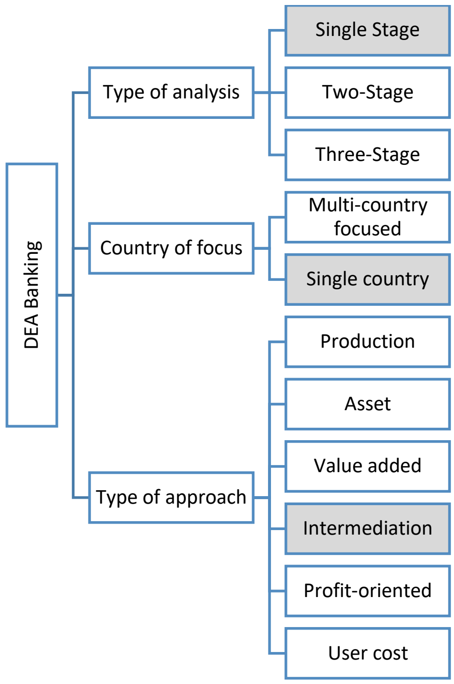
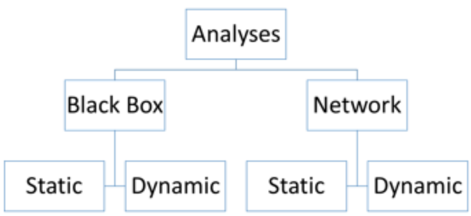


Figure 1.5 Categories chapter 3

To position the contribution of this paper, the feedback mechanism used for this analysis falls into the subcategory of Regression Analysis; however, unlike previous contributions, ours use regression analysis within a feedback mechanism allows for no-inputs or no-outputs situations.

1.3.3 Chapter 4

In this chapter, the main focus is to find out which banking-operating environments are more efficient from our data set. To find out the best model for addressing this research question, four different types of DEA models. (Static black box, Dynamic black box, Network, and Dynamic-Network SBM), were performed.



The classification criteria for this chapter shows the position of the contribution; namely, single country analyses vs. cross-country analyses, analyses without environmental variables vs. analyses with environmental variables, and single-stage analyses vs. multi-stage analyses (see figure 1.6).

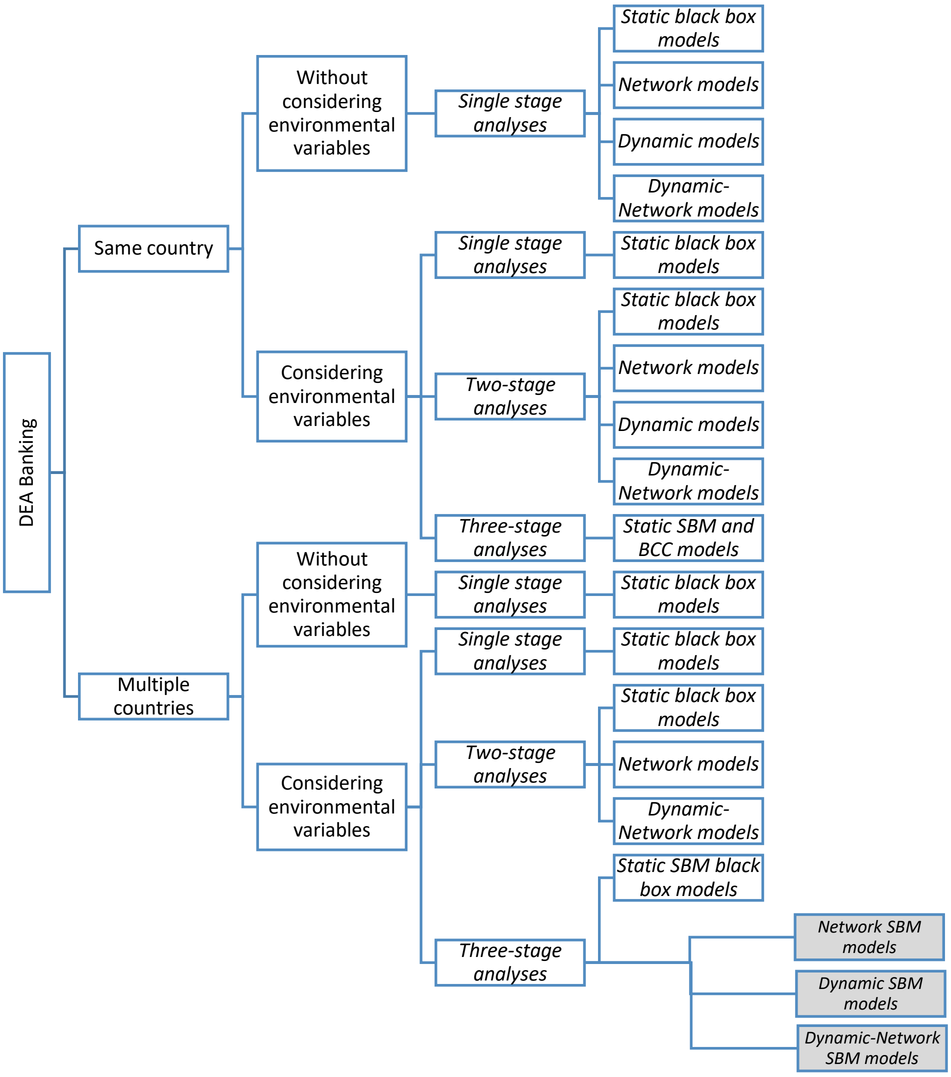


Figure 1.6 Categories chapter 4

Therefore this analysis is positioned among DEA studies in commercial banks as part of the multi-country assessment, considering environmental variables, using a three-stage analysis. Note in figure # that no assessment with these characteristics has been done using, Network model, Dynamic model and Dynamic-Network model. This study follows the path presented in red circles (see figure 1.7).

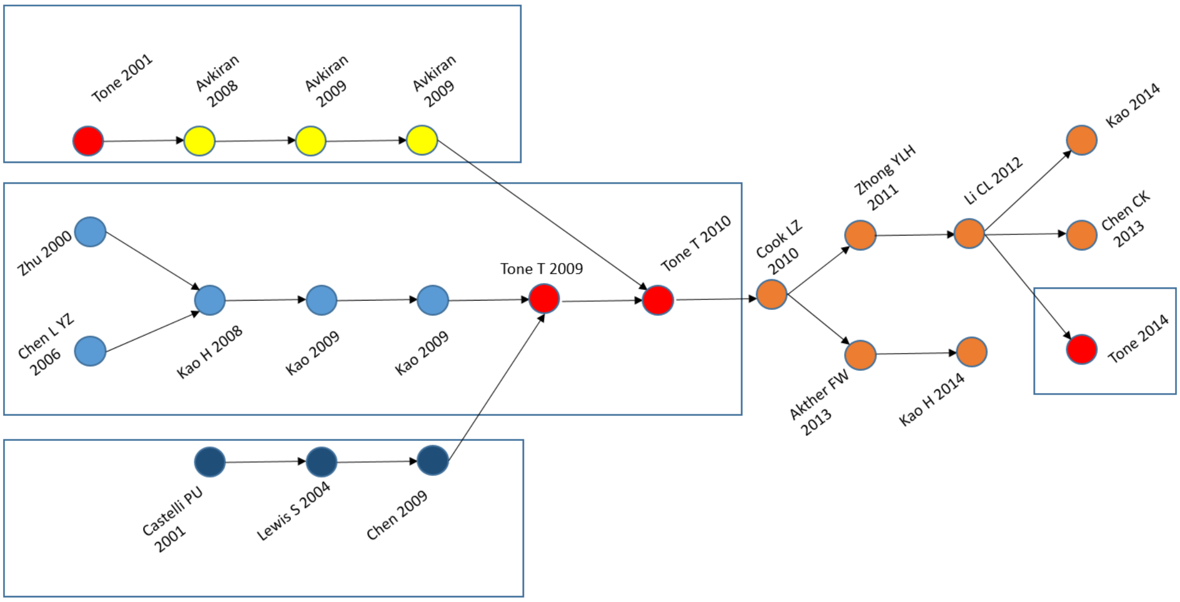


Figure 1.7 Main Path

Studies using a *three-stage in* multiple countries only have used *Static black box models* such as Pastor, 2002 (Spain, Italy, France and Germany), Avkiran, 2009b (Australia & New Zealand), and Thoraneenitiyan & Avkiran, 2009 (Indonesia, South Korea, Thailand, Malaysia and the Philippines). However, these studies are concerned with removing the impact of the environment. This chapter is concerned in assessing the relative efficiency of the operating environments of banks, this is possible by using the same bank for all the countries, under assessments, mainly HSBC. To the best of our knowledge, no attempt has been made to investigate the relative efficiency of operating environments. This chapter aims at filling this gap.

1.4 THESIS STATEMENT

This section summarises the content of this thesis. In section 1.4.1 the general summary of the thesis is presented. Section 1.4.2 presents the structure of the thesis and the content of each chapter. Section 1.4.3 presents the 9 research questions addressed in the thesis (6 main research questions and 3 secondary research questions). Finally, section 1.4.4 highlights the contributions of the thesis by chapter.

1.4.1 Summary

Even though DEA has been developed with the passing of the years, this methodology has a series of homogeneity assumptions. The contribution of this Thesis is to counteract this disadvantage. Therefore, it is presented with a variety of DEA models with some other models and techniques, creating hybrids methods to deal with the heterogeneity conditions in banks. The DEA models were selected to evaluate the banking' specific operational characteristics. Some of these models are considered as the best options to explain better the process and stages of bank operation, taking into account its internal components.

1.4.2 Thesis structure

This thesis presents a different way to deal with heterogeneity in DMUs using a series of DEA models. The remainder of this thesis is organized as follows: In Chapter 2, it is presented the current state-of-the-art research on data envelopment analysis (DEA) in the banking sector, with an emphasis on static DEA methodologies. In Chapter 3, the particular features of the UK banking sector and its related data required are evaluated with a new DEA-based analysis framework with a regression-based feedback mechanism, unlike previous studies, the DEA models used within the proposed framework could use both inputs and outputs, only inputs, or only outputs. Finally, Chapter 4, it is investigated the relative efficiency of the financial-operating environment, the banking operating environment is proxy by an international bank operating in several countries around the globe; namely, HSBC Holdings PLC.

1.4.2 Research questions

This thesis addressed 9 research questions, (6 main research questions and 3 secondary research questions). These questions can be found in chapter 2, 3 and 4, where the discussion and analysis are presented. The research questions are the following:

<u>Chapter 2</u>

This chapter provides the reader with a snapshot of the main types of empirical investigations covered in DEA with banking application, and the variables used in the analysis. This collection of papers used exclusively static DEA. Two main research questions are addressed:

(1) Which are the measures of inputs, outputs and other variables used in analyses of banks' performance evaluation (when not properly reflected in the definition)?

(2) What are the proxies for inputs and outputs used in the literature that can be found in current banking databases?

<u>Chapter 3</u>

This chapter is concerned with variable selection especially when the lack of discrimination is a concern. Three main research questions and two secondary research questions are addressed:

(3) How do DEA analyses with and without a regression-based feedback mechanism compare?

(4) How effective is a regression-based feedback mechanism in improving discrimination in DEA?

(5) When a feedback mechanism is used to inform the researcher or analyst about the relevance of the choices of inputs and outputs in a DEA analysis, how do radial models (e.g., CCR, BCC) and non-radial models (e.g., SBM) compare?

From a practical perspective, we are questioning whether the efficiency determinants identified in previous studies (i.e., inputs and outputs in DEA analysis under the intermediation approach) are actually (empirically) contributing to efficiency or not and whether methodological choices (e.g., choice of DEA model to use, choice of metrics or proxies of performance criteria) have something to do with it.

For the sake of completeness and update of analyses, we also addressed two conventional research questions:

(6) Are UK commercial banks managed efficiently?

(7) What are the drivers of UK Commercial Banks' efficiency?

However, unlike previous contributions, which focus on the few largest UK commercial banks, these last two research questions are addressed for the whole UK commercial banking system.

In our application, it turned out that the UK banking data set we used requires and justifies the use of DEA models without explicit inputs or outputs when variable selection is informed by a feedback mechanism.

Note that the feedback mechanism does not need to be regression-based.

Chapter 4

The chapter evaluates one specific bank, mainly HSBC, in 25 different countries using different DEA analysis (models and orientations), where the heterogeneity in the operating environment is the main concern. One main research questions and one secondary research questions are addressed:

Main research question.
(8) Which banking-operating environments are more efficient?

Secondary research question.

(9) How different DEA analyses (i.e., Static black box SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM) compare in addressing the main research question?

1.4.4 Contributions

1.4.4.1 Chapter 2 (Paper I):

<u>An Account of DEA-Based Contribution in the Banking Sector</u>

In this chapter, the current state-of-the-art research on Data Envelopment Analysis in the assessment on the relative performance of the banking sector with an emphasis on static DEA methodologies is reported. The literature has been summarized into tables that provide useful information for researchers about the usual measures used in this type of analyses such as inputs, outputs, environmental variables, dependent variables, explanatory variables, data size, periods of analysis, source of data and the combination of different techniques combined with DEA models. Additionally, this chapter provides a classification of the main research questions among these studies. Finally, this chapter provides a classification for inputs and outputs used in the literature and propose proxies of these variables that can be found in current banking databases available for researchers.

1.4.4.2 Chapter 3 (Paper II):

<u>Assessing Efficiency Profiles of UK Commercial Banks: A DEA Analysis with Regression-Based Feedback</u>

In this chapter, it is proposed a new DEA-based analysis framework with a regression-based feedback mechanism, where regression analysis provides DEA with feedback that informs about the relevance of the inputs and the outputs chosen by the analyst. Unlike previous studies, the DEA models used within the proposed framework could use both inputs and outputs, only inputs, or only outputs. So far, the UK banking sector remains relatively under-researched despite its crucial importance to the UK economy. We use the proposed framework to address several research questions related to both the efficiency of the UK commercial banking sector and DEA analyses with and without regression-based feedback. Empirical results suggest that, on average, the commercial banks operating in the UK—whether domestic or foreign—are yet to achieve acceptable levels of overall technical efficiency, pure technical efficiency, and scale efficiency. On the other hand, DEA analyses with and without a regression-based feedback mechanism seem to provide consistent findings; however, in general, DEA analyses without feedback tend to over- or under-estimate efficiency scores depending on the orientation of the analyses. Furthermore, in general, a regression-based feedback mechanism proves effective at improving discrimination in DEA analyses unless the initial choice of inputs and outputs is well informed.

1.4.4.3 Chapter 4 (Paper III):

Which Banking-Operating Environment is More Efficient? A Cross-Country Efficiency Analysis

Several DEA studies investigated the efficiency of banks using Static, Dynamic, Network, and Dynamic-Network DEA frameworks with and without environmental variables. To the best of our knowledge, no attempt has been made to investigate the relative efficiency of banks' operating environments. This chapter aims at filling this gap by analysing the efficiency of HSBC in different operating environments or countries over time. The choice of a single bank; namely, HSBC, is motivated by isolating the operating environment effect on efficiency and thus avoiding any bias that would result from the relative (in)efficiency of different banks within the same operating environment. From a methodological perspective, Static black box, Dynamic black box, Network, and Dynamic-Network frameworks with and without environmental variables are used to assess the relative efficiency of different operating environments and their results compared. Empirical results revealed that countries such as the UK and Russia (respectively, Argentina, Bangladesh, Brazil, India, Indonesia, Mexico, Poland, Sri Lanka, Uruguay, and Vietnam) provide a relatively efficient (respectively, relatively inefficient) operating environment. These findings suggest that the banking-operating environments of Argentina, Bangladesh, Brazil, India, Indonesia, Mexico, Poland, Sri Lanka, Uruguay, and Vietnam should be improved to incentivize more bankers to consider investing in these countries, which would improve the economy as a whole, on one hand, and competition and financial services / loan offerings, on the other hand.

1.5 FUTURE WORK

As the literature survey presented in section 1.3.3, a potential research area where heterogeneity in Network DEA models should be considered. Low-efficiency levels in Network models are more common than in Static models. In Network models, we are dealing with interdependent units and therefore, the intensity vectors of each subunit are different. Therefore, when the technical efficiency of the DMU is measured with the Network model, the results suggest very low-efficiency levels. One way to fix the low levels of heterogeneity in Network models is by fixing the lambda or intensity vector for each subunit. However, the discrimination power of the model would be diminished and the results obtained would be very similar to those in Static models. In this sense, the no identical lambda in the subunits is a characteristic that Network models should keep. Therefore, a way to have more reliable efficiency scores by keeping the core of the Network models is by dealing with heterogeneity.

The heterogeneity in Network models in the DUM as such, because of the subunits and the assessment of the internal structure in the analysis, and in the environment. A systematic method to improve the measurement of technical efficiency aiming fairness in the evaluation in Network DEA model can be relevant for application studies and can lead to answer the following questions:

1) Does the lower levels of efficiency in Network models can be fixed by dealing with heterogeneity?

2) Does the assessment of the relative efficiency in Network models is affected more in the internal structure or the external environment?

The result of the analysis should be compared to take account of the impact on the efficiency score when taking into consideration the heterogeneity in DMUs, environment, and scale.

Overall, as future research, methods to deal with heterogeneity DMUs related to factors such as semantic and scale should be explored using Network models. Heterogeneity affecting the efficiency scores should not be confused with management inefficiency.

1.6 CONCLUSIONS

There is evidence that units within a group of evaluation always present heterogeneity characteristics. One of the most used methods for measuring the relative efficiency of a group of similar entities in transforming selected inputs into outputs is Data Envelopment Analysis (DEA). These entities, known as DMUs, are assumed homogeneous. However, the DMUs are most of the time non-homogeneous. Therefore, the selection of inputs and outputs has to be methodical. A set of variables that are not strongly related to the efficiency objective can affect the discriminatory power of DEA. Heterogeneity is found not only in the DMUs but also in the environment/contextual variables. Therefore, the main objective of this thesis is to contribute in both the DEA field, through its methodological contributions, and to the banking sector, through its application of the methodological contributions in assessing banks' efficiency profiles under heterogeneity conditions. In sum, two main methodological contributions are proposed.

The first contribution consists of proposing a regression-based feedback mechanism along with new DEA models. This contribution falls into the subcategory of Regression Analysis; however, unlike previous contributions, ours use regression analysis within a feedback mechanism and allows for no-inputs or no-outputs situations (i.e., DEA models without explicit inputs or outputs). The proposed methodology is useful for variable selection especially when the lack of discrimination is a concern, such as in the UK banking system. From a practical perspective, we are questioning whether the efficiency determinants identified in previous studies (i.e., inputs and outputs in DEA analysis under the intermediation approach) are actually (empirically) contributing to efficiency or not and whether methodological choices (e.g., choice of DEA model to use, choice of metrics or proxies of performance criteria) have something to do with it. In chapter 3, five research question was set out. The main conclusions of those research questions are summarized as follows. First, The UK commercial banks need further efficiency improvements. Second, UK commercial banks' measures of efficiency seem to be driven by the inputs and outputs identified by researchers so far, except when the combinations of measures and their interaction along with their slacks and the type of DEA models used for estimating efficiency scores come into play. Third, DEA analyses with and without a regression-based feedback mechanism seem to provide consistent findings in terms of inefficiency; however, compared to DEA analyses with feedback, in general, DEA analyses without feedback tend to over- or underestimate efficiency scores depending on whether the analyses are input-oriented or output-oriented. Fourth, in general, a regression-based feedback mechanism proves effective at improving discrimination in DEA analyses unless the initial choice of inputs and outputs is well informed. Finally, ignoring slacks might result in the regression-based feedback suggesting that some efficiency determinants should be discarded when they should not, which suggest that, in practice, one should use slacks-based measures of efficiency instead of the conventional ones whenever possible, on one hand, and remind us of the importance for the DEA community to design new SBM based metrics to measure pure technical efficiency and scale efficiency, which are yet to be proposed, on the other hand.

The second contribution consists of assessing the efficiency profiles of banks' operating environments. So far, studies on banks' efficiency with data development analysis (DEA) have been concerned only in assessing the efficiency profiles of banks with or without taking account of variables that reflect the characteristics of their operating environments or identifying environmental drivers of the efficiency profiles of banks. To be more specific, we intend to address; which banking-operating environments are more efficient? In order to address this research question, we used HSBC data from 25 different operating environments or countries. The choice of a single bank; namely, HSBC, is motivated by isolating the operating environment effect on efficiency and thus avoiding any bias that would result from the relative efficiency of different banks within the same operating environment. Two approaches are assessed to complement each other and help to decision-makers. The first alternative uses a country's operating environment of banks as the unit of analysis or decision making unit (DMU), whereas the second alternative uses a bank as the DMU whose efficiency evaluation takes account of the features of its operating environment. Another contribution of chapter 4 consists of using Dynamic SBM, Network SBM, and Dynamic-Network SBM within the proposed three-stage analyses, only Static black box models have been used previously. The outcomes of this research question suggest that the importance of the environmental variables in explaining the efficiency differences among countries. The operating environment can advantage or disadvantage banks' efficiency. Also, these findings suggest that an in-depth analysis (where the internal production process is considered) is better to detect the impact of the banking-operating environment. The Dynamic – Network model is a better choice for this type of analysis for all the approaches (1st approach, 2nd approach and 2nd approach adjusted for environmental variables). Overall, this analysis demonstrates that some banks operating under less favourable circumstances would have to perform better (higher efficiency score) if they operated in a more favourable economic environment.

CHAPTER II

AN ACCOUNT OF DEA-BASED CONTRIBUTION IN THE BANKING SECTOR

2.1 INTRODUCTION

In this chapter, we shall report on the current state-of-the-art research on Data Envelopment Analysis (DEA) in the banking sector with emphasis on static DEA methodologies.

DEA is a data-driven, non-parametric, frontier-based methodology originally designed for the relative performance evaluation of a set of entities commonly referred to as Decision Making Units (DMUs). Within a DEA framework, benchmarking is done with respect to the best or the worst peers rather than the average performers, which is the case of other methodologies such as stochastic frontier analysis. Since the publication of the seminal paper by Charnes, Cooper and Rhodes in 1978, DEA has witnessed growing popularity amongst academics and practitioners as suggested by the relatively large number of both methodological and application-oriented publications (Seiford, 1996; Emrouznejad et al., 2008; and Liu et al., 2013). In banking, DEA typically addresses two types of problems; namely, performance evaluation problems, and risk assessment problems. With respect to performance evaluation problems, the DEA literature on banking could be further divided into two categories depending on whether one is concerned with assessing the relative performance of banks, or the relative performance of the branches of a given bank. As to risk assessment problems in the banking sector, the DEA literature could also be further divided into several categories depending on whether one is concerned with distress and bankruptcy of banks, or distress and default of bank's customers. In this chapter, the focus is on assessing the relative performance of commercial banks.

The remainder of this chapter is organized as follows. In section 2.2, it is provide a detailed account of the literature on the performance evaluation of banks using static DEA methodologies. In section 2.3, it is provide a summary of the current state-of-the-art. Finally, Section 2.4 concludes this chapter. The rest of the methodologies used in his thesis are reported in chapters 3 and 4.

2.2 PERFORMANCE EVALUATION OF BANKS: A DETAILED ACCOUNT

In this section, we report in detail on the literature on the relative performance evaluation of banks using static DEA methodologies in chronological order. As early as 1938, empirical studies investigated the performance of banks and their risk of failure either directly or indirectly (Secrist, 1938; and, Kumar and Ravi, 2007)

The first use of DEA in banking can be traced back to Rangan et al. (1988) who investigated a sample of 215 US banks with data from 1986. They used the CCR model presented in Charnes et al. (1978), to compute an overall technical efficiency index and the BCC model by Banker et al. (1984) to compute a pure technical efficiency index. These indexes or scores were computed using three inputs (i.e. labour, capital and purchased funds) and five outputs (i.e. real estate loans, commercial and industrial loans, consumer loans, demand deposits, and time and savings deposits). Scale efficiency was then computed as the ratio of the CCR score to the BCC score. The empirical results revealed that, on average, the banks in their sample had an overall technical efficiency index of 70% and that the source of inefficiency was mainly technical, as their scale efficiency index was 97%. In addition, after linearly regressing the overall technical efficiency and the pure technical efficiency against the bank size, the level of product diversity and the extent to which bank branching was allowed, the empirical results revealed that the technical efficiency of the banks was positively related to size, negatively related to product diversity, and not related to the extent to which branch banking was allowed.

In 1990, Ferrier and Lovell, used an input-oriented variable-returns-to-scale (VRS) model with both categorical and continuous environmental variables – an approach first proposed by Banker and Morey (1986) – to assess the pure technical efficiency of a sample of 575 US banks with data from 1984. This model was fed with three inputs (i.e. labour, occupancy costs and expenditure on furniture and equipment, and expenditure on materials), five outputs (i.e. number of demand deposit accounts, number of time deposit accounts, number of real estate loans, number of instalment loans and number of commercial loans) and 12 environmental variables (i.e. average size of demand deposit account, average size of time deposit account, average size of real estate loan, average size of instalment loan, average size of commercial loan, location in unit or branch, number of branches operated, membership of a multibank holding company, and institutional type (non-commercial, savings and loan, mutual savings, and credit union). They also used an input-oriented VRS cost allocation model with both categorical and continuous environmental variables to investigate the cost efficiency of banks by decomposing the amount by which cost is increased into technical and allocative inefficiencies, where their cost allocation model minimized the cost-weighted sum of inputs under a set of constraints similar to the above-mentioned VRS model with environmental variables. Their empirical results revealed that the banks in their sample exhibited a relatively high technical inefficiency and modest allocative inefficiency relative to a technology that exhibits increasing returns to scale, where the most efficient banks belonged to the smallest size class, and this efficiency advantage enabled them to compete despite the potential cost disadvantage they suffered owing to the structure of the efficient technology.

In the same year, Elyasiani and Mehdian (1990) investigated the rate of technological change (RTC) of a sample of 191 US banks between 1980 and 1985, where the RTC was defined $1 - \theta_{CCR-IO}^{1980;1985} / \theta_{CCR-IO}^{1980}$, $\theta_{CCR-IO}^{1980;1985}$ was the overall technical efficiency index computed by solving an input-oriented CCR model (CCR-I) using 1980 and 1985 data, and θ_{CCR-IO}^{1980} was the overall technical efficiency index computed by solving a CCR-I model using 1980 data only. Both of the CCR-IO models used four inputs (i.e. deposits, total demand deposits, capital and labour) and four outputs (i.e. investment, real estate loans, commercial and industrial loans, and other loans), where the choice of these inputs and outputs was motivated by an intermediation perspective on banks, where the intermediation approach or perspective considers banks as intermediation agents that collect funds and provide loans and other assets. In addition, RTCs were linearly regressed against the intensities of inputs and outputs obtained from the solution of CCR-IO models. The first-stage empirical results suggested that had the banks included in the sample been fully efficient in 1980, on average, they could have produced the same level of output with 89.55%of the inputs they actually used. Also, Elyasiani and Mehdian found that the efficiency frontier shifted inward between 1980 and 1985, reflecting a high pace of technological advancement achieved by the banks in the sample. The pace, however, varied significantly across the banks, with some banks even regressing over time. In the second-stage analysis, regression analysis revealed that technological change, over the sample period, was non-neutral and essentially labour biased.

At the same time, Aly et al. (1990) investigated the overall technical, pure technical, scale, cost and allocative efficiencies of a sample of 322 independent US banks with data from 1986. The overall and pure technical efficiency measures were computed by solving a CCR-IO model and a BCC-IO model, respectively. Then, the scale efficiency measure was computed as the ratio of the CCR-IO score to the BCC-IO score. The cost efficiency measure – also known as the overall efficiency measure – was computed as the ratio of minimum cost to actual cost, where the minimum cost was determined by solving a cost allocation model under the constant returns-to-scale regime. Finally, the measure of allocative efficiency was computed as the ratio of cost efficiency to technical efficiency. The CCR-IO, BCC-IO and cost allocation models used three inputs (i.e. labour, capital and loanable funds) and five outputs (i.e. demand deposits, real estate loans, commercial and industrial loans, consumer loans, and other loans), and the costs used in the allocation model were the price of labour, as measured by the ratio of total expenditure on employees to the total number of employees, a proxy for the price of capital, as measured by the ratio of total expenditure on premises and fixed assets to book value, and the price of loanable funds, as measured by the ratio of the sum of interest expenses on time deposits and other loanable funds to loanable funds. The empirical results suggested a low level of overall efficiency, which was mainly technical in nature rather than allocative. In addition, it was found that the distributions of efficiency measures for branching and non-branching banks were not significantly different.

Charnes et al. (1990) were the first to propose a cone-ratio (CR) CCR-IO model, which they used, with data from 1980 to 1985, to assess the relative performance of 48 US commercial banks drawn from the top 300 banks headquartered in America which were also members of Federal Deposit Insurance Corporation (FDIC). The CRCCR- IO model was fed with four inputs (i.e. total operating expenses, total noninterest expenses, provision for loan losses and actual loan losses) and four outputs (i.e. total operating income, total interest income, total non-interest income and total net loans). The empirical results remain illustrative of DEA analysis.

Several studies revealed that minority-owned banks (MOBs) charged higher loan rates, paid lower deposit rates and yet consistently failed to achieve profitability ratios comparable to those of the non-minority-owned banks (NMOBs) – see, for example, Fukuyama et al. (1999). Elyasiani and Mehdian (1992), looked into whether this phenomenon was due to technical, scale, cost and/or allocative inefficiencies or whether it was caused by factors outside the control of the MOB management (e.g. limited portfolio choices due to deposit instability, scarcity of profitable lending opportunities, higher operating costs due to neighbourhood location, and higher loan losses and information-gathering costs due to the particular clientele that MOBs serve), by investigating the relationship between bank ownership and efficiency for a sample of 160 US banks with data from 1988. Their CCR-IO, BCC-IO and cost allocation models were fed with four inputs (i.e. certificates of deposit and time and savings deposits; demand deposits; labour; and capital) and four outputs (i.e. commercial and industrial loans, real estate loans, other loans and investment securities), and the costs used in the allocation model were measured by the sum of interest on deposits, wages, and expenses on premises, machinery and equipment. The findings supported the hypothesis that, when the regional, regulatory, size and maturity characteristics of banks were abstracted, the efficiency differentials between MOBs and NMOBs were not statistically significant.

Yue (1992) assessed the management of 60 US commercial banks for the period ranging from 1984 to 1990 using CCR-IO and weighted additive models with four inputs (i.e. interest expenses, non-interest expenses, transaction deposits and non-transaction deposits) and three outputs (i.e. interest income, non-interest income and total loans), where bank deposits were disaggregated into transaction and non-transaction deposits because they had different turnover and cost structures. The additive model was first proposed by Charnes et al. (1985). The weighting scheme used by the weighted additive model consisted of the inverses of the absolute values of the inputs and outputs. The efficiency score, however, was computed as follows:

$$\left(\sum_{i=1}^{m} x_{i,j}^{*} + \sum_{r=1}^{s} y_{r,j}^{*}\right) \Big/ \left(\sum_{i=1}^{m} x_{i,j} + \sum_{r=1}^{s} y_{r,j} + \sum_{r=1}^{s} s_{r,j}^{+}\right)$$

where $x_{i,j}^{*}$ and $y_{r,j}^{*}$ denote the inputs and outputs, respectively, of the projection of DMU_j on the efficiency frontier. In addition, Yue also performed a window analysis to find out about the evolution of DEA efficiency scores and to identify the most stable and the most variable banks in terms of their seven-year average DEA scores. This chapter has been included in our survey because of the quality of its pedagogical exposition of DEA. The empirical results remain illustrative of DEA analysis.

Some studies revealed that the quality and efficiency of bank management was a leading cause of failure (Mayer and Pifer, 1970; Sinkey 1975; Fraser 1976; Martin 1977; Pantalone and Platt, 1987; and, Seballos and Thomson, 1990), either by analysing financial indicators of non-failed and failed banks using statistical tests or by using modelling and prediction frameworks such as regression analysis, logistic regression analysis and discriminant analysis. Barr et al. (1993) made use of a DEA model, namely, the CCR-IO model of Charnes, Cooper and Rhodes (1978), to assess the managerial efficiency of banks for a sample of 930 US banks over a period ranging from December 1984 to December 1998. They chose six inputs (i.e. full-time equivalent employees, salary expenses, premises and fixed assets, other non-interest expenses, total interest expenses, and purchased funds) and three outputs (i.e. core deposits, earning assets and total interest income) to capture the importance of management to a bank's survival – these variables were used as proxies to reflect the quality of management in making decisions related to input allocation and the product mix needed to attract deposits and make loans and investments. The empirical results revealed statistically significant differences in management quality scores between surviving and failing banks, which tended to increase as the failure date approached, suggesting that a DEA analysis could prove a valuable tool in detecting signs of distress before failure takes place. Barr et al. (1994), using the same sample of banks, compared the performance of two probit models with and without CCR scores as proxies for management quality, along with some financial ratios as proxies for the remaining dimensions of the CAMEL scoring system (i.e. equity capital/total loans as a proxy for capital adequacy, non-performing loans/total assets as a proxy for asset quality, net income/total assets as a proxy for earnings ability, and large deposits/total assets as a proxy for liquidity) and a proxy for the local economic climate (i.e. percentage of change in residential construction), in predicting bank failure with logit and probit models from the literature, and reported that the CCR-IO scores enhanced the classification accuracy of the model significantly. Then, in 1997, Barr and Siems performed an additional analysis with the same methodological choices as made by Barr et al. (1994) and a sample of 1010 US banks to assess the sensitivity of the results to misclassification of costs, and reported similar findings than Barr and Seiford (1994).

Grabowski et al. (1997) investigated the relative performance of two organizational forms, namely, branch banking and a bank holding company, by comparing the overall, allocative, technical, pure technical and scale efficiencies of a sample of 522 US banks affiliated to multibank holding companies and 407 US banks with branches, with data from 1989. The CCR-IO, BCC-IO and allocation models were fed with three inputs (i.e. labour, capital and loanable funds) and five outputs (i.e. real estate loans, commercial and industrial loans, consumer loans, demand deposits, and investment securities), and the costs used in the allocation model were the price of labour, as measured by the ratio of annual salaries plus employee benefits to the number of full-time equivalent employees on the payroll at the end of the year; the price of capital, as measured by the ratio of annual expenses for premises and fixed assets to the book value of the premises and fixed assets at the end of the year; and the price of loanable funds, as measured by the ratio of annual interest and expenses on time deposits and other borrowed funds to the dollar value of the end-of-the-year time deposits and the other borrowed funds. The empirical findings suggested that branch banking was a more efficient organizational form than a bank holding company.

Fukuyama (1993) studied the performance of a sample of 143 Japanese commercial banks with data from 1991 by comparing their overall technical, pure technical, and scale efficiencies. The CCR-IO and BCC-IO models with VRS and non-increasing returns to scale (NIRS) used in this study were fed with three inputs (i.e. labour, capital and funds from customers) and two outputs (i.e. revenue from loans and revenue from other business activities) under the assumption that interest rates were the same for any loan type across banks. He also investigated the relationship between bank size (as measured by total assets, on the one hand, and total revenue, on the other hand) and returns to scale. Finally, he looked into whether the form of organization (i.e. city banks, regional banks or former sogo banks) implied different levels of efficiency, using non-parametric tests (i.e. the median test, Kruskal–Wallis test, van der Waerden test and Savage test) and analysis of variance. His empirical results suggested that the major cause of overall technical inefficiency was pure technical inefficiency, not scale inefficiency. Nonetheless, there still existed some degree of scale inefficiency. The scale inefficiency for pooled data was found to be mainly due to increasing returns to scale. When commercial banks were divided into three organizational forms

– city banks, regional banks and former sogo banks – similar statements could be made for regional and former sogo banks, but not for city banks. With respect to both asset and revenue size definitions, scale efficiency was weakly associated with bank size, while a relationship of bank size to pure technical efficiency and to overall technical efficiency was not clearly indicated.

Favero and Papi (1995) investigated the efficiency of a sample of 174 Italian banks with data from 1991 using a two-stage analysis framework. To be more specific, in the first stage, they analysed the technical and scale efficiencies of commercial banks using CCR-IO and BCC-IO scores derived under two different perspectives, namely, the asset approach and the intermediation approach. Under the asset approach, these models were fed with five inputs (i.e. labour, capital, financial capital available for investment, loanable funds (i.e. current accounts and savings deposits), certificates of deposit (CDs), and net funds borrowed by other banks) and three outputs (i.e. loans to other banks and non-financial institutions, investment in securities and bonds, and non-interest income). Under the intermediation approach, the same inputs and outputs were used except that current accounts and savings deposits were shifted from being inputs to being outputs. In the second stage, Favero and Papi linearly regressed the BCC-IO scores against size (measured by a categorical variable reflecting major, large, medium, small and minor sizes, which were defined with reference to deposits, capital and managed external funds), productive specialization (measured by the ratio of the profit from banking services to the total intermediation margin, where the latter was defined as the sum of profit from banking services, profit from non-banking services and interest margin), ownership (measured by a categorical variable, where POP = banche popolan, CR = Casse di Risparmio, BIN = banche di interesse nazionale, BCO = banche di credito ordinario and ICDP = istituti di credito di diritto pubblico), market structure (measured by the difference between the regional interest rate on loans and the average national interest rate on loans, weighted to take ‘bad credit’ into account), and localization (measured by two indicators, where the first indicator took account of the size of the population of the area of localization and whether that area was industrial or rural, and the second indicator was a categorical variable reflecting the region, namely, Northern Italy, Central Italy or Southern Italy). The empirical results suggested that, for the sample under consideration, Italian banks in 1991 operated on average at 88% of their potential overall technical efficiency and achieved about 97% of scale efficiency under the intermediation approach. These figures, however, were lower by 10% or so under the asset approach. The second-stage analysis revealed that specialization was the only variable that seemed to consistently explain the efficiency.

Zaim (1995) investigated the effect of the 1980 financial liberalization of the banking sector in Turkey on the efficiency of a sample of 95 commercial banks by performing pre- and post-financial-liberalization analyses and comparing the overall, allocative, technical, pure technical and scale efficiencies of banks. The measures of these efficiencies were computed directly or indirectly by solving input-oriented CRS, VRS, IRS, NIRS and cost allocation models with both categorical and uncontrollable continuous environmental variables. These models were fed with four inputs (i.e. total number of employees, total interest expenditure, depreciation expenditure and expenditure on materials), four outputs (i.e. total balance of demand deposits, total balance of time deposits, total balance of short-term loans and total balance of long-term loans), and four environmental variables. Two of the latter were considered as uncontrollable inputs (i.e. number of branches and institutional type (1 for national banks and 0 for foreign banks)) and the other two as uncontrollable outputs (i.e. average size of demand deposit accounts and average size of time deposit accounts). In the cost allocation model, the price of labour was measured by the ratio of total expenditure on salaries and fringe benefits to the total number of employees; however, the prices of the remaining inputs were set to 1 on the assumption that all banks faced the same input prices. The empirical results, based on averages of DEA scores, suggested that the financial reform had succeeded in stimulating the commercial banks to take measures that would enhance both their technical and their allocative efficiencies. In addition, this study revealed that state banks were more efficient than their private counterparts, which for the Turkish banking industry contradicted the hypothesis that public ownership is inherently less inefficient. Furthermore, banks seemed to have gone through a considerable scale adjustment and were successful in achieving the optimal scale. Last but not least, the effects of allocative and technical inefficiencies on cost increases were different for private and state banks; to be more specific, while state banks were more vulnerable to allocative inefficiency, the effect of technical inefficiency on cost increases was more dominant for private banks.

Miller and Noulas (1996) investigated the efficiency of a sample of 201 US large commercial banks with data from 1984 to 1990 using a two-stage analysis framework. In the first stage, they analysed the technical and scale efficiencies of banks using CCR-IO and BCC-IO scores. The models were fed with four inputs (i.e. total transaction deposits, total non-transaction deposits, total interest expenses and total noninterest expenses) and six outputs (i.e. commercial and industrial loans, consumer loans, real estate loans, investments, total interest income, and total non-interest income). In the second stage, Miller and Noulas linearly regressed the overall technical efficiency scores against bank size (measured by total assets), profitability (measured by the ratio of net operating income to total assets), market power (the ratio of bank deposits to the total deposits in the state within which the bank operated) and location (measured by several different dummy variables for location – one that reflected the degree of metropolitanization and two that captured regional aspects of the US). The empirical results suggested, on one hand, that the average inefficiency, including both pure technical and scale inefficiency, across all 201 banks was small at just over 5%, which was due to the stiffer competition for markets and market share in the late 1980s that forced more efficiency on bank operations, and that the majority of banks were too large and experienced decreasing returns to scale. On the other hand, larger and more profitable banks had higher pure technical efficiency. Market power did not seem to have significantly affected efficiency. Finally, if bank size and profitability effects were held constant, banks in the Mideast (or

Northeast) had significantly higher pure technical efficiency in the latter half of the 1980s.

Thompson et al. (1996) investigated the efficiency of a sample of 48 US large commercial banks with data from 1980 to 1990 using CCR-IO, assurance region (AR) CCR-IO, linked-cone (LC) CCR-IO and allocative LC-CCR-IO (i.e. maximum profit ratio and minimum profit ratio) models fed with five inputs (i.e. total labour in terms of number of employees; total physical capital in terms of book value of bank premises, furniture and equipment; total purchased funds, including federal funds purchased, large (> $100 k) CDs, foreign deposits and other liabilities for borrowed money; total number of branches, including the main office; and total deposits, including demand deposits, time and savings deposits, and small CDs) and two outputs (i.e. total loans, including commercial/industrial, instalment and real estate loans, and total noninterest income), where the space of admissible multipliers was specified by imposing bounding constraints on the relative magnitude of the multipliers that take account of the range of values of inputs and outputs. The empirical results revealed that maximum profit ratios were relatively low across the 48 banks in each year analysed, which suggests that all 48 banks analysed were assured of losses. The authors of the study claimed that their results were in accordance with the low actual profit ratios observed.

Bhattacharyya et al. (1997) investigated the impact of liberalization of the banking sector in India on performance using a sample of 70 commercial banks with data from 1986 to 1991 and a two-stage analysis framework. In the first stage, pure technical efficiency and scale efficiency scores were computed by solving output-oriented CCR and BCC models (CCR-O and BCC-O) fed with two inputs (i.e. interest expenses and operating expenses) and three outputs (i.e. advances, investments and deposits). Then, in the second stage, the pure technical efficiency scores were regressed against six bank-specific exogenous variables that took account of the expansion of the banking sector into suburban and rural areas as well as national and international regulatory requirements (i.e. number of branches in rural areas, number of branches in suburban areas, number of branches in urban areas, number of branches in metropolitan areas, ratio of priority sector lending to total advances, and capital adequacy ratio), along with time dummies to model the evolution of bank performance through time relative to performance in 1986, and ownership-type dummies. The regression framework was based on stochastic frontier analysis, which allows one to decompose variations in pure technical efficiency scores into three components related to time, ownership and random noise. Once the stochastic frontier analysis model (without ownership-type dummies) was estimated, the authors of the study estimated an index of efficiency change as the difference between time dummy coefficients in two consecutive periods, following the lead of Baltagi and Griffin (1988). The empirical findings suggested that publicly owned Indian banks were the most efficient, followed by foreign-owned banks and privately owned Indian banks. In addition, out of the 43 banks that turned out to be on the efficiency frontier, 33 displayed decreasing returns to scale. Furthermore, only foreign-owned frontier banks showed any tendency towards increasing or constant returns to scale. However, an analysis of the index of efficiency change by bank category suggested that publicly owned Indian banks experienced a decline in performance, foreign-owned banks experienced an improvement in performance and privately owned Indian banks did not experience any trend in their performance. Finally, the authors found that, on average, across all three ownership forms and throughout the sample period, only 5.7% of calculated efficiency variation remained unexplained by interaction between temporal and ownership form effects.

Pastor et al. (1997) investigated the efficiency, differences in technology, and productivity of the Spanish banking system and performed a comparison with six European countries and the US for the year 1992. The sample details can be summarized as follows: 168 US banks, 45 Austrian banks, 59 Spanish banks, 22 German banks, 18 UK banks, 31 Italian banks, 17 Belgian banks and 67 French banks. To be more specific, CCR-IO and BCC-IO models were used to investigate efficiency and differences in technology, whereas Malmquist indices computed under the constant-returns- to-scale assumption were used to investigate productivity change. The choice of Malmquist indices

– instead of the productivity change indices of Fisher (1922) and Törnqvist (1936) – was motivated by the fact that Malmquist indices are decomposable into technical efficiency (catching up) and technical change (frontier shifts). The CCR-IO and BCC-IO models were fed with two inputs (i.e. non-interest expenses other than personnel expenses, and personnel expenses) and three outputs (i.e. loans, other productive assets and deposits). Note that the efficiency scores were obtained by solving these models so that each bank was compared with its own banking system, whereas the productivity indices were obtained by solving CCRIO so that a bank was compared with a frontier composed of other banking systems as well. The empirical findings suggested that French, Spanish and Belgian banks were the most efficient ones, whereas UK, Austrian and German banks were the least efficient. In addition, some evidence of scale inefficiencies in Austrian, German and US banks was found, and almost no trace of scale inefficiency was found in the French and UK samples. On the other hand, with respect to productivity, the empirical results revealed that Austrian, Italian, German and Belgian banks were more productive than US, UK, French and Spanish ones. Furthermore, the decomposition of the Malmquist index into catching up and distance from the efficiency frontier revealed that different banks operated under different combinations of the two factors; for example, banks in countries such as Spain and France showed relatively high efficiency and a relatively low level of technology simultaneously, whereas other banks in countries such as Austria and Germany combined a very productive technology with a low level of efficiency.

Taylor et al. (1997) investigated the efficiency and profitability of 13 Mexican commercial banks with data from 1989 to 1991 using the CCR-IO model, the BCC-IO model, the cone-ratio assurance region (CR-AR-IO) model under CRS and the LCAR profit model (Thompson and Thrall, 1994). These models were fed with two inputs (i.e. total deposits and total non-interest expenses) and one output (i.e. total income). The main finding lay in the fact that DEA-inefficient banks could have higher profits than DEA-efficient banks.

Thus, although LC-profitability and DEA-efficiency are different concepts, they can complement each other in an empirical analysis.

Chen (1998) investigated the impact of liberalization on the performance of Taiwanese commercial banks using a sample of seven publicly owned and 27 privately owned banks with data from 1996 and a two-stage analysis framework. In the first stage, overall technical, pure technical and scale efficiency scores were computed using CCR-IO and BCC-IO models fed with three inputs (i.e. labour, assets and interest expenses) and four outputs (i.e. loans services, investments, interest income and non-interest income). Chen compared the overall technical efficiency scores of this set-up with seven other set-ups where different measures of different criteria were used (e.g. deposits as an alternative to interest expenses, and business loans and individual loans as an alternative to loan services) to assess the impact of the choice of measures on the efficiency scores, on the one hand, and considered additional inputs or outputs (e.g. number of branches), on the other hand. In the second stage, the efficiency scores were linearly regressed against ownership (as measured by a dummy variable representing public and private ownership) and bank size (as measured by assets, staff or deposit balances). The empirical findings suggested that the whole sample mean of the overall technical efficiency was quite high (0.969); that is, Taiwanese commercial banks could have produced the same level of output by using 96.9% of the input actually used. In addition, publicly owned banks (with an average overall technical efficiency of 0.923) were relatively less efficient than the privately owned ones (with an average overall technical efficiency of 0.979). The decomposition of overall technical efficiency into pure technical efficiency and scale efficiency revealed that, on average, these scores were very close; however, publicly owned banks were less scale efficient than they were pure technically efficient. On the other hand, ownership seemed to be the main driver of the differences in efficiency scores.

Chu and Lim (1998) investigated the relationship between the share prices of six local Singapore-listed groups of banks and their efficiency using a two-stage analysis framework, with data from 1992 to 1996. In the first stage, overall technical, pure technical and scale efficiencies were computed by solving CCR-OO and BCC-OO models fed with three inputs (i.e. shareholders' fund, interest expenses, and operating expenses including provisions) and two outputs (i.e. annual increase in average assets, and total income or profit, depending on the perspective from which one looks at banks). In the second stage, annual stock returns (adjusted for capitalization changes) were linearly regressed against percentage changes in efficiency scores, where the super-efficiency model of Andersen and Petersen (1993) was used instead of the CCR model to compute these scores, which allowed the authors of the study to break the ties between banks on the efficiency frontier and thus enhance the statistical fit. The empirical findings suggested that all banks within the sample under consideration had higher overall and pure technical efficiency scores when computed using total income – rather than total profit – as an output. In addition, larger banks were in general more efficient than smaller ones, regardless of the type of efficiency. On the other hand, the second-stage results suggested that the percentage changes in share prices were better explained by percentage changes in the super-efficiency scores computed with total profit – rather than total income – as an output, which could be explained by the fact that shareholders are more concerned with their profits/dividends than with the banks' income.

Pastor (2002) investigated the efficiency of four European banking systems (i.e. commercial banks in Spain, Italy, France and Germany, with data from 1988 to 1994), adjusted for credit risk and environment using a three-phase methodology, where credit risk was measured by bad loans and decomposed into internal and external components. To be more specific, in the first phase, an indicator of risk management efficiency was computed using one of three methodologies (i.e. a single-stage, two-stage or three-stage input-oriented methodology), where the proportion of bad loans attributable to bad risk management (as measured by the provision for loans losses, PLL), the volume of loans, and economic-cycle-related environmental variables (i.e. the coefficient of variation of the nominal GDP for the period, the growth rate of the nominal GDP for the period and the cumulative annual growth rate in the last five years) were taken into account. In the second phase, an efficiency measure adjusted for credit risk due to internal factors was computed using a BCC-IO model fed with three inputs (i.e. personnel expenses, operating costs and proportion of PLL due to internal factors) and three outputs (i.e. loans, deposits and other earning assets). Finally, in the third phase, an efficiency measure adjusted for both credit risk due to internal factors and the environment was computed using an input-oriented VRS model with environmental variables, fed with the three inputs used in phase 2 adjusted for slacks, along with the economic-cycle-related environmental variables mentioned above, as well as efficiency-related environmental variables which were structural (i.e. per capita wages, density of deposits, national income per branch and capital adequacy ratio), used as inputs or outputs depending on whether they were to be maximized or minimized. The empirical results suggested that the ranking of countries changed substantially when credit risk was considered in the performance evaluation of banks. However, environmental variables did not seem to have a marked effect on efficiency. Finally, increased competition generated by the deregulation of the EU banking system did not seem to have pushed banks into riskier business and/or behaviour.

Drake et al. (2006) investigated the impact of macroeconomic and regulatory factors on the efficiency of the Hong Kong banking system using a three-stage analysis framework. The sample details can be summarized as follows: 59 banks (1995), 66 banks (1996), 52 banks (1997), 66 banks (1998), 62 banks (1999), 61 banks (2000) and 47 banks (2001). The first stage of the analysis used BCC-IO and SBM-IO models to compute efficiency scores and slacks. In the second stage, the radial and non-radial slacks were regressed against environmental variables – divided into macroeconomic continuous variables and regulatory categorical variables – and the inputs were adjusted by the difference between the predicted maximum slack and the predicted slack. These adjusted inputs were then used in the third stage to compute new efficiency scores using BCC-IO and SBM-IO models, respectively. This three-stage analysis framework was implemented under both the profit-oriented approach and the intermediation approach. Under the profit-oriented approach, both the BCCIO and the SBM-IO models were fed with three inputs (i.e. employee expenses, other non-interest expenses and loan loss provisions) and three outputs (i.e. net interest income, net commission income and total other income). On the other hand, under the intermediation approach, both the BCC-IO and the SBM-IO models were fed with four inputs (i.e. personnel expenses, total deposits + total money market funds + total other funding, total fixed assets, and loan loss provisions and other provisions) and three outputs (i.e. total customer loans + total other lending, total other earning assets, and other non-interest income). The empirical results suggested that Hong Kong banks, on average, exhibited a relatively high degree of inefficiency regardless of whether BCC or SBM scores were used. Such high levels of inefficiency are common in bank efficiency studies which do not incorporate environmental factors. In addition, the dominant external influence on efficiency in the Hong Kong banking system is the macroeconomic cycle. Furthermore, the authors of the study found, as expected, that not incorporating environmental factors would lead to biased efficiency scores. Also, they found that the efficiency scores were generally higher under the intermediation approach than under the profit approach. Finally, the authors reported that once environmental factors were taken into account, the intermediation approach offered little scope for discriminating between bank categories, compared with the profit-oriented approach, which produced a much greater diversity in relative efficiency scores, both across different asset size groups and across different categories of banks.

Liu and Tone (2008) investigated the efficiency of the Japanese banking sector by performing a three-stage analysis on a sample of Japanese commercial banks. The details of the sample can be summarized as follows: 138 banks (1997), 134 banks (1998), 133 banks (1999), 129 banks (2000) and 126 banks (2001). In the first stage, Liu and Tone solved output-oriented weighted SBM (WSBM-OO) models (Cooper et al. 2006) to compute efficiency scores and slacks, where the WSBM-OO model was fed with three inputs (i.e. interest expenses, credit costs, and general and administrative expenses) and two outputs (i.e. interest-accruing loans and lending revenues). In the second stage, they regressed the normalized slacks obtained in the first stage against environmental variables using a doubly heteroscedastic stochastic frontier analysis framework to allow control for the impacts of both environmental factors and statistical noise, along with a mechanism to adjust the outputs to an ideal level where there was an absence of environmental influences and random shocks. Within the doubly heteroscedastic stochastic frontier analysis framework, the authors of the study used three categories of environmental variables, namely, environmental variables used within the log-linear Cobb–Douglas function (i.e. monetary aggregate to GDP ratio, bank lending to GDP ratio, short-term risk spread, long-term risk spread, Japan premium, real land price index, real GDP growth index, real stock price index and real bankrupt debt per case), environmental variables used in the heteroscedastic model of the technical efficiency term (i.e. residuals in the non-performing loan ratio and residuals in the capital adequacy ratio) and environmental variables used in the heteroscedastic model of the noise or random shock term (i.e. bank heterogeneity in the non-performing loan ratio and bank heterogeneity in the capital adequacy ratio). Finally, in the third and last stage, these adjusted outputs were used alongside the original inputs to compute efficiency scores using WSBM-OO. The empirical results revealed that the mean efficiency scores had a volatile pattern when the characteristics of the operating environment of the banks and random noise were not controlled for, which hid the learning process of bankers. However, after controlling for the impacts of environmental factors and statistical noise, the mean efficiency scores exhibited a stable upward trend, while the standard deviation narrowed over time, suggesting that Japanese bankers were in fact learning from past experience.

In the next section, we shall analyse the literature surveyed above and provide the big picture on the current state of the art of static DEA in banking.

2.3 CURRENT STATE OF THE ART SUMMARIZED

So far, the overall technical efficiency, pure technical efficiency, scale efficiency, and cost and allocative efficiencies of banks have been investigated by a variety of studies – see the previous section for details. In terms of the DEA-based methodologies used in these investigations, they fall into three main categories, namely, single-stage, two-stage and three-stage methodologies.

The single-stage methodologies consist of using a DEA model with or without environmental variables to compute the efficiency scores of banks. To be more specific, a typical single-stage methodology uses one or several classical DEA models (e.g. the CCR, BCC, SBM, assurance region, cone ratio, linked-cone and allocative models) with or without environmental variables to compute relevant efficiency scores (e.g. overall technical, pure technical, scale, cost and allocative efficiency scores), as well as slacks. Although single-stage methodologies have been and are still very popular, in practice they are not without limitations. In fact, in many practical settings, the choice of inputs and outputs is often not subject to scrutiny, which might lead to biased performance profiles due to over- or under-estimated efficiency scores. One way to overcome this issue is to double-check whether the inputs and outputs are actually responsible for the performance figures. A simple approach to addressing this issue is to regress the efficiency scores against the inputs and outputs and reconsider the choice of those inputs and outputs accordingly. In sum, this issue can be overcome by using an iterative two-stage methodology, which can be summarized as follows:

- *Stage 1*. Given a specific choice of inputs and outputs, compute the efficiency scores most relevant for the analysis under consideration, as well as slacks, using the appropriate DEA models.

- *Stage 2*. Regress the efficiency scores computed in Stage 1 against the inputs and outputs chosen in Stage 1 using a regression framework, reconsider the choice of those inputs and outputs accordingly, and go to Stage 1 if necessary.

On the other hand, when environmental variables are taken into account in a relative performance evaluation exercise, the efficiency scores obtained with a single stage methodology are environmentally biased in that the environment of a bank might advantage or disadvantage that bank relative to others and therefore lead to an unfair comparison. This issue can be overcome by using a two-stage methodology, which can be summarized as follows:

• *Stage 1*. Compute the efficiency scores most relevant for the analysis under consideration, as well as slacks, using the appropriate classical DEA models fed with the relevant environment-independent inputs and outputs (e.g. financial information).

• *Stage 2.* Regress the efficiency scores computed in Stage 1 against environmental variables using a regression framework or a non-linear one to find whether or not the efficiency is environment-related, and estimate new efficiency scores that control for the environment if necessary.

Note, however, that the efficiency scores obtained by this two-stage process will still be environmentally biased because the inputs and outputs used in Stage 1 are not adjusted for the environment. In order to properly control for the environmental variables, one can use a three-stage methodology, which can be summarized as follows:

• *Stage 1.* Compute the efficiency scores most relevant for the analysis under consideration, as well as slacks, using the appropriate classical DEA models fed with the relevant environment-independent inputs and outputs (e.g. financial information). It would be unfair to use the efficiency scores obtained at this stage for an evaluation of the relative performance of banks, since these operate in different environments, which could advantage or disadvantage them.

• *Stage 2*. Filter the slacks computed in Stage 1 for the influence of environmental variables using a DEA framework. To be more specific, if the DEA analysis is input-oriented, then the inputs are the slacks computed in Stage 1 and the environmental variables amongst those under consideration which are to be minimized, whereas the outputs are the environmental variables amongst those under consideration which are to be maximized. On the other hand, if the DEA analysis is output-oriented, then the outputs are the slacks computed in Stage 1 and the environmental variables amongst those under consideration which are to be maximized, whereas the inputs are the environmental variables amongst those under consideration which are to be minimized. Finally, if the DEA analysis is non-oriented, the input surpluses computed in Stage 1 (i.e. input-related slacks) and the environmental variables amongst those under consideration which are to be minimized are used as inputs, whereas the output shortfalls computed in Stage 1 (i.e. output-related slacks) and the environmental variables amongst those under consideration which are to be maximized are used as outputs. The resulting filtered slacks are then used to adjust the inputs, outputs or both depending on the orientation of the DEA model.

• *Stage 3*. Compute the efficiency scores most relevant for the analysis under consideration, as well as slacks, using the appropriate DEA models fed with the adjusted inputs and outputs computed in Stage 2. The efficiency scores thus obtained are environment-independent and therefore more appropriate for an evaluation of the relative performance of banks.

The reader is referred to Table 2.1 for a snapshot of the literature on DEA-based methodologies or analyses and the underlying models, and to Table 2.2 for a summary of the response and explanatory variables used in multistage analyses. As to the inputs and outputs with which the DEA models used in the above-mentioned methodologies are fed, their choice is typically driven by the perspective from which banks are assessed, namely, the intermediation approach, the asset approach, the production approach – sometimes referred to as the profit approach – and the value added approach.

The intermediation approach or perspective considers banks as intermediation agents that collect funds and provide loans and other assets. The asset approach is a variant of the intermediation approach which considers banks as financial intermediaries between liability holders and those who receive bank funds. The production approach considers banks as production units that transform inputs into outputs, or producers of deposit accounts and loan services. In the literature, the production approach is sometimes referred to as the profit approach – although we believe there is a distinction between these two approaches because, under the profit approach, profit should guide the choice of inputs and outputs. Finally, under the value added approach, the share of value added guides the choice of inputs and outputs. We refer the reader to Table 2.3 for a snapshot of the literature on the choice of inputs and outputs under each of these approaches and to Table 2.4 for a summary of the measures of inputs and outputs and other variables used in analyses of banks' performance (when not properly reflected in the definition). For a summary of the environmental variables used in DEA analyses, we refer the reader to Table 2.5. Also, Table 2.6 provides a summary of the data used in assessing the performance of banks, the period of analysis, and the data provider or database. Since the empirical results and related findings of any DEA analysis are sample-dependent, it would be inappropriate to make any attempt to draw any general conclusions – for the main findings of different studies, the reader is referred to the previous section. However, to conclude this section, we would like to provide the reader with a snapshot of the main types of empirical investigations covered in our survey, summarized in the following bullet points:

- Investigation of the *relationship between type of ownership and efficiency*. For example, Elyasiani and Mehdian (1992) considered minority-owned and nonminority- owned US banks, Bhattacharyya et al. (1997) considered publicly owned Indian banks, privately owned Indian banks and foreign-owned banks, and Chen (1998) considered publicly owned and privately owned Taiwanese banks.

• Investigation of the *relationship between type of organizational form and efficiency*. For example, Aly et al. (1990) considered unit banking and branch banking in the US, Grabowski et al. (1993) considered branch banking and bank holding companies in the US, Fukuyama (1993) considered city banks, regional banks and former sogo banks in Japan, and Zaim (1995) considered state banks and private banks in Turkey.

• Investigation of the *relationship between some measure of efficiency and one or several endogenous or exogenous variables*. For example, Aly et al. (1990) considered size, extent of product diversity and level of urbanization; Fukuyama (1993) considered bank size; Favero and Papi (1995) considered bank size, productive specialization, ownership, market structure and localization; Miller and Noulas (1996) considered bank size, profitability, market power and location; Bhattacharyya et al. (1997) considered six bank-specific exogenous variables that take account of the expansion of the banking sector into suburban and rural areas, as well as national and international regulatory requirements (i.e. number of branches in rural areas, number of branches in suburban areas, number of branches in urban areas, number of branches in metropolitan areas, ratio of priority sector lending to total advances, and capital adequacy ratio), along with ownership type; and Chen (1998) considered ownership and bank size.

• Investigation of the *effect of an event on the efficiency of banks*. For example, Zaim (1995) considered the effect of post-1980 financial liberalization policies on the economic efficiency of Turkish commercial banks, and Drake et al. (2006) considered the impact of macroeconomic and regulatory factors on the efficiency of the Hong Kong banking system.

2.4 CONCLUSION

In this chapter, we have provided a detailed account of DEA-based contributions in the banking sector, with emphasis on static conventional DEA models, often referred to as black box models. Our account starts from the first paper on DEA in banking, published in 1988, and covers all major contributions to date. Apart from assessing the efficiency profiles of banks, the authors of these contributions have investigated the relationship between the type of ownership and efficiency, the relationship between the type of organizational form and efficiency, the relationship between some measure of efficiency and one or several endogenous or exogenous variables, and the effect of an event (e.g. deregulation) on the efficiency of banks. For those researchers who are unfamiliar with this field, we have summarized the literature into tables that provide snapshots of the landscape of this research area. These snapshots could also serve as an 'aide-memoire' for readers who are familiar with DEA and its applications in banking.

APPENDICES

Table 2.1 Summary of Analyses and Underlying Models for Assessing the Performance of Banks

Reference	First Stage Models	Second Stage Models	Third Stage Models
Single Stage Analysis			
Ferrier and Lovell (1990)	Input-oriented VRS and VRS Cost Allocation models with both Categorical and Continuous Environmental Variables	N/A	N/A
Charnes et al. (1990)	CR-CCR-IO	N/A	N/A
Elyasiani and Mehdian (1992)	CCR-IO; BCC-IO; Cost Allocation model	N/A	N/A
Yue (1992)	CCR-IO; Weighted ADD; Window Analysis	N/A	N/A
Grabowski et al. (1993)	CCR-IO; BCC-IO; Cost Allocation model	N/A	N/A
Barr et al. (1993)	CCR-IO	N/A	N/A
Fukuyama (1993)	CCR-IO; BCC-IO with VRS and NIRS	N/A	N/A
Zaim (1995)	Input-oriented CRS, VRS, IRS, NIRS and Cost Allocation models with both Categorical and Uncontrollable Continuous Environmental Variables	N/A	N/A
Pastor et al. (1997)	Input-oriented CRS and VRS models with both Categorical and Continuous Environmental Variables; Malmquist Indices	N/A	N/A

Taylor et al. (1997)	CCR-IO; BCC-IO; CRS-CR-AR-IO; LC-AR based Profit model	N/A	N/A
Two-Stage Analysis			
Rangan et al. (1988)	CCR; BCC	Linear Regression Analysis	N/A
Elyasiani and Mehdian (1990)	CCR-IO; Rate of Technological Change (RTC)	Linear Regression Analysis	N/A
Aly et al. (1990)	CCR-IO; BCC-IO; Cost Allocation model	Linear Regression Analysis	N/A
Favero and Papi (1995)	CCR-IO; BCC-IO	Linear Regression Analysis	N/A
Miller and Noulas (1996)	CCR-IO; BCC-IO	Linear Regression Analysis	N/A
Bhattacharyya et al. (1997)	CCR-OO; BCC-OO	Stochastic Frontier Analysis	N/A
Chen (1998)	CCR-IO; BCC-IO	Linear Regression Analysis	N/A
Chu and Lim (1998)	CCR-OO; BCC-OO	Linear Regression Analysis	N/A
Barr et al. (1994)	CCR-IO	Logit & Probit Analyses	N/A
Barr and Siems (1997)	CCR-IO	Logit & Probit Analyses	N/A
Three-Stage Analysis			
Pastor (2002)	(1) Input-oriented VRS with Environmental Variables; (2) BCC-IO & Regression with Environmental Variables; (3) BCC-IO, Input-oriented VRS with Environmental Variables & BCC-IO	BCC-IO	Input-oriented VRS with Environmental Variables

Drake et al. (2006)	BCC-IO; SBM-IO	Tobit Analysis with both Categorical and Continuous Environmental Variables	BCC-IO; SBM-IO with inputs adjusted for slacks
Liu and Tone (2008)	WSBM-OO	Doubly Heteroscedastic Stochastic Frontier Analysis with Environmental Variables	WSBM-OO with outputs adjusted for slacks

Table 2.2 Summary of Response & Explanatory Variables used in Second Stage Models for Assessing the Performance of Banks

Reference	Response/Dependent Variable	Explanatory Variables
Rangan et al. (1988)	Overall Technical Efficiency; Pure Technical Efficiency	Bank Size (+); Level of Product Diversity (-); Extent to which Bank Branching is allowed (no relationship)
Elyasiani and Mehdian (1990)	Rate of Technological Change (RTC)	Intensities ($\lambda_j s$) of Deposits, Total Demand Deposit, Capital and Labour obtained from the solution to CCR-IO model
Aly et al. (1990)	Efficiency Measures	Bank Size; Bank Product Diversity; Degree of Urbanization that characterizes a Bank's Environment
Favero and Papi (1995)	Pure Technical Efficiency	Bank Size; Productive Specialization; Ownership; Market Structure; Localization
Miller and Noulas (1996)	Pure Technical Efficiency	Bank Size; Profitability; Market Power; Location
Bhattacharyya et al. (1997)	Pure Technical Efficiency	Number of branches in rural areas; Number of branches in suburban areas; Number of branches in urban areas; Number of branches in metropolitan areas; Ratio of priority sector lending to total Advances; Capital adequacy ratio; Time dummies show

		how bank performance evolves through time relative to performance in 1986; Ownership dummies corresponding to the three ownership forms
Chen (1998)	Overall Technical Efficiency; Pure Technical Efficiency; Scale Efficiency	Ownership; Size; Other bank characteristics
Chu and Lim (1998)	Annual Stock Returns (adjusted for capitalisation changes)	Percentage changes in super-efficiency scores
Pastor (2002)	Risk Management Efficiency without correcting for Environmental Variables	Economic cycle related environmental variables; i.e., coefficient of variation of the nominal GDP of the period; growth rate of nominal GDP of the period; cumulative annual growth rate in the last five years
Drake et al. (2006)	Radial Slacks (respectively, Non-radial Slacks)	Macroeconomic variables: Private consumption expenditure; government expenditure; gross fixed capital formation; net export of goods; net export of services; discount window base rate; unemployment; retail sales values; expenditure on housing; and the current account balance. Regulatory variables: Dummy variable for the Hong Kong property crash/Asian financial crisis; dummy variable for handover to the People's Republic of China; dummy variable for 1999 (Hong Kong Monetary Authority agreed to phase out the remaining interest rate controls (i.e., caps); and a dummy variable for 2001 (remaining interest rate controls removed).
Liu and Tone (2008)	Normalized slacks obtained in the first stage	Environmental variables used within the log-linear Cobb-Douglas function: Monetary

		aggregate to GDP ratio; Bank lending to GDP ratio; Short-term risk spread; Long-term risk spread, Japan premium; Real land price index; Real GDP growth index; Real stock price index; Real bankrupt debt per case. Environmental variables used in the heteroscedastic model of the technical efficiency term: Residuals in non-performing loan ratio; Residuals in capital adequacy ratio. Environmental variables used in the heteroscedastic model of the noise or random shock term: Bank heterogeneity in non-performing loan ratio; Bank heterogeneity in capital adequacy ratio.

Table 2.3 Summary of Inputs and Outputs used in DEA Models for Assessing the Performance of Banks

Reference	Inputs	Outputs
Intermediation Approach		
Rangan et al. (1988)	Labour; Capital; Purchased Funds	Real Estate Loans; Commercial & Industrial Loans; Consumer Loans; Demand Deposits; Time & Saving Deposits
Ferrier and Lovell (1990)	Total number of employees; Occupancy Costs & Expenditure on Furniture and Equipment; Expenditure on Materials	Number of Demand Deposit Accounts; Number of time deposit accounts; Number of Real Estate Loans; Number of Instalment Loans; Number of commercial loans
Charnes et al. (1990)	Total operating expense; Total noninterest expense; Provision for loan losses; Actual loan losses	Total operating income; Total interest income; Total noninterest income; Total net loans

Elyasiani and Mehdian (1990)	Labour; Capital; Deposits; Total Demand Deposits	Investment; Real Estate Loans; Commercial & Industrial Loans; Other Loans
Aly et al. (1990)	Labour; Capital; Loanable Funds	Demand Deposits; Real Estate Loans; Commercial & Industrial Loans; Consumer Loans; Other Loans
Elyasiani and Mehdian (1992)	Labour; Capital; Certificates of Deposit, Time & Savings Deposits; Demand Deposits	Commercial & Industrial Loans; Real Estate Loans; Other Loans; Investment Securities
Yue (1992)	Interest Expenses; Non-interest Expenses; Transaction Deposits; Non-transaction Deposits	Interest Income; Non-interest Income; Total Loans
Grabowski et al. (1993)	Labour; Capital; Loanable funds	Real Estate Loans; Commercial and Industrial Loans; Consumer Loans; Demand Deposits; Investment Securities
Fukuyama (1993)	Labour; Capital; Funds from Customers	Revenue from Loans; Revenue from Other Business Activities
Zaim (1995)	Total number of employees; Total interest expenditures; Depreciation expenditures; Expenditures on materials	Total Balance of Demand Deposits; Total Balance of Time Deposits; Total Balance of Short-term Loans; Total Balance of Long-term Loans
Favero and Papi (1995)	Labour; Capital; Financial capital available for investment; Loanable funds (i.e., certificates of deposit or CDs); Net funds borrowed by other banks	Current Accounts and Savings Deposits; Loans to other banks and non-financial Institutions; Investment in Securities and Bonds; Non-interest Income
Miller and Noulas (1996)	Total transactions deposits; Total non-transactions deposits, Total interest expense; Total non-interest expense	Commercial and Industrial Loans; Consumer Loans; Real Estate Loans; Investments; Total Interest Income; Total Non-Interest Income
Taylor et al. (1997)	Total deposits; Total non-interest expense	Total Income
Chen (1998)	Labour; Assets; Interest Expense	Loans Services; Investments; Interest

		Income, Non-Interest Income
Drake et al. (2006)	Personnel expenses; Total deposits + Total money market funds + Total other funding; Total fixed assets; Loan loss provisions and other provisions	Total customer loans + Total other lending; Total other earning assets; Other non-interest income
Asset Approach		
Favero and Papi (1995)	Labour; Capital; Financial capital available for investment; Loanable funds (i.e., current accounts and savings deposits, CDs); Net funds borrowed by other banks	Loans to other banks and non-financial Institutions; investment in securities and bonds; non-interest income
Value Added Approach		
Bhattacharyya et al. (1997)	Interest expense; Operating expense	Advances to the priority sector activities; Investments; Deposits
Pastor et al. (1997)	Non-interest expenses other than personnel expenses; Personnel expenses	Loans; Other productive assets including all existing deposits with banks, short-term investments, other investments, and equity investments; Deposits including customer and short-term funding which is the sum of demand, savings, time, interbank, and other deposits
Chu and Lim (1998)	Shareholders' Fund; Interest Expenses; Operating Expenses (including provisions)	Annual Increase in Average Assets as a proxy for future income or future profit; Total Income or Profit depending on whether X-efficiency or P-efficiency are evaluated
Pastor (2002)	Personnel Expenses; Operating Costs excluding Personnel Expenses and including Financial Costs; Proportion of provision for loans' losses due to internal factors; all inputs adjusted for slacks (for third phase); Structural environmental variables: Per capita wages;	Loans; Deposits; Other earning assets; Economic cycle environmental variables: Coefficient of variation of the nominal GDP of the period

	Density of deposits; National income per branch; Capital adequacy ratio; Economic cycle environmental variables: Growth rate of nominal GDP of the period; Cumulative annual growth rate in the last five years	
Production / Profit-oriented Approach		
Drake et al. (2006)	Employee expenses; Other non-interest expenses; Loan loss provisions	Net interest income; Net commission income; Total other income
Liu and Tone (2008)	Interest expenses; Credit Costs; General and administrative expenses	Interest-accruing loans; Lending revenues

Table 2.4 Summary of Measures of Inputs, Outputs, and Other Variables used in Analyses of Banks Performance

Variable	Measure & Reference
Labour	Number of full-time employees on the payroll (Rangan et al., 1988, Elyasiani and Mehdian, 1990, Aly et al., 1990, Elyasiani and Mehdian, 1992, Grabowski et al., 1993, Fukuyama, 1993, Favero and Papi, 1995, Chen, 1988, Pastor, 2002); Employee Expenses (Drake et al., 2006)
Capital	Book value of premises and fixed assets (Rangan et al., 1988, Elyasiani and Mehdian, 1990, Aly et al., 1990, Elyasiani and Mehdian, 1992, Grabowski et al., 1993, Favero and Papi, 1995); Bank premises and equipment, suspense payments for constitutions unfinished and surety deposits and intangibles (Fukuyama, 1993)
Purchased funds	Certificates of deposit greater than $100,000, Notes and Debentures, and other borrowed funds (Rangan et al., 1988)
Deposits	Saving & Time Deposits – including large ($100,000 or more) negotiable certificates of deposits (CDs) – and Total Demand Deposits (Elyasiani and Mehdian, 1990, 1992); Transaction deposits and Non-transaction deposits (Yue, 1992); Customer and short-term funding, which is the sum of demand, savings, time, interbank, and other deposits (Pastor et al., 1997, Pastor 2002)
Total loans	Loans and Leases net of unearned income (Yue, 1992); Business and Individual Loans (Chen, 1988)

Loanable funds	Sum of time deposits and other borrowed funds (Grabowski et al., 1993)
Funds from Customers	Part of the liabilities in the balance sheet including deposits, CDs, call money, bills sold, borrowed money, foreign exchanges and others (Fukuyama, 1993)
Shareholders' Fund	Capital provided by bank's shareholders (Chu and Lim, 1998)
Interest expenses	Expenses for Federal Funds, Purchase and Sale of Securities, and Interest on Demand Notes and other Borrowed Money (Yue, 1992); Interest on Deposit (savings, fixed or time, and current or checking) Accounts (Chu and Lim, 1998); External Financial Cost (Liu and Tone, 2008);
Non-interest expenses	Salaries, expenses associated with premises and fixed assets, taxes and other expenses (Yue, 1992); Non-interest expenses other than personnel expenses (Pastor et al., 1997, Drake et al., 2006)
Operating Expenses	Operating Expenses including provisions (Chu and Lim, 1998)
General & Administrative Expenses	Cost of information production, in an economic sense (Liu and Tone, 2008)
Credit Cost	Credit cost covers unexpected, expected and realized losses due to credit risk exposures and is calculated as Transfer to reserve for possible loan losses + net provision of specific reserve for possible loan losses + write-off claims + losses in sale of claims - recoveries of written-off claims (Liu and Tone, 2008)
Interest income	Interest and fee income on loans, income from lease-financing receivables, interest and dividend income on securities, and other income (Yue, 1992); Net interest income (Drake et al., 2006)
Non-interest income	Service charges on deposit accounts, income from fiduciary activities and other non-interest income (Yue, 1992)
Interest-accruing Loans	Loans & bills discounted + 0.5*customers' liabilities for acceptances & guarantees - loans to borrowers in legal bankruptcy + past due loans in arrears by 6 months or more (Liu and Tone, 2008). In Japan, banks are required to stop accruing interest on a loan that is past due for 6 months or more.
Investments	Government securities and shares & securities of public and private enterprises (Chen, 1998)
Revenue from Loans	Interest on loans and discounts and interest on bills bought – these are the traditional primary business activities of banks (Fukuyama, 1993); Lending

	revenue computed as Net interest income + net fees & commission income (Liu and Tone, 2008)
Bad Loans attributable to Bad Risk Management	Provision for loans' losses (Pastor, 2002, Drake et al., 2006)
Revenue from Other Business Activities	Total operating income minus any other operating income after deducting gains on foreign exchange and trading account securities transactions as well as gains on sales and redemption of bonds minus Revenue from Loans (Fukuyama, 1993)
Bank Size	Total Deposits (Rangan et al., 1988, Aly et al., 1990); Number of Branches (Aly et al., 1990); Assets, Staff, or Deposits (Chen, 1998)
Level of Product Diversity	Minus the logarithm of the sum over products of the squared proportion of a bank's total dollar revenue or sales accounted for by a product (Rangan et al., 1988, Aly et al., 1990)
Extent to which Bank Branching is allowed	Categorical variable that takes values of 0, 1 or 2 depending on whether no branch banking is allowed by the state, limited branch banking is allowed, or unlimited branch banking is allowed (Rangan et al., 1988)
Degree of Urbanization that characterizes a Bank's Environment	Measured by two dummy variables. The first takes on a value of one if the bank operates in a Standard Metropolitan Statistical Area (SMSA), but not in a Consolidated Metropolitan Statistical Area (CMSA), zero otherwise. The second dummy variable takes on a value of one if the bank operates in an SMSA that is also part of a CMSA, zero otherwise. (Aly et al., 1990)

Table 2.5 Summary of Environmental Variables used in DEA Analyses for Assessing the Performance of Banks

Reference	Inputs	Outputs
Intermediation Approach		
Ferrier and Lovell (1990)	*Categorical Environmental variables*: Institutional Type (Non-commercial; Savings & Loan; Mutual savings; Credit Union); Membership of a Multibank Holding Company; Location in Unit or Branch	
	Number of Branches Operated	Average Size of Demand Deposit Account; Average Size of Time Deposit Account; Average Size of Real Estate Loan; Average Size of

		Instalment Loan, Average Size of Commercial Loan
Zaim (1995)	*Categorical Environmental variables*: Institutional Type (National Bank; Foreign Bank)	
	Number of Branches as uncontrollable input	Average Size of Demand Deposit Accounts; Average Size of Time Deposit Accounts as uncontrollable outputs
Value Added Approach		
Pastor (2002)	*Economic environmental variables*: coefficient of variation of the nominal GDP of the period *Efficiency related / Structural environmental variables*: capital adequacy ratio	*Economic environmental variables*: growth rate of nominal GDP of the period; cumulative annual growth rate in the last five years; per capita wages *Efficiency related / Structural environmental variables*: density of deposits; national income per branch
Profit-oriented Approach		
Drake et al. (2006)	*Regulatory variables*: dummy variable for the Hong Kong property crash/Asian financial crisis; dummy variable for handover to the People's Republic of China; dummy variable for 1999 (Hong Kong Monetary Authority agreed to phase out the remaining interest rate controls (i.e., caps); and a dummy variable for 2001 (remaining interest rate controls removed) *Macroeconomic variables*: private consumption expenditure; government expenditure; gross fixed capital formation; net export of goods; net export of services; discount window base rate; unemployment; retail sales values; expenditure on housing; and the current account balance	
Liu and Tone (2008)	Monetary aggregate to GDP ratio; Bank lending to GDP ratio; Short-term risk spread; Long-term risk spread; Japan premium; Real land price index; Real GDP growth index; Real stock price index; and Real bankrupt debt per case	

Table 2.6 Summary of Data, Period of Analysis, and Its Source used in Assessing the Performance of Banks

Reference	**Data/DMUs**	**Period of Analysis**	**Source of Data / Data Provider**
Rangan et al. (1988)	215 US Banks	1986	Federal Deposit Insurance Corporation

Ferrier and Lovell (1990)	575 US Banks	1984	The Federal Reserve System's Functional Cost Analysis Program
Charnes et al. (1990)	48 US commercial banks drawn from the top 300 banks headquartered in America which are also members of Federal Deposit Insurance Corporation (FDIC)	1980 to 1985	Federal Deposit Insurance Corporation (FDIC)
Elyasiani and Mehdian (1990)	191 US Banks	1980; 1985	Call and Income Report tapes published by the National Technical Information Service (NTIS) of the Department of Commerce
Aly et al. (1990)	322 Independent US Banks	1986	Federal Deposit Insurance Corporation tapes on the Reports of Condition and Reports of Income (Call Reports)
Elyasiani and Mehdian (1992)	160 Minority-owned and nonminority-owned US Banks selected to be from the same state, county, SMSA, CMSA, and the same Federal Reserve districts to control for geographical factors and regulatory environment	1988	1988 Call and Income Report tapes
Yue (1992)	60 of the largest US Commercial Banks located in Missouri	1984 to 1990	Not provided
Grabowski et al. (1993)	522 US banks affiliated with multibank holding companies & 407 US banks with branches	1989	FDIC files on the Report of Income and Condition (Call Report)

Fukuyama (1993)	143 Japanese Commercial Banks	1991	Analysis of Financial Statements of All Banks from the Federation of Bankers Associations of Japan
Barr et al. (1993)	930 US banks	December 1984 to December 1989	Not provided
Zaim (1995)	95 Turkish Commercial Banks	1981 (39 banks) & 1990 (56 banks)	Banks Association of Turkey
Favero and Papi (1995)	174 Italian Commercial Banks	1991	Centrale dei Bilanci-ABI data set
Miller and Noulas (1996)	201 US Large Commercial Banks	1984 to 1990	Call Report data – reports of Condition and Income
Thompson et al. (1996)	48 US large commercial banks	1980 to 1990	Federal Deposit Insurance Corporation (FDIC) reports
Bhattacharyya et al. (1997)	70 Indian Commercial Banks	1986 to 1991	Indian Banks' Association
Pastor et al. (1997)	168 US banks, 45 Austrian Banks, 59 Spanish Banks, 22 German Banks, 18 UK Banks, 31 Italian Banks, 17 Belgian Banks; 67 French Banks	1992	International Bank Credit Analysis Ltd
Taylor et al. (1997)	13 Mexican Commercial Banks	1989 to 1991	Comision Nacional Bancaria (National Banking Commission)
Chen (1998)	7 publicly-owned and 27 privately-owned Taiwanese Commercial Banks	1996	Not provided
Chu and Lim (1998)	6 local Singapore-listed groups of banks	1992 to 1996	End-of-the-year stock prices, duly adjusted for capitalisation changes, are obtained from Dbank

			financial database which is maintained at the National University of Singapore
Pastor (2002)	Commercial Banks in Spain, Italy, France, and Germany resulting in 2598 bank-year observations	1988 to 1994	IBCA Ltd., an international rating agency which homogenizes the information and classifies firms in terms of specialization, so that the accounting uniformity is guaranteed; Data on environmental variables is taken from the Economic Bulletin of the Bank of Spain, Bank Profitability, Eurostat and National Statistical Institute of Spain (INE).
Drake et al. (2006)	Hong Kong Banks 59 (1995); 66 (1996); 52 (1997); 66 (1998); 62 (1999); 61 (2000); 47 (2001).	1995 to 2001	Bank-scope
Liu and Tone (2008)	Japanese Commercial Banks 138 (1997); 134 (1998); 133 (1999); 129 (2000); 126 (2001).	1997 to 2001	Multiple data sources: Japanese Bankers Association; Bank of Japan; Government of Japan; Japanese Ministry of Land, Infrastructure and Transport; Tokyo Commercial & Industrial Research.

CHAPTER III

ASSESSING EFFICIENCY PROFILES OF UK COMMERCIAL BANKS: A DEA ANALYSIS WITH REGRESSION-BASED FEEDBACK

3.1 INTRODUCTION

In this chapter, we assess the efficiency profiles of UK commercial banks. The UK banking system has specific distinctive features which distinguish it from other banking systems. In fact, the UK banking system is relatively big compared to the banking systems of other countries. Its size is the result of a combination of factors including its history, as the UK has been a financial centre since the eighteenth century. As a financial hub, the UK banking system offers the benefits of clustering such as higher productivity and wage. The robustness of the UK legal and regulatory structure along with the implicit government subsidy and its openness to trade and capital flow seem to provide attractive incentives and flexibility for foreign banks to do business in the UK and for domestic banks to do business abroad. As a result of some of these features, UK has the largest banking sector on a residency basis compared to US, Japan and the ten largest EU Economies with foreign banks on a residency basis, from 56 different countries, owning approximately 50% of the UK banking sector assets. In addition, nearly 1/5 of the global banking activity is booked in the UK. The contribution of foreign banks to the UK banking system and its economy is substantial as suggested by a growth from around 100% of nominal GDP in 1975 to around 450% of nominal GDP in 2013. This growth of 350% is due to the relatively large assets and liabilities account of foreign banks residing in the UK and representing more than four times the median figure for OECD countries. Last, but not least, the international nature of the UK banking system—foreign banks have a large operation in the UK and UK banks have a large operation abroad—along with the continuous reengineering of UK banking regulations enhances its banking system resilience. For more details on the features of the UK banking system, we refer the reader to the Bank of England publications (e.g., Davies et al. 2010; Bush et al. 2014; Burrows et al. 2015).

In this chapter, we propose a revised methodological framework; namely, Data Envelopment Analysis (DEA) with a regression-based feedback mechanism along with new DEA models (i.e., DEA models without explicit inputs or outputs), and use it to assess the efficiency profiles of UK commercial banks. The proposed methodology is useful for variable selection especially when the lack of discrimination is a concern. It is used to address three research questions: (1) how do DEA analyses with and without a regression-based feedback mechanism compare? (2) how effective is a regression-based feedback mechanism in improving discrimination in DEA? and (3) when a feedback mechanism is used to inform the researcher or analyst about the relevance of the choices of inputs and outputs in a DEA analysis, how do radial models (e.g., CCR, BCC) and non-radial models (e.g., SBM) compare? From a practical perspective, we are questioning whether the efficiency determinants identified in previous studies (i.e., inputs and outputs in DEA analysis under the intermediation approach) are actually (empirically) contributing to efficiency or not and whether methodological choices (e.g., choice of DEA model to use, choice of metrics or proxies of performance criteria) have something to do with it. For the sake of completeness and update of analyses, we also address two conventional research questions: (4) are UK commercial banks managed efficiently? and (5) what are the drivers of UK Commercial Banks' efficiency? However, unlike previous contributions, which focus on the few largest UK commercial banks, these last two research questions are addressed for the whole UK commercial banking system. In our application, it turned out that the UK banking data set we used requires and justifies the use of DEA models without explicit inputs or outputs when variable selection is informed by a feedback mechanism. Note that the feedback mechanism does not need to be regression-based.

The remainder of this chapter is organised as follows. In Sect. 3.2, we classify the literature on efficiency assessment in banking according to several criteria and critically discuss some of the choices made in the literature. In Sect. 3.3, we propose a DEA-based sequential decision making process with regression-based feedback adjustment mechanisms along with new DEA models. In Sect. 3.4, we summarise our empirical investigation and its findings. Finally, Sect. 3.5 concludes the chapter.

3.2 LANDSCAPE OF RESEARCH ON EFFICIENCY ASSESSMENT IN BANKING

Research papers on efficiency assessment in banking could be classified into several categories depending on one's choice of the classification criterion. In this chapter, we use three criteria to classify the literature on static DEA analyses; namely, type of analysis, type of approach, and country of focus.

With respect to the type of analysis, the literature could be divided into three categories. The first category of studies uses Single Stage Analysis—see Figure 3.1 for a flow chart of a typical single stage analysis (e.g., Ferrier and Lovell 1990; Elyasiani and Mehdian 1992; Yue 1992; Grabowski et al. 1993; Fukuyama 1993; Zaim1995; Pastor et al. 1997; Barr et al. 1993; Lozano-Vivas et al. 2002).

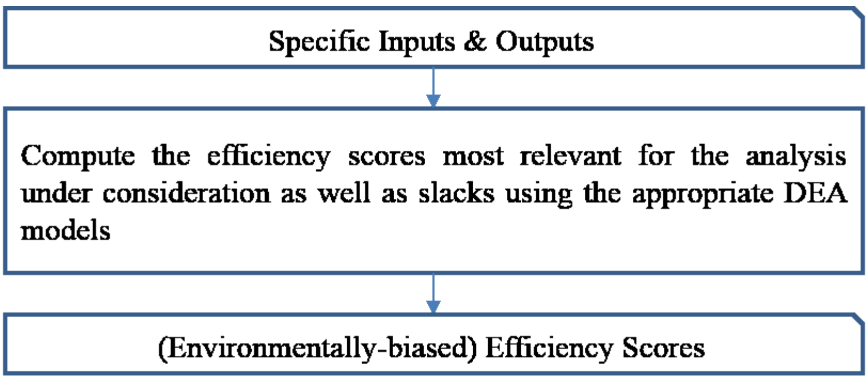


Figure 3.1 Main Steps of a Single Stage Analysis

The second category of studies uses Two-Stage Analysis to overcome environment bias—see Figure 3.2 for a flow chart of a typical two-stage analysis (e.g., Rangan et al. 1988; Elyasiani and Mehdian 1990; Aly et al. 1990; Favero and Papi 1995; Miller and Noulas 1996; Bhattacharyya et al. 1997; Chen 1998; Chu and Lim 1998; Barr et al. 1994; Barr and Siems 1997; Pasiouras 2008; Wanke and Barros 2014; Kwon and Lee 2015; Du et al. 2018). Note however that the efficiency scores obtained with a two-stage analysis would still be environmentally-biased, because the inputs and outputs used in the first stage are not adjusted for environment. In order to properly control for these environmental variables, one could use a three-stage methodology. Finally the third category of studies uses Three-Stage Analysis—see Figure 3.3 for a flowchart of a typical three-stage analysis (e.g., Pastor 2002; Drake et al. 2006; Liu and Tone 2008; Avkiran 2009; Liu 2018).

With respect to the type of assessment perspective, which drives the choices of inputs and outputs, we classify the literature into six categories; namely, the intermediation approach or perspective (e.g., Rangan et al. 1988; Ferrier and Lovell 1990; Charnes et al. 1990; Elyasiani and Mehdian 1990, 1992; Aly et al. 1990; Yue 1992; Grabowski et al. 1993; Fukuyama 1993; Zaim 1995; Favero and Papi 1995; Miller and Noulas 1996; Taylor et al. 1997; Chen 1998; Drake et al. 2006; Liu 2018), the asset approach (e.g., Favero and Papi 1995), the production approach (e.g., Drake et al. 2006; Liu and Tone 2008), the value added approach (e.g., Bhattacharyya et al. 1997; Pastor et al. 1997; Chu and Lim 1998; Pastor 2002; Das and Ghosh 2006), the profit-oriented approach (e.g., Berger and Mester 2003; Drake et al. 2006; Liu and Tone 2008), and the user cost approach (e.g., Hancock 1985a, b; Fixler and Zieschang 1992).

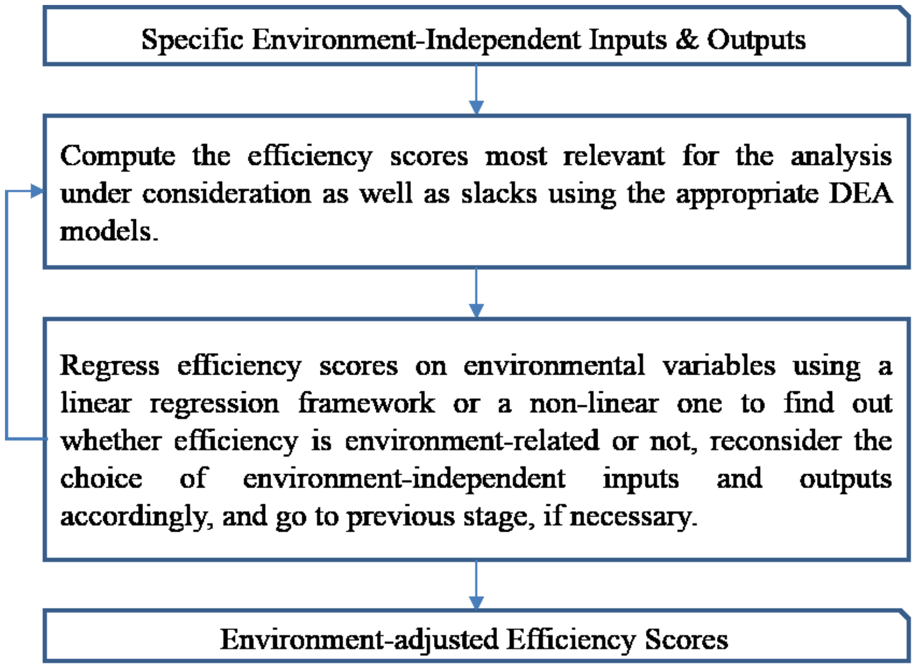


Figure 3.2 Main Steps of a Two-Stage Analysis

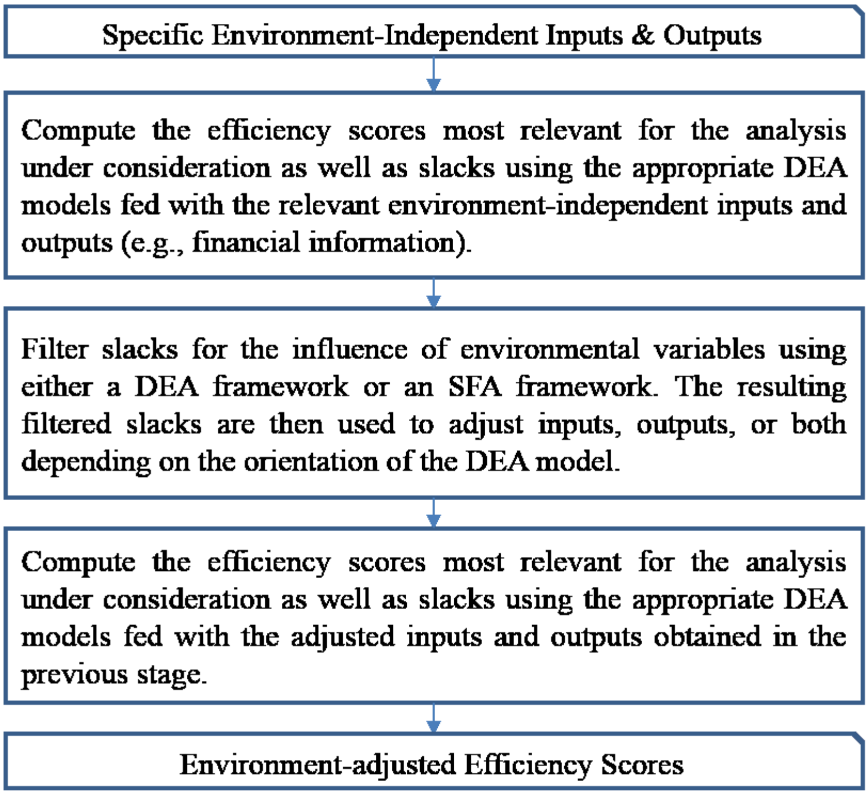


Figure 3.3 Main Steps of a Three-Stage Analysis

Recall that the intermediation approach considers banks as intermediation agents who collect funds and provide loans and other assets. The asset approach is a variant of the intermediation approach, which consider banks as financial intermediaries between liability holders and those who receive bank funds. The production approach considers banks as production units that transform inputs into outputs, or producers of deposit accounts and loan services. Under the value added approach, the share of value added guides the choice of inputs and outputs. Under the profit approach, profit guides the choice of inputs and outputs. Finally, under the user cost approach, the net contribution to bank revenue determines the nature of inputs and outputs.

As to the country of focus, the literature could be divided into two main categories. The first category consists of single country focused studies and covers US Banks (Rangan et al. 1988; Ferrier and Lovell 1990; Elyasiani and Mehdian 1990, 1992; Aly et al. 1990;Yue 1992;Miller and Noulas 1996; Kwon and Lee 2015), UK Banks (Drake 2001; Webb 2003; Webb et al. 2010; Tanna et al. 2011), Italian Banks (Favero and Papi 1995), Turkish Banks (Zaim 1995; Kutlar et al. 2017), Japanese Banks (Fukuyama 1993; Liu and Tone 2008), Taiwanese Banks (Chen 1998; Liu 2018), Hong Kong Banks (Drake et al. 2006), Singaporean Banks (Chu and Lim 1998), Indian Banks (Bhattacharyya et al. 1997), Mozambique Banks (Wanke et al. 2016), and Korean Banks (Lee et al. 2017). The second category consists of multi-country focused studies and covers banks in several countries such as US, Australian, New Zealand, Austrian, Spanish, German, UK, Italian, Belgian, French, Danish, Luxembourg, Dutch, and Portuguese Banks (e.g., Pastor et al. 1997; Pastor 2002; Lozano-Vivas et al. 2002; Casu and Molyneux 2003; Pasiouras 2008; Avkiran 2009).

To conclude this section, it is worthy to mention that single country focused studies on banks using static DEA analyses (Drake 2001; Webb 2003; Webb et al. 2010; Tanna et al. 2011) focused exclusively on the few largest commercial banks in the UK, whereas this chapter considers the whole UK commercial banking sector. We also would like to point out that other DEA methodologies have been used to assess the efficiency of banks; for example, Network DEA (e.g., Matthews 2013; Grigoroudis et al. 2013; Akther et al. 2013; Fukuyama and Matousek 2017;Gulati andKumar 2017), NetworkDEA with undesirable variables (e.g., An et al. 2015; Liu et al. 2015), Dynamic DEA (e.g., Avkiran and Goto 2011; Fukuyama and Weber 2015, 2017a), Dynamic Network DEA (e.g., Avkiran 2015; Chao et al. 2015; Fukuyama and Weber 2015, 2017a; Zha et al. 2016; Wu et al. 2016; Fukuyama and Weber 2017b), Fuzzy DEA (e.g., Wang et al. 2014a; Wanke et al. 2016; Hatami-Marbini et al. 2017), DEA with Bootstrapping (e.g., Ferrier and Hirschberg 1997), Fuzzy DEA with Bootstrapping (e.g.,Wanke et al. 2016), and Stochastic DEA (e.g., Kao and Liu 2009). For a recent survey, we refer the reader to Kaffash and Marra (2017).

In the next section, we propose a DEA analysis with a regression-based feedback mechanism along with new DEA models to assess the efficiency profiles of banks, which we apply in the following section to the UK banking sector.

3.3 A DEA ANALYSIS WITH REGRESSION-BASED FEEDBACK MECHANISM

In this section, we shall describe the methodology and models we propose for assessing the efficiency profile of UK commercial banks. The proposed methodology is a sequential decision making process with a feedback adjustment mechanism; namely, a DEA-based analysis with a regression-based feedback mechanism.

DEA was first proposed by Charnes et al (1978) as a frontier-based non-parametric approach to the relative performance evaluation of a set of n entities commonly referred to as decision making units ($DMUs$), where $DMUs$ are viewed as production systems that make use of the same set of m inputs to produce the same set of s outputs. For each DMU, lot sizing decisions of both inputs and outputs are made by its management; that is, the quantity $x_{i,k}$ of input i $(i = 1, \dots, m)$ used by DMU_k $(k = 1, \dots, n)$ and the quantity $y_{r,k}$ of output r $(r = 1, \dots, s)$ produced by DMU_k $(k = 1, \dots, n)$. Unlike parametric methodologies, DEA does not require an explicit specification of the form of the production function, or equivalently the relationship between inputs and outputs. DEA is a mathematical programming-based methodology – for a detailed text on DEA, we refer the reader to Cooper et al. (2007).

In this chapter, we are concerned with measuring overall technical efficiency, pure technical efficiency, and scale efficiency of UK commercial banks. Unlike previous studies, the particular features of UK banking data require additional types of DEA models. Therefore, we shall use both input- and output-oriented CCR models (Charnes et al. 1978); both input- and output-oriented BCC models (Banker et al. 1984); BCC models without explicit inputs, BCC-WEI, or without explicit outputs, BCC-WEO (Lovell and Pastor 1999); input-oriented, output-oriented, and non-oriented SBM models (Tone, 2001); and SBM-WEI model (Liu et al. 2011) and SBM-WEO model that we propose. CCR and BCC models are described in Table 3.1, BCC models without explicit inputs or outputs are described in Table 3.2, SBM models are described in Table 3.3, and SBM models without explicit inputs or outputs are described in Table 3.4, where θ_k denotes the technical efficiency of DMU_k and measures the efficiency with which DMU_k transforms inputs into outputs, which reflects the quality of its management decisions, λ_j denotes the weight assigned to DMU_j in constructing the "ideal" benchmark of DMU_k; that is, its projection on the efficiency frontier, and $s_{i,k}^-$ and $s_{r,k}^+$ denote the slacks in input i and output r, respectively, which represent input excess and output shortfall. Recall that most DEA analyses make use of one or several inputs and one or several outputs; however, in some situations one might not have to use any inputs or any outputs – these situations or models are referred to as DEA models or analyses without explicit inputs or without explicit outputs. In a DEA analysis with a regression-based feedback mechanism one might have to discard all inputs or all outputs when regression analysis suggests that they do not drive or explain differences in efficiency profiles. However, in general, in DEA applications the use of DEA models without explicit inputs could be justified when one assumes that inputs are considered similar and equal for all DMUs as they operate, for example, in the same market (e.g., Halkos & Salamouris, 2004). On the other hand, the use of DEA models without explicit outputs could be justified when one assumes that outputs are considered similar and equal for all DMUs as they operate, for example, under specific legislation or supply markets with fixed shares on which DMUs could not act upon in the short to medium term.

The flowchart of the proposed methodology is outlined in Figure 3.4. Within this methodological framework, given a set of relevant environment-independent inputs and outputs specified by the analyst or researcher, DEA analysis with both inputs and outputs is first performed to compute the relevant efficiency scores for the analysis under consideration (e.g., overall technical efficiency, pure technical efficiency, scale efficiency) as well as slacks by solving the appropriate DEA models (e.g., CCR, BCC, SBM models).

For our banking application, inputs and outputs are supplied from banks' financial statements (i.e., balance sheet and income statement). These inputs and outputs are environment-independent because the study is performed on UK banks only, on one hand, and we do not test any specific event-related hypotheses, on the other hand. Then, the DEA scores are regressed on the initial inputs and output supplied by the analyst to find out whether they are statistically significant or not; that is, whether they drive the efficiency scores or not – any inputs or outputs which are not relevant (i.e., not statistically significant) are then discarded and the DEA analysis with both inputs and outputs is performed with a reduced set of inputs and outputs. When regression analysis suggests that none of the inputs or none of the outputs chosen by the analyst are relevant, DEA analysis without explicit inputs or without explicit outputs is performed using the relevant DEA models mentioned above. In sum, regression analysis provides DEA with feedback that informs DEA about the relevance of the inputs and outputs chosen by the analyst. For information regarding the assumptions of the regression used in this chapter, we refer the reader to Simar and Wilson, 2007.

Before we proceed with the application of the proposed DEA analysis with regression-based feedback, we hereafter position our contribution with respect to the literature on variable selection in DEA.

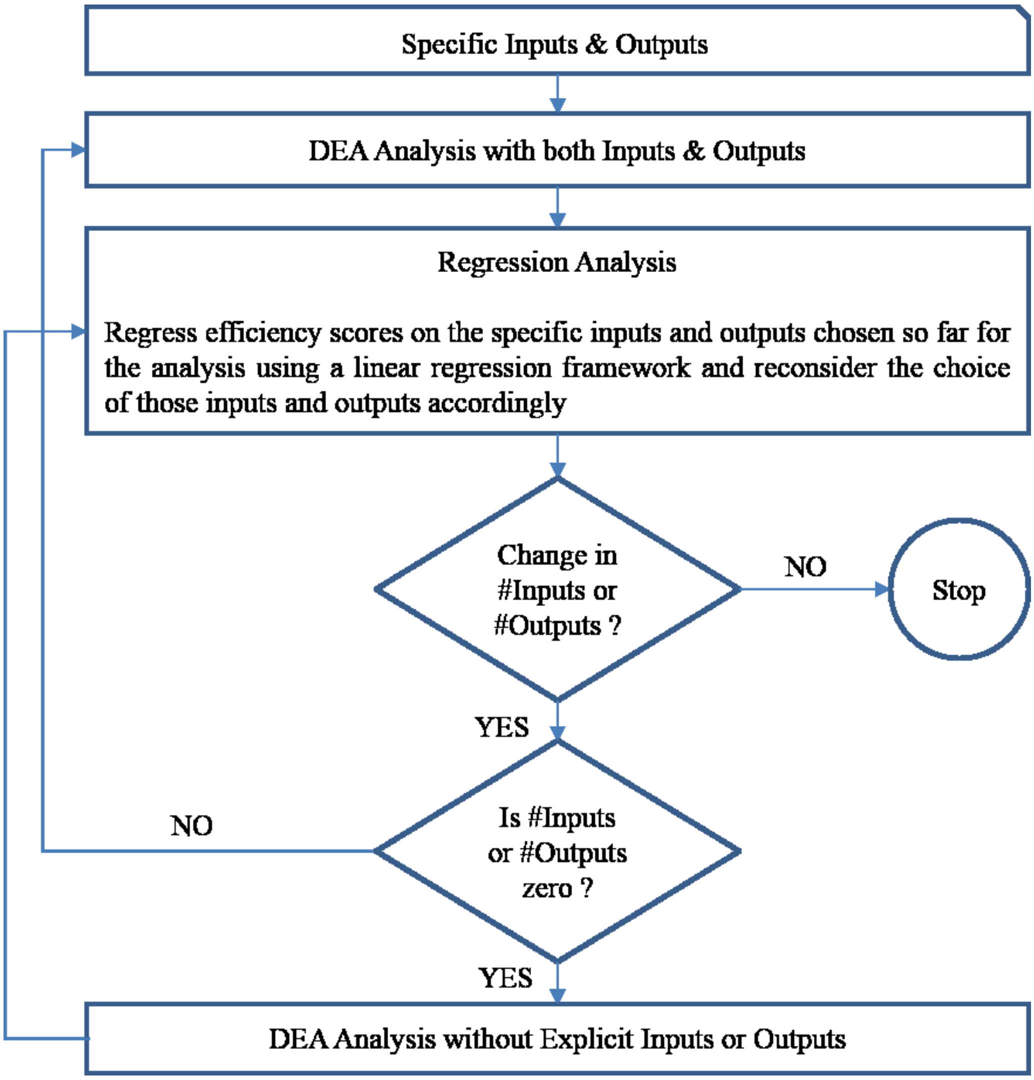


Figure 3.4 DEA Analysis with Regression-based Feedback

Table 3.1 BCC Models without Explicit Inputs or Outputs

Formulation	Description
Objective Function	
θ_k	θ_k is to be minimised or maximised depending on whether the analysis is without explicit output or without explicit inputs
Constraints	
$\sum_{j=1}^{n} \lambda_j x_{i,j} \leq \theta_k \cdot x_{i,k}, i = 1, \dots, m$ OR	For each input i ($i = 1, \dots, m$), the amount used by DMU_k's "ideal" benchmark; i.e., its projection on the efficiency frontier, should at most be equal to the amount used by DMU_k adjusted for the degree of technical efficiency of DMU_k, or for each output r ($r = 1, \dots, s$), the amount produced by DMU_k's "ideal" benchmark should be at least as large as the amount produced by

$\sum_{j=1}^{n} \lambda_j y_{r,j} \geq \theta_k \cdot y_{r,k}, r = 1, \dots, s$	DMU_k adjusted for the degree of technical efficiency of DMU_k depending on whether the analysis is without explicit output or without explicit inputs
$\sum_{j=1}^{n} \lambda_j = 1$	The technology is convex
$\lambda_j \geq 0, j = 1, \dots, n$ θ_k unrestricted	Other requirements including non-negativity

Table 3.2 SBM Models without Explicit Inputs or Outputs

Formulation	Description
Objective Function	
$\rho_k = 1 - \frac{1}{m}\sum_{i=1}^{m} \frac{s_{i,k}^{-}}{x_{i,k}}$ OR $\rho_k = 1/\left(1 + \frac{1}{s}\sum_{r=1}^{s} \frac{s_{r,k}^{+}}{y_{r,k}}\right)$	One of these ρ_k formulations is to be minimised depending on whether the analysis is without explicit output or without explicit inputs
Constraints	
$\sum_{j=1}^{n} \lambda_j x_{i,j} + s_{i,k}^{-} = x_{i,k}, i = 1, \dots, m$ OR $\sum_{j=1}^{n} \lambda_j y_{r,j} - s_{r,k}^{+} = y_{r,k}, r = 1, \dots, s$	For each input i ($i = 1, \dots, m$), the amount used by DMU_k's "ideal" benchmark; i.e., its projection on the efficiency frontier, should at most be equal to the amount used by DMU_k, or for each output r ($r = 1, \dots, s$), the amount produced by DMU_k's "ideal" benchmark; i.e., its projection on the efficiency frontier, should be at least as large as the amount produced by DMU_k depending on whether the analysis is without explicit output or without explicit inputs
$\sum_{j=1}^{n} \lambda_j = 1$	This constraint requires the technology to be convex; however, it could be relaxed.
$\lambda_j \geq 0, j = 1, \dots, n$ $s_{i,k}^{-} \geq 0, i = 1, \dots, m$ OR $s_{r,k}^{+} \geq 0, r = 1, \dots, s$	The weights λ_js are required to be non-negative as well as the relevant slacks depending on whether the analysis is without explicit output or without explicit inputs

So far, such literature could be divided into (1) Judgemental Screening or Expert Opinions such as Fuzzy Delphi Method (Arsad et al., 2017); (2) Statistical Tests and Bootstrapping (e.g., Banker 1996; Olson et al., 1980; Simar & Wilson, 2001; Nataraja & Johnson, 2011); (3) Dimensionality Reduction Techniques such as Principal Component Analysis (Ueda and Hoshiai, 1997; Adler and Golany, 2001, 2002; Cinca and Molinero, 2004; Adler and Yazhemsky, 2010; Nataraja and Johnson, 2011); and (4) Variable Reduction Techniques such as Correlation Analysis and Variants (Nunamaker, 1985; Jenkins & Anderson, 2003; Eskelinen, 2017; Adler & Yazhemsky, 2010), Copula (Alpay and Akturk Hayat, 2017), Efficiency Contribution Measure (Pastor et al., 2002; Nataraja & Johnson, 2011; Eskelinen, 2017), Stepwise Procedures (Norman & Stoker, 1991; Sigala, 2004; Wagner & Shimshak, 2007; Subramanyam, 2016; Sharma & Yu, 2015), Akaike's Information Criterion rule (Li et al., 2017), Directional Technology Distance Function (Guarda et al., 2013), Regression Analysis (Lewin et al., 1982; Fanchon, 2003; Ruggiero, 2005; Luo et al., 2012; Golany & Roll, 1989); Decision Tree Analysis (Lim, 2008; Jain et al., 2016), and Genetic Algorithms (Madhanagopal and Chandrasekaran, 2014). Our contribution falls into the subcategory of Regression Analysis; however, unlike previous contributions, ours use regression analysis within a feedback mechanism and allows for no-inputs or no-outputs situations.

In the next section, we shall apply the proposed methodology to assess the efficiency profile of UK commercial banks.

3.4 EMPIRICAL STUDY

In our empirical investigation, we used all UK commercial banks for which data is available From Bankscope, provided by Bureau van Dijk, over a period of 29 years; namely, 1987–2015. Our dataset includes 109 commercial banks and consists of a total number of 1171 bank-year observations or decision making units.

The choice of the inputs and outputs with which DEA models are fed is driven by the intermediation approach, where banks are considered as intermediation agents who collect funds and provide loans and other assets. For a discussion on the choice of inputs and outputs in banking applications, we refer the reader to Fethi and Pasiouras (2010). Our survey and classification of the inputs and outputs used in the literature (see Ouenniche et al. 2017) along with an analysis of the balance sheet and the income statement of UK commercial banks revealed that inputs are typically chosen based on resources, costs, or financial burden, whereas outputs are typically chosen based on bank's ability to provide financial services (i.e., Loans and Deposits), generate revenue (i.e., Income and Investments) and acquire more assets (i.e., Investments). However, our critical analysis of such choices suggests that some authors' choices—especially of inputs based on financial burden rather penalize the very means by which banks are able to perform their lending operations. Therefore, we selected inputs based only on resources (i.e., Labor as measured by Personnel Expenses—because the number of employees was not available for all UK banks; Capital as measured by Fixed Assets/Physical Capital or Equity/Financial Capital) and costs (i.e., Total Interest Expense; Total Expenses not including Personnel Expense). As to outputs, we selected them based on the ability of a bank to provide financial services (i.e., Gross Loans; Total Customer Deposits) and generate revenue (i.e., Total Income; Gross Interest and Dividend Income). We did not consider the ability of banks to acquire more assets or to make investments because small UK banks, which are part of our sample, are not quite involved in off-balance sheet activities. These chosen criteria could however be measured in different ways. In our empirical experiments, we used four setups or scenarios each corresponding to a different combination of measures—see Table 3.3 for details.

Table 3.3 Choices of Measures of Inputs and Outputs for DEA Analyses

Setup	Inputs					Output			
	Personnel Expenses	Fixed Assets	Equity	Total Interest Expense	Total Expenses not including Personnel Expense	Gross Loans	Total Customer Deposits	Gross Interest and Dividend Income	Total Income
1	x	x		x		x	x	x	
2	x	x			x	x	x		x
3	x		x	x		x	x	x	
4	x		x		x	x	x		x

A snapshot of the 109 UK commercial banks in our dataset is summarized in Table 3.4 (see "Appendix"), where the figures are measured in millions of USD. Table 3.5 provides a snapshot of the leading UK commercial banks (see "Appendix"). Analysis of raw data on UK commercial banks in our dataset revealed that Pareto's Law holds; that is, eight leading banks (i.e., 8/109 ~_ 7% of UK commercial banks); namely, National Westminster Bank Plc—NatWest, The Royal bank of Scotland, Ulster bank, Lloyds bank, Bank of Scotland, Barclays, HSBC Bank Plc, and Standard Chartered Bank, together account for almost 87% of the stock of UK customer lending and deposits. In addition, as highlighted by some statistics on fixed assets, as a proxy for size (i.e., the first quartile of total assets in Table 3.5 is 400% bigger than the third quartile of total assets in Table 3.4); the UK commercial banks in our dataset, excluding the largest eight, are altogether smaller than the smallest bank of the largest ones. We also performed several analyses by size (e.g., total assets); market share (e.g., total customer deposits, gross loans), gross profitability (e.g., total income), operational expenses (e.g., personnel expenses), and origin (e.g., domestic, foreign)—see Table 3.6 in "Appendix". These analyses also support Pareto's Law. In addition, they highlight the importance of foreign banks in the UK; in fact, although foreign banks represent 38% of the total UK commercial banks as compared to 55% of domestic banks but the largest eight, their market share is bigger. Last, but not least, assuming that Personnel Expenses are a good proxy for the number of employees, the largest bank; namely, Barclays Bank Plc, employs about 50% of the labor used by all small domestic banks. We also investigated the UK commercial banks' ownership structure and found out that ownership structure is not a discriminatory feature, since 1 foreign bank in residency and 2 local banks are Limited Liability Corporations, 1 foreign bank in residency and 2 local banks are Mutual/Co-ops, and the remaining banks; that is, 39 foreign banks in residency and 64 local banks are Stock Corporations.

DEA analyses of the UK commercial banking sector, as represented by the 109 commercial banks in our dataset, are summarized as follows:

First, in input-oriented analyses (see Tables 3.7, 3.9 in "Appendix"), numerical results suggest that in the UK commercial banking system the combination of choices of measures of inputs matters; in other words, how resources and expenses are proxied as well as the combinations of these proxies matter for banks' levels of efficiencies. To be more specific, equity or financial capital (setups 4 and 3), as a proxy for resources, enhances on average overall technical efficiency (OTE) or CCR scores, overall technical efficiency adjusted for mix efficiency (adj- OTE) or SBM scores; pure technical efficiency (PTE) or BCC scores, and scale efficiency (SE) better than fixed assets or physical capital (setups 1 and 2); therefore, UK commercial banks are better at managing their equity or liquidity than their fixed assets, which is in line with the intermediation role of the banks. On the other hand, total expenses not including personnel expense (setups 4 and 2), as a proxy for expenses, seems to enhance on average OTE, adj-OTE, PTE, and SE better than total interest expense (setups 1 and 3). Judged on their use of inputs, on average, UK commercial banks fall short on overall technical efficiency, pure technical efficiency, and scale efficiency—see Tables 3.7 and 3.9. In fact, depending on the choice of measures of inputs across setups, average CCR scores vary between 0.3144 and 0.6119, average SBM scores (i.e., overall technical efficiency adjusted for mix efficiency) vary between 0.3577 and 0.5646, average BCC scores vary between 0.5132 and 0.6976, and average SE scores vary between 0.667 and 0.8796. In sum, the management of the UK commercial banking sector seems to be in need of further improvements. Commercial banks in the fourth quartile however seem to be scale efficient to a large extent; therefore, for these banks any further efficiency improvement efforts should be put on pure technical efficiency.

Second, most DEA analyses in banking have focused on input-oriented analyses, which is typically justified by the fact that bank managers have more control over the management of inputs than outputs. This is an arguable point of view as some outputs could be acted upon through better and more focused commercial strategies and marketing campaigns. In addition, in practice, the analysis of output-oriented DEA scores could provide important insight. Motivated by these concerns, we also performed output-oriented analyses of the UK commercial banks—see Tables 3.8 and 3.9 in "Appendix". In output-oriented analyses (see Tables 3.8, 3.9), numerical results suggest that, in the UK commercial banking system, the choices of measures of outputs as well as the combinations of choices of measures of inputs matter; in other words, how income is proxied as well as the combinations of proxies of inputs matter for banks' levels of efficiencies. To be more specific, regardless of the choice of inputs proxies, on average, OTE, PTE and SE are enhanced when total income (setups 2 and 4) is used as a proxy for income compared to gross interest and dividend income (setups 1 and 3). Consequently, on average, the management of UK commercial banks seem to be good at managing total income, but less so in generating gross interest and rewarding their shareholders through dividends. However, average adj-OTE figures are affected by both the choice of income proxies and the combinations of proxies of inputs; in fact, setup 4 enhances adj-OTE more than setup 3 followed by setup 2 then setup 1. Finally, in terms of scale efficiency, output-oriented results are in line with the input-oriented ones.

Third, regression feedback informs the analyst about the relevance of his or her choices of efficiency drivers (i.e., inputs and outputs). Our empirical analysis shows that taking account of regression feedback to revise DEA models always enhances discrimination and adjusts DEA scores downwards or upwards, depending on whether the DEA analysis is input-oriented or output-oriented—see Tables 3.7 to 3.15 in "Appendix". Note that, in the case of the UK commercial banks in our sample, the conclusions with respect to the efficiency profiles of banks remain the same. In sum, regardless of whether DEA analyses are performed with or without regression feedback, the UK commercial banking sector is in need of further efficiency improvements.

Fourth, in addition to enhancing discrimination amongst DMUs and adjusting their DEA scores, which in itself is a major issue in DEA applications, feedback reveals a completely new story on the actual drivers of a range of efficiency measures and exposes the importance of the choice of DEA models in estimating these measures. In the following paragraphs, we shall provide evidence of these claims.

In our empirical analysis, we used two types of regression feedback—see Tables 3.10, 3.11, 3.12, 3.13, 3.14 and 3.15 in "Appendix". The first regression feedback—referred to as input focus regression analysis—involves regressing DEA scores on inputs. The second regression feedback—referred to as output focus regression analysis—involves regressing DEA scores on outputs. Depending on the statistical significance of inputs (respectively, outputs), some inputs (respectively, outputs) may have to be discarded and the DEA scores recomputed with a reduced set of inputs (respectively, outputs), if necessary. Note however that, in some cases, none of the inputs (respectively, outputs) proves to explain the behavior of DEA scores in which case DEA models without explicit inputs (respectively, explicit outputs) would have to be solved—as illustrated by Setup 4 in output focus regression. So far, this case has not been encountered by or reported in previous studies, which has motivated the new methodological design in this research.

A summary of the statistically significant input and output drivers of efficiency is provided in Table 3.16, where Labor, as measured by Personnel expenses, seems to be the most consistent input driver of efficiency scores across all setups and DEA analyses, whereas the provision of financial services, as measured by Gross Loans, seems to be the most consistent output driver of efficiency scores across all setups and DEA analyses. The relevance of remaining drivers however depends on both the setups or combinations of drivers and the DEA analyses. Notice, however, that those setups (i.e., choices of combinations of drivers) that make the UK commercial banking sector look more efficient (e.g., Setup 4 without feedback) are the ones that are most affected by the regression feedback, on one hand, and those setups that lead to more conservative estimates of efficiency scores (e.g., Setup 1 without feedback) are less or not at all affected by the regression feedback, on the other hand. Therefore, the regression feedback serves as a correction mechanism in that it adjusts over and under-estimated scores. These findings have important implications on the relevance of the choices of inputs and outputs and the combinations of their measures; in fact, they often tell the opposite story revealed by DEA analyses without regression feedback. For example, input-oriented DEA analyses without regression feedback suggested that UK commercial banks are better at managing their financial capital than their physical capital, which is in line with the intermediation role of the banks, but when feedback is incorporated the management of UK commercial banks does not seem to be doing such good job anymore in managing equity. In sum, the lessons to be learned could be summarized as follows. From the perspective of banks' managers, DEA analyses without feedback make them look better, and most importantly it backs up their strategies of being intermediation agents in the economy. However, regulators and investors might be better off performing DEA analyses with feedback, alongside DEA analyses without feedback, to unveil different pictures.

Furthermore, with respect to the importance of the choice of DEA models in estimating efficiency measures, DEA analyses with input focus regression feedback provides a good example. In fact, empirical results suggest that, in some setups, DEA scores estimated by CCR and BCC models are not driven by the initial choice of inputs. For example, under Setup 2, CCR and BCC scores are only driven by Personnel Expenses. Interestingly, under the same setup, SBM scores are driven by Personnel Expenses, Fixed Assets (physical capital), and Total Expenses not including Personnel Expense. Further investigation of this fact revealed that the slacks associated with Fixed Assets, and Total Expenses not including Personnel Expense turn out to be important in magnitude, but ignored by radial measures of efficiency. SBM scores however take these slacks into account and thus avoid the elimination of Fixed Assets, and Total Expenses not including Personnel Expense through regression feedback. In sum, ignoring slacks might result in the regression-based feedback suggesting that some efficiency determinants should be discarded when they should not. These findings suggest that, in practice, one should use slacks-based measures of efficiency instead of the conventional ones whenever possible, on one hand, and remind us of the importance for the DEA community to design new SBM based metrics to measure pure technical efficiency and scale efficiency, which are yet to be proposed, on the other hand.

Finally, our analysis of DEA scores of domestic and foreign banks suggests that their efficiency profiles are very similar regardless of which DEA models or regression analysis focus is used to estimate the scores—see, for example, Tables 3.17, 3.18, 3.19 and 3.20 in "Appendix" for illustration. Also, our analysis of DEA scores of large and smaller banks suggests that their efficiency profiles are very different. In fact, large banks are more overall technically efficient and pure technically efficient than the small ones, but the large ones seem to be less scale efficient than the small banks regardless of which DEA models or regression analysis focus is used to estimate the scores—see, for example, Tables 3.21, 3.22, 3.23 and 3.24 in “Appendix” for illustration.

In sum, our empirical analyses provided the following answers to our research questions. First, UK commercial banks need further efficiency improvements. Second, UK commercial banks’ measures of efficiency seem to be driven by the inputs and outputs identified by researchers so far except when the combinations of measures and their interaction along with their slacks and the type of DEA models used for estimating efficiency scores come into play. Third, DEA analyses with and without a regression-based feedback mechanism seem to provide consistent findings in terms of inefficiency; however, compared to DEA analyses with feedback, in general DEA analyses without feedback tend to over- or underestimate efficiency scores depending on whether the analyses are input-oriented or output oriented. Fourth, in general, a regression-based feedback mechanism proves effective at improving discrimination in DEA analyses unless the initial choice of inputs and outputs is well informed. Last, but not least, ignoring slacks might result in the regression-based feedback suggesting that some efficiency determinants should be discarded when they should not, which suggest that, in practice, one should use slacks-based measures of efficiency instead of the conventional ones whenever possible, on one hand, and remind us of the importance for the DEA community to design new SBM based metrics to measure pure technical efficiency and scale efficiency, which are yet to be proposed, on the other hand.

3.5 CONCLUSION

In this chapter, we investigated the efficiency profiles of the UK commercial banking sector using a new DEA-based analysis framework with a regression-based feedback mechanism, where DEA models could use both inputs and outputs, only inputs, or only outputs. Note that the use of DEA models without explicit inputs or outputs is required when the regression based feedback mechanism informs DEA analysis that all inputs or all outputs should be discarded, because they do not drive efficiency, which turned out to be the case in our empirical analysis of UK banking data. The proposed DEA analysis design was used to address several research questions related to both the UK commercial banking sector and DEA analyses with and without regression-based feedback—see Sect. 4 for details on our findings. Amongst these findings, it turned out that performing DEA analyses with radial models such as CCR and BCC, which ignore slacks in computing technical efficiency scores, might result in the regression-based feedback suggesting that some efficiency drivers should be discarded when they should not. Therefore, we recommend that, in practice, one should use slacks-based measures of efficiency instead of the conventional ones whenever possible. These findings remind us of the importance for the DEA community to design new SBM based metrics to measure pure technical efficiency and scale efficiency, which are yet to be proposed.

APPENDICES

See Tables 3.4 to 3.24.

Statistics	Inputs					Output			
	Personnel Expenses	Fixed Assets	Total Assets – Total Liabilities	Total Interest Expense	Total Expenses not including Personnel Expense	Gross Loans	Total Customer Deposits	Gross Interest and Dividend Income	Total Income
Minimum	145	3	496	17	176	155	2	156	592
1st Quartile	3,084	952	37,825	4,430	7,824	79,031	88,376	11,060	29,423
2nd Quartile	8,900	5,184	184,532	27,658	45,300	559,289	566,231	57,864	151,137
3rd Quartile	102,738	44,899	788,590	182,050	339,226	3,971,509	3,188,962	352,378	1,272,411
Maximum	20,018,117	28,031,677	104,117,263	57,559,609	63,550,393	1,113,372,106	887,561,640	73,422,162	164,071,334
Mean	587,769	523,085	4,136,704	1,279,699	1,907,944	42,454,571	36,800,174	2,295,624	6,341,943
Std. Dev.	2,207,552	2,217,200	14,238,836	4,567,619	6,356,927	143,155,173	123,979,458	7,477,161	20,947,952

Table 3.4 Statistics on All UK Commercial Banks in Our Dataset

Statistics	Inputs					Output			
	Personnel Expenses	Fixed Assets	Total Assets – Total Liabilities	Total Interest Expense	Total Expenses not including Personnel Expense	Gross Loans	Total Customer Deposits	Gross Interest and Dividend Income	Total Income
Minimum	399,483	406,371	4,013,775	302,794	769,471	51,423,159	28,122,407	1,204,932	3,390,042
1st Quartile	2,603,403	2,244,140	21,507,171	5,308,666	10,213,000	275,469,780	259,803,728	13,710,215	40,757,916
2nd Quartile	5,818,473	4,407,448	33,460,279	10,110,862	16,524,428	404,934,564	372,874,000	20,017,169	57,496,490
3rd Quartile	8,911,865	7,688,636	63,639,245	15,534,106	25,620,037	680,819,266	547,769,283	30,769,484	93,498,785
Maximum	20,018,117	28,031,677	104,117,263	57,559,609	63,550,393	1,113,372,106	887,561,640	73,422,162	164,071,334
Mean	6,378,980	5,842,691	42,820,658	12,205,320	18,872,460	441,836,080	393,482,462	22,820,758	64,658,760
Std. Dev.	4,833,962	5,421,576	28,886,641	10,099,372	12,450,209	262,830,397	213,471,361	13,940,763	39,175,418

Table 3.5 Statistics on the Largest UK Commercial Banks in Our Dataset

	# Banks	Percentage	Personnel Expenses	Percentage	Fixed Assets	Percentage	Gross Loans	Percentage	Total Customer Deposits	Percentage	Total Income
All Commercial Banks	109	100%	688,278,073	100%	612,533,104	100%	49,714,302,196	100%	43,093,003,273	100%	7,426,415,455
5 Largest UK Banking Groups	8	7%	606,003,076	88%	555,055,662	91%	41,974,427,620	84%	37,380,833,843	87%	6,142,582,203
Local Banks	68	62%	644,949,192	94%	577,851,194	94%	45,167,923,292	91%	39,630,979,746	92%	6,793,674,300
Foreign Bans	41	38%	43,328,882	6%	34,681,910	6%	4,546,378,903	9%	3,462,023,527	8%	632,741,155
Local Banks - Largest Banks	60	55%	38,946,115	6%	22,795,532	4%	3,193,495,672	6%	2,250,145,903	5%	651,092,097

Table 3.6 Additional Analyses of the UK Commercial Banking Sector

	Statistics on CCR-IO Scores				Statistics on BCC-IO Scores				Statistics on SE-IO Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	0.0318	0.033	0.0357	0.0632	0.044	0.0381	0.0358	0.0637	0.0641	0.2525	0.041	0.263
1st Quartile	0.1937	0.3091	0.2908	0.4773	0.2845	0.3815	0.3904	0.5557	0.4721	0.6363	0.6609	0.8195
2nd Quartile	0.2612	0.3902	0.418	0.6057	0.4423	0.5129	0.5441	0.6894	0.689	0.8529	0.854	0.9431
3rd Quartile	0.3729	0.4999	0.5875	0.7514	0.7094	0.7578	0.7944	0.867	0.895	0.9665	0.9674	0.9887
Maximum	1	1	1	1	1	1	1	1	1	1	1	1
Mean	0.3144	0.4297	0.4512	0.6119	0.5132	0.5733	0.591	0.6976	0.667	0.7846	0.7847	0.8796
Std. Dev.	0.1978	0.1829	0.2203	0.1967	0.2716	0.237	0.2502	0.1965	0.2466	0.1997	0.2189	0.1473

Table 3.7 Summary Statistics on Input-oriented Scores of Overall Technical, Pure Technical and Scale Efficiencies without Regression Feedback

	Statistics on CCR-OO Scores				Statistics on BCC-OO Scores				Statistics on SE-OO Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	1	1	1	1	1	1	1	1	1	1	1	1
1st Quartile	2.6815	2.0002	1.7022	1.3308	1.3562	1.3233	1.2774	1.1791	1.0808	1.0266	1.0326	1.0078
2nd Quartile	3.8284	2.5626	2.3925	1.6511	2.4235	2.026	1.9246	1.5049	1.3652	1.1287	1.1204	1.0455
3rd Quartile	5.162	3.2357	3.4386	2.0952	3.6867	2.7762	2.8629	1.919	2.0277	1.4916	1.3582	1.1365
Maximum	31.4064	30.3305	28.02	15.822	30.698	20.6932	18.6209	11.8291	12.0431	4.2375	14.2522	2.2664
Mean	4.3804	2.7956	3.1031	1.8955	2.9497	2.2414	2.43	1.7138	1.7408	1.3365	1.3369	1.1152
Std. Dev.	2.9099	1.6866	2.5788	1.0475	2.3493	1.4107	1.8062	0.9311	1.0381	0.4509	0.8369	0.1736

Table 3.8 Summary Statistics on Output-oriented Scores of Overall Technical, Pure Technical and Scale Efficiencies without Regression Feedback

	Statistics on SBM-IO Scores				Statistics on SBM-OO Scores				Statistics on SBM Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	0.0011	0.0022	0.0012	0.0023	0.0001	0.0001	0.0002	0.0002	0.0001	0.0001	0.0002	0.0002
1st Quartile	0.157	0.2528	0.2765	0.4	0.0933	0.1177	0.1406	0.1546	0.0703	0.1069	0.1246	0.1404
2nd Quartile	0.2511	0.3572	0.4168	0.5547	0.2271	0.2559	0.299	0.3406	0.1664	0.2247	0.2716	0.3219
3rd Quartile	0.4587	0.5607	0.6651	0.7169	0.5096	0.533	0.5514	0.6255	0.3947	0.4615	0.5262	0.5947
Maximum	1	1	1	1	1	1	1	1	1	1	1	1
Mean	0.3577	0.4373	0.4807	0.5646	0.3366	0.3572	0.3829	0.4104	0.2898	0.3269	0.364	0.3931
Std. Dev.	0.2868	0.2586	0.2771	0.2417	0.3091	0.3053	0.3023	0.3068	0.3054	0.2981	0.3035	0.303

Table 3.9 Summary Statistics on SBM Efficiency Scores without Regression Feedback

	Statistics on CCR-IO Scores				Statistics on BCC-IO Scores				Statistics on SE-IO Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	0.0211	0.0085	0.0357	0.0085	0.044	0.0091	0.0358	0.0091	0.0372	0.0939	0.0410	0.0939
1st Quartile	0.1429	0.0855	0.2908	0.0855	0.2845	0.1129	0.3904	0.1129	0.3322	0.3385	0.6612	0.3385
2nd Quartile	0.2042	0.1095	0.418	0.1095	0.4423	0.1811	0.5441	0.1811	0.4852	0.7046	0.8541	0.7046
3rd Quartile	0.2931	0.1451	0.5875	0.1451	0.7094	0.3455	0.7944	0.3455	0.7027	0.9524	0.9674	0.9524
Maximum	1	1	1	1	1	1	1	1	1	1	1	1
Mean	0.2424	0.1264	0.4512	0.1264	0.5132	0.276	0.591	0.276	0.5247	0.6477	0.7847	0.6477
Std. Dev.	0.1633	0.0085	0.2203	0.0772	0.2716	0.2371	0.2502	0.2371	0.2408	0.3040	0.2189	0.3040

Table 3.10 Summary Statistics on Input-oriented Scores of Overall Technical, Pure Technical and Scale Efficiencies with Input Focused Regression Feedback

	Statistics on CCR-OO Scores				Statistics on BCC-OO Scores				Statistics on SE-OO Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	1	1	1	1	1	1	1	1	1	1	1	1
1st Quartile	4.1603	6.8929	1.7022	6.8929	1.3562	2.3027	1.4465	2.3027	1.6245	1.0380	1.0328	1.0380
2nd Quartile	5.8167	9.1365	2.3925	9.1365	2.4235	4.8168	2.4248	4.8168	2.3409	1.7774	1.1205	1.7774
3rd Quartile	8.2587	11.6993	3.4386	11.6993	3.6867	8.3935	4.1161	8.3935	3.6181	3.7435	1.3580	3.7435
Maximum	94.342	117.8434	28.02	117.8434	30.698	49.6054	41.4108	49.6054	21.4901	10.6462	14.2522	10.6462
Mean	7.4828	9.9778	3.1031	9.9778	2.9497	5.9386	3.4743	5.9386	0.3354	2.5006	1.3369	2.5006
Std. Dev.	6.2755	7.2698	2.5788	7.2698	2.3493	4.8377	3.6333	4.8377	0.3089	1.7216	0.8369	1.7216

Table 3.11 Summary Statistics on Output-oriented Scores of Overall Technical, Pure Technical and Scale Efficiencies with Input Focused Regression Feedback

	Statistics on SBM-IO Scores				Statistics on SBM-OO Scores				Statistics on SBM Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	0.0011	0.0022	0.0012	0.0001	0.0002	0.0001	0.0002	0.0002	0.0002	0.0001	0.0002	0.0002
1st Quartile	0.1602	0.2528	0.2765	0.0386	0.0884	0.1177	0.1406	0.1546	0.0704	0.1069	0.1246	0.1221
2nd Quartile	0.2449	0.3572	0.4168	0.0782	0.188	0.2559	0.299	0.3406	0.1478	0.2247	0.2716	0.3085
3rd Quartile	0.4734	0.5607	0.6651	0.2046	0.4104	0.533	0.5514	0.6255	0.3566	0.4615	0.5262	0.5708
Maximum	1	1	1	1	1	1	1	1	1	1	1	1
Mean	0.343	0.4373	0.4807	0.1817	0.2913	0.3572	0.3829	0.4104	0.2618	0.3269	0.364	0.3737
Std. Dev.	0.2677	0.2586	0.2771	0.2404	0.2799	0.3053	0.3023	0.3068	0.2773	0.2981	0.3035	0.2955

Table 3.12 Summary Statistics on SBM Efficiency Scores with Input Focused Regression Feedback

	Statistics on CCR-IO Scores				Statistics on BCC-IO Scores				Statistics on SE-IO Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	0.0011	0.023	0.0011	0.016	0.0358	0.0283	0.0358	0.0304	0.0099	0.1863	0.0099	0.1628
1st Quartile	0.1617	0.2632	0.1617	0.4441	0.3581	0.3388	0.3581	0.4404	0.3574	0.4997	0.3574	0.8085
2nd Quartile	0.2664	0.3271	0.2664	0.5736	0.5251	0.4492	0.5251	0.5759	0.5805	0.6676	0.5805	0.9329
3rd Quartile	0.3837	0.4101	0.3837	0.7234	0.762	0.7008	0.762	0.7487	0.7440	0.8438	0.7440	0.9875
Maximum	1	1	1	1	1	1	1	1	1	1	1	1
Mean	0.2937	0.358	0.2937	0.5788	0.5627	0.5278	0.5627	0.5964	0.5570	0.6633	0.5570	0.8693
Std. Dev.	0.1781	0.1533	0.1781	0.1991	0.258	0.2403	0.258	0.2042	0.2468	0.2027	0.2468	0.1559

Table 3.13 Summary Statistics on Input-oriented Scores of Overall Technical, Pure Technical and Scale Efficiencies with Output Focused Regression Feedback

	Statistics on CCR-OO Scores				Statistics on BCC-OO Scores				Statistics on SE-OO Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	1	1	1	1	1	1	1	1	1	1	1	1
1st Quartile	2.6815	2.4386	2.6062	1.6638	1.4829	1.8382	1.323	1.8382	1.1480	1.1283	1.2511	1.1283
2nd Quartile	3.8284	3.0572	3.7533	2.1944	2.6466	3.0555	2.0381	3.0555	1.4734	1.4679	1.6070	1.4679
3rd Quartile	5.162	3.7992	6.191	2.8296	4.027	3.9226	3.1517	3.9226	2.2064	1.9900	2.4887	1.9900
Maximum	31.4064	43.5696	947.6238	257.9347	47.3749	350.5737	47.3749	350.5737	12.0431	5.3689	132.4496	5.3689
Mean	4.3804	3.3063	7.665	2.7958	3.3081	3.5811	2.8136	3.5811	1.8552	1.6342	2.6234	1.6342
Std. Dev.	2.9099	2.0551	41.5639	7.9682	3.0596	10.8695	2.7962	10.8695	1.1070	0.6150	6.0733	0.6150

Table 3.14 Summary Statistics on Output-oriented Scores of Overall Technical, Pure Technical and Scale Efficiencies with Output Focused Regression Feedback

	Statistics on SBM-IO Scores				Statistics on SBM-OO Scores				Statistics on SBM Scores			
	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4	Setup 1	Setup 2	Setup 3	Setup 4
Minimum	0.0003	0.0022	0.0002	0.0000	0.0001	0.0001	0.0002	0.0001	0.0001	0.0001	0.0002	0.0000
1st Quartile	0.0965	0.2528	0.1421	0.0062	0.1084	0.0815	0.1606	0.0875	0.0474	0.1069	0.1385	0.0640
2nd Quartile	0.1873	0.3572	0.2727	0.0397	0.2448	0.1891	0.3672	0.2726	0.1164	0.2247	0.3173	0.2040
3rd Quartile	0.3776	0.5607	0.487	0.1580	0.4845	0.4292	0.6017	0.4653	0.3141	0.4615	0.5625	0.3701
Maximum	1	1	1	1	1	1	1	1	1	1	1	1
Mean	0.2956	0.4373	0.3435	0.1203	0.3375	0.2975	0.4112	0.3265	0.2446	0.3269	0.3837	0.2737
Std. Dev.	1.3633	0.2586	0.2702	0.1795	0.2953	0.2919	0.3024	0.2824	0.2951	0.2981	0.3019	0.2641

Table 3.15 Summary Statistics on SBM Efficiency Scores with Output Focused Regression Feedback

		Input-Focus Regression Analysis						
	Inputs	CCR-IO	BCC-IO	CCR-OO	BCC-OO	SBM-IO	SBM-OO	SBM
Setup 1	Personnel Expenses	X	X		X	X	X	X
	Fixed Assets		X	X	X	X	X	X
	Total Interest Expense	X	X	X	X	X	X	X
Setup 2	Personnel Expenses	X	X	X	X	X	X	X
	Fixed Assets					X	X	X
	Total Expenses not including Personnel Expense					X	X	X
Setup 3	Personnel Expenses	X	X	X	X	X	X	X
	Total Assets – Total Liabilities	X	X	X	X	X	X	X
	Total Interest Expense	X	X	X		X	X	X
Setup 4	Personnel Expenses	X	X	X	X	X	X	X
	Total Assets – Total Liabilities						X	X
	Total Expenses not including Personnel Expense						X	
		Out-Focus Regression Analysis						
	Outputs	CCR-IO	BCC-IO	CCR-OO	BCC-OO	SBM-IO	SBM-OO	SBM
Setup 1	Gross Loans	X	X	X	X	X	X	X
	Total Customer Deposits	X	X	X	X	X	X	X
	Gross Interest and Dividend Income	X		X				
Setup 2	Gross Loans	X	X	X	X	X	X	X
	Total Customer Deposits	X	X	X		X	X	X
	Total Income					X		X
Setup 3	Gross Loans	X	X	X	X	X	X	X
	Total Customer Deposits		X		X		X	X
	Gross Interest and Dividend Income							
Setup 4	Gross Loans	X	X	X	X		X	X
	Total Customer Deposits	X						
	Total Income							

Table 3.16 Summary of Drivers of Efficiency Scores after Regression Feedback

	CCR-IO Input Focused Regression Feedback							
	Setup 1		Setup 2		Setup 3		Set up 4	
	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
Minimum	0.0211	0.0318	0.0085	0.0189	0.0357	0.0381	0.0085	0.0189
1st Quartile	0.1439	0.1334	0.0855	0.0855	0.3193	0.2357	0.0855	0.0855
2nd Quartile	0.2094	0.1974	0.1084	0.1114	0.4568	0.3536	0.1084	0.1114
3rd Quartile	0.2978	0.2779	0.1420	0.1588	0.6216	0.5317	0.1420	0.1588
Maximum	1	1	1	1	1	1	1	1
Mean	0.2526	0.2233	0.1213	0.1361	0.4860	0.3862	0.1213	0.1361
Std. Dev.	0.1760	0.1345	0.0606	0.1007	0.2163	0.2132	0.0606	0.1007

Table 3.17 Summary of CCR-IO Efficiency Scores for Domestic and Foreign Banks

	BCC-IO Input Focused Regression Feedback							
	Setup 1		Setup 2		Setup 3		Setup 4	
	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
Minimum	0.0440	0.0869	0.0091	0.0214	0.0358	0.0778	0.0091	0.0214
1st Quartile	0.2962	0.2704	0.1118	0.1179	0.4216	0.3455	0.1118	0.1179
2nd Quartile	0.4563	0.4322	0.1787	0.1843	0.5990	0.4898	0.1787	0.1843
3rd Quartile	0.7545	0.6343	0.3529	0.3303	0.8609	0.6890	0.3529	0.3303
Maximum	1	1	1	1	1	1	1	1
Mean	0.5295	0.4828	0.2811	0.2667	0.6252	0.5270	0.2811	0.2667
Std. Dev.	0.2784	0.2561	0.2466	0.2182	0.2519	0.2343	0.2466	0.2182

Table 3.18 Summary of BCC-IO Efficiency Scores for Domestic and Foreign Banks

	SE-IO Input Focused Regression Feedback							
	Setup 1		Setup 2		Setup 3		Setup 4	
	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
Minimum	0.1027	0.0372	0.0939	0.1627	0.1742	0.0410	0.0939	0.1627
1st Quartile	0.3190	0.3618	0.3293	0.3637	0.6802	0.6347	0.3293	0.3637
2nd Quartile	0.4759	0.4960	0.7037	0.7140	0.8671	0.8282	0.7037	0.7140
3rd Quartile	0.7191	0.6735	0.9458	0.9616	0.9640	0.9726	0.9458	0.9616
Maximum	1	1	1	1	1	1	1	1
Mean	0.5270	0.5204	0.6390	0.6640	0.7998	0.7565	0.6390	0.6640
Std. Dev.	0.2414	0.2398	0.3084	0.2955	0.1975	0.2521	0.3084	0.2955

Table 3.19 Summary of SE-IO Efficiency Scores for Domestic and Foreign Banks

	SBM-IO Input Focused Regression Feedback							
	Setup 1		Setup 2		Setup 3		Setup 4	
	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign	Domestic	Foreign
Minimum	0.0011	0.0024	0.0072	0.0022	0.0035	0.0012	0.0001	0.0009
1st Quartile	0.1711	0.1272	0.2747	0.2239	0.3180	0.1955	0.0443	0.0272
2nd Quartile	0.2800	0.2148	0.3773	0.3130	0.4583	0.3628	0.0820	0.0678
3rd Quartile	0.5165	0.3848	0.6080	0.4890	0.7197	0.5651	0.2151	0.1722
Maximum	1	1	1	1	1	1	1	1
Mean	0.3858	0.3017	0.4651	0.3853	0.5237	0.4005	0.1941	0.1586
Std. Dev.	0.2919	0.2674	0.2591	0.2499	0.2754	0.2623	0.2499	0.2197

Table 3.20 Summary of SBM-IO Efficiency Scores for Domestic and Foreign Banks

	CCR-IO Input Focused Regression Feedback							
	Setup 1		Setup 2		Setup 3		Set up 4	
	Large	Small	Large	Small	Large	Small	Large	Small
Minimum	0.1300	0.0211	0.0830	0.0085	0.3554	0.0357	0.0830	0.0085
1st Quartile	0.2020	0.1369	0.1205	0.0833	0.4724	0.2809	0.1205	0.0833
2nd Quartile	0.2681	0.1986	0.1423	0.1066	0.5468	0.3990	0.1423	0.1066
3rd Quartile	0.3100	0.2853	0.1728	0.1407	0.6769	0.5766	0.1728	0.1407
Maximum	0.6683	1.0001	0.3385	1.0000	1.0000	1.0000	0.3385	1.0000
Mean	0.2731	0.2397	0.1507	0.1243	0.5681	0.4409	0.1507	0.1243
Std. Dev.	0.0979	0.1676	0.0467	0.0790	0.1292	0.2237	0.0467	0.0790

Table 3.21 Summary of CCR-IO Efficiency Scores for Large and Small Banks

	BCC-IO Input Focused Regression Feedback							
	Setup 1		Setup 2		Setup 3		Set up 4	
	Large	Small	Large	Small	Large	Small	Large	Small
Minimum	0.5697	0.0440	0.4789	0.0091	0.6457	0.0358	0.4789	0.0091
1st Quartile	0.8125	0.2750	0.6691	0.1085	0.9045	0.3753	0.6691	0.1085
2nd Quartile	0.9531	0.4145	0.7886	0.1676	0.9905	0.5117	0.7886	0.1676
3rd Quartile	1.0000	0.6304	0.9426	0.2806	1.0000	0.7357	0.9426	0.2806
Maximum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Mean	0.8988	0.4791	0.7891	0.2306	0.9313	0.5609	0.7891	0.2306
Std. Dev.	0.1211	0.2543	0.1627	0.1830	0.0989	0.2369	0.1627	0.1830

Table 3.22 Summary of BCC-IO Efficiency Scores for Large and Small Banks

	SE-IO Input Focused Regression Feedback							
	Setup 1		Setup 2		Setup 3		Set up 4	
	Large	Small	Large	Small	Large	Small	Large	Small
Minimum	0.1311	0.0372	0.0939	0.1228	0.3636	0.0410	0.0939	0.1228
1st Quartile	0.2375	0.3670	0.1737	0.4111	0.5094	0.7003	0.1737	0.4111
2nd Quartile	0.2818	0.5177	0.1854	0.7496	0.6040	0.8827	0.1854	0.7496
3rd Quartile	0.3369	0.7360	0.1936	0.9615	0.7120	0.9721	0.1936	0.9615
Maximum	0.6683	1.0001	0.3385	1.0000	1.0000	1.0000	0.3385	1.0000
Mean	0.3041	0.5443	0.1907	0.6882	0.6124	0.8000	0.1907	0.6882
Std. Dev.	0.1002	0.2399	0.0368	0.2835	0.1291	0.2188	0.0368	0.2835

Table 3.23 Summary of SE-IO Efficiency Scores for Large and Small Banks

	SBM-IO Input Focused Regression Feedback							
	Setup 1		Setup 2		Setup 3		Set up 4	
	Large	Small	Large	Small	Large	Small	Large	Small
Minimum	0.4181	0.0011	0.5055	0.0022	0.5229	0.0012	0.3192	0.0001
1st Quartile	0.5547	0.1486	0.6706	0.2425	0.7071	0.2690	0.6217	0.0354
2nd Quartile	0.8138	0.2337	0.8843	0.3404	0.9272	0.3983	0.7432	0.0709
3rd Quartile	1.0000	0.3873	1.0000	0.5017	1.0000	0.6097	0.8952	0.1405
Maximum	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
Mean	0.7857	0.3185	0.8266	0.4028	0.8538	0.4477	0.7386	0.1324
Std. Dev.	0.2068	0.2602	0.1750	0.2356	0.1598	0.2606	0.1814	0.1735

Table 3.24 Summary of SBM-IO Efficiency Scores for Large and Small Banks

CHAPTER IV

WHICH BANKING-OPERATING ENVIRONMENT IS MORE EFFICIENT?

A CROSS-COUNTRY EFFICIENCY ANALYSIS

4.1 INTRODUCTION

So far, studies on banks' efficiency with data development analysis (DEA) have been concerned with assessing the efficiency profiles of banks with or without taking account of variables that reflect the characteristics of their operating environments, or identifying environmental drivers of the efficiency profiles of banks. To the best of our knowledge, none of these studies assessed the efficiency profiles of banks' operating environments. In this chapter, we intend to fill this gap using DEA methodologies. To be more specific, we intend to address two research questions. The first and main research question is; which banking-operating environments are more efficient? In addition, the second research question is a secondary one; namely, how different DEA analyses (i.e., Static black box SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM) compare in addressing the main research question?

Since the publication of the seminal paper by Charnes, Cooper and Rhodes in 1978, where the conventional CCR model of Data Envelopment Analysis has been proposed, DEA as a field has substantially evolved both methodologically and in terms of applications. So far, efficiency and productivity studies in the banking sector proved to be amongst the most popular application areas (e.g., Emrouznejad & Yang 2018). The popularity of DEA in this field, amongst others, is due to its unique features such as its non-parametric nature, it benchmarks against the best practice performers rather than the average performers. It allows one to identify targets for improvement, it does not need any functional specification of the relationship between inputs and outputs, it provides a variety of efficiency measures most suitable for a variety of applications (e.g., overall technical efficiency, pure technical efficient, scale efficiency, mix efficiency, overall technical efficiency adjusted for mix inefficiency, cost efficiency, profit efficiency, allocative efficiency). It provides a wide range of models to perform analyses at the aggregate level (i.e., Static black box models such as CCR, BCC, SBM models) and the detailed level (i.e., Network models). In addition, DEA models allow one to perform both Static analyses (e.g., CCR, BCC, SBM, and Network models) and Dynamic analyses (e.g., Dynamic models, Dynamic-Network models).

The literature on DEA in banking could be classified into several categories depending on the choice of the classification criterion or criteria. In this chapter, we make use of classification criteria that are most relevant to position our contribution; namely, single country analyses vs. cross-country analyses, analyses without environmental variables vs. analyses with environmental variables, and single stage analyses vs. multi-stage analyses.

The *first category* of studies uses DEA to investigate the efficiency of banks in the *same country without* considering *environmental variables* in computing efficiency scores. These studies could be classified into four categories depending on the type of DEA model used for analysis: (1) *Static black box models*; e.g., USA (Charnes et al. 1990; Elyasiani and Mehdian, 1992; Grabowski et al. 1993; Barr et al. 1993) Japan (Fukuyama,1993); Mexico (Taylor et al. 1997); (2) *Network models*; e.g., USA, (Liang et al, 2008; Holod & Lewis, 2011); Japan (Fukuyama & Weber, 2010; Fukuyama & Matousek, 2017); Turkey (Fukuyama & Matousek, 2011); Taiwan (Yang & Liu, 2012; Kao & Liu, 2014); Bangladesh (Akther et al. 2013); Brazil (Wanke & Barros, 2014); and China (Wang et al. 2014b; Liu et al. 2015); (3) *Dynamic models*; e.g., Iran (Shafiee et al. 2013); and (4) *Dynamic-Network models*; e.g., Japan (Fukuyama & Weber, 2013, 2015, 2017a); Taiwan (Yu et al. 2013; Chao et al. 2015, 2017); China (Avkiran 2015; Zha et al. 2016). Note that all these studies perform a single stage analysis.

The *second category* of studies uses DEA to investigate the efficiency of banks in the *same country* while considering *environmental variables*. These studies could be classified into three main categories depending on whether they use a single stage analysis, a two-stage analysis, or a three-stage analysis. Each of these three categories could be refined by considering the type of DEA model used as follows. *Single stage analyses* have only considered *Static models*, which incorporate environmental variables as inputs or outputs depending on whether smaller or larger values are preferred; e.g., US (Ferrier & Lovell, 1990); Turkey (Zaim, 1995). *Two-stage analyses*, as the name suggests, perform a first stage analysis using one of a variety of models to compute efficiency scores without considering any environmental variables. Then, in the second stage, a regression framework (e.g., regression analysis, stochastic frontier analysis, logistic regression analysis, probit analysis) is typically used to find out about the environmental drivers of efficiency. The DEA models used in the first stage could be classified as follows: (1) *Static black box models*; e.g., US (Rangan et al. 1988; Elyasiani and Mehdian 1990; Aly et al. 1990; Miller & Noulas 1996; Simar & Wilson 2007; Berger & Mester, 1997), UK (Drake 2001; Webb 2003; Webb et al. 2010; Tanna et al. 2011), Italy (Favero & Papi 1995), Japan (Fukuyama 1993), Taiwan (Chen 1998), Singapore (Chu & Lim 1998), China (Du et al. 2018), Mozambique (Wanke et al. 2016) and India (Bhattacharyya et al. 1997); (2) *Network models*; e.g., India (Gulati et al. 2017) and Japan (Fukuyama & Matousek, 2017); (3) *Dynamic models*; e.g., Japan (Avkiran and Goto, 2011), Brazil (Wanke et al. 2015), USA (Berger & Mester, 2003) and (4) *Dynamic-Network models*; e.g., Taiwan (Lu et al. 2014). As to *three-stage analyses*, so far only *Static* SBM and BCC models have been used in the first stage to compute efficiency scores without taking account of environmental variables (e.g., Drake el al. 2006; Liu & Tone, 2008; Liu, 2018). Then, slacks are regressed on environmental variables in a second stage, where the fitted regression model is used to predict the slacks. The predicted slacks are then used to adjust inputs (respectively, outputs). Finally, in the third stage, the DEA model used in the first stage is solved again to compute environment-adjusted efficiency scores, but this time the model is fed with adjusted inputs and/or adjusted outputs depending on whether the analysis is input-oriented, output-oriented, or non-oriented.

The *third category* of studies uses DEA to investigate the efficiency of banks in *multiple countries without* taking account of *environmental variables* in computing efficiency scores. Studies in this category are rather scarce and make use of single stage analyses where Static models have mainly been used; e.g., US, Austria, Spain, Germany, UK, Italy, Belgium and France (Pastor el al. 1997).

The *fourth category* of studies uses DEA to investigate the efficiency of banks in *multiple countries* while considering *environmental variables*. These studies could also be classified into three main categories depending on whether they use a single stage analysis, a two-stage analysis, or a three-stage analysis. *Single stage analyses* have only considered Static models, which incorporate environmental variables as inputs or outputs depending on whether smaller or larger values are preferred; e.g., Belgium, Denmark, France, Germany, Italy, Luxembourg, Netherlands, Portugal, Spain and UK (Lozano-Vivas et al., 2002). So far, *two-stage analyses* perform a first stage analysis using either a (1) *Static black box model*; e.g., France, Gernamy, Italy, Spain and UK (Casu & Molyneux, 2003); Germany and Australia (Hauner, 2005); 95 countries (Pasiouras, 2008); China, India, Malaysia, Russia and Thailand (Du & Sim, 2016); (2) a *Network model*; e.g., UAE (Avkiran, 2009a); and (3) a *Dynamic-Network model*; e.g., Indonesia, Malaysia, the Philippines, Singapore, and Thailand (Wu et al. 2016). Finally, *three-stage analyses* similar in design to the ones mentioned above have so far been implemented for assessing the efficiency of banks in multiple countries using only *Static black box models*; e.g., Spain, Italy, France and Germany (Pastor, 2002), and Australia & New Zealand (Avkiran, 2009b); Indonesia, South Korea, Thailand, Malaysia and the Philippines (Thoraneenitiyan & Avkiran, 2009).

Our analysis of the above literature revealed that, regardless of the methodology used (i.e., single stage analyses, two-stage analyses, or three-stage analyses) and the types of models (i.e., Static black box DEA models, Dynamic DEA models, Network DEA models, or Dynamic-Network DEA models), previous studies were either concerned with assessing the efficiency of banks without or with environmental variables being taken account of, or identifying environmental drivers of efficiency of banks (e.g., Pasiouras & Kosmidou, 2007; Pasiouras, 2008; Pasiouras et al., 2009; Azad et al. 2017). This chapter has a different focus in that it is concerned with assessing the relative efficiency of the operating environments of banks. To the best of our knowledge, no attempt has been made to investigate the relative efficiency of operating environments. This chapter aims at filling this gap. To be more specific, we propose two alternative frameworks for assessing the relative efficiency of banks' operating environments. The first alternative uses a country's operating environment of banks as the unit of analysis or decision making unit (DMU); whereas the second alternative uses a bank as the DMU, whose efficiency evaluation takes account of the features of its operating environment. To operationalise the second framework, in this chapter, we have chosen HSBC in different operating environments or countries. The choice of a single bank; namely, HSBC, is motivated by isolating the operating environment effect on efficiency and thus avoiding any bias that would result from the relative efficiency of different banks within the same operating environment. Note that these modelling frameworks are complementary in that the first one would naturally reflect better the perspective of a first group of stakeholders such as governments and the international monetary fund (IMF), whereas the second modelling framework would be most attractive for a second group of stakeholders such as bankers and investors. In practice, however, a bank would implement the second modelling framework using another bank of similar characteristics that is already operating in the countries of interest. Another contribution of this chapter consists of using Dynamic SBM, Network SBM, and Dynamic-Network SBM within our three-stage analyses.

The remainder of the chapter unfolds as follows. Section 4.2 summarises our methodological choices for implementing the above mentioned alternative solutions to the evaluation of operating environments of banks. Section 4.3

presents empirical analyses and summarises our findings. Finally, section 4.4 concludes the chapter.

4.2 RESEARCH QUESTIONS AND METHODOLOGICAL CHOICES

In this chapter, we address two research questions. The first and main research question is; which banking-operating environments are more efficient? The second research question is a secondary one; namely, how different DEA analyses (i.e., Static black box SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM) compare in addressing the main research question? In the remainder of this section, we first summarise, justify our choices of environmental variables, and describe our conceptual models of the operating environment of banks – see section 4.2.1. Then, we summarise, justify our choices of inputs, outputs, and environmental variables, and describe our conceptual models of banks – see section 4.2.2. Finally, a generic three-stage procedure for purging inputs and outputs from the effect of environmental variables, its justification and its implementation are presented in section 4.2.3. The mathematical programming formulations for operationalising our DEA analysis are summarised in the appendix.

4.2.1 Implementation Decisions of the First Alternative Solution

The environmental variables used in this research are a proxy for explaining particular features in each country. Through our survey of the literature – see Tables 4.1 and 4.2, we inventoried environmental variables used in DEA studies, from this survey the environmental variables were categorized in four groups as follows:

1) Bank Structural / Operating Environment Variables includes
2) Banking Sector Environmental Variables
3) Economic Environment Variables
4) Institutional Environment Variables

Table 4.1 Summary of Environmental variables used in DEA studies on assessing banks' efficiency

Environmental Variables	
Bank Structural / Operating Environment Variables	**Categorical variables:** Institutional Type: Non-commercial; Savings & Loan; Mutual savings; Credit Union (Ferrier & Lovell, 1990); Institutional Type: National Bank; Foreign Bank (Zaim, 1995); Nationality of parent bank (Liu, 2018); Membership of a Multibank Holding Company (Ferrier & Lovell, 1990); Location of Unit or Branch (Ferrier & Lovell, 1990). **Continuous Variables:** Number of Branches (Ferrier & Lovell, 1990; Zaim, 1995; Liu & Tone, 2008); Average Size of Demand Deposit Account (Ferrier & Lovell, 1990; Zaim, 1995); Average Size of Time Deposit Account (Ferrier & Lovell, 1990; Zaim, 1995); Average Size of Real Estate Loan (Ferrier & Lovell, 1990); Average Size of Instalment Loan (Ferrier & Lovell, 1990), Average Size of Commercial Loan (Ferrier & Lovell, 1990); Years of bank establishment (Liu, 2018); Size of bank as measured by Logarithm of a bank's total assets (Thoraneenitiyan & Avkiran, 2009).
Banking Sector Environmental Variables	Risk pricing practices as measured by Short-term risk spread & Long-term risk spread for each of the types of commercial banks (Liu & Tone, 2008); and Real bankrupt debt per case (Liu & Tone, 2008); Monetary aggregate to GDP ratio (Liu & Tone, 2008); Bank lending to GDP ratio (Liu & Tone, 2008); Density of Demand (Lozano et al., 2002); Branch Density (Lozano et al., 2002); and Branches per Capita (Lozano et al., 2002); National Income per Branch (Lozano et al., 2002; Pastor, 2002); and Deposit per Branch (Lozano et al., 2002); Equity over Total Assets (Lozano et al., 2002); Return on Equity (Lozano et al., 2002); capital adequacy ratio (Pastor, 2002); density of deposits (Pastor, 2002); Market concentration index (Thoraneenitiyan & Avkiran, 2009); Inter-bank interest rate (Thoraneenitiyan & Avkiran, 2009); Intermediation ratio (Thoraneenitiyan & Avkiran, 2009); Foreign bank entry (Thoraneenitiyan & Avkiran, 2009).
Economic Environment Variables	private consumption expenditure (Drake el al., 2006); government expenditure (Drake el al., 2006); gross fixed capital formation (Drake el al., 2006); net export of goods (Drake el al., 2006); net export of services (Drake el al., 2006); discount window base rate (Drake el al., 2006); unemployment (Drake el al., 2006); retail sales values (Drake el al., 2006); expenditure on housing (Drake el al., 2006); current account balance (Drake el al., 2006); Real GDP growth index (Liu & Tone, 2008); Real land price index (Liu & Tone, 2008); Real stock price index (Liu & Tone, 2008); Income per Capita (Lozano et al., 2002); Salary per Capita (Lozano et al., 2002; Pastor, 2002); Population Density

	(Lozano et al., 2002); growth rate of nominal GDP of the period (Pastor, 2002); cumulative annual growth rate in the last five years (Pastor, 2002); coefficient of variation of the nominal GDP of the period (Pastor, 2002); Average 90-day bank bill rate (Avkiran, 2009b); Per capita GDP (Thoraneenitiyan & Avkiran, 2009); IMF supports (Thoraneenitiyan & Avkiran, 2009).
Institutional Environment Variables	State intervention (Thoraneenitiyan & Avkiran, 2009); Capital requirements (Pasiouras, 2008); Private monitoring (Pasiouras, 2008); Restrictions on banks activities (Pasiouras, 2008); Official disciplinary power (Pasiouras, 2008); Deposit insurance scheme (Pasiouras, 2008); Entry requirements (Pasiouras, 2008).

Table 4.2 Summary of Environmental variables used in DEA studies on identifying the drivers of banks' efficiency

References	**Environmental Variables**	
Single Country (three-stage analysis)		
Static Model		
Drake el al. (2006) (Profit oriented approach)	*Regulatory variables:* dummy variable for the Hong Kong property crash/Asian financial crisis; dummy variable for handover to the People's Republic of China; dummy variable for 1999 (Hong Kong Monetary Authority agreed to phase out the remaining interest rate controls (i.e., caps); and a dummy variable for 2001 (remaining interest rate controls removed) *Macroeconomic variables:* private consumption expenditure; government expenditure; gross fixed capital formation; net export of goods; net export of services; discount window base rate; unemployment; retail sales values; expenditure on housing; and the current account balance	
Liu & Tone, (2008) (Profit oriented approach)	Monetary aggregate to GDP ratio; Bank lending to GDP ratio; Short-term risk spread; Long-term risk spread; Japan premium; Real land price index; Real GDP growth index; Real stock price index; and Real bankrupt debt per case	
Liu, (2018) (Intermediate apporach)	Number of bank branches, Years of bank establishment, Nationality of parent bank	
Multiple countries (three-stage analysis)		
Static Model		
	Inputs	**Outputs**
Pastor, (2002) (Value Added approach)	*Economic environmental variables:* coefficient of variation of the nominal GDP of the period *Efficiency related / Structural environmental*	*Economic environmental variables:* growth rate of nominal GDP of the period; cumulative annual growth rate in the last five years; per capita wages

	variables: capital adequacy ratio	*Efficiency related / Structural environmental variables:* density of deposits; national income per branch
Avkiran, (2009b) (Intermediate apporach)	Average 90-day bank bill rate	
Thoraneenitiyan & Avkiran, (2009) (Intermediation approach)	*Restructuring measure*: Domestic bank mergers, Foreign bank entry, State intervention *Country specification:* Market concentration index, Inter-bank interest rate, Intermediation ratio, Per capita GDP, and IMF supports. *Control for individual banks:* Logarithm of a bank's total assets (which is a bank- and year-specific control variable for bank size.	

We used two criteria (i.e., high correlations between variables, and availability of data) to reduce such list of variables into seven variables. In addition, these variables needed to fit all the DEA models performed in this study (i.e., Static black box SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM). In other words, the objective is to use a set of environmental variables that will shape our performance evaluation exercise in such a way that the efficiency scores obtained with different DEA analyses are comparable. We focus on those environmental variables in Table 4.1.

The first environmental variable is *Population Growth*; it considers the annual population growth of all residents regardless of legal status or citizenship. A fast increment of the growth rate can affect the distribution of resources of the residents (e.g., food, water, electricity) and change in the demand of infrastructure (e.g., schools, hospitals, housing, roads) that could not be supplied by the country. This phenomenon could be also seen as a threatening by neighbouring countries. The second environmental variable is *Inflation* as measured by the consumer price index; this reflects the annual percentage change in the cost to the average consumer of acquiring a basket of goods and services. The third environmental variable is *Bank capital to assets*; this includes tier 1 capital, which is a common feature in all countries' banking systems, and total regulatory capital. This variable is used to monitor the financial stability of the banking system. The goal is to assure healthy financial systems that can increase the economic activity and welfare of a country. On the other hand, an unstable financial system can disrupt financial activity and impose widespread costs on the economy. In other words, the ratio of bank capital to assets is a measure of how solvent and resilience a bank is and to which extent banks can deal with unexpected losses. The fourth environmental variable is *Bank nonperforming loans to total gross loans*; this variable measures the bank health and efficiency by identifying problems with asset quality in the loan portfolio. Moreover, it is used to monitor the strength of financial systems. A high value could indicate issues in the credit portfolio. The fifth environmental variable is *Gross Domestic Product* (GDP) per capita growth; it represents the sum of value added by all its producers and reflects the country's economic output that accounts for its population. The sixth environmental variable is *Wage and salaried workers* in a "paid employment jobs". Those countries with a high proportion of this variable can signify advanced economic development. The last environmental variable is *Domestic credit to the private sector by banks*; the importance of this variable is concerned to its impact in the productivity growth. By giving domestic credit to the private sector in combination with government playing a complementary role of regulation, funding, and service provision, social and economic issues such as poverty, can be reduced by creating jobs and providing better basic services such as health, education, and housing. A high credit offer accelerates not only the countries' finances production but also consumption, which at the same time affects the overall economy.

In this first alternative framework, the four conceptual models of the operating environment of banks (Static black box SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM), used all the seven environmental variables described above for comparison purpose. Also in all the DEA models, *Population growth* and *Inflation* variables are considered "Inputs", and *Bank nonperforming loans to total gross loans* variable is considered "As Input" Link for the Network model and "As Bad" (undesirable) Carry-over in the Dynamic model and Dynamic-Network model. The rest of the variables are treated "As Output" Links, "As Good" (desirable) Carry-overs, or as "Outputs" depending on the model. For the Network model and Dynamic-Network model, we opted for a serial two-stage structure; our stages represent the Economic and Institution environment that feeds the Banking-operating environment. In the conceptual model, the institutional level decisions and economic stability, affect the banking-operating environment. We are mainly concerned with assessing the relative efficiency of the country's operating environment of banks, with respect to the ability to provide an optimal operating environment for banking activities. For a graphical description of our conceptual models of banks, we refer the reader to Figures 4.1 - 4.4

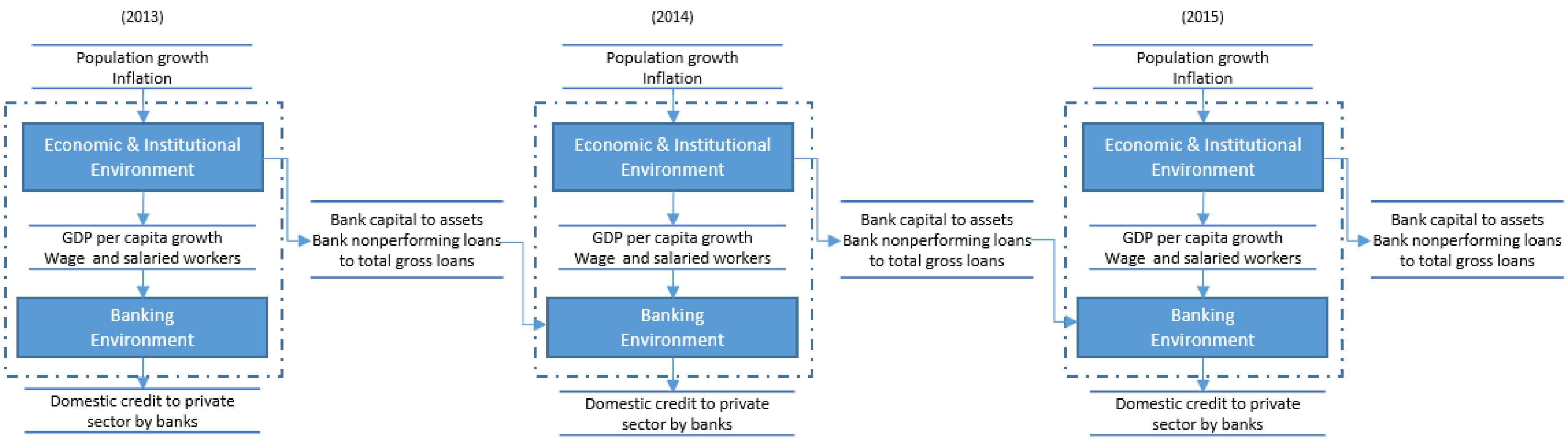


Figure 4.1 Dynamic-Network SBM-based Conceptual Model of Operating Environments

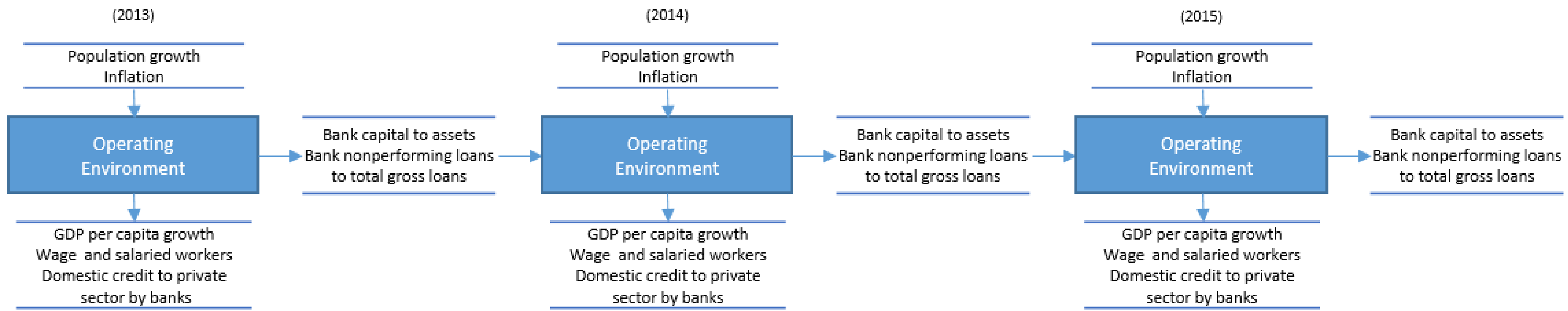


Figure 4.2 Dynamic SBM-based Conceptual Model of Operating Environments

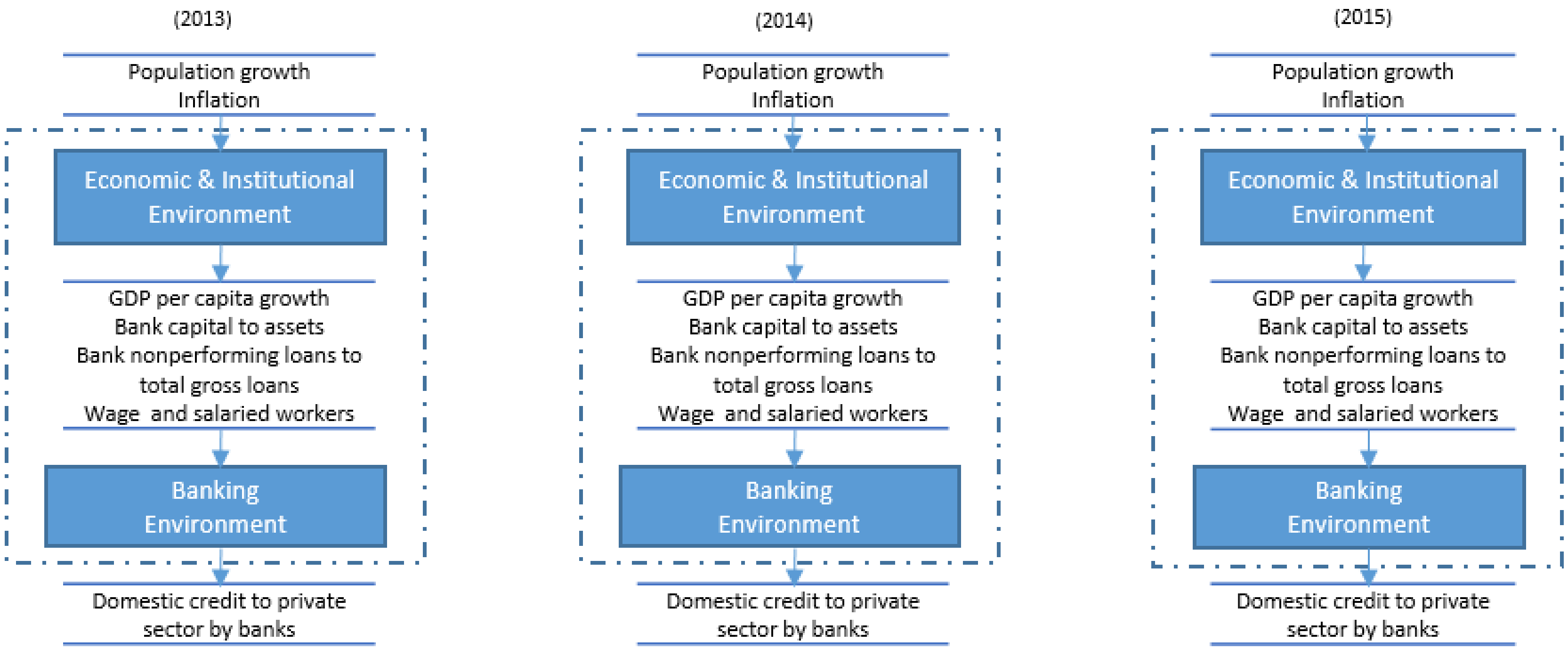


Figure 4.3 Network SBM-based Conceptual Model of Operating Environments

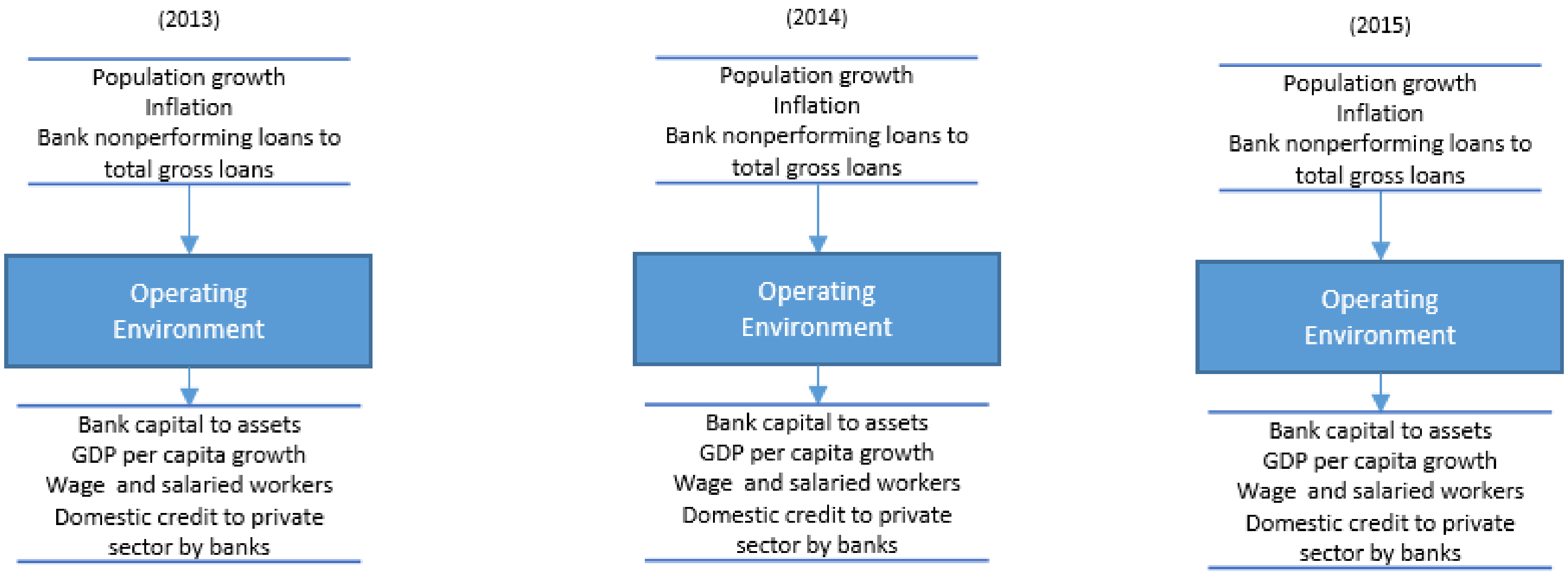


Figure 4.4 Static SBM-based Conceptual Model of Operating Environments

4.2.2 Implementation Decisions of the Second Alternative Solution

Recall that, with respect to the type of perspective from which banks are assessed, the literature could be classified into six categories; namely, the intermediation approach or perspective, the asset approach, the production approach, the value added approach, the profit-oriented approach, and the user cost approach. For a brief description of these approaches, we refer the reader to Ouenniche and Carrales (2018). In this research, we are concerned with the relative assessment of the operating environments of banks and to what extent such environments allow banks to contribute to the economy as intermediation agents who collect funds and provide loans and other assets, and thus we shall adopt the *intermediation approach*.

As mentioned earlier, in this research, we use a variety of DEA analyses (i.e., Static SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM) to address our main research question. An important objective of ours is to choose the set of variables that will shape our performance evaluation exercise in such a way that the efficiency scores obtained with different DEA analyses are comparable. Note that, in actual settings, the world is Dynamic and therefore carryovers from one period of analysis to the next are a reality. Whether one chooses to perform DEA analysis at an aggregate level (i.e., use Static black box models) or at a detailed level (i.e., use Network models) depends on the stakeholders sponsoring the analysis. Therefore, in practice, the choice of inputs and outputs for Static models should, in principle, reflect (at least) the Dynamic nature of the world and eventually its detailed configuration, if different analyses are to be compared. We shall take account of these observations to make the final choices of our inputs, outputs, and environmental variables.

As we perform a variety of SBM analyses, we summarise in Table 4.3 the Network structures used in the most general modelling framework; i.e., Dynamic-Network SBM, for the reader to appreciate our conceptual modelling choices. Note that all the surveyed papers model a bank as a serial two-stage Network with the exception of Chao et al (2017) who use a serial three-stage

Network. In this chapter, we also opt for a serial three-stage Network structure; however, our stages represent different activities; namely, funding, lending, and profit generation. In addition, in all our analyses, we are concerned with assessing the relative efficiency of banks with respect to the ability of their management to *attract depositors, provide loans, and generate profit.* The choices of inputs, outputs, and links to implement Network SBM analyses as well as the additional carryovers to implement Dynamic-Network SBM analyses are informed by our literature survey on inputs, outputs, links and carryovers used in DEA the relevant DEA studies – see Tables 4.4 – 4.5. In order to have a complete picture, we also surveyed the literature on inputs, outputs and carryovers used in SBM and Dynamic SBM studies as an additional source of information – see Tables 4.6 – 4.7. Based on the analysis of these tables and the objectives of this study, we made the following choices.

First, for Dynamic-Network SBM analysis, we use Total Expenses as an input to the funding activity and consider Customer Deposits as an output of this activity. Customer Deposits are then used as input to the lending activity whose output is Net Loans. Finally, Net Loans are used as an input to the profit generating activity whose outputs are Net Interest Revenue and Net Operating Profit. In order to link the time periods, Liquid Assets and Loan Loss Reserves are considered as carryovers. When the time dimension is ignored, as in Network SBM analysis, Liquid Assets would be considered as an additional output to the funding activity, whereas Loan Loss Reserves would be considered as an additional output to the lending activity. On the other hand, when the bank is viewed as a black box but changes from one period of analysis to the next matter, as in Dynamic SBM analysis, Total Expenses remain the input to the bank, Customer Deposits, Net Loans, Net Interest Revenue, and Net Operating Profit would be considered as outputs of the bank, and Liquid Assets and Loan Loss Reserves would remain as carryovers. Finally, when the internal structure or processes and time are both ignored, as in SBM analyses, Total Expenses and Loan Loss Reserves would be considered as inputs whereas Customer Deposits, Liquid Assets, Net Loans, Net Interest Revenue, and Net Operating Profit would be considered as outputs. Note that, in line with Ouenniche and Carrales (2018), Customer Deposits are used as output to avoid penalising the very means by which banks are able to perform their lending operations. For a graphical description of our conceptual models of banks, we refer the reader to Figures 4.5 – 4.8.

As to the choice of the environmental variables, we use the same ones presented in the previous section. In the next section, we shall describe how inputs and outputs could be purged from the effect of the operating environment of banks.

Table 4.3 Summary of Network structures in Dynamic-Network SBM studies on banks

Reference	First Stage	Second Stage	Third Stage
Yu et al., (2013)	Deposit	Lending	
Lu et al., (2014)	Resource Utilization	Investment	
Avkiran (2015)	Interest-bearing operations	Non-interest operations	
Zha et al., (2016)	Productivity	Profitability	
Wu et al., (2016)	Managerial efficiency	Profitability Efficiency	
Chao et al., (2015)	Capability	Efficiency	Profitability

Table 4.4 Summary of Inputs, Outputs and Links used in Network DEA studies on assessing banks efficiency under the intermediation approach

Single Country			
References	**Inputs**	**Outputs**	**Links**
Intermediation Approach			
Akther et al. (2013)	Labour, Physical capital, and Equity capital	Loans, Investments, and Bad loans	Deposit
Wanke & Barros (2014)	Number of branches and Number of employees	Equity and Permanent assets	Administrative expenses, and Personnel expenses
Not defined (adapted)			
Liang et al. (2008)	Fixed assets, numbers of employees, and IT investment	Profits, and Fraction of loans recovered	Deposits
Holod & Lewis (2011)	Fixed assets, and Employees	Loans, and Other earning assets	Deposits
Fukuyama & Weber (2010)	Labour, Physical capital, and Financial equity capital	Loans, and Securities investments	Deposits
Fukuyama & Matousek (2017)	Labour, and Capital	Loans, Nonperforming loans, and Securities investments	Deposits
Fukuyama & Matousek (2011)	Labour (the number of employees), and Capital (the book value of premises and fixed assets)	Loans, and Securities.	Deposits
Wang et al. (2014b)	Fixed assets (asset value of physical capital), and Labour (number of full-time	Non-interest incomes (which includes fees, com- missions, investment and other business income), Interest incomes (which refers to incomes that	Deposits (which include current deposits and time deposits)

	employees hired)	are primarily derived from loans), and Non-performing loans or bad loan (problem loans for which borrowers are unable to make repayment.)	
Liu et al. (2015)	Employees, Fixed assets, Operating expenses	Market value, Earnings per share, and Volatility	Profit, Loans, and Nonperforming loans

Table 4.5 Summary of Inputs, Outputs, Links and Carryovers used in Dynamic-Network DEA studies on assessing banks efficiency under the intermediation approach

Single Country				
References	**Inputs**	**Outputs**	**Links**	**Carryovers**
Intermediation approach				
Fukuyama & Weber (2015)	Labour, Capital, and Equity	Loans, and Securities	Deposit, and Other raised funds	Non-performing Loans, Assets from loans, and Assets from securities
Avkiran (2015)	Personnel Expenses, and Other Operating expense	Interest income on Loans, and Other interest income	Interest expense on customer deposits, Other interest expense, Net fees and commissions, Other operating income, and Number of referrals	Proportion of fruitless referrals, and Non-performing loans ratio
Lu et al. (2014)	Staff expenses, Other expenses, and	Profit, and Interest Income	Loans, Deposits, and Other earning assets	Property, plant and Equipment, and

	Operating assets			Investment assets
Not defined (adapted)				
Fukuyama & Weber (2013)	Labour, Capital, and Equity	Loans, and securities	Deposit	Nonperforming loans, and Unused assets
Fukuyama & Weber (2017b)	Labour, Physical capital, and Net assets (equity)	Performing loans, and Securities	Deposits, and Other raised funds	Non-performing loans, and Carryover assets from securities
Fukuyama & Weber (2017a)	Labour, Physical capital, and Equity capital	Loans, and Securities	Deposits, and Other raised funds	Non-performing loans, and Assets
Yu et al. (2013)	Labour, Fixed asset, and Operating expenses	Loans, and Securities investment	Deposit	Non-performing loan
Chao et al. (2015)	Operating cost, and Asset depreciation expense (Capital utilization expense)	Revenue	(1-2) Customer capital (deposit), Human capital, Process capital, Innovation capital (2-3) Loans, Investments, Write-offs	Non-performing Loans, and Loan loss reserves
Chao et al. (2017)	Operating cost, Capital utilization expenses / Asset depreciation expense (depreciations)	Interest Income, non-interest income, and Earnings per share (EPS)	Investments, Performing loans, Write-offs of Bad debt, and Business volume	Nonperforming loans, and Net Worth
Zha et al. (2016)	Interest cost, and Operation cost	Interest income, and Non-interest	Deposit	Non-performing loan generated in the current year

		(Desirable outputs)		
Multiple Countries				
Intermediation approach				
Wu et al. (2016)	Personnel expenses, and Operating expenses	Net interest income	Loans, Other earnings assets, and Deposits	Liquid assets, and Fixed assets

Table 4.6 Summary of Inputs and Outputs used in Static black box DEA studies on assessing banks' efficiency under the intermediation approach

Single Country		
References	**Inputs**	**Outputs**
Charnes et al (1990)	Total operating expense, Total noninterest expense, Provision for loan losses, Actual loan losses.	Total operating income, Total interest income, Total noninterest income, Total net loans
Rangan et al. (1988)	Labour; Capital; Purchased Funds	Real Estate Loans; Commercial & Industrial Loans; Consumer Loans; Demand deposits; Time & Saving Deposits
Ferrier and Lovell (1990)	Total number of employees; Occupancy Costs & Expenditure on Furniture and Equipment; Expenditure on Materials	Number of demand deposit accounts; Number of time deposit accounts; Number of real estate loans; Number of instalment loans; Number of commercial loans
Elyasiani and Mehdian (1990)	Labour; Capital; Deposits; Total Demand Deposits	Investment; Real Estate Loans; Commercial & Industrial Loans; Other Loans

Aly et al. (1990)	Labour; Capital; Loanable Funds	Demand Deposits; Real Estate Loans; Commercial & Industrial Loans; Consumer Loans; Other Loans
Elyasiani and Mehdian (1992)	Labour; Capital; Certificates of deposit, time & savings deposits; Demand deposits	Commercial & industrial loans; Real estate loans; Other loans; Investment securities
Fukuyama (1993)	Labour; Capital; Funds from Customers	Revenue from Loans; Revenue from Other Business Activities
Zaim (1995)	Total number of employees; Total interest expenditures; Depreciation expenditures; Expenditures on materials	Total balance of demand deposits; Total balance of time deposits; Total balance of short-term loans; Total balance of long-term loans
Miller and Noulas (1996)	Total transactions deposits; Total non-transactions deposits, Total interest expense; Total non-interest expense	Commercial and industrial loans; Consumer loans; Real estate loans; Investments; Total Interest Income; Total Non-Interest Income
Chen (1998)	Labour; Assets; Interest Expense	Loans Services; Investments; Interest Income, Non-Interest Income
Drake et al. (2006)	Personnel expenses; Total deposits + Total money market funds + Total other funding; Total fixed assets; Loan loss provisions and other provisions	Total customer loans + Total other lending; Total other earning assets; Other non-interest income
Kao & Liu (2014)	Labour, Physical capital, Purchased funds	Demand deposits, Short-term loans, and Medium-and- long-term loans
Liu (2018)	Personnel expenses, Operating expenses (not including personnel expenses and network expenses), Fixed assets, Total deposits, Network expenses (inputs for providing online banking services), and Bank diversification.	Interest revenues, and Non-interest revenues

Multiple Countries		
Casu & Molyneux (2003)	Total cost (interest expenses, Non-interest expenses, personnel expenses), and Total deposits (Total customers and short term funding).	Total loans, and Other earnings assets
Hauner (2005)	Number of employees, Average interest rate in percent, Average expenses per employee.	Loans to banks, Loans to customers, Fixed-interest securities
Pasiouras (2008)	Customer deposits and short term funding (i.e. total deposits), Total costs (interest expenses and non-interest expenses), and Equity.	Loans, Other earnings assets, and Non-interest income
Avkiran (2009b)	Interest expense, and Non-interest expense	Interest income and Non-interest income.
Thoraneenitiyan & Avkiran (2009)	Total deposits, Labour capital (measured by the proxy measure of personnel expenses), and Physical capital (other operating expenses)	Loans, Investments and other earning assets, Fee income, and off-balance sheet items.

Table 4.7 Summary of Inputs, Outputs and Carryovers used in Dynamic DEA studies on assessing banks efficiency under the intermediation approach

Single Country			
References	**Inputs**	**Outputs**	**Carryover**
Shafiee et al. (2013)	Average monthly salaries, Operating expense	Total value of loans	Loan losses (bad link), Net profit (good link)
Wanke et al. (2015)	Non-interest expenses	Total equity, Liquid assets, and Total assets.	Loan losses reserves, Net income

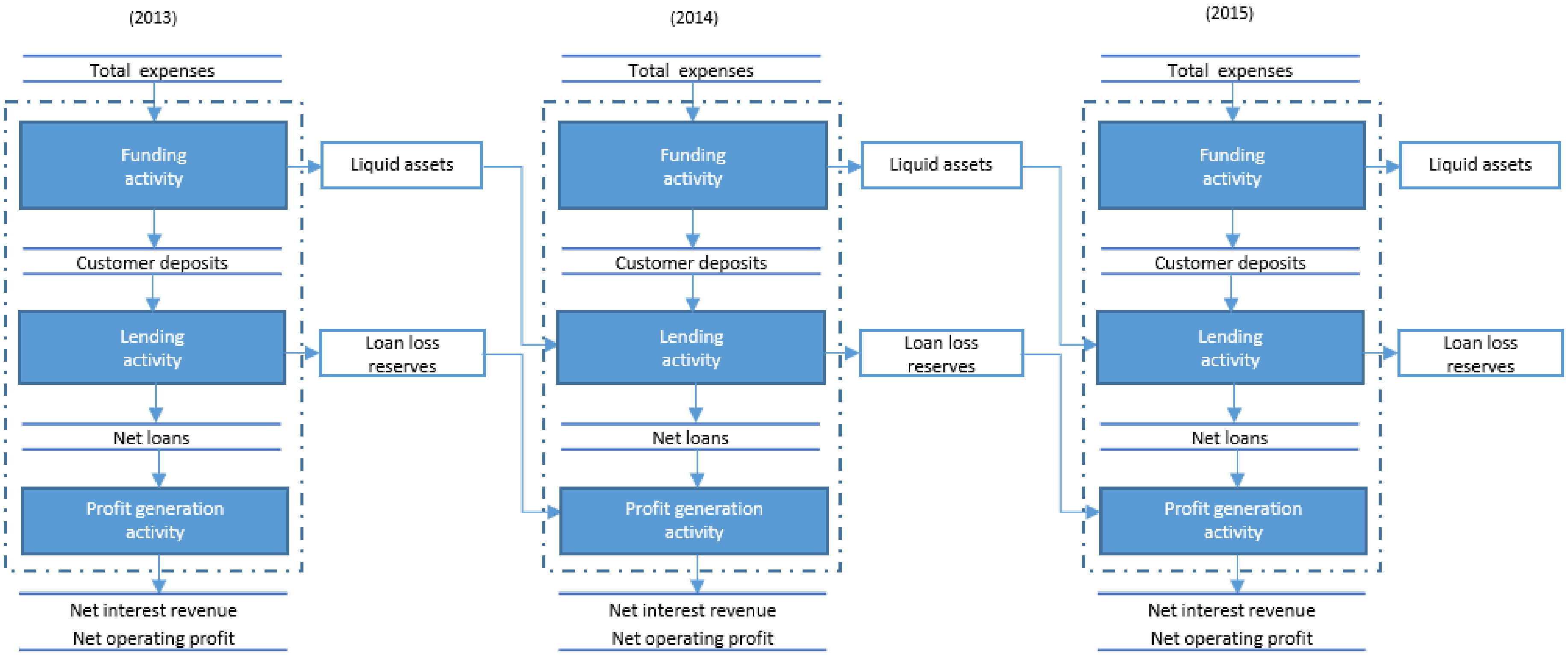


Figure 4.5 Dynamic-Network SBM-based Conceptual Model of Banks

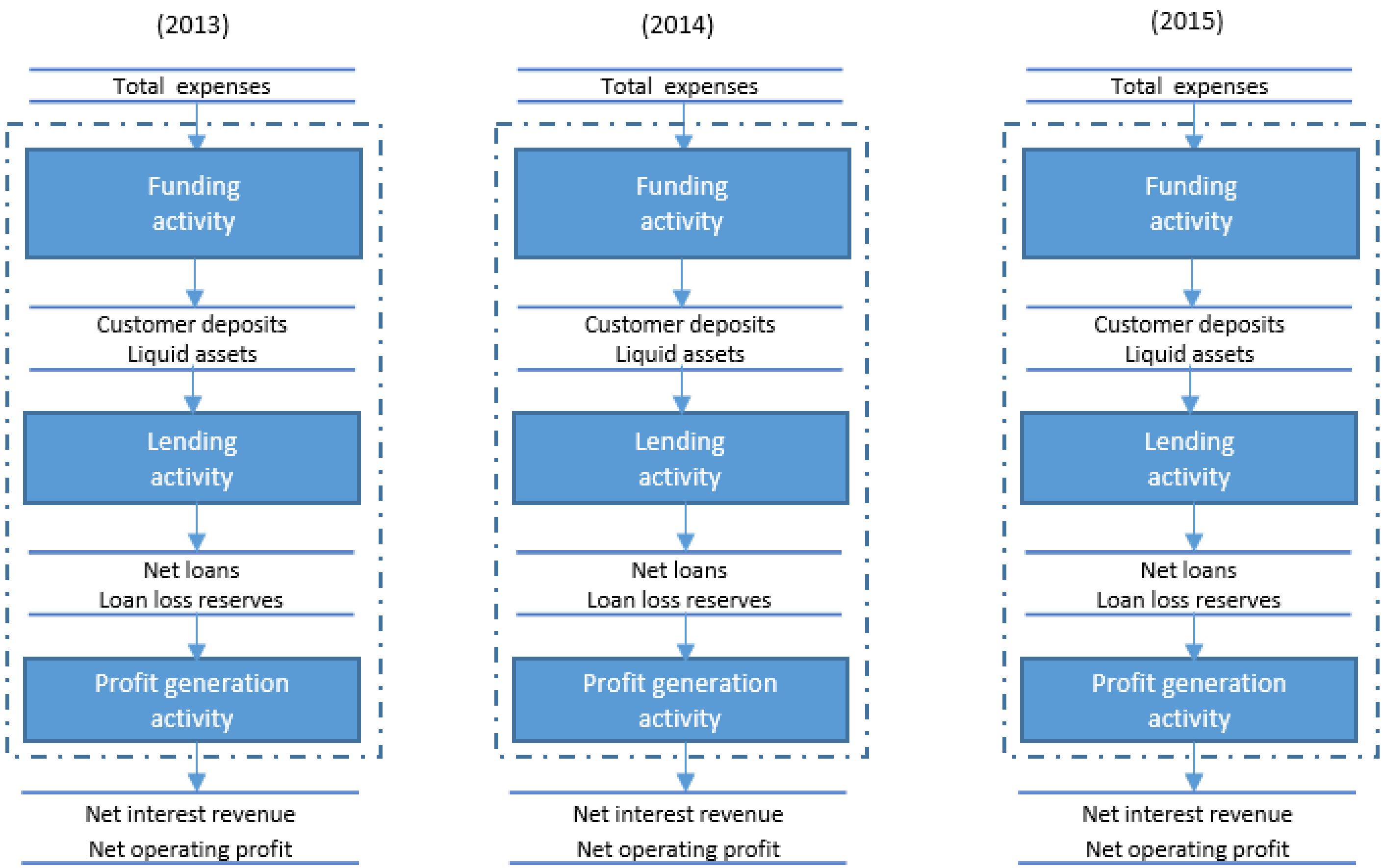


Figure 4.6 Network SBM-based Conceptual Model of Banks

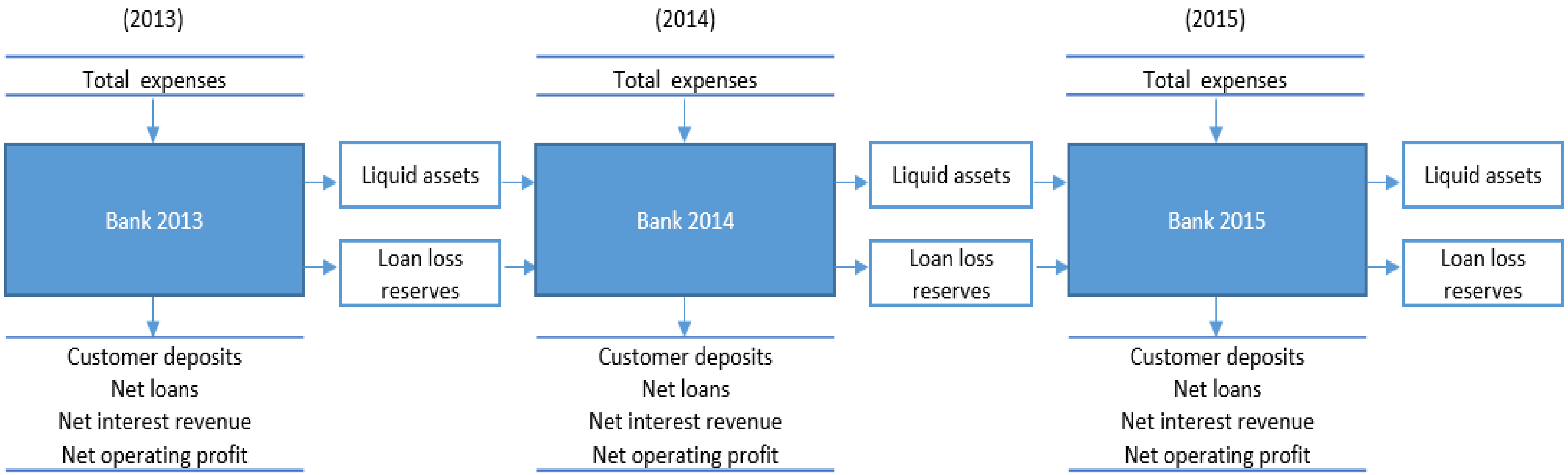


Figure 4.7 Dynamic SBM-based Conceptual Model of Banks

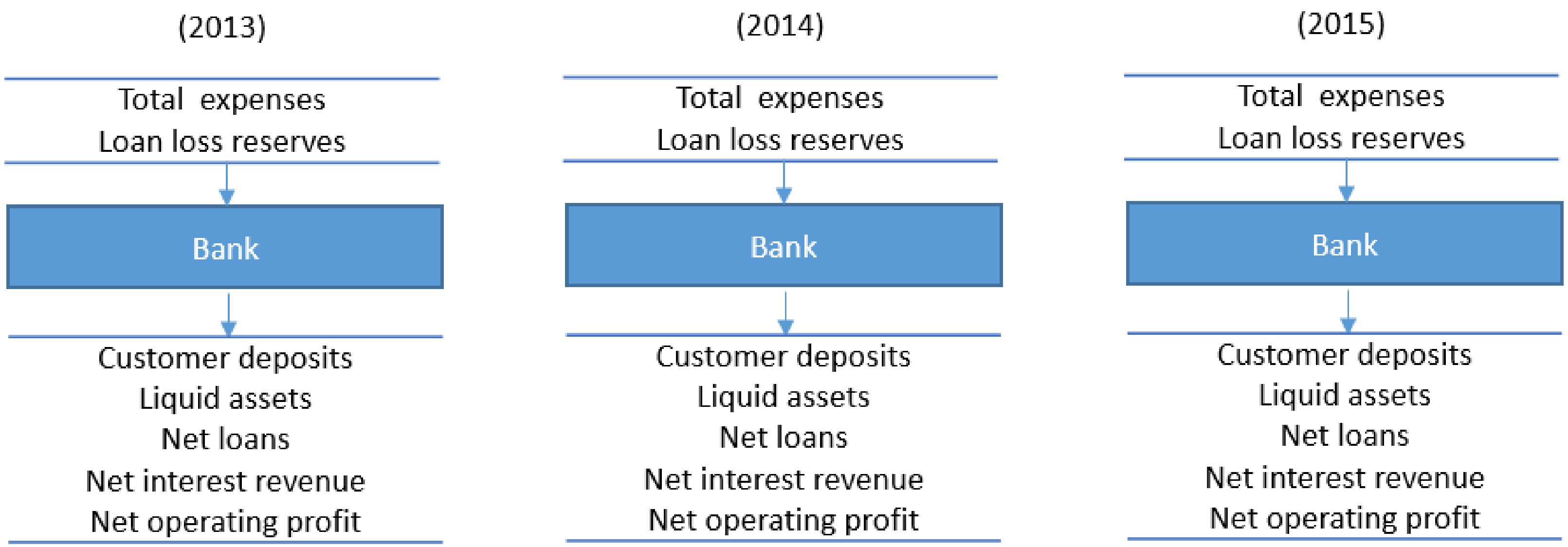


Figure 4.8 Static SBM-based Conceptual Model of Banks

4.2.3 A Generic Three-Stage Procedure, Its Justification and Its Implementation

Single stage analyses with environmental variables require that the set of inputs and outputs be expanded with the environmental variables, which could disadvantage or advantage a DMU or its operating environment depending on whether such variables are classified as input or as output prior to the analysis. To overcome this bias, environmental variables have been considered as non-discretionary (e.g., Banker and Morey, 1986). As pointed out by Fried et al. (1999), the non-discretionary or uncontrollable variables influence the position of the frontier, but they are held constant in the calculation of the radial efficiency measure. However, this approach still requires a classification of the non-discretionary environmental variables into inputs and outputs prior to the analysis. In order to identify which of the non-discretionary environmental variables are better used as inputs and which ones are better used as outputs, Lozano-Vivas et al (2002) proposed a two-step solution under two assumption; namely, (1) the banks of the countries with bad environmental conditions would get better efficiency scores if they were performing in a more favorable environment, and (2) if the higher (lower) the value of an environmental variable, the higher (lower) the efficiency scores for the complete model, then the environmental variable is an output-type variable; otherwise; i.e., the opposite relationship holds, the environmental variable is an input-type variable. In the first step, a basic BCC model is solved twice for each environmental variable, where its classification as input or output is reversed. The influence of choice of an environmental variable as input or output on the efficiency scores allows one to decide on whether it should be classified as input-type or output-type. In the second step, these environmental variables are considered as non-discretionary and added to a BCC model with discretionary regular inputs and outputs and non-discretionary environmental variables of input-type and output-type using a forward stepwise procedure to avoid a lack of discrimination. Coelli et al. (2005) suggest an alternative approach to identifying which of the non-discretionary environmental variables are better used as inputs and which ones are better used as outputs by considering non-discretionary variables as neutral variables, where the neutrality of a non-discretionary variable is ensured by setting the corresponding constraint as an equality constraint. The signs of the dual variables associated with these constraints indicate whether the variables have favourable or unfavourable effects upon efficiency scores – this information is then used to re-run the model with the appropriate inequalities specified. Although the above-mentioned bias has been reduced by Lozano-Vivas et al (2002) and Coelli et al. (2005) proposals, it remains that the slacks have not been taken account of, on one hand, and the discretionary inputs and outputs have not been "cleaned" of the potential environmental impact, on the other hand.

As to two-stage analyses, they are essentially used for identifying environmental drivers of efficiency of banks, and finding out about the direction and magnitude of influence of these drivers on the efficiency scores. Information on the direction and magnitude of influence of environmental drivers of efficiency could then be used to setup a new DEA analysis of single stage type. However, two-stage approaches neither take account of slacks nor "clean" discretionary inputs and outputs of the potential environmental impact. Therefore, two-stage approaches are irrelevant for this research.

Finally, three-stage analyses are designed to overcome the issues of single stage analyses and more. In fact, by design, three-stage analyses do not require the specification of environmental variables as inputs or outputs prior to the DEA analysis; both take account of slacks and "clean" discretionary inputs and outputs of the potential environmental impact; and provide efficiency scores purged of the influences of the operating environment. A generic three-stage analysis could be summarised as follows:

Stage 1: Perform a DEA analysis by solving an *appropriate DEA model* fed with the relevant discretionary inputs and outputs to compute efficiency scores and slacks. Note that, depending on the choice of the DEA model, the slacks obtained might be non-radial slacks or total slacks (i.e., sum of radial and non-radial slacks). In case the chosen DEA model only provides non-radial slacks, one would have to compute the total slacks. Note also that the relevant total slacks depend on whether the DEA analysis is input-oriented, output-oriented, or non-oriented; to be more specific, input-oriented analyses only consider total input slacks, say $S_{i,j,t}^{-}$, output-oriented analyses only consider total output slacks, say $S_{r,j,t}^{+}$, and non-oriented analyses consider both total input slacks $S_{i,j,t}^{-}$ and total output slacks $S_{r,j,t}^{+}$.

Stage 2: Regress the relevant total slacks on environmental variables using an *appropriate regression framework*. Then, the relevant discretionary inputs and/or outputs are adjusted for the environmental impact and eventually for statistical noise depending on the choice of the regression framework. Note that, depending on whether the DEA analysis is input-oriented, output-oriented or non-oriented, inputs, outputs, or both are adjusted. Note also that the adjustment mechanism depends on the choice of the regression framework. In fact, when Tobit is chosen as the regression framework (Fried et al., 1999; Drake et al., 2006; Avkiran, 2009b), once the relevant regression models are fitted to the data, the predictions of the relevant slacks are computed; that is, $\hat{S}_{i,j,t}^{-}$, $\hat{S}_{r,j,t}^{+}$, or both. Then, the maximum predicted input slack, the minimum predicted output slack, or both are computed – depending on whether the analysis is input-oriented, output-oriented or non-oriented, and the relevant discretionary inputs and/or outputs are adjusted for the environmental impact as follows:

$$x_{i,j,t}^{adjusted} = x_{i,j,t} + \left(\max_{j=1,\dots,n}\{\hat{S}_{i,j,t}^{-}; t = 1,..,T\} - \hat{S}_{i,j,t}^{-}\right); \forall i, j, t$$

and

$$y_{r,j,t}^{adjusted} = y_{r,j,t} + \left(\hat{S}_{r,j,t}^{+} - \min_{j=1,\dots,n}\{\hat{S}_{r,j,t}^{+}; t = 1,..,T\}\right); \forall r, j, t.$$

On the other hand, when stochastic frontier analysis (SFA) is chosen as the regression framework (Fried et al., 2002; Pastor, 2002; Liu & Tone, 2008; Avkiran & Rowlands, 2008; Thoraneenitiyan & Avkiran; 2009b; Liu, 2018), once the relevant regression models are fitted to the data, predictions of the amounts of the relevant slacks attributable to environmental factors are computed; that is, $z_j\hat{\beta}^i$, $z_j\hat{\beta}^r$, or both, and predictions of the amounts of the relevant slacks attributable to statistical noise or measurement error found in the sample are computed; that is, $\hat{v}_{i,j,t}$, $\hat{v}_{r,j,t}$, or both. Then, the maximum and/or minimum predicted amounts of the relevant slacks attributable to environmental factors and statistical noise are computed – depending on the orientation of the analysis, and the relevant discretionary inputs and/or outputs are adjusted for both the environmental impact and the statistical noise as follows:

$$x_{i,j,t}^{adjusted} = x_{i,j,t} + \left(\max_{j=1,\dots,n}\{z_j\hat{\beta}^i\} - z_j\hat{\beta}^i\right) + \left(\max_{j=1,\dots,n}\{\hat{v}_{i,j,t}\} - \hat{v}_{i,j,t}\right);\ \forall i,j,t$$

and

$$y_{r,j,t}^{adjusted} = y_{r,j,t} + \left(z_j\hat{\beta}^r - \min_{j=1,\dots,n}\{z_j\hat{\beta}^r\}\right) + \left(\hat{v}_{r,j,t} - \min_{j=1,\dots,n}\{\hat{v}_{r,j,t}\}\right);\ \forall r,j,t.$$

Notice that the above adjustment mechanism is based on benchmarking against the least or most favourable environment observed in the sample and the least or most fortunate situation (i.e. regarding measurement errors) found in the sample depending on the orientation of the analysis. One exception however is Liu & Tone (2008), where the adjustment mechanism is based on benchmarking against the average behaviour instead of the best or worst behaviour, which is a source of concern for the next stage where DEA analysis is performed.

Stage 3: Use the relevant adjusted inputs, $x_{i,j,t}^{adjusted}$, the relevant adjusted outputs, $y_{r,j,t}^{adjusted}$, or both to compute new efficiency scores using the chosen DEA model.

In our implementation of this generic three-stage analysis, the *appropriate DEA model* is chosen amongst Static SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM, and the *appropriate regression* *framework* is chosen as SFA so that both environmental impact and statistical noise are adjusted for.

As to purging variables from any environmental effect, we argue that whether the DEA analysis is input-oriented, output-oriented, or non-oriented, both inputs and outputs should be “cleaned” from the effect of the environment – otherwise, the efficiency scores would be biased in that they would not convey the “true” picture.

4.3 EMPIRICAL ANALYSES AND FINDINGS

In this section, we provide information on our dataset – see section 4.3.1. In section 4.3.2, we summarise our findings based on the first approach. In section 4.3.3, we summarise our findings based on the second approach. Finally, in section 4.3.4 we provide some managerial guidelines.

4.3.1 Dataset

It is well established that operating environments have an effect on technical efficiency. To the best of our knowledge, no attempt has been made to investigate the relative efficiency of banking-operating environments as such. The banking-operating environment is proxied by an international bank operating in several countries around the globe; namely, HSBC Holdings PLC. The choice of a single bank as a proxy of the external environment is meant to avoid any bias that would result from the relative efficiency of different banks within the same operating environment. This study used HSBC bank information from Orbis banking focus provided by Bureau van Dijk (Balance sheets and income statements data). The dataset includes 25 banks from different countries among four continents (Argentina, Armenia, Bangladesh, Brazil, Canada, Chile, China, Egypt, France, India, Indonesia, Malaysia, Malta, Mauritius, Mexico, Oman, Poland, Russian Federation, Sri Lanka, Turkey, United Arab Emirates, United Kingdom, United States of America, Uruguay and Vietnam). The Environmental variables of the 25 countries were obtained from the Databank, provided by the database of World Bank database world development indicators.

The empirical results are divided into two groups:

4.3.2 First Approach Based Empirical Results and Findings

Under the first approach to the relative performance evaluation of countries' operating environment of banks, the unit of analysis or decision making unit (DMU) is a country's operating environment of banks. This approach would be most useful to stakeholders such as governments and the international monetary fund (IMF), as it reflects better their perspective. Note, however, that the outcome of this type of analysis would complement the outcome of the second approach for bankers. Recall that one of our research questions is concerned with how different DEA analyses (i.e., Static SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM) compare in finding out which banking-operating environments are more efficient? In general, DEA scores estimated with different DEA models (i.e., Static SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM) are not directly comparable. In fact, when a single DEA analysis is to be performed, the organisation of the data would depend on whether one performs a Static black box analysis (e.g., SBM), a Dynamic black box analysis (e.g., DSBM), a Network analysis (e.g., NSBM), or a Dynamic-Network analysis (e.g., DNSBM). For Static black box analysis (e.g., SBM), DMUs would be banks for single period analysis, and bank-year observations for multi-period analysis where time is taken account of implicitly. For Dynamic black box analysis (e.g., DSBM), DMUs would be banks. In addition, a period is required; e.g., year. However, Dynamic DEA analyses could be implemented in a Network framework in which case DMUs would be bank-year observations. For Network analysis (e.g., NSBM), DMUs would be banks for single period analysis, and bank-year observations for multi-period analysis where time is taken account of implicitly. In addition, processes would have to be specified by means of their nodes (i.e., activity-year) and the links between them. Finally, for Dynamic-Network analysis (e.g., DNSBM), DMUs would be bank-year observations. In addition, processes would have to be specified by means of their nodes (i.e., activity-year) and the links between them along with carry-overs. However, when multiple DEA analyses have to be performed and their outcome/scores compared, DMUs would be asses accordingly with the nature of the model (dynamic or static) to be able to see the impact of taking account of the time and also focus in the Bank (25 observations) as the DMU.

The efficiency scores estimated with Static black box SBM, Network SBM, Dynamic SBM and Dynamic-Network SBM, along with related statistics are summarised in figures 4.9 - 4.16 and in columns 2 - 3 of Tables 4.17 - 4.40 of appendix as supplementary material. Since the summary statistics are aggregate measures and therefore would in cases like ours hide some relevant information, we provide the efficiency scores for each country and each year –see tables 4.8 - 4.10 in the appendix. The main findings unfold as follows.

First, as expected, the Static black box SBM model is less discriminatory than Dynamic SBM, Network SBM, and Dynamic-Network SBM, as it does not take count of any Dynamics through time nor of the processes. The Dynamic SBM model is more discriminatory than the Static black box SBM model, which suggests that there are important changes through time of the characteristics of the operating environments under consideration; the Dynamic SBM modelling framework has properly captured these changes. The discriminatory power of the Network SBM model is even greater than the one of the Dynamic SBM model, which suggests that the processes of each operating environment under consideration are even more important in assessing the relative performance of such environments. Finally, as one would expect, the Dynamic-Network SBM modelling framework is the most discriminating one and the most appropriate modelling framework of the operating environments of banks.

Second, the countries' operating environments of banks such as Canada, China, Oman, UAE and UK were fully efficient in all the periods (2013, 2014 2015), all the orientations (IO, OO, NO), and all the models (Static black box SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM). On the other hand, Bangladesh, Brazil, Egypt, Mexico, Sri Lanka, Turkey, and Vietnam were inefficient in all the periods (2013, 2014 2015) all the orientations (IO, OO, NO), and all the models (Static black box SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM). There are countries that were fully efficient in all the periods, orientations and models except for the Dynamic-Network OO and the Dynamic Network NO, this is the case of Argentina, Armenia, France, Indonesia, Malta, Russia and USA. The rest of the countries' operating environments of banks, behave as follows. Chile and India were only fully efficient in the Statics models (Black box and Network) for the periods 2013 and 2015 respectively. Malaysia was fully efficient in all the Static black box models and Dynamic models for all the periods and orientations, and only efficient in the Network model OO, but inefficient in the Dynamic model for all the orientations as well as for the Network IO and NO model, both 2013 and 2015. Mauritius was only fully efficient in the Statics models (Black box and Network) in all the periods (2013, 2014 2015) and all the orientations (IO, OO, NO). Poland was inefficient in the Network and Dynamic-Network models OO and NO and efficient in the rest of the models. Finally, Uruguay was fully efficient in most of the models except for Network OO 2015, NO 2015 and Dynamic-Network OO and NO.

To sum up, the Static black box model and Dynamic model had the same number of efficient DMU through the same period for different orientations. The Network model was quite constant, however, in the Dynamic Network model, the number of DMUs fully efficient is 14 under the IO model but in the OO and NO models, there are only five fully efficient DMUs. We can assume that when we analyse the internal structure and consider the effect of time in each country, we can see that the main strategy of the counties is focused in minimizing the inputs rather that maximized the outputs.

4.3.3 Second Approach Based Empirical Results and Findings

The first alternative uses a country's operating environment of banks as the unit of analysis or decision making unit (DMU), whereas the second alternative uses a bank as the DMU whose efficiency evaluation takes account of the features of its operating environment. To operationalize the second framework, in this chapter, we have chosen HSBC in different operating environments or countries. The choice of a single bank; namely, HSBC, is motivated by isolating the operating environment effect on efficiency and thus avoiding any bias that would result from the relative efficiency of different banks within the same operating environment. Note that these modelling frameworks are complementary in that the first one would naturally reflect better the perspective of a first group of stakeholders such as governments and the international monetary fund (IMF), whereas the second modelling framework would be most attractive for a second group of stakeholders such as bankers and investors. In practice, however, a bank would implement the second modelling framework using another bank of similar characteristics that is already operating in the countries of interest.

The second approach is divided in two analysis. The first analysis presents the evaluation of banks' operating environments efficiency scores considering its environmental impact and conditions (without adjustment). In other words, the environmental variables are incorporated into the models. The efficiency scores estimated with Static black box SBM, Network SBM, Dynamic SBM and Dynamic-Network SBM, for the second approach without adjustment, along with related statistics are summarized in figures 4.9-4.16 and in columns 4-7 of Tables 4.17 - 4.40 of appendix as supplementary material. Since the summary statistics are aggregate measures and therefore would in cases like ours hide some relevant information, we provide the efficiency scores for each country and each year - see tables 4.11 - 4.13 in the appendix. The main findings unfold as follows for the second approach without adjustment.

First, the discriminatory power of the models goes in the same line that in the analysis outcomes of the first approach, as expected, the Static black box SBM model is less discriminatory than Dynamic SBM, Network SBM, and Dynamic-Network SBM, as it does not take count of any Dynamics through time nor of the processes. The Dynamic SBM model is more discriminatory than the Static black box SBM model, which suggests that there are important changes through time of the characteristics of the operating environments under consideration; the Dynamic SBM modelling framework has properly captured these changes. The discriminatory power of the Network SBM model is even greater than the one of the Dynamic SBM model, which suggests that the processes of each operating environment under consideration are even more important in assessing the relative performance of such environments. Finally, as one would expect, the Dynamic-Network SBM modelling framework is the most discriminating one and the most appropriate modelling framework of the operating environments of banks. Under this framework, in 2013-2015 only the UK was fully efficient in all the orientations. Second, across the IO Static black box SBM, Network SBM, Dynamic SBM and Dynamic-Network SBM models, only the banks in Mauritius, the UK, and the USA were fully efficient. However, in the OO and NO Static black box SBM, Network SBM, Dynamic SBM and Dynamic-Network SBM models, only the UK bank was fully efficient. HSBC in the USA was fully efficient in all the models except for Dynamic Network OO and NO. On the other hand, Argentina, Brazil, Chile, Indonesia, Mexico, Oman, Poland, Turkey, and Uruguay were inefficient in all the periods (2013, 2014, and 2015), all the orientations (IO, OO, and NO), and all the models (Static SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM). The rest of the HSBC banks such as Armenia, Bangladesh, Canada, China, France, Mauritius, Russia, and Sri Lanka were fully efficient in the Static black box model for all the periods and orientations. Under the Network model, the HSBC banks that were fully efficient in all the periods (2013, 2014, and 2015), under IO were France and Mauritius, under OO China and Russia and none bank in the NO model across all the periods, just the bank in Armenia (2013) and Russia (2013, 2015) . Finally, under the Dynamic Network model, the HSBC banks that were fully under IO model were France and Mauritius, under OO is Russia, and under NO none.

In summary, the Static black box model and Dynamic model had the same number efficient DMU through the same period for different orientations. The Network model was quite constant but the Dynamic Network model dropped from having 4 DMU fully efficient under the IO model to has 2 fully DMU in the OO and just 1 in the NO models. We can assume that when we analyse the internal structure and consider the effect of time in each bank, we can see that the main strategy of the banks is focus in minimizing the inputs rather that maximized the outputs.

The second analysis presents the evaluation of banks' operating environments efficiency scores without considering its environmental impact and conditions (adjusted with tree-stage analyses). The efficiency scores estimated with Static black box SBM, Network SBM, Dynamic SBM and Dynamic-Network SBM, for the second approach adjusted for the effect of the environment, along with related statistics are summarized in Tables 4.17 - 4.40. Since the summary statistics are aggregate measures and therefore would in cases like ours hide some relevant information, we provide the efficiency scores for each country and each year - see tables 4.14 - 4.16 in the appendix. The main findings unfold for the second approach with adjustment will be discussed in the next section.

Figure 4.9 Summary of Dynamic Network SBM Analyses over 2013-2015

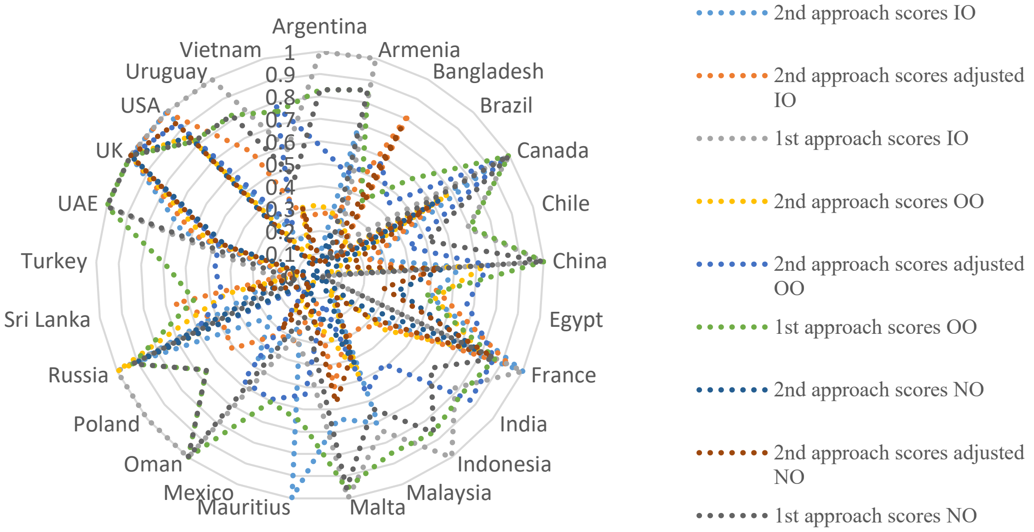


Figure 4.10 Summary of Dynamic SBM Analyses over 2013-2015

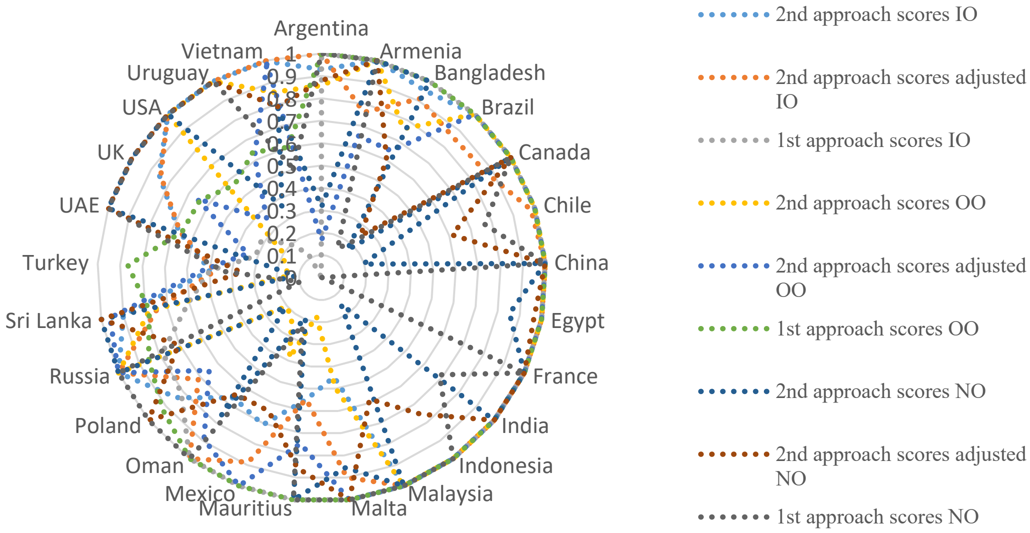


Figure 4.11 Summary of Network SBM Analyses for 2013

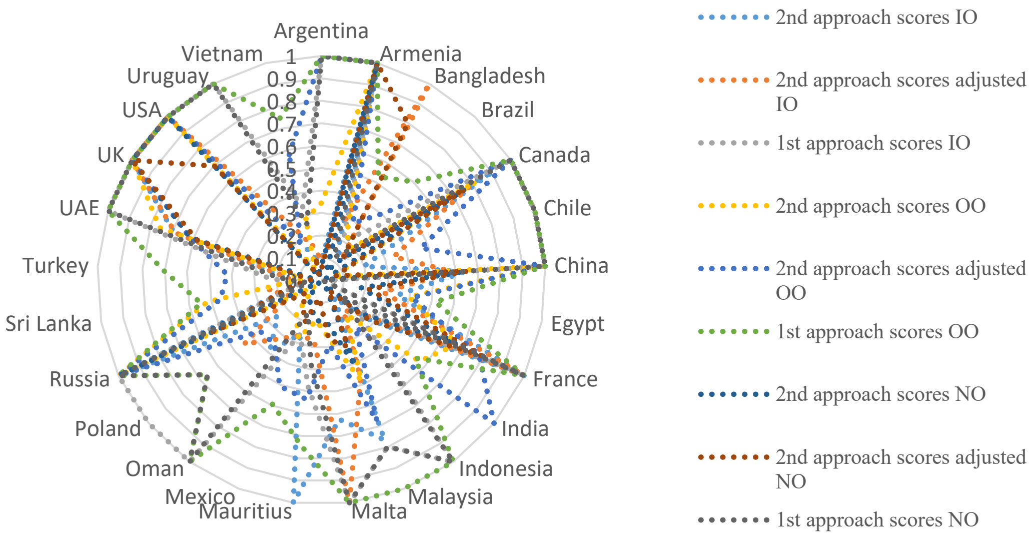


Figure 4.12 Summary of Network SBM Analyses for 2014

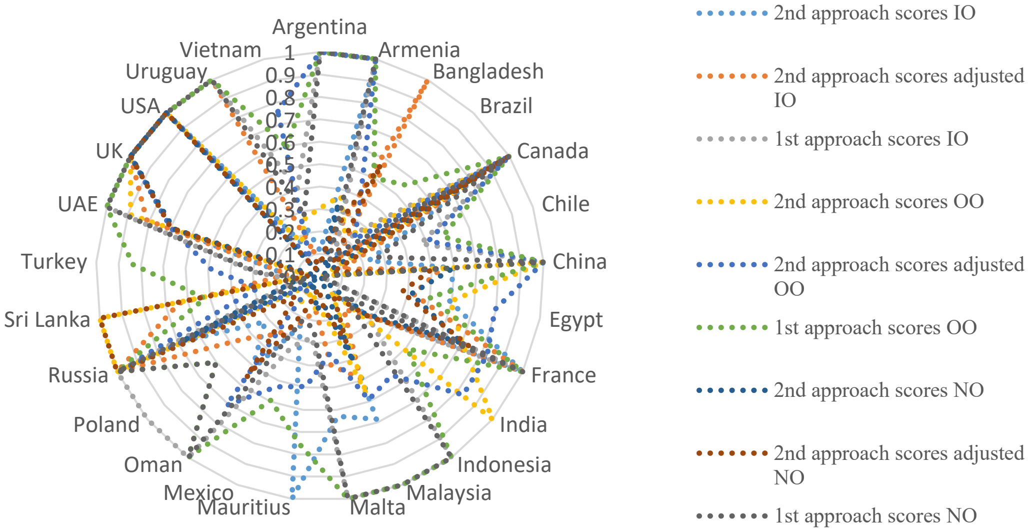


Figure 4.13 Summary of Network SBM Analyses for 2015

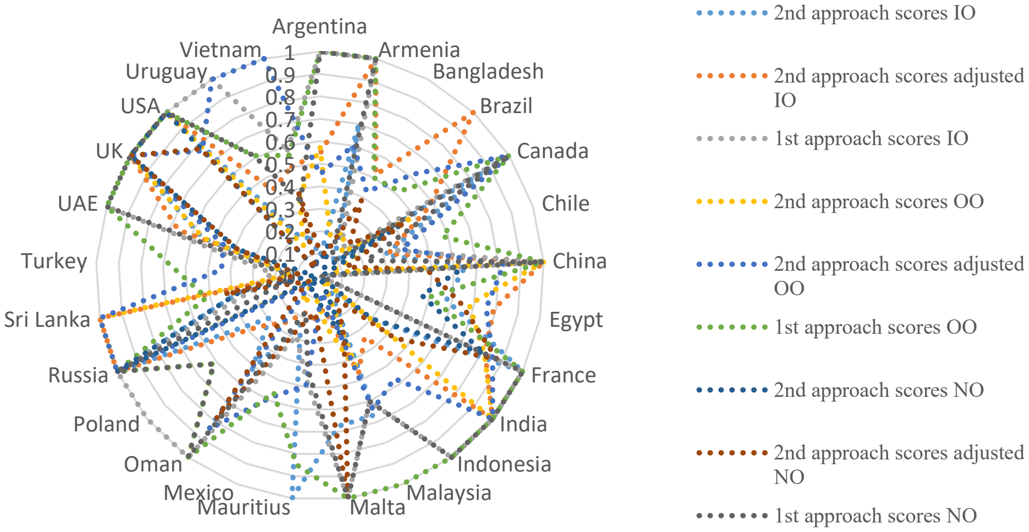


Figure 4.14 Summary of Static Black-Box SBM Analyses for 2013

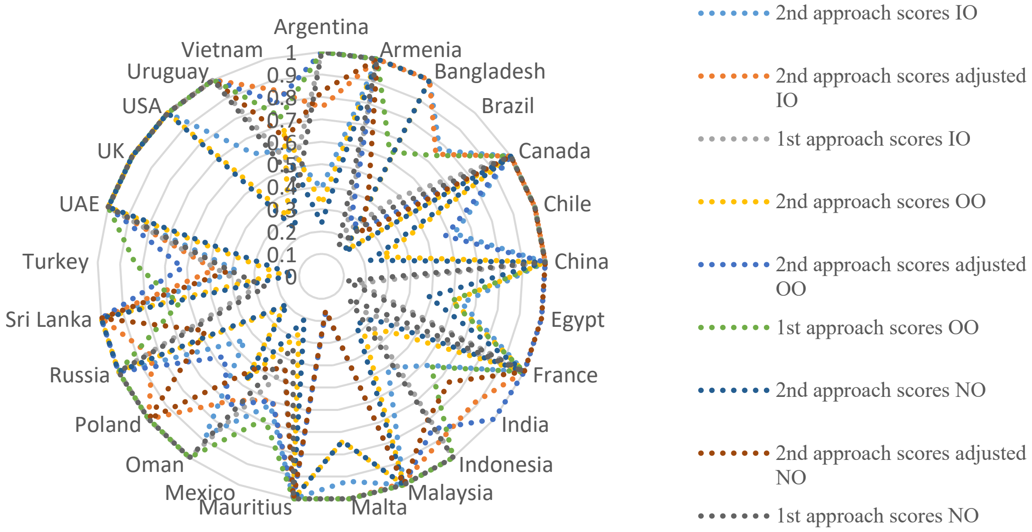


Figure 4.15 Summary of Static Black-Box SBM Analyses for 2014

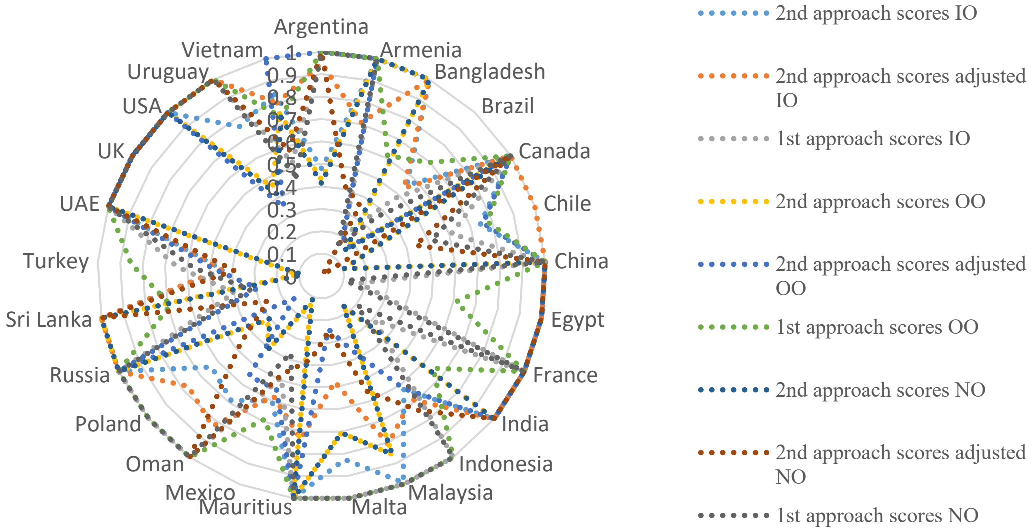
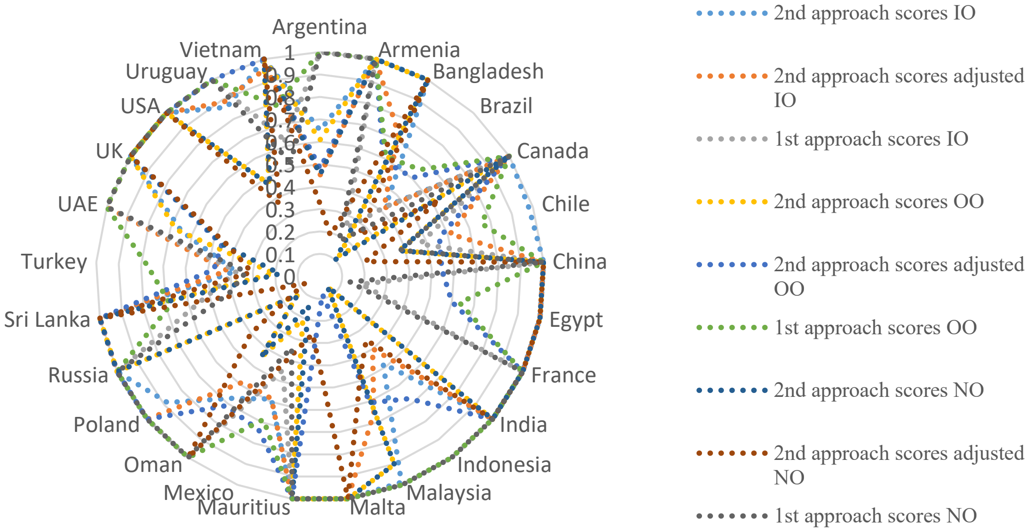


Figure 4.16 Summary of Static Black-Box SBM Analyses for 2015



4.3.4 Managerial Guidelines

Now we will compare the banks' efficiency scores considering its environmental impact and conditions (the environmental variables are incorporated into the models) and the bank's efficiency scores not considering its environmental impact and conditions (the environmental variables are not incorporated into the models) - See figures 4.17 - 4.19 This analysis demonstrates that some banks operating under less favorable circumstances would have to perform better (higher efficiency score) if they operated in a more favorable economic environment. In the previous analysis of the efficiency scores of the countries' operating environments in the first approach and the analysis of the bank's efficiency scores in the second approach. We could notice the discriminant analysis and the importance of taking into account the internal structure and the time effect to assess the efficiency score of a DMU, provided by the Dynamic Network model. Therefore, the managerial guidelines will analyze only the results of the Dynamic Network model.The main findings unfold as follows:

In the Dynamic-Network *input-oriented model*, the HSBC banks located in countries' operating environments of banks such as *the UK* and *the USA* were not affected by the impact of countries' operating environments of banks. Therefore, these banking-operating environment are not advantaging or disadvantaging the banks' efficiency under the input oriented assessment. However, the banks in *Armenia, Canada, Chile, China, France, Malaysia, Malta, Mauritius, Oman, Russia, Turkey, and UAE* have been strongly advantaged by their countries' operating environments of banks. Therefore, when the impact of the environmental variables is removed from the efficiency measures, the efficiency score decrease. On the other hand, the banks *Argentina, Bangladesh, Brazil, Egypt, India, Indonesia, Mexico, Poland, Sri Lanka, Uruguay, and Vietnam* have been strongly disadvantaged by their countries' operating environments of banks but when the impact of the environmental variables is removed from the efficiency measures, the efficiency scores increase.

In the Dynamic-Network *output-oriented models*, the HSBC banks located in countries' operating environments of banks such as *the UK* was not affected by the impact of countries' operating environments of banks. Therefore, this banking-operating environment is not advantaging or disadvantaging the banks' efficiency. However, in *Malta, Russia, and UAE* have been strongly advantaged by their countries' operating environments of banks. Therefore, when the impact of the environmental variables is removed from the efficiency measures, the efficiency score decrease. On the other hand, the banks in *Argentina, Armenia, Bangladesh, Brazil, Canada, Chile, China, Egypt, France, India, Indonesia, Malaysia, Mauritius, Mexico, Oman, Poland, Sri Lanka, Turkey, USA Uruguay, and Vietnam* have been strongly disadvantaged by their countries' operating environments of banks but when the impact of the environmental variables is removed from the efficiency measures, the efficiency scores increase.

Finally, in the Dynamic-Network *non-oriented model*, the HSBC banks located in countries' operating environments of banks such as *the UK* was not affected by the impact of countries' operating environments of banks. Therefore, this banking-operating environment is not advantaging or disadvantaging the banks' efficiency. However, in *Armenia, Canada, China, Egypt, Malaysia, Mauritius, and Russia,* have been strongly advantaged by their countries' operating environments of banks. Therefore, when the impact of the environmental variables is removed from the efficiency measures, the efficiency score decrease. On the other hand, the banks in *Argentina, Bangladesh, Brazil, Chile, France, India, Indonesia, Malta, Mexico, Oman, Poland, Sri Lanka, Turkey, UAE, USA Uruguay, and Vietnam* have been strongly disadvantaged by their countries' operating environments of banks but when the impact of the environmental variables is removed from the efficiency measures, the efficiency scores increase. In summary under the Dynamic Network OO model, the DMU were more disadvantaged than advantaged, compared with the Dynamic Network IO and Dynamic Network NO models. This effect might be related to the fact that countries are more concerned in controlling and bringing stability to the economy (income) than in supporting the profit generation of the banks (output). Without the effect of the countries' operating environments, banks could get a better efficiency score. In fact, in average the output-oriented approach has the highest efficiency scores compared with the input-oriented and non-oriented models.

Figure 4.17 – 4.19 represents graphically the difference between the 2nd approach scores without adjustment and the 2nd approach with adjusted scores. The black bar means that the DMU has been advantaged. The white bar means that the DMU has been disadvantaged.

Figure 4.17 Advantaged and disadvantaged DMUs

Dynamic-Network input-oriented model

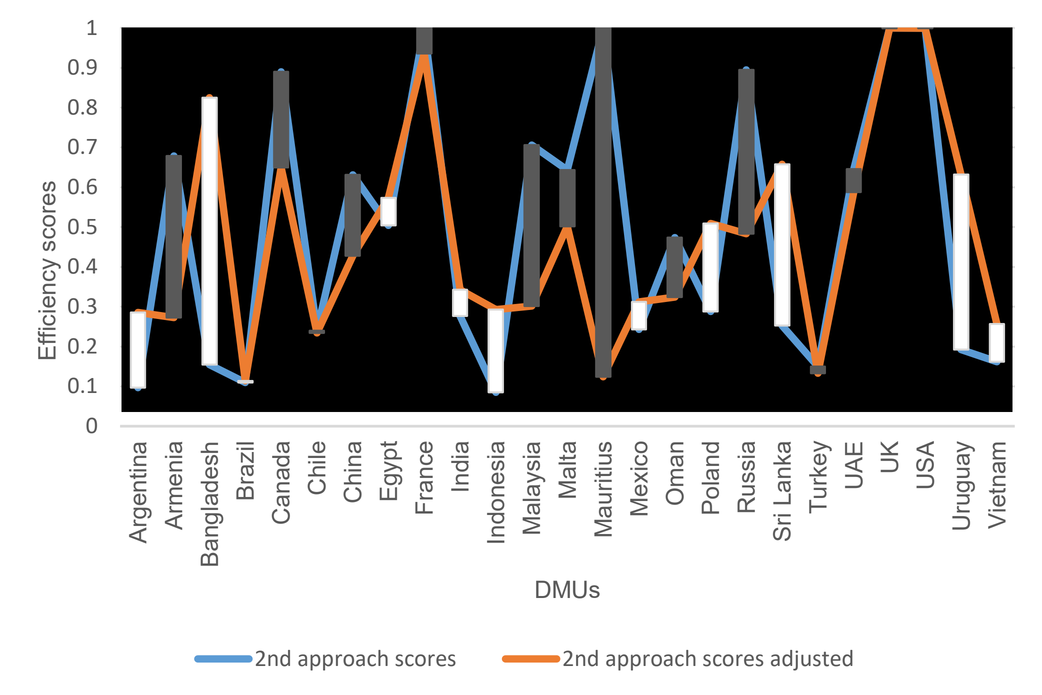


Figure 4.18 Advantaged and disadvantaged DMUs

Dynamic-Network output-oriented model

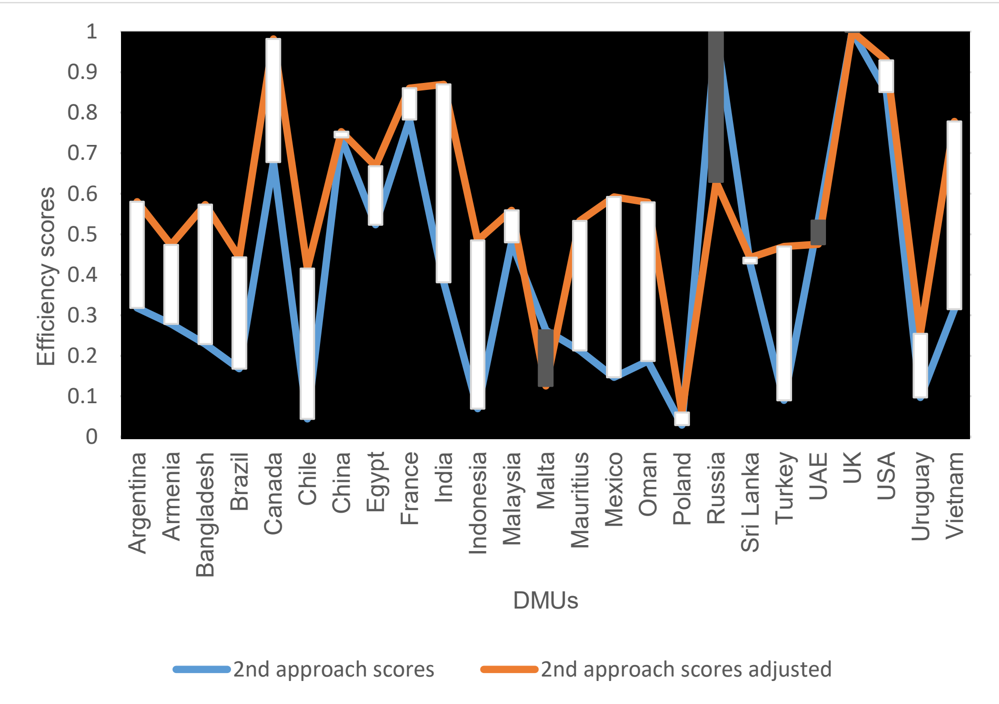
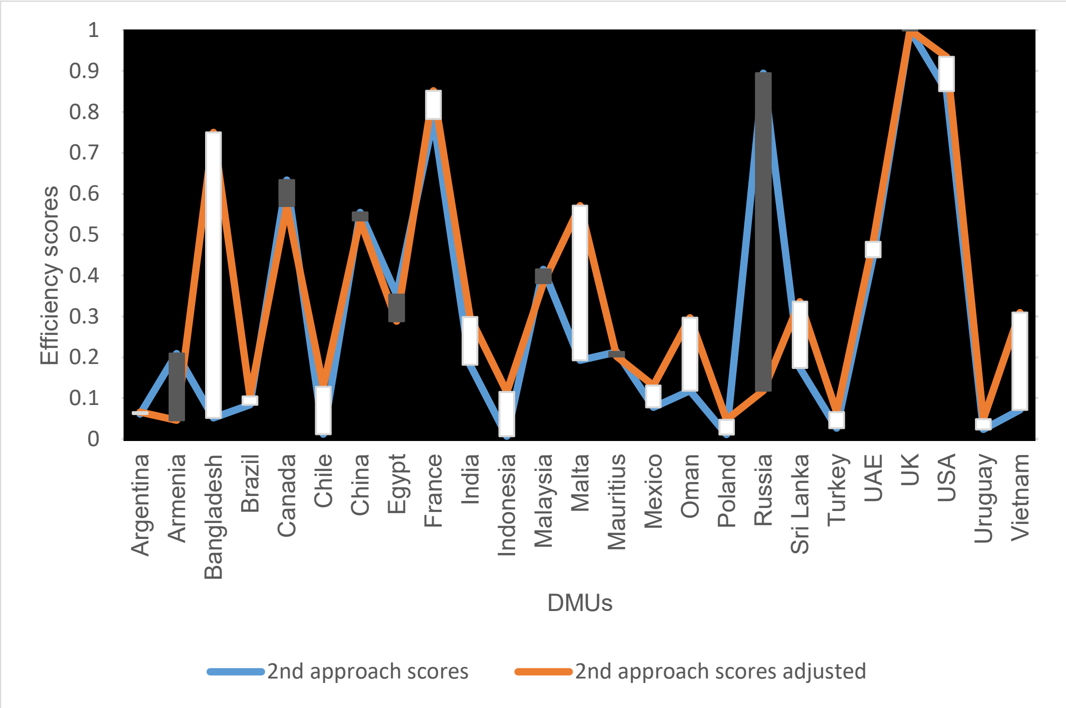


Figure 4.19 Advantaged and disadvantaged DMUs
Dynamic-Network non-oriented model



4.4 CONCLUSION

In this study, we assessed the efficiency profiles of banks' operating environments. To be more specific, we intend to address two research questions. The first and main research question is; which banking-operating environments are more efficient? These findings suggest the importance of the environmental variables in explaining the efficiency differences among countries. The operating environment can advantage or disadvantage banks' efficiency. Russia's operating environments is the one that advantaged the most. However, Russia's operating environment is not the most efficient because is leveraging Russian banks. In this study, the outcomes disclosed that the UK is the most efficient operating environment. In the first approach, the UK as a country was fully efficient in all the models, all periods and orientations. In the second approach, for the first analysis (without adjustment) the HSBC bank in the UK was the only bank fully efficient in all the models, all periods and orientations. Moreover, when the impact of the environmental variables was removed (adjusted), the HSBC bank in the UK remained fully efficient in all the models, all periods and orientations. In this sense, the operating environment helped when needed to help but not to the point of levering the bank. In fact, it would seem that the operating environment of the back do not affect the bank’s operations at all. Nevertheless, the reality is that the Operating environment and the Bank are efficient together and separate.

The second research question is, how different DEA analyses (i.e., Static SBM, Dynamic SBM, Network SBM, and Dynamic-Network SBM) compare in addressing the main research question? These findings suggest that an in-depth analysis (where the internal production process is considered) is better to detect the impact of the banking-operating environment. Dynamic –Network model is a better choice for this type of analysis for all the approaches (1st approach, 2nd approach and 2nd approach adjusted for environmental variables).

Overall, this analysis demonstrates that some banks operating under less favorable circumstances would have to perform better (higher efficiency score) if they operated in a more favorable economic environment. The outcomes of this study complement each other and help to decision makers. Therefore, those operating environments that disadvantaged the bank's efficiency should motivate the injection of capital in order to improve their macroeconomic conditions and incentivize the banking activity or review the financial policies. This information would be most useful to stakeholders such as governments and the international monetary fund (IMF), as it reflects better their scope. As for those, operating environment that advantaged the bank's efficiency should review their internal operation and regulatory fulfilment. This information would be most useful to bankers.

APPENDIX

Table 4.8 Summary of Input-oriented efficiency scores estimated on assessing the Countries' operating environment of banks

	1st approach scores input-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	IO	IO	IO	IO	IO	IO	IO	IO
Minimum	0.166	0.172	0.188	0.003	0.010	0.000	0.000	0.003
1st Quartile	0.474	0.525	0.525	0.604	0.307	0.299	0.365	0.407
Median	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3rd Quartile	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.793	0.793	0.812	0.786	0.718	0.704	0.727	0.735
Std. Dev.	0.309	0.292	0.284	0.328	0.369	0.372	0.353	0.342
Efficient DMU	17	16	17	16	15	15	15	14
Efficient DMU	68%	64%	68%	64%	60%	60%	60%	56%

Table 4.9 Summary of Output-oriented efficiency scores estimated on assessing the Countries' operating environment of banks

	1st approach scores output-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	OO	OO	OO	OO	OO	OO	OO	OO
Minimum	0.590	0.611	0.610	0.566	0.516	0.500	0.500	0.381
1st Quartile	0.738	0.734	0.772	0.852	0.660	0.595	0.573	0.658
Median	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.823
3rd Quartile	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.922
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.900	0.892	0.903	0.901	0.847	0.822	0.818	0.788
Std. Dev.	0.152	0.150	0.146	0.152	0.195	0.212	0.215	0.171
Efficient DMU	17	16	17	16	15	14	14	5
Efficient DMU	68%	64%	68%	64%	60%	56%	56%	20%

Table 4.10 Summary of Non-oriented efficiency scores estimated on assessing the Countries' operating environment of banks

	1st approach scores non-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Minimum	0.116	0.113	0.136	0.002	0.006	0.000	0.000	0.002
1st Quartile	0.411	0.459	0.414	0.502	0.191	0.235	0.219	0.288
Median	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.817
3rd Quartile	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.922
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.770	0.763	0.784	0.764	0.677	0.654	0.661	0.634
Std. Dev.	0.342	0.329	0.322	0.349	0.397	0.404	0.382	0.340
Efficient DMU	17	16	17	16	14	14	13	5
Efficient DMU	68%	64%	68%	64%	56%	56%	52%	20%

Table 4.11 Summary of Input-oriented efficiency scores without adjustment estimated on assessing the Banks' operating environments

	2nd approach scores input-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Minimum	0.378	0.440	0.377	0.448	0.089	0.077	0.083	0.085
1st Quartile	0.622	0.686	0.672	0.840	0.158	0.172	0.209	0.192
Median	0.922	1.000	1.000	1.000	0.347	0.514	0.514	0.474
3rd Quartile	1.000	1.000	1.000	1.000	0.905	0.692	0.703	0.706
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.800	0.847	0.862	0.880	0.496	0.492	0.506	0.493
Std. Dev.	0.225	0.191	0.207	0.176	0.358	0.329	0.329	0.327
Efficient DMU	12	13	14	13	6	4	5	4
Efficient DMU	48%	52%	56%	52%	24%	16%	20%	16%

Table 4.12 Summary of Output-oriented efficiency scores without adjustment estimated on assessing the Banks' operating environments

	2nd approach scores output-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	**OO**	**OO**	**OO**	**OO**	**OO**	**OO**	**OO**	**OO**
Minimum	0.158	0.106	0.062	0.144	0.042	0.015	0.021	0.029
1st Quartile	0.321	0.406	0.449	0.385	0.193	0.153	0.141	0.168
Median	0.743	1.000	1.000	1.000	0.346	0.305	0.366	0.315
3rd Quartile	1.000	1.000	1.000	1.000	0.760	1.000	0.810	0.534
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.682	0.704	0.728	0.730	0.464	0.484	0.458	0.394
Std. Dev.	0.333	0.355	0.350	0.342	0.337	0.382	0.365	0.292
Efficient DMU	12	13	14	13	5	7	6	2
Efficient DMU	48%	52%	56%	52%	20%	28%	24%	8%

Table 4.13 Summary of Non-oriented efficiency scores without adjustment estimated on assessing the Banks' operating environments

	2nd approach scores non-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Minimum	0.126	0.084	0.057	0.115	0.012	0.004	0.002	0.007
1st Quartile	0.241	0.406	0.449	0.316	0.044	0.041	0.059	0.061
Median	0.742	1.000	1.000	1.000	0.179	0.124	0.138	0.182
3rd Quartile	1.000	1.000	1.000	1.000	0.648	0.597	0.445	0.445
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.651	0.698	0.708	0.718	0.342	0.313	0.304	0.298
Std. Dev.	0.360	0.361	0.365	0.356	0.361	0.329	0.331	0.307
Efficient DMU	12	13	14	13	4	2	3	1
Efficient DMU	48%	52%	56%	52%	16%	8%	12%	4%

Table 4.14 Summary of Input-oriented efficiency scores with adjustment estimated on assessing the Banks' operating environments

	2nd approach scores adjusted for environmental variables input-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	IO	IO	IO	IO	IO	IO	IO	IO
Minimum	0.477	0.449	0.399	0.474	0.088	0.070	0.094	0.114
1st Quartile	0.858	0.733	0.610	0.849	0.171	0.153	0.338	0.286
Median	1.000	1.000	1.000	0.982	0.279	0.425	0.546	0.428
3rd Quartile	1.000	1.000	1.000	1.000	0.686	1.000	1.000	0.632
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.909	0.853	0.828	0.886	0.449	0.502	0.608	0.471
Std. Dev.	0.145	0.184	0.229	0.151	0.322	0.357	0.320	0.259
Efficient DMU	15	13	14	11	5	7	8	1
Efficient DMU	60%	52%	56%	44%	20%	28%	32%	4%

Table 4.15 Summary of Output-oriented efficiency scores with adjustment estimated on assessing the Banks' operating environments

	2nd approach scores adjusted for environmental variables output-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	OO	OO	OO	OO	OO	OO	OO	OO
Minimum	0.157	0.159	0.080	0.167	0.185	0.048	0.053	0.060
1st Quartile	0.621	0.351	0.588	0.650	0.411	0.484	0.454	0.470
Median	1.000	1.000	0.739	0.983	0.535	0.701	0.641	0.573
3rd Quartile	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.753
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.818	0.709	0.765	0.808	0.624	0.646	0.674	0.581
Std. Dev.	0.262	0.329	0.253	0.249	0.287	0.298	0.279	0.236
Efficient DMU	15	13	12	12	8	7	7	1
Efficient DMU	60%	52%	48%	48%	32%	28%	28%	4%

Table 4.16 Summary of Non-oriented efficiency scores with adjustment estimated on assessing the Banks' operating environments

	2nd approach scores adjusted for environmental variables non-oriented models							
	Static Black Box SBM			Dynamic SBM	Network SBM			Dynamic Network SBM
	2013	2014	2015	2013-2015	2013	2014	2015	2013-2015
DMU	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Minimum	0.153	0.006	0.076	0.256	0.023	0.039	0.039	0.046
1st Quartile	0.571	0.417	0.323	0.644	0.089	0.081	0.125	0.115
Median	1.000	0.742	0.486	0.965	0.215	0.285	0.378	0.297
3rd Quartile	1.000	1.000	1.000	1.000	0.647	0.699	0.477	0.535
Maximum	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Mean	0.791	0.693	0.628	0.826	0.361	0.407	0.388	0.347
Std. Dev.	0.272	0.320	0.345	0.217	0.320	0.360	0.295	0.287
Efficient DMU	14	12	11	12	2	5	2	1
Efficient DMU	56%	48%	44%	48%	8%	20%	8%	4%

Table 4.17 Comparative analysis of Banks' operating environments efficiency scores assessed with Dynamic-Network IO model.

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Dynamic Network (2013-2015)					
COUNTRY	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Argentina	0.097	0.286	-0.189	disadvantaged	1.000	Efficient
Armenia	0.679	0.273	0.406	advantaged	1.000	Efficient
Bangladesh	0.155	0.825	-0.671	disadvantaged	0.190	Inefficient
Brazil	0.110	0.114	-0.004	disadvantaged	0.256	Inefficient
Canada	0.890	0.650	0.240	advantaged	1.000	Efficient
Chile	0.240	0.234	0.006	advantaged	0.691	Inefficient
China	0.631	0.428	0.204	advantaged	1.000	Efficient
Egypt	0.504	0.573	-0.069	disadvantaged	0.003	Inefficient
France	1.000	0.936	0.064	advantaged	1.000	Efficient
India	0.277	0.343	-0.066	disadvantaged	0.783	Inefficient
Indonesia	0.085	0.293	-0.208	disadvantaged	1.000	Efficient
Malaysia	0.706	0.302	0.403	advantaged	0.742	Inefficient
Malta	0.643	0.502	0.141	advantaged	1.000	Efficient
Mauritius	1.000	0.124	0.876	advantaged	0.407	Inefficient
Mexico	0.243	0.312	-0.068	disadvantaged	0.295	Inefficient
Oman	0.474	0.324	0.150	advantaged	1.000	Efficient
Poland	0.288	0.509	-0.221	disadvantaged	1.000	Efficient
Russia	0.895	0.483	0.412	advantaged	1.000	Efficient
Sri Lanka	0.253	0.658	-0.405	disadvantaged	0.165	Inefficient
Turkey	0.150	0.133	0.017	advantaged	0.257	Inefficient
UAE	0.646	0.588	0.058	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	0.999	0.001	no affected	1.000	Efficient
Uruguay	0.192	0.632	-0.441	disadvantaged	1.000	Efficient
Vietnam	0.162	0.257	-0.095	disadvantaged	0.581	Inefficient

Table 4.18 Comparative analysis of Banks' operating environments efficiency scores assessed with Dynamic-Network OO model

	2nd approach scores	**2nd approach scores adjusted**	**Scores difference**	**Environment effect**	**1st approach scores**	**Operating environment (efficient or inefficient)**
	Dynamic Network (2013-2015)					
COUNTRY	**OO**	**OO**	**OO**	**OO**	**OO**	**OO**
Argentina	0.318	0.580	-0.262	disadvantaged	0.830	Inefficient
Armenia	0.279	0.474	-0.195	disadvantaged	0.856	Inefficient
Bangladesh	0.229	0.573	-0.344	disadvantaged	0.381	Inefficient
Brazil	0.168	0.443	-0.275	disadvantaged	0.592	Inefficient
Canada	0.678	0.982	-0.304	disadvantaged	1.000	Efficient
Chile	0.044	0.415	-0.371	disadvantaged	0.703	Inefficient
China	0.739	0.753	-0.015	disadvantaged	1.000	Efficient
Egypt	0.523	0.668	-0.145	disadvantaged	0.476	Inefficient
France	0.783	0.860	-0.077	disadvantaged	0.864	Inefficient
India	0.381	0.870	-0.489	disadvantaged	0.823	Inefficient
Indonesia	0.070	0.485	-0.415	disadvantaged	0.862	Inefficient
Malaysia	0.480	0.559	-0.080	disadvantaged	0.853	Inefficient
Malta	0.263	0.126	0.138	advantaged	0.957	Inefficient
Mauritius	0.213	0.533	-0.320	disadvantaged	0.658	Inefficient
Mexico	0.147	0.592	-0.445	disadvantaged	0.604	Inefficient
Oman	0.187	0.579	-0.392	disadvantaged	1.000	Efficient
Poland	0.029	0.060	-0.031	disadvantaged	0.658	Inefficient
Russia	1.000	0.629	0.371	advantaged	0.922	Inefficient
Sri Lanka	0.428	0.442	-0.013	disadvantaged	0.572	Inefficient
Turkey	0.090	0.470	-0.380	disadvantaged	0.685	Inefficient
UAE	0.534	0.475	0.059	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	0.851	0.929	-0.077	disadvantaged	0.821	Inefficient
Uruguay	0.097	0.254	-0.157	disadvantaged	0.817	Inefficient
Vietnam	0.315	0.778	-0.463	disadvantaged	0.757	Inefficient

Table 4.19 Comparative analysis of Banks' operating environments efficiency scores assessed with Dynamic-Network NO model

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Dynamic Network (2013-2015)					
COUNTRY	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Argentina	0.061	0.066	-0.005	disadvantaged	0.830	Inefficient
Armenia	0.209	0.046	0.163	advantaged	0.856	Inefficient
Bangladesh	0.052	0.750	-0.699	disadvantaged	0.080	Inefficient
Brazil	0.084	0.104	-0.020	disadvantaged	0.165	Inefficient
Canada	0.633	0.570	0.063	advantaged	1.000	Efficient
Chile	0.012	0.128	-0.116	disadvantaged	0.504	Inefficient
China	0.554	0.535	0.019	advantaged	1.000	Efficient
Egypt	0.353	0.288	0.065	advantaged	0.002	Inefficient
France	0.783	0.852	-0.069	disadvantaged	0.864	Inefficient
India	0.182	0.298	-0.116	disadvantaged	0.644	Inefficient
Indonesia	0.007	0.115	-0.108	disadvantaged	0.862	Inefficient
Malaysia	0.415	0.381	0.034	advantaged	0.637	Inefficient
Malta	0.193	0.571	-0.378	disadvantaged	0.957	Inefficient
Mauritius	0.213	0.202	0.011	advantaged	0.288	Inefficient
Mexico	0.078	0.131	-0.053	disadvantaged	0.191	Inefficient
Oman	0.118	0.297	-0.179	disadvantaged	1.000	Efficient
Poland	0.011	0.047	-0.037	disadvantaged	0.658	Inefficient
Russia	0.895	0.118	0.777	advantaged	0.922	Inefficient
Sri Lanka	0.174	0.336	-0.162	disadvantaged	0.103	Inefficient
Turkey	0.027	0.066	-0.039	disadvantaged	0.192	Inefficient
UAE	0.445	0.482	-0.037	disadvantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	0.851	0.935	-0.083	disadvantaged	0.821	Inefficient
Uruguay	0.024	0.049	-0.025	disadvantaged	0.817	Inefficient
Vietnam	0.071	0.309	-0.238	disadvantaged	0.453	Inefficient

Table 4.20 Comparative analysis of Banks' operating environments efficiency scores assessed with Network IO model 2013

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2013					
COUNTRY	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Argentina	0.089	0.088	0.001	advantaged	1.000	Efficient
Armenia	1.000	0.171	0.829	advantaged	1.000	Efficient
Bangladesh	0.153	1.000	-0.847	disadvantaged	0.204	Inefficient
Brazil	0.130	0.134	-0.004	disadvantaged	0.307	Inefficient
Canada	0.905	0.783	0.121	advantaged	1.000	Efficient
Chile	0.199	0.339	-0.140	disadvantaged	1.000	Efficient
China	0.648	0.593	0.054	advantaged	1.000	Efficient
Egypt	0.347	0.279	0.068	advantaged	0.010	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	0.273	0.234	0.038	advantaged	0.198	Inefficient
Indonesia	0.095	0.165	-0.070	disadvantaged	1.000	Efficient
Malaysia	0.767	0.475	0.293	advantaged	0.799	Inefficient
Malta	0.625	1.000	-0.375	disadvantaged	1.000	Efficient
Mauritius	1.000	0.269	0.731	advantaged	0.477	Inefficient
Mexico	0.258	0.265	-0.007	disadvantaged	0.259	Inefficient
Oman	0.394	0.322	0.072	advantaged	1.000	Efficient
Poland	0.253	0.446	-0.192	disadvantaged	1.000	Efficient
Russia	1.000	0.159	0.841	advantaged	1.000	Efficient
Sri Lanka	0.119	0.241	-0.123	disadvantaged	0.105	Inefficient
Turkey	0.158	0.144	0.014	advantaged	0.253	Inefficient
UAE	0.694	0.686	0.008	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.200	0.278	-0.078	disadvantaged	1.000	Efficient
Vietnam	0.101	0.159	-0.057	disadvantaged	0.338	Inefficient

Table 4.21 Comparative analysis of Banks' operating environments efficiency scores assessed with Network OO model 2013

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2013					
COUNTRY	OO	OO	OO	OO	OO	OO
Argentina	0.346	1.000	-0.654	disadvantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	0.231	0.291	-0.060	disadvantaged	0.527	Inefficient
Brazil	0.198	0.411	-0.213	disadvantaged	0.601	Inefficient
Canada	0.815	1.000	-0.185	disadvantaged	1.000	Efficient
Chile	0.053	0.465	-0.412	disadvantaged	1.000	Efficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	0.398	0.411	-0.014	disadvantaged	0.516	Inefficient
France	0.669	0.775	-0.107	disadvantaged	1.000	Efficient
India	0.567	1.000	-0.433	disadvantaged	0.543	Inefficient
Indonesia	0.190	0.259	-0.069	disadvantaged	1.000	Efficient
Malaysia	0.482	0.674	-0.192	disadvantaged	1.000	Efficient
Malta	0.262	0.291	-0.029	disadvantaged	1.000	Efficient
Mauritius	0.181	0.535	-0.354	disadvantaged	0.741	Inefficient
Mexico	0.278	0.507	-0.229	disadvantaged	0.594	Inefficient
Oman	0.193	0.353	-0.160	disadvantaged	1.000	Efficient
Poland	0.042	0.356	-0.314	disadvantaged	0.660	Inefficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	0.518	0.459	0.059	advantaged	0.546	Inefficient
Turkey	0.085	0.422	-0.337	disadvantaged	0.707	Inefficient
UAE	0.760	0.619	0.141	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.060	0.185	-0.125	disadvantaged	1.000	Efficient
Vietnam	0.282	0.578	-0.296	disadvantaged	0.747	Inefficient

Table 4.22 Comparative analysis of Banks' operating environments efficiency scores assessed with Network NO model 2013

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2013					
COUNTRY	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Argentina	0.066	0.052	0.014	advantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	0.044	0.798	-0.753	disadvantaged	0.116	Inefficient
Brazil	0.130	0.145	-0.015	disadvantaged	0.189	Inefficient
Canada	0.753	0.760	-0.007	disadvantaged	1.000	Efficient
Chile	0.012	0.067	-0.054	disadvantaged	1.000	Efficient
China	0.648	0.647	0.001	advantaged	1.000	Efficient
Egypt	0.179	0.215	-0.036	disadvantaged	0.006	Inefficient
France	0.669	0.790	-0.121	disadvantaged	1.000	Efficient
India	0.238	0.281	-0.043	disadvantaged	0.113	Inefficient
Indonesia	0.027	0.055	-0.028	disadvantaged	1.000	Efficient
Malaysia	0.410	0.318	0.092	advantaged	0.799	Inefficient
Malta	0.189	0.268	-0.080	disadvantaged	1.000	Efficient
Mauritius	0.181	0.079	0.102	advantaged	0.377	Inefficient
Mexico	0.129	0.201	-0.073	disadvantaged	0.160	Inefficient
Oman	0.092	0.140	-0.048	disadvantaged	1.000	Efficient
Poland	0.012	0.090	-0.078	disadvantaged	0.660	Inefficient
Russia	1.000	0.557	0.443	advantaged	1.000	Efficient
Sri Lanka	0.086	0.129	-0.043	disadvantaged	0.061	Inefficient
Turkey	0.024	0.048	-0.024	disadvantaged	0.191	Inefficient
UAE	0.615	0.585	0.030	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	0.697	0.303	advantaged	1.000	Efficient
Uruguay	0.015	0.023	-0.008	disadvantaged	1.000	Efficient
Vietnam	0.039	0.089	-0.050	disadvantaged	0.260	Inefficient

Table 4.23 Comparative analysis of Banks' operating environments efficiency scores assessed with Network IO model 2014

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2014					
COUNTRY	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Argentina	0.114	0.070	0.044	advantaged	1.000	Efficient
Armenia	0.887	0.123	0.763	advantaged	1.000	Efficient
Bangladesh	0.147	1.000	-0.853	disadvantaged	0.152	Inefficient
Brazil	0.115	0.110	0.005	advantaged	0.299	Inefficient
Canada	0.870	1.000	-0.130	disadvantaged	1.000	Efficient
Chile	0.229	0.101	0.128	advantaged	0.472	Inefficient
China	0.597	0.542	0.055	advantaged	1.000	Efficient
Egypt	0.590	0.425	0.166	advantaged	0.000	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	0.259	0.274	-0.014	disadvantaged	0.272	Inefficient
Indonesia	0.077	0.182	-0.105	disadvantaged	1.000	Efficient
Malaysia	0.685	0.491	0.194	advantaged	1.000	Efficient
Malta	0.629	0.398	0.231	advantaged	1.000	Efficient
Mauritius	1.000	0.153	0.847	advantaged	0.275	Inefficient
Mexico	0.238	0.221	0.017	advantaged	0.338	Inefficient
Oman	0.514	0.317	0.197	advantaged	1.000	Efficient
Poland	0.318	0.436	-0.119	disadvantaged	1.000	Efficient
Russia	0.685	1.000	-0.315	disadvantaged	1.000	Efficient
Sri Lanka	0.114	0.641	-0.527	disadvantaged	0.102	Inefficient
Turkey	0.158	0.142	0.016	advantaged	0.293	Inefficient
UAE	0.692	0.814	-0.121	disadvantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.172	1.000	-0.828	disadvantaged	1.000	Efficient
Vietnam	0.213	0.114	0.099	advantaged	0.405	Inefficient

Table 4.24 Comparative analysis of Banks' operating environments efficiency scores assessed with Network OO model 2014

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2014					
COUNTRY	OO	OO	OO	OO	OO	OO
Argentina	0.305	1.000	-0.695	disadvantaged	1.000	Efficient
Armenia	0.369	1.000	-0.631	disadvantaged	1.000	Efficient
Bangladesh	0.230	0.368	-0.138	disadvantaged	0.500	Inefficient
Brazil	0.262	0.225	0.036	advantaged	0.559	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.015	0.508	-0.493	disadvantaged	0.574	Inefficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	0.594	0.794	-0.200	disadvantaged	0.500	Inefficient
France	0.702	0.825	-0.124	disadvantaged	1.000	Efficient
India	1.000	0.829	0.171	advantaged	0.508	Inefficient
Indonesia	0.083	0.546	-0.463	disadvantaged	1.000	Efficient
Malaysia	0.567	0.591	-0.024	disadvantaged	1.000	Efficient
Malta	0.176	0.348	-0.172	disadvantaged	1.000	Efficient
Mauritius	0.153	0.495	-0.343	disadvantaged	0.751	Inefficient
Mexico	0.074	0.530	-0.456	disadvantaged	0.595	Inefficient
Oman	0.139	0.712	-0.572	disadvantaged	1.000	Efficient
Poland	0.057	0.048	0.009	advantaged	0.602	Inefficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	1.000	0.282	0.718	advantaged	0.523	Inefficient
Turkey	0.047	0.484	-0.438	disadvantaged	0.837	Inefficient
UAE	0.889	0.701	0.189	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.171	0.092	0.078	advantaged	1.000	Efficient
Vietnam	0.266	0.758	-0.492	disadvantaged	0.597	Inefficient

Table 4.25 Comparative analysis of Banks' operating environments efficiency scores assessed with Network NO model 2014

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2014					
COUNTRY	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Argentina	0.048	0.052	-0.004	disadvantaged	1.000	Efficient
Armenia	0.338	0.187	0.151	advantaged	1.000	Efficient
Bangladesh	0.040	0.569	-0.529	disadvantaged	0.083	Inefficient
Brazil	0.115	0.081	0.034	advantaged	0.176	Inefficient
Canada	0.870	1.000	-0.130	disadvantaged	1.000	Efficient
Chile	0.004	0.056	-0.052	disadvantaged	0.276	Inefficient
China	0.597	0.500	0.097	advantaged	1.000	Efficient
Egypt	0.415	0.371	0.043	advantaged	0.000	Inefficient
France	0.702	0.739	-0.037	disadvantaged	1.000	Efficient
India	0.259	0.285	-0.025	disadvantaged	0.142	Inefficient
Indonesia	0.007	0.103	-0.096	disadvantaged	1.000	Efficient
Malaysia	0.411	0.315	0.096	advantaged	1.000	Efficient
Malta	0.124	0.150	-0.027	disadvantaged	1.000	Efficient
Mauritius	0.153	0.054	0.099	advantaged	0.235	Inefficient
Mexico	0.041	0.153	-0.112	disadvantaged	0.209	Inefficient
Oman	0.081	0.557	-0.476	disadvantaged	1.000	Efficient
Poland	0.019	0.140	-0.121	disadvantaged	0.602	Inefficient
Russia	0.685	1.000	-0.315	disadvantaged	1.000	Efficient
Sri Lanka	0.114	1.000	-0.886	disadvantaged	0.057	Inefficient
Turkey	0.011	0.046	-0.035	disadvantaged	0.276	Inefficient
UAE	0.686	0.699	-0.013	disadvantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.029	0.039	-0.009	disadvantaged	1.000	Efficient
Vietnam	0.066	0.068	-0.003	disadvantaged	0.285	Inefficient

Table 4.26 Comparative analysis of Banks' operating environments efficiency scores assessed with Network IO model 2015

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2015					
COUNTRY	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Argentina	0.089	0.546	-0.457	disadvantaged	1.000	Efficient
Armenia	0.703	1.000	-0.297	disadvantaged	1.000	Efficient
Bangladesh	0.165	0.516	-0.351	disadvantaged	0.213	Inefficient
Brazil	0.085	1.000	-0.915	disadvantaged	0.162	Inefficient
Canada	0.893	0.577	0.317	advantaged	1.000	Efficient
Chile	0.306	0.321	-0.015	disadvantaged	0.365	Inefficient
China	0.649	1.000	-0.351	disadvantaged	1.000	Efficient
Egypt	0.575	0.789	-0.214	disadvantaged	0.000	Inefficient
France	1.000	0.816	0.184	advantaged	1.000	Efficient
India	0.298	1.000	-0.702	disadvantaged	1.000	Efficient
Indonesia	0.083	0.338	-0.255	disadvantaged	1.000	Efficient
Malaysia	0.666	0.466	0.200	advantaged	0.602	Inefficient
Malta	0.675	0.147	0.528	advantaged	1.000	Efficient
Mauritius	1.000	0.191	0.809	advantaged	0.470	Inefficient
Mexico	0.234	0.177	0.057	advantaged	0.287	Inefficient
Oman	0.514	0.255	0.259	advantaged	1.000	Efficient
Poland	0.294	0.356	-0.062	disadvantaged	1.000	Efficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	0.357	1.000	-0.643	disadvantaged	0.288	Inefficient
Turkey	0.134	0.094	0.040	advantaged	0.216	Inefficient
UAE	0.552	0.664	-0.112	disadvantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.209	0.438	-0.230	disadvantaged	1.000	Efficient
Vietnam	0.170	0.503	-0.333	disadvantaged	0.581	Inefficient

Table 4.27 Comparative analysis of Banks' operating environments efficiency scores assessed with Network OO model 2015

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2015					
COUNTRY	**OO**	**OO**	**OO**	**OO**	**OO**	**OO**
Argentina	0.576	0.454	0.122	advantaged	1.000	Efficient
Armenia	0.184	0.603	-0.419	disadvantaged	1.000	Efficient
Bangladesh	0.221	0.430	-0.209	disadvantaged	0.500	Inefficient
Brazil	0.142	0.627	-0.485	disadvantaged	0.519	Inefficient
Canada	0.491	1.000	-0.509	disadvantaged	1.000	Efficient
Chile	0.054	0.384	-0.330	disadvantaged	0.573	Inefficient
China	1.000	0.823	0.177	advantaged	1.000	Efficient
Egypt	0.679	0.755	-0.076	disadvantaged	0.500	Inefficient
France	0.810	0.851	-0.041	disadvantaged	1.000	Efficient
India	1.000	1.000	0.000	no affected	1.000	Efficient
Indonesia	0.021	0.566	-0.546	disadvantaged	1.000	Efficient
Malaysia	0.457	0.641	-0.183	disadvantaged	1.000	Efficient
Malta	0.229	0.076	0.153	advantaged	1.000	Efficient
Mauritius	0.108	0.491	-0.382	disadvantaged	0.847	Inefficient
Mexico	0.111	0.580	-0.469	disadvantaged	0.559	Inefficient
Oman	0.141	0.845	-0.705	disadvantaged	1.000	Efficient
Poland	0.034	0.053	-0.018	disadvantaged	0.614	Inefficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.515	Inefficient
Turkey	0.129	0.440	-0.311	disadvantaged	0.662	Inefficient
UAE	0.548	0.453	0.095	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	0.766	0.234	advantaged	1.000	Efficient
Uruguay	0.154	1.000	-0.846	disadvantaged	0.612	Inefficient
Vietnam	0.366	1.000	-0.634	disadvantaged	0.555	Inefficient

Table 4.28 Comparative analysis of Banks' operating environments efficiency scores assessed with Network NO model 2015

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Network 2015					
COUNTRY	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Argentina	0.059	0.108	-0.049	disadvantaged	1.000	Efficient
Armenia	0.138	0.103	0.035	advantaged	1.000	Efficient
Bangladesh	0.043	0.386	-0.343	disadvantaged	0.116	Inefficient
Brazil	0.072	0.196	-0.124	disadvantaged	0.095	Inefficient
Canada	0.445	0.447	-0.002	disadvantaged	1.000	Efficient
Chile	0.017	0.125	-0.108	disadvantaged	0.219	Inefficient
China	0.649	0.477	0.172	advantaged	1.000	Efficient
Egypt	0.463	0.637	-0.174	disadvantaged	0.000	Inefficient
France	0.810	0.872	-0.062	disadvantaged	1.000	Efficient
India	0.298	0.435	-0.137	disadvantaged	1.000	Efficient
Indonesia	0.002	0.129	-0.128	disadvantaged	1.000	Efficient
Malaysia	0.317	0.293	0.024	advantaged	0.602	Inefficient
Malta	0.154	1.000	-0.846	disadvantaged	1.000	Efficient
Mauritius	0.108	0.165	-0.057	disadvantaged	0.423	Inefficient
Mexico	0.059	0.247	-0.188	disadvantaged	0.173	Inefficient
Oman	0.079	0.791	-0.712	disadvantaged	1.000	Efficient
Poland	0.010	0.125	-0.115	disadvantaged	0.614	Inefficient
Russia	1.000	0.056	0.944	advantaged	1.000	Efficient
Sri Lanka	0.357	0.433	-0.076	disadvantaged	0.164	Inefficient
Turkey	0.030	0.092	-0.062	disadvantaged	0.156	Inefficient
UAE	0.392	0.389	0.003	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	0.778	0.222	advantaged	1.000	Efficient
Uruguay	0.033	0.039	-0.006	disadvantaged	0.612	Inefficient
Vietnam	0.064	0.378	-0.314	disadvantaged	0.346	Inefficient

Table 4.29 Comparative analysis of Banks' operating environments efficiency scores assessed with Dynamic IO model

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Dynamic (2013-2015)					
COUNTRY	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Argentina	0.928	1.000	-0.072	disadvantaged	1.000	Efficient
Armenia	1.000	0.761	0.239	advantaged	1.000	Efficient
Bangladesh	0.954	0.912	0.042	advantaged	1.000	Efficient
Brazil	1.000	0.859	0.141	advantaged	1.000	Efficient
Canada	1.000	0.872	0.128	advantaged	1.000	Efficient
Chile	1.000	0.982	0.018	advantaged	1.000	Efficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	1.000	1.000	0.000	no affected	1.000	Efficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	1.000	Efficient
Indonesia	1.000	1.000	0.000	no affected	1.000	Efficient
Malaysia	1.000	1.000	0.000	no affected	1.000	Efficient
Malta	0.448	0.899	-0.451	disadvantaged	1.000	Efficient
Mauritius	0.548	0.547	0.002	advantaged	1.000	Efficient
Mexico	0.707	0.886	-0.179	disadvantaged	1.000	Efficient
Oman	0.663	1.000	-0.337	disadvantaged	1.000	Efficient
Poland	0.840	0.713	0.126	advantaged	0.811	Inefficient
Russia	1.000	1.000	0.000	no affected	0.783	Inefficient
Sri Lanka	0.899	0.746	0.153	advantaged	0.604	Inefficient
Turkey	0.497	0.474	0.023	advantaged	0.497	Inefficient
UAE	0.669	0.663	0.006	advantaged	0.309	Inefficient
UK	0.857	0.849	0.008	advantaged	0.316	Inefficient
USA	1.000	1.000	0.000	no affected	0.206	Inefficient
Uruguay	1.000	1.000	0.000	no affected	0.123	Inefficient
Vietnam	0.997	0.999	-0.002	disadvantaged	0.003	Inefficient

Table 4.30 Comparative analysis of Banks' operating environments efficiency scores assessed with Dynamic OO model

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Dynamic (2013-2015)					
COUNTRY	**OO**	**OO**	**OO**	**OO**	**OO**	**OO**
Argentina	0.857	0.167	0.689	advantaged	1.000	Efficient
Armenia	1.000	0.654	0.346	advantaged	1.000	Efficient
Bangladesh	0.758	0.645	0.113	advantaged	1.000	Efficient
Brazil	1.000	1.000	0.000	no affected	1.000	Efficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	1.000	1.000	0.000	no affected	1.000	Efficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	1.000	1.000	0.000	no affected	1.000	Efficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	1.000	Efficient
Indonesia	1.000	1.000	0.000	no affected	1.000	Efficient
Malaysia	1.000	1.000	0.000	no affected	1.000	Efficient
Malta	0.497	1.000	-0.503	disadvantaged	1.000	Efficient
Mauritius	0.174	0.747	-0.573	disadvantaged	1.000	Efficient
Mexico	0.385	1.000	-0.615	disadvantaged	1.000	Efficient
Oman	0.226	0.892	-0.666	disadvantaged	1.000	Efficient
Poland	0.202	0.650	-0.448	disadvantaged	0.920	Inefficient
Russia	1.000	1.000	0.000	no affected	0.852	Inefficient
Sri Lanka	0.782	0.960	-0.178	disadvantaged	0.782	Inefficient
Turkey	0.144	0.527	-0.383	disadvantaged	0.865	Inefficient
UAE	0.175	0.347	-0.172	disadvantaged	0.655	Inefficient
UK	0.198	0.657	-0.459	disadvantaged	0.642	Inefficient
USA	1.000	0.357	0.643	advantaged	0.566	Inefficient
Uruguay	1.000	0.618	0.382	advantaged	0.637	Inefficient
Vietnam	0.854	0.983	-0.128	disadvantaged	0.600	Inefficient

Table 4.31 Comparative analysis of Banks' operating environments efficiency scores assessed with Dynamic NO model

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Dynamic (2013-2015)					
COUNTRY	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Argentina	0.316	0.879	-0.563	disadvantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	1.000	0.604	0.396	advantaged	0.148	Inefficient
Brazil	0.168	0.256	-0.088	disadvantaged	0.236	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.196	0.613	-0.417	disadvantaged	0.767	Inefficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	0.854	0.965	-0.111	disadvantaged	0.002	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	0.682	Inefficient
Indonesia	0.148	0.754	-0.607	disadvantaged	1.000	Efficient
Malaysia	1.000	0.584	0.416	advantaged	1.000	Efficient
Malta	0.855	1.000	-0.145	disadvantaged	1.000	Efficient
Mauritius	1.000	0.857	0.143	advantaged	1.000	Efficient
Mexico	0.192	0.640	-0.448	disadvantaged	0.230	Inefficient
Oman	0.758	0.644	0.113	advantaged	1.000	Efficient
Poland	0.209	1.000	-0.791	disadvantaged	1.000	Efficient
Russia	1.000	0.705	0.295	advantaged	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.097	Inefficient
Turkey	0.115	0.358	-0.243	disadvantaged	0.434	Inefficient
UAE	1.000	1.000	0.000	no affected	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.363	1.000	-0.637	disadvantaged	1.000	Efficient
Vietnam	0.780	0.787	-0.007	disadvantaged	0.502	Inefficient

Table 4.32 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box IO model 2013

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Static Black-Box 2013					
COUNTRY	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Argentina	0.391	0.753	-0.362	disadvantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	1.000	1.000	0.000	no affected	0.225	Inefficient
Brazil	0.770	0.746	0.025	advantaged	0.474	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.622	1.000	-0.378	disadvantaged	1.000	Efficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	0.637	1.000	-0.363	disadvantaged	0.166	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	0.623	0.885	-0.261	disadvantaged	0.248	Inefficient
Indonesia	0.504	0.904	-0.400	disadvantaged	1.000	Efficient
Malaysia	1.000	0.991	0.009	advantaged	1.000	Efficient
Malta	0.922	1.000	-0.078	disadvantaged	1.000	Efficient
Mauritius	1.000	1.000	0.000	no affected	1.000	Efficient
Mexico	0.618	0.594	0.023	advantaged	0.449	Inefficient
Oman	0.878	0.685	0.192	advantaged	1.000	Efficient
Poland	0.445	1.000	-0.555	disadvantaged	1.000	Efficient
Russia	1.000	0.834	0.166	advantaged	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.311	Inefficient
Turkey	0.378	0.477	-0.099	disadvantaged	0.460	Inefficient
UAE	1.000	1.000	0.000	no affected	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.625	1.000	-0.375	disadvantaged	1.000	Efficient
Vietnam	0.582	0.858	-0.276	disadvantaged	0.494	Inefficient

Table 4.33 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box OO model 2013

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Static Black-Box 2013					
COUNTRY	**OO**	**OO**	**OO**	**OO**	**OO**	**OO**
Argentina	0.321	1.000	-0.679	disadvantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	1.000	0.268	0.732	advantaged	0.633	Inefficient
Brazil	0.158	0.315	-0.157	disadvantaged	0.738	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.284	0.581	-0.297	disadvantaged	1.000	Efficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	0.597	1.000	-0.403	disadvantaged	0.590	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	0.382	1.000	-0.618	disadvantaged	0.634	Inefficient
Indonesia	0.329	0.842	-0.512	disadvantaged	1.000	Efficient
Malaysia	1.000	1.000	0.000	no affected	1.000	Efficient
Malta	0.743	0.157	0.586	advantaged	1.000	Efficient
Mauritius	1.000	1.000	0.000	no affected	1.000	Efficient
Mexico	0.276	0.598	-0.322	disadvantaged	0.684	Inefficient
Oman	0.576	0.707	-0.132	disadvantaged	1.000	Efficient
Poland	0.219	0.563	-0.344	disadvantaged	1.000	Efficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.647	Inefficient
Turkey	0.189	0.621	-0.431	disadvantaged	0.829	Inefficient
UAE	1.000	1.000	0.000	no affected	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.303	1.000	-0.697	disadvantaged	1.000	Efficient
Vietnam	0.671	0.801	-0.130	disadvantaged	0.734	Inefficient

Table 4.34 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box NO model 2013

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Static Black-Box 2013					
COUNTRY	NO	NO	NO	NO	NO	NO
Argentina	0.237	0.824	-0.586	disadvantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	1.000	0.436	0.564	advantaged	0.158	Inefficient
Brazil	0.147	0.264	-0.117	disadvantaged	0.392	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.230	1.000	-0.770	disadvantaged	1.000	Efficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	0.488	1.000	-0.512	disadvantaged	0.116	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	0.300	0.740	-0.439	disadvantaged	0.160	Inefficient
Indonesia	0.263	0.800	-0.537	disadvantaged	1.000	Efficient
Malaysia	1.000	1.000	0.000	no affected	1.000	Efficient
Malta	0.742	0.153	0.589	advantaged	1.000	Efficient
Mauritius	1.000	1.000	0.000	no affected	1.000	Efficient
Mexico	0.208	0.443	-0.235	disadvantaged	0.343	Inefficient
Oman	0.576	0.512	0.064	advantaged	1.000	Efficient
Poland	0.195	1.000	-0.805	disadvantaged	1.000	Efficient
Russia	1.000	0.571	0.429	advantaged	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.254	Inefficient
Turkey	0.126	0.410	-0.284	disadvantaged	0.411	Inefficient
UAE	1.000	1.000	0.000	no affected	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.241	1.000	-0.759	disadvantaged	1.000	Efficient
Vietnam	0.512	0.634	-0.122	disadvantaged	0.417	Inefficient

Table 4.35 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box IO model 2014

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Static Black-Box 2014					
COUNTRY	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Argentina	0.479	0.950	-0.472	disadvantaged	1.000	Efficient
Armenia	1.000	0.707	0.293	advantaged	1.000	Efficient
Bangladesh	1.000	1.000	0.000	no affected	0.205	Inefficient
Brazil	0.556	0.537	0.019	advantaged	0.473	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.746	1.000	-0.254	disadvantaged	0.609	Inefficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	1.000	1.000	0.000	no affected	0.172	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	0.307	Inefficient
Indonesia	0.625	0.680	-0.055	disadvantaged	1.000	Efficient
Malaysia	0.992	0.808	0.184	advantaged	1.000	Efficient
Malta	0.826	0.476	0.350	advantaged	1.000	Efficient
Mauritius	1.000	0.733	0.267	advantaged	1.000	Efficient
Mexico	0.600	0.579	0.021	advantaged	0.488	Inefficient
Oman	0.686	0.829	-0.143	disadvantaged	1.000	Efficient
Poland	0.637	0.773	-0.137	disadvantaged	1.000	Efficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.397	Inefficient
Turkey	0.440	0.449	-0.009	disadvantaged	0.645	Inefficient
UAE	1.000	1.000	0.000	no affected	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.761	1.000	-0.239	disadvantaged	1.000	Efficient
Vietnam	0.839	0.797	0.042	advantaged	0.525	Inefficient

Table 4.36 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box OO model 2014

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Static Black-Box 2014					
COUNTRY	OO	OO	OO	OO	OO	OO
Argentina	0.429	1.000	-0.571	disadvantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	1.000	0.200	0.800	advantaged	0.613	Inefficient
Brazil	0.175	0.176	-0.001	disadvantaged	0.695	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.106	0.759	-0.654	disadvantaged	0.779	Inefficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	1.000	1.000	0.000	no affected	0.611	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	0.646	Inefficient
Indonesia	0.176	0.621	-0.445	disadvantaged	1.000	Efficient
Malaysia	0.856	0.351	0.505	advantaged	1.000	Efficient
Malta	0.706	0.239	0.467	advantaged	1.000	Efficient
Mauritius	1.000	1.000	0.000	no affected	1.000	Efficient
Mexico	0.136	0.546	-0.411	disadvantaged	0.688	Inefficient
Oman	0.406	0.552	-0.146	disadvantaged	1.000	Efficient
Poland	0.311	0.159	0.152	advantaged	1.000	Efficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	1.000	0.292	0.708	advantaged	0.686	Inefficient
Turkey	0.106	0.477	-0.371	disadvantaged	0.851	Inefficient
UAE	1.000	1.000	0.000	no affected	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.453	0.350	0.103	advantaged	1.000	Efficient
Vietnam	0.748	1.000	-0.252	disadvantaged	0.734	Inefficient

Table 4.37 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box NO model 2014

	2nd approach scores	2nd approach scores adjusted	Scores difference	Environment effect	1st approach scores	Operating environment (efficient or inefficient)
	Static Black-Box 2014					
COUNTRY	NO	NO	NO	NO	NO	NO
Argentina	0.412	1.000	-0.588	disadvantaged	1.000	Efficient
Armenia	1.000	0.417	0.583	advantaged	1.000	Efficient
Bangladesh	1.000	0.358	0.642	advantaged	0.154	Inefficient
Brazil	0.153	0.006	0.147	advantaged	0.364	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.106	0.441	-0.335	disadvantaged	0.515	Inefficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	1.000	1.000	0.000	no affected	0.113	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	0.207	Inefficient
Indonesia	0.165	0.742	-0.576	disadvantaged	1.000	Efficient
Malaysia	0.855	0.555	0.300	advantaged	1.000	Efficient
Malta	0.706	0.249	0.458	advantaged	1.000	Efficient
Mauritius	1.000	0.375	0.625	advantaged	1.000	Efficient
Mexico	0.113	0.471	-0.358	disadvantaged	0.370	Inefficient
Oman	0.406	1.000	-0.594	disadvantaged	1.000	Efficient
Poland	0.300	0.469	-0.169	disadvantaged	1.000	Efficient
Russia	1.000	0.266	0.734	advantaged	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.322	Inefficient
Turkey	0.084	0.391	-0.307	disadvantaged	0.572	Inefficient
UAE	1.000	1.000	0.000	no affected	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.418	1.000	-0.582	disadvantaged	1.000	Efficient
Vietnam	0.729	0.581	0.147	advantaged	0.459	Inefficient

Table 4.38 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box IO model 2015

	2nd approach scores	**2nd approach scores adjusted**	**Scores difference**	**Environment effect**	**1st approach scores**	**Operating environment (efficient or inefficient)**
	Static Black-Box 2015					
COUNTRY	**IO**	**IO**	**IO**	**IO**	**IO**	**IO**
Argentina	0.652	0.451	0.202	advantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	1.000	0.726	0.274	advantaged	0.243	Inefficient
Brazil	0.428	0.416	0.011	advantaged	0.426	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.982	0.610	0.372	advantaged	0.469	Inefficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	1.000	1.000	0.000	no affected	0.188	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	1.000	Efficient
Indonesia	0.481	0.399	0.081	advantaged	1.000	Efficient
Malaysia	0.988	0.655	0.333	advantaged	1.000	Efficient
Malta	1.000	1.000	0.000	no affected	1.000	Efficient
Mauritius	1.000	1.000	0.000	no affected	1.000	Efficient
Mexico	0.588	0.587	0.001	advantaged	0.448	Inefficient
Oman	0.672	0.583	0.089	advantaged	1.000	Efficient
Poland	0.883	1.000	-0.117	disadvantaged	1.000	Efficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.525	Inefficient
Turkey	0.377	0.415	-0.038	disadvantaged	0.372	Inefficient
UAE	0.650	1.000	-0.350	disadvantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.860	0.887	-0.027	disadvantaged	1.000	Efficient
Vietnam	1.000	0.960	0.040	advantaged	0.627	Inefficient

Table 4.39 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box OO model 2015

	2nd approach scores	**2nd approach scores adjusted**	**Scores difference**	**Environment effect**	**1st approach scores**	**Operating environment (efficient or inefficient)**
	Static Black-Box 2015					
COUNTRY	**OO**	**OO**	**OO**	**OO**	**OO**	**OO**
Argentina	0.608	0.482	0.126	advantaged	1.000	Efficient
Armenia	1.000	1.000	0.000	no affected	1.000	Efficient
Bangladesh	1.000	0.588	0.412	advantaged	0.610	Inefficient
Brazil	0.126	0.604	-0.479	disadvantaged	0.652	Inefficient
Canada	1.000	1.000	0.000	no affected	1.000	Efficient
Chile	0.371	0.561	-0.190	disadvantaged	0.759	Inefficient
China	1.000	0.544	0.456	advantaged	1.000	Efficient
Egypt	1.000	0.599	0.401	advantaged	0.634	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	1.000	Efficient
Indonesia	0.062	0.675	-0.612	disadvantaged	1.000	Efficient
Malaysia	0.901	0.607	0.294	advantaged	1.000	Efficient
Malta	1.000	0.080	0.920	advantaged	1.000	Efficient
Mauritius	1.000	1.000	0.000	no affected	1.000	Efficient
Mexico	0.209	0.739	-0.529	disadvantaged	0.686	Inefficient
Oman	0.449	0.713	-0.264	disadvantaged	1.000	Efficient
Poland	0.131	1.000	-0.869	disadvantaged	1.000	Efficient
Russia	1.000	1.000	0.000	no affected	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.679	Inefficient
Turkey	0.205	0.474	-0.269	disadvantaged	0.772	Inefficient
UAE	0.675	0.460	0.215	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.472	1.000	-0.528	disadvantaged	1.000	Efficient
Vietnam	1.000	1.000	0.000	no affected	0.788	Inefficient

Table 4.40 Comparative analysis of Banks' operating environments efficiency scores assessed with Static black box NO model 2015

	2nd approach scores	**2nd approach scores adjusted**	**Scores difference**	**Environment effect**	**1st approach scores**	**Operating environment (efficient or inefficient)**
	Static Black-Box 2015					
COUNTRY	**NO**	**NO**	**NO**	**NO**	**NO**	**NO**
Argentina	0.455	0.323	0.133	advantaged	1.000	Efficient
Armenia	1.000	0.189	0.811	advantaged	1.000	Efficient
Bangladesh	1.000	1.000	0.000	no affected	0.177	Inefficient
Brazil	0.104	0.255	-0.151	disadvantaged	0.296	Inefficient
Canada	1.000	0.632	0.368	advantaged	1.000	Efficient
Chile	0.371	0.212	0.159	advantaged	0.377	Inefficient
China	1.000	1.000	0.000	no affected	1.000	Efficient
Egypt	1.000	1.000	0.000	no affected	0.136	Inefficient
France	1.000	1.000	0.000	no affected	1.000	Efficient
India	1.000	1.000	0.000	no affected	1.000	Efficient
Indonesia	0.057	0.352	-0.295	disadvantaged	1.000	Efficient
Malaysia	0.901	0.486	0.415	advantaged	1.000	Efficient
Malta	1.000	1.000	0.000	no affected	1.000	Efficient
Mauritius	1.000	0.259	0.741	advantaged	1.000	Efficient
Mexico	0.139	0.404	-0.265	disadvantaged	0.342	Inefficient
Oman	0.449	1.000	-0.551	disadvantaged	1.000	Efficient
Poland	0.131	0.402	-0.271	disadvantaged	1.000	Efficient
Russia	1.000	0.076	0.924	advantaged	1.000	Efficient
Sri Lanka	1.000	1.000	0.000	no affected	0.414	Inefficient
Turkey	0.180	0.306	-0.126	disadvantaged	0.330	Inefficient
UAE	0.452	0.424	0.028	advantaged	1.000	Efficient
UK	1.000	1.000	0.000	no affected	1.000	Efficient
USA	1.000	1.000	0.000	no affected	1.000	Efficient
Uruguay	0.464	0.369	0.095	advantaged	1.000	Efficient
Vietnam	1.000	1.000	0.000	no affected	0.525	Inefficient

BIBLIOGRAPHY

Adler, N., & Golany, B. (2001). Evaluation of deregulated airline networks using data envelopment analysis combined with principal component analysis with an application to Western Europe. European Journal of Operational Research, 132, 260–273.

Adler, N., & Yazhemsky, E. (2010). Improving discrimination in data envelopment analysis: PCA–DEA or variable reduction. European Journal of Operational Research, 202, 273–284.

Akther, S., Fukuyama, H., & Weber, W. L. (2013). Estimating two-stage network slacks-based inefficiency: An application to Bangladesh banking. Omega, 41(1), 88–96.

Alpay, O., & Akturk Hayat, E. (2017). Copula approach to select input/output variables for DEA. An International Journal of Optimization and Control: Theories & Applications, 7(1), 28–34.

Aly, H.Y., Grabowski, R., Pasurka, C. & Rangan, N. (1990) Technical, scale, and allocative efficiencies in US banking: An empirical investigation. Review of Economics and Statistics, 211–218.

An, Q., Chen, H., Wu, J., & Liang, L. (2015). Measuring slacks-based efficiency for commercial banks in China by using a two-stage DEA model with undesirable output. Annals of Operations Research, 235(1), 13–35.

Andersen, P. and Petersen, N.C. (1993) A procedure for ranking efficient units in data envelopment analysis. Management Science, 39, 1261–1264.

Arsad, R., Abdullah,M. N., Alias, S.,&Isa, Z. (2017). Selection input output by restriction using DEAmodels based on a fuzzy Delphi approach and expert information. Journal of Physics: Conference Series, 892(1), 012010.

Avkiran, N.K. and Rowlands, T., (2008). How to better identify the true managerial performance: state of the art using DEA. Omega, 36(2), pp.317-324.

Avkiran, N. K., (2009a). Opening the black box of efficiency analysis: An illustration with UAE banks. Omega, 37(4), 930-941.

Avkiran, N. K., (2009b). Removing the impact of environment with units-invariant efficient frontier analysis: An illustrative case study with intertemporal panel data. Omega, 37(3), 535-544.

Avkiran, N. K., & Goto, M. (2011). A tool for scrutinizing bank bailouts based on multi-period peer benchmarking. Pacific-Basin Finance Journal, 19(5), 447–469.

Avkiran, N. K. (2015). An illustration of dynamic network DEA in commercial banking including robustness tests. Omega, 55, 141–150.

Azad, M. A. K., Munisamy, S., Masum, A. K. M., Saona, P., & Wanke, P., (2017). Bank efficiency in Malaysia: a use of malmquist meta-frontier analysis. Eurasian Business Review, 7(2), 287-311.

Badunenko, O., and Tauchmann, H., 2018. Simar and Wilson two-stage efficiency analysis for Stata, FAU Discussion Papers in Economics, No. 08/2018, Friedrich Alexander-Universität Erlangen-Nürnberg, Institute for Economics,Erlangen.

Baltagi, B.H. and Griffin, J.M. (1988) A general index of technical change. Journal of Political Economy, 20–41.

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science, 30, 1078–1092.

Banker, R. D., & Morey, R. C., (1986). Efficiency analysis for exogenously fixed inputs and outputs. Operations research, 34(4), 513-521.

Banker, R. D. (1996). Hypothesis tests using data envelopment analysis. The Journal of Productivity Analysis, 7, 139–159.

Barr, R. S., Seiford, L. M., & Siems, T. F. (1993). An envelopment-analysis approach to measuring the managerial efficiency of banks. Annals of Operations Research, 45, 1–19.

Barr, R. S., Seiford, L. M.,& Siems, T. F. (1994). Forecasting bank failure: A non-parametric frontier estimation approach. Louvain Economic Review, 60(4), 417–429.

Barr, R.S. and Siems, T.F. (1997) Bank failure prediction using DEA to measure management quality, in Interfaces in Computer Science and Operations Research (eds R.S. Barr, R.V. Helgason and J.L. Kennington), Springer, pp. 341–365.

Berger, A. N., & Mester, L. J., (1997). Inside the black box: What explains differences in the efficiencies of financial institutions? Journal of Banking & Finance, 21(7), 895-947.

Berger, A. N., & Mester, L. J. (2003). Explaining the dramatic changes in performance of US banks: Technological change, deregulation, and dynamic changes in competition. Journal of Financial Intermediation, 12, 57–95.

Bhattacharyya, A., Lovell, C. K., & Sahay, P. (1997). The impact of liberalization on the productive efficiency of Indian commercial banks. European Journal of Operational Research, 98, 332–345.

Burrows, O., Low, K., & Cumming, F. (2015).Mapping the UK financial system. Bank of England, Quarterly Bulletin, Q2, 114–129.

Bush, O., Knott, S., & Peacock, C. (2014).Why is the UK banking system so big and is that a problem? Bank of England, Quarterly Bulletin, Q4, 385–395.

Casu, B.,& Molyneux, P. (2003). A comparative study of efficiency in European banking. Applied Economics, 35(17), 1865–1876.

Chao, C. M., Yu, M. M., & Wu, H. N. (2015). An application of the dynamic network DEA model: The case of banks in Taiwan. Emerging Markets Finance and Trade, 51(sup1), S133–S151.

Chao, C.-M., Yu, M.-M., Lee, Y.-T., & Hsiao, B., (2017). Measurement of banking performance in a dynamic multiactivity network structure: Evidence from banks in Taiwan. Emerging Markets Finance and Trade, 53(4), 786-805.

Charnes, A., Cooper, W. W., & Rhodes, E., (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 2(6), 429-444.

Charnes, A., Cooper, W.W., Golany, B., Seiford, L. and Stutz, J. (1985) Foundations of data envelopment analysis for Pareto–Koopmans efficient empirical production functions. Journal of Econometrics, 30, 91–107.

Charnes, A., Cooper, W. W., Huang, Z. M., & Sun, D. B. (1990). Polyhedral cone-ratio DEA models with an illustrative application to large commercial banks. Journal of econometrics, 46(1–2), 73–91.

Chen, T.-Y. (1998) A study of bank efficiency and ownership in Taiwan. Applied Economics Letters, 5, 613–616.

Chu, S. F., & Lim, G. H. (1998). Share performance and profit efficiency of banks in an oligopolistic market: Evidence from Singapore. Journal of Multinational Financial Management, 8, 155–168.

Cinca, C. S., & Molinero, C. M. (2004). Selecting DEA specifications and ranking units via PCA. Journal of the Operational Research Society, 55, 521–528.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E., 2005. An introduction to efficiency and productivity analysis: Springer Science & Business Media.

Cooper, W.W., Seiford, L.M. & Tone, K. (2006). Introduction to Data Envelopment Analysis and Its Uses: With DEA-Solver Software and References, Springer Science & Business Media.

Cooper, W. W., Seiford, L. M., & Tone, K. (2007). Data envelopment analysis: A comprehensive text with models, applications, references and DEA-solver software (2nd ed.). Berlin: Springer.

Das, A., & Ghosh, S. (2006). Financial deregulation and efficiency: An empirical analysis of Indian banks during the post reform period. Review of Financial Economics, 15(3), 193–221.

Davies, R., Richardson, P., Katinaite, V., & Manning, M. (2010). Evolution of the UK banking system. Bank of England, Quarterly Bulletin, Q4, 321–332.

Drake, L. (2001). Efficiency and productivity change in UK banking. Applied Financial Economics, 11, 557–571.

Drake, L., Hall, M. J., & Simper, R. (2006). The impact of macroeconomic and regulatory factors on bank efficiency: A non-parametric analysis of Hong Kong's banking system. Journal of Banking & Finance, 30, 1443–1466.

Du, K., & Sim, N., 2016. Mergers, acquisitions, and bank efficiency: Cross-country evidence from emerging markets. Research in International Business and Finance, 36, 499-510.

Du, K., Worthington, A. C., & Zelenyuk, V. (2018). Data envelopment analysis, truncated regression and double-bootstrap for panel data with application to Chinese banking. European Journal of Operational Research, 265(2), 748–764.

Elyasiani, E. and Mehdian, S.M. (1990) A nonparametric approach to measurement of efficiency and technological change: The case of large US commercial banks. Journal of Financial Services Research, 4, 157–168.

Elyasiani, E. and Mehdian, S. (1992) Productive efficiency performance of minority and nonminority-owned banks: A nonparametric approach. Journal of Banking and Finance, 16, 933–948.

Emrouznejad, A., Parker, B.R. and Tavares, G. (2008) Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA. Socio-Economic Planning Sciences, 42, 151–157.

Emrouznejad, A., & Yang, G.-l., (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. Socio-Economic Planning Sciences, 61, 4-8.

Eskelinen, J. (2017). Comparison of variable selection techniques for data envelopment analysis in a retail bank. European Journal of Operational Research, 259(2), 778–788.

Fanchon, P. (2003). Variable selection for dynamic measures of efficiency in the computer industry. International Advances in Economic Research, 9(3), 175–188.

Favero, C. A., & Papi, L. (1995). Technical efficiency and scale efficiency in the Italian banking sector: A non-parametric approach. Applied Economics, 27, 385–395.

Ferrier, G. D., & Lovell, C. K. (1990).Measuring cost efficiency in banking: Econometric and linear programming evidence. Journal of Econometrics, 46, 229–245.

Ferrier,G. D.,& Hirschberg, J.G. (1997).Bootstrapping confidence intervals for linear programming efficiencynscores: With an illustration using Italian banking data. Journal of Productivity Analysis, 8(1), 19–33.

Fethi, M. D., & Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. European Journal of Operational Research, 204, 189–198.

Fisher, I. (1922). The Making of Index Numbers: A Study of Their Varieties, Tests, and Reliability, Houghton Mifflin.

Fixler, D. J., & Zieschang, K. D. (1992). User costs, shadow prices, and the real output of banks. In Output measurement in the service sectors (pp. 219–243). University of Chicago Press.

Fraser, D.R. (1976). The determinants of bank profits: An analysis of extremes. Financial Review, 11, 69–87.

Fried, H. O., Schmidt, S. S., & Yaisawarng, S., 1999. Incorporating the operating environment into a nonparametric measure of technical efficiency. Journal of Productivity Analysis, 12(3), 249-267.

Fried, H. O., Lovell, C. K., Schmidt, S. S., & Yaisawarng, S., 2002. Accounting for environmental effects and statistical noise in data envelopment analysis. Journal of Productivity Analysis, 17(1), 157-174.

Fukuyama, H. (1993) Technical and scale efficiency of Japanese commercial banks: A non-parametric approach. Applied Economics, 25, 1101–1112.

Fukuyama, H., Guerra, R. and Weber, W.L. (1999) Efficiency and ownership: Evidence from Japanese credit cooperatives. Journal of Economics and Business, 51(6), 473–487.

Fukuyama, H., & Weber, W. L., (2010). A slacks-based inefficiency measure for a two-stage system with bad outputs. Omega, 38(5), 398-409.

Fukuyama, H., & Matousek, R., (2011). Efficiency of Turkish banking: Two-stage network system. Variable returns to scale model. Journal of International Financial Markets, Institutions and Money, 21(1), 75-91.

Fukuyama, H., & Weber, W. L., (2013). A dynamic network DEA model with an application to Japanese Shinkin banks. Efficiency and Productivity Growth: Modelling in the Financial Services Industry, 193-213.

Fukuyama, H., & Weber, W. L. (2015). Measuring Japanese bank performance: A dynamic network DEA approach. Journal of Productivity Analysis, 44(3), 249–264.

Fukuyama, H., & Weber, W., (2017a). Measuring bank performance with a dynamic network Luenberger indicator. Annals of Operations Research, 250(1), pp.85-104.

Fukuyama, H., & Weber, W. L., (2017b). Japanese bank productivity, 2007–2012: A dynamic network approach. Pacific Economic Review, 22(4), 649-676.

Fukuyama, H., & Matousek, R. (2017). Modelling bank performance: A network DEA approach. European Journal of Operational Research, 259(2), 721–732.

Golany, B., & Roll, Y. (1989). An application procedure for DEA. Omega, 17(3), 237–250.

Grabowski, R., Rangan, N., & Rezvanian, R., 1993. Organizational forms in banking: An empirical investigation of cost efficiency. Journal of Banking & Finance, 17(2-3), 531-538.

Grigoroudis, E., Tsitsiridi, E., & Zopounidis, C. (2013). Linking customer satisfaction, employee appraisal, and business performance: An evaluation methodology in the banking sector. Annals of Operations Research, 205(1), 5–27.

Guarda, P., Rouabah, A., & Vardanyan, M. (2013). Identifying bank outputs and inputs with a directional technology distance function. Journal of Productivity Analysis, 40(2), 185–195.

Gulati, R., & Kumar, S. (2017). Analysing banks' intermediation and operating efficiencies using the two stage network DEA model: The case of India. International Journal of Productivity and Performance Management, 66(4), 500–516.

Halkos, G. E., & Salamouris, D. S. (2004). Efficiency measurement of the Greek commercial banks with the use of financial ratios: A data envelopment analysis approach. Management Accounting Research, 15, 201–224.

Hancock, D. (1985a). Bank profitability, interest rates, and monetary policy. Journal of Money, Credit and Banking, 17(2), 189–202.

Hancock, D. (1985b). The financial firm: Production with monetary and nonmonetary goods. Journal of Political Economy, 93(5), 859–880.

Hatami-Marbini, A., Agrell, P. J., Tavana, M., & Khoshnevis, P. (2017). A flexible cross-efficiency fuzzy data envelopment analysis model for sustainable sourcing. Journal of Cleaner Production, 142, 2761–2779.

Hauner, D., 2005. Explaining efficiency differences among large German and Austrian banks. Applied Economics, 37(9), 969-980.

Holod, D., & Lewis, H. F., 2011. Resolving the deposit dilemma: A new DEA bank efficiency model. Journal of Banking & Finance, 35(11), 2801-2810.

Jain, R. K., Natarajan, R., & Ghosh, A. (2016). Decision tree analysis for selection of factors in DEA: An application to banks in India. Global Business Review, 17(5), 1162–1178.

Jenkins, L., & Anderson, M. (2003). A multivariate statistical approach to reducing the number of variables in data envelopment analysis. European Journal of Operational Research, 147(1), 51–61.

Kaffash, S., & Marra, M. (2017). Data envelopment analysis in financial services: A citations network analysis of banks, insurance companies and money market funds. Annals of Operations Research, 253(1), 307–344.

Kao, C., & Liu, S. T. (2009). Stochastic data envelopment analysis in measuring the efficiency of Taiwan commercial banks. European Journal of Operational Research, 196(1), 312–322.

Kao, C., & Liu, S.-T., (2014). Multi-period efficiency measurement in data envelopment analysis: The case of Taiwanese commercial banks. Omega, 47, 90-98.

Kumar, P.R. and Ravi, V. (2007) Bankruptcy prediction in banks and firms via statistical and intelligent techniques – A review. European Journal of Operational Research, 180, 1–28.

Kutlar, A., Kabasakal, A., & Ekici, M. S. (2017). Efficiency of commercial banks in Turkey and their comparison: Application of DEA with Tobit analysis. International Journal of Mathematics in Operational Research, 10(1), 84–103.

Kwon, H.-B., & Lee, J. (2015). Two-stage production modeling of large U.S. banks: A DEA-neural network approach. Expert Systems with Applications, 42(19), 6758–6766.

Lee, Y. J., Joo, S.-J., & Park, H. G. (2017). An application of data envelopment analysis for Korean banks with negative data. Benchmarking: An International Journal, 24(4), 1052–1064.

Lewin, A. Y., Morey, R. C., & Cook, T. J. (1982). Evaluating the administrative efficiency of courts. Omega, 10(4), 401–411.

Li, Y., Shi, X., Yang, M., & Liang, L. (2017). Variable selection in data envelopment analysis via Akaike's information criteria. Annals of Operations Research, 253, 453–476.

Liang, L., Cook, W. D., & Zhu, J., (2008). DEA models for two-stage processes: Game approach and efficiency decomposition. Naval Research Logistics (NRL), 55(7), 643-653.

Lim, S. (2008). A decision tree-based method for selection of input–output factors in DEA. In Proceedings of the 2008 international conference on artificial intelligence, ICAI 2008, 14–17 July 2008.

Liu, J., & Tone, K. (2008). A multistage method to measure efficiency and its application to Japanese banking industry. Socio-Economic Planning Sciences, 42, 75–91.

Liu, W. B., Zhang, D. Q., Meng, W., Li, X. X., & Xu, F. (2011). A study of DEA models without explicit inputs. Omega: The International Journal of Management Science, 39(5), 472–480.

Liu, J.S., Lu, L.Y.Y., Lu, W.-M. and Lin, B.J.Y. (2013) A survey of DEA applications. Omega, 41, 893–902.

Liu, W., Zhou, Z., Ma, C., Liu, D., & Shen, W. (2015). Two-stage DEA models with undesirable input intermediate- outputs. Omega, 56, 74–87.

Liu, H.-H. (2018). Applying three-stage DEA on the operational performance of foreign banks in Taiwan. International Review of Applied Economics, 32(1), 104–118.

Lovell, C. A. K., & Pastor, J. T. (1999). Radial DEA models without inputs or without outputs. European Journal of Operational Research, 118, 46–51.

Lozano-Vivas, A., Pastor, J. T., & Pastor, J. M. (2002). An efficiency comparison of European banking systems operating under different environmental conditions. Journal of Productivity Analysis, 18(1), 59–77.

Lu, W.M., Kweh, Q.L., Nourani, M. and Wang, W.K., (2014), December. The Effects of Intellectual Capital on Dynamic Network Bank Performance. In Proceedings of International Conference on Contemporary Economic Issues 2014 (p. 71).

Luo, Y., Bi, G., & Liang, L. (2012). Input/output indicator selection for DEA efficiency evaluation: An empirical study of Chinese commercial banks. Expert Systems with Applications, 39(1), 1118–1123.

Madhanagopal, R., & Chandrasekaran, R. (2014). Selecting appropriate variables for DEA using genetic algorithm (GA) search procedure. International Journal of Data Envelopment Analysis and Operations Research, 1(2), 28–33.

Martin, D. (1977) Early warning of bank failure: A logit regression approach. Journal of Banking & Finance, 1, 249–276.

Matthews, K. (2013). Risk management and managerial efficiency in Chinese banks: A network DEA framework. Omega, 41(2), 207–215.

Meyer, P.A. and Pifer, H.W. (1970) Prediction of bank failures. Journal of Finance, 25, 853–868.

Miller, S. M., & Noulas, A. G. (1996). The technical efficiency of large bank production. Journal of Banking & Finance, 20, 495–509.

Nataraja, N. R.,&Johnson, A. L. (2011).Guidelines for using variable selection techniques in data envelopment analysis. European Journal of Operational Research, 215, 662–669.

Norman,M.,&Stoker, B. (1991). Data envelopment analysis: The assessment of performance. London:Wiley.

Nunamaker, T. R. (1985). Using data envelopment analysis to measure the efficiency of non-profit organizations: A critical evaluation. Managerial and decision Economics, 6(1), 50–58.

Olson, J. A., Schmidt, P., & Waldman, D. A. (1980). A Monte Carlo study of estimators of stochastic frontier production functions. Journal of Econometrics, 13, 67–82.

Ouenniche, J., Carrales, S., Fukuyama, H., & Tone, K. (2017). An account of DEA-based contributions in the banking sector. In K. Tone (Ed.), Advances in DEA theory and applications: With examples in forecasting models. Wiley series in operations research and management science. ISBN: 978-1-118-94562-9.

Ouenniche, J., & Carrales, S. (2018). Assessing efficiency profiles of UK commercial banks: a DEA analysis with regression-based feedback. Annals of Operations Research, 266(1-2), 551-587.Pantalone, C.C. and Platt, M.B. (1987) Predicting commercial bank failure since deregulation. New England Economic Review, 37–47.

Pasiouras, F., & Kosmidou, K., (2007). Factors influencing the profitability of domestic and foreign commercial banks in the European Union. Research in International Business and Finance, 21(2), 222-237.

Pasiouras, F. (2008). International evidence on the impact of regulations and supervision on banks' technical efficiency: An application of two-stage data envelopment analysis. Review of Quantitative Finance and Accounting, 30(2), 187–223.

Pasiouras, F., (2008). International evidence on the impact of regulations and supervision on banks' technical efficiency: an application of two-stage data envelopment analysis. Review of Quantitative Finance and Accounting, 30(2), 187-223.

Pasiouras, F., Tanna, S., & Zopounidis, C., (2009). The impact of banking regulations on banks' cost and profit efficiency: Cross-country evidence. International Review of Financial Analysis, 18(5), 294-302.

Pastor, J., Perez, F., & Quesada, J. (1997). Efficiency analysis in banking firms: An international comparison. European Journal of Operational Research, 98, 395–407.

Pastor, J. M., (2002). Credit risk and efficiency in the European banking system: A three-stage analysis. Applied Financial Economics, 12(12), 895-911.

Rangan, N., Grabowski, R., Aly, H. Y., & Pasurka, C., (1988). The technical efficiency of US banks. Economics Letters, 28(2), 169-175.

Ruggiero, J. (2005). Impact assessment of input omission on DEA. International Journal of Information Technology and Decision Making, 4(03), 359–368.

Seballos, L.D. andThomson, J.B. (1990) Underlying causes of commercial bank failures in the 1980s. Economic Commentary, Sep., Federal Reserve Bank of Cleveland, ISSN 0428-1276.

Secrist, H. (1938) National Bank Failures and Non-failures: An Autopsy and Diagnosis, Principia Press.

Seiford, L. (1996) Data envelopment analysis: The evolution of the state of the art (1978–1995). Journal of Productivity Analysis, 7, 99–137.

Shafiee, M., Sangi, M., & Ghaderi, M., 2013. Bank performance evaluation using dynamic DEA: A slacks-based measure approach. Journal of Data Envelopment Analysis and Decision Science, 2013(26), 1-12.

Sharma, M. J., & Yu, S. J. (2015). Stepwise regression data envelopment analysis for variable reduction. Applied Mathematics and Computation, 253, 126–134.

Sigala, M., Airey, D., Jones, P., & Lockwood, A. (2004). ICT paradox lost? A stepwise DEA methodology to evaluate technology investments in tourism settings. Journal of Travel Research, 43(2), 180–192.

Simar, L., & Wilson, P. W. (2001). Testing restrictions in nonparametric efficiency models. Communications in Statistics-Simulation and Computation, 30(1), 159–184.

Simar, L., & Wilson, P. W., (2007). Estimation and inference in two-stage, semi-parametric models of production processes. Journal of Econometrics, 136(1), 31-64.

Sinkey, J.F. (1975) A multivariate statistical analysis of the characteristics of problem banks. Journal of Finance, 30, 21–36.

Subramanyam, T. (2016). Selection of input–output variables in data envelopment analysis: Indian commercial banks. International Journal of Computer & Mathematical Sciences, 5(6), 2347–8527.

Tanna, S., Pasiouras, F., & Nnadi, M. (2011). The effect of board size and composition on the efficiency of UK banks. International Journal of the Economics of Business, 18, 441–462.

Taylor,W.M., Thompson, R. G., Thrall, R. M., & Dharmapala, P. (1997). DEA/AR efficiency and profitability of Mexican banks a total income model. European Journal of Operational Research, 98(2), 346–363.

Thompson, R., Dharmapala, P., Humphrey, D., Taylor, W. and Thrall, R. (1996) Computing DEA/AR efficiency and profit ratio measures with an illustrative bank application. Annals of Operations Research, 68, 301–327.

Thompson, R.G. and Thrall, R.M. (1994). Polyhedral assurance regions with linked constraints, in New Directions in Computational Economics (eds W.W. Cooper and A.B. Whinston), Springer, pp. 121–133.

Thoraneenitiyan, N., & Avkiran, N. K., 2009. Measuring the impact of restructuring and country-specific factors on the efficiency of post-crisis East Asian banking systems: Integrating DEA with SFA. Socio-Economic Planning Sciences, 43(4), 240-252.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, 130, 498–509.

Törnqvist, L. (1936) Consumption price index, Bank of Finland.

Ueda, T., & Hoshiai, Y. (1997). Application of principal component analysis for parsimonious summarization of DEA inputs and/or outputs. Journal of the Operations Research Society of Japan, 40(4), 466–478.

Wagner, J. M., & Shimshak, D. G. (2007). Stepwise selection of variables in data envelopment analysis: Procedures and managerial perspectives. European Journal of Operational Research, 180(1), 57–67.

Wang, W. K., Lu, W. M., & Liu, P. Y. (2014a). A fuzzy multi-objective two-stage DEA model for evaluating the performance of US bank holding companies. Expert Systems with Applications, 41(9), 4290–4297.

Wang, K., Huang, W., Wu, J., & Liu, Y.-N., (2014b). Efficiency measures of the Chinese commercial banking system using an additive two-stage DEA. Omega, 44, 5-20.

Wanke, P., & Barros, C. (2014). Two-stage DEA: An application to major Brazilian banks. Expert Systems with Applications, 41(5), 2337–2344.

Wanke, P., Barros, C. P., & Faria, J. R., (2015). Financial distress drivers in Brazilian banks: A dynamic slacks approach. European Journal of Operational Research, 240(1), 258-268.

Wanke, P., Barros, C. P., & Emrouznejad, A. (2016). Assessing productive efficiency of banks using integrated fuzzy-DEA and bootstrapping: A case of

Mozambican banks. European Journal of Operational Research, 249(1), 378–389.

Webb, R. (2003). Levels of efficiency in UK retail banks: A DEA window analysis. International Journal of the Economics of Business, 10, 305–322.

Webb, R., Bryce, C., &Watson, D. (2010). The effect of building society demutualisation on levels of relative efficiency at large UK commercial banks. Journal of Financial Regulation and Compliance, 18, 333–355.

Wu, Y.-C., Ting, I. W. K., Lu, W.-M., Nourani, M., & Kweh, Q. L., (2016). The impact of earnings management on the performance of ASEAN banks. Economic Modelling, 53, 156-165.

Yang, C., & Liu, H.-M., (2012). Managerial efficiency in Taiwan bank branches: A network DEA. Economic Modelling, 29(2), 450-461.

Yu, M.M., Chen, L.H., Chen, K.C. and Tone, K., (2013). Operational efficiency in Taiwan banks with consideration of nonperforming loans: A dynamic network DEA. In Workshop on DNDEA, 106-8677.

Yue, P. (1992). Data envelopment analysis and commercial bank performance: A primer with applications to Missouri banks. Federal Reserve Bank of St. Louis Review, 74, 31–45.

Zaim, O. (1995). The effect of financial liberalization on the efficiency of Turkish commercial banks. Applied Financial Economics, 5, 257–264.

Zha, Y., Liang, N., Wu, M., & Bian, Y., (2016). Efficiency evaluation of banks in China: A dynamic two-stage slacks-based measure approach. Omega, 60, 60-72.