Composite Index Construction in Performance Evaluation: A Network DEA Approach

By

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Abstract

Performance evaluation is vital to business or operations in decision-making, productivity enhancement, and continuous improvement. Effective performance assessment is essential in assisting firms or organizations to execute their strategic goals, and evaluate their competitive capabilities, operations strategy, and other actions. However, it can be difficult to implement performance evaluation and benchmarking due to the complex relations among various performance metrics for specific operations or entities under consideration. The current study focuses on composite index construction in performance evaluation via a data-oriented tool called data envelopment analysis (DEA).

DEA is a linear programming based approach for evaluating relative performances of similar operations or decision-making units (DMUs). When multiple performance metrics exist, DEA has been proven an effective tool for multiple-factor reconciliation and best-practice identification. Under big data modeling, the traditional DEA is not sufficient to deal with information and value that are hidden within data. The current dissertation develops a network DEA technique for performance metrics that are inter-linked as in network structures. We consider the internal data structures of DMUs by expanding existing simple network structures of performance measures. Unlike the existing network DEA models which can be solved via linear programming, network DEA models in the current study are non-linear due to the complexity of the performance data's network structures. We use the second-order cone programming (SOCP) technique to solve the non-linear network DEA models.

The current study applies the new network DEA technique to provide a performance evaluation index for eight major airlines from 2006 to 2016 via considering both operations and economics metrics. The new technique is also applied to evaluate the globalization performance via constructing composite globalization indices for countries by integrating globalization indicators in political, economic and social dimension.

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Chapter I Introduction

1.1 Introduction

Since it was coined by Charnes et.al (1978), data envelopment analysis (DEA) has been regarded as an effective data-oriented tool for performance evaluation and benchmarking. Not only can it be used for traditional uses, such as evaluate production efficiency and productivity measurement, but also can be applied to productivity analytics, performance evaluation, benchmarking, comprehensive index construction, and others (Zhu, 2020). Especially, with the development of big data in operation analytics, DEA, in particular, network DEA, is also treated as a data-enabled analytic (Zhu, 2020) tool to solve cases that have complex nature of relations among metrics under consideration. The network DEA system has been an important area of development in DEA in recent ten years. Under a network DEA framework, in addition to the inputs and outputs, a set of intermediate measures exists in-between stages.

In terms of big data, organizations and individuals treat operations management as a significant area in big data analytics for both practitioners and academic studies. However, whether they use the best technique and how to determine the best technique while doing big data analysis in operations are still under development (Choi et al., 2018). Here, the current dissertation implements the network DEA system into applications under the context of big data, which provides an alternative to do performance evaluation and comprehensive index construction. Worthy of a special mention is that DEA requires very few assumptions and can be used in cases which have been resistant to other approaches.

The remaining sections of this chapter are organized as the followings. Section 1.2 provides an overview of the background and motivations. In section 1.3, it illustrates research problems. Finally, section 1.4 is about the structure of this study.

1.2 Backgrounds and motivations

Big data has been a research buzzword since it was introduced by Roger Mougalas from O'Reilly Media in 2005. There are various definitions of big data, but three "V" features are called its common characteristics: volume, variety, and velocity, which stand for the large datasets, different types of data from myriad sources, and real-time data collected, respectively. With operations management as a more and more important area in big data analytics, over eight hundreds of publications have been found in the Web of Science database. Among them, over six hundred came up since 2017. Big data has been applied to many operations management topical areas, such as optimization, forecasting, inventory management, supply chain management, risk analysis, and others. For comprehensive reviews about literature, more information can be found in Addo-Tenkorang and Helo (2016) and Choi, et al. (2018).

Big data analytics create values for countries, organizations, companies, and individuals, at the same time, they reveal significant challenges of transferring data into useful information. The increasing number of applications in big data analytics in operations management leads to high demand for efficient data analytic methods and techniques. However, as mentioned in Choi, et al. (2018), effective techniques that have been utilized in operation analytics in the big data area are still under development, which motivates to develop this dissertation. This study introduces an alternative big data-related analytics technique called DEA, which has been approved as an effective tool in performance evaluation, benchmarking, and comprehensive index construction since it was introduced by Charnes et.al (1978).

As mentioned before, big data has three common characteristics: volume, variety, and velocity. Under the context of DEA, Zhu (2020) proposes that the number of decision-making units (DMUs) can be regarded as the “volume”, special algorithms are needed in a short period in order to process a large amount of DMUs is related to the “velocity”, and different types of inputs and outputs in DEA reflects the “variety”. Except for the three “V”, Zhu (2020) also mentions that “value is another important dimension of big data and it sits at the top of the big data pyramid” as it is highly relevant to the ability to obtain useful information from data. This current dissertation focus on dealing with the fourth “V”, the “Value” dimension in big data.

Few publications have been found in terms of applying DEA in the context of big data in current existing literature. According to the Web of Science database, less than thirty publications are utilizing DEA in big data modeling. Most of them focus on evaluating efficiency or performance evaluation, especially in the environment area (An, et al., 2017; Chen and Jia, 2017; Chu, et al., 2018; Song, et al., 2018). For example, Song, et al. (2018) present the opportunities and applications for theories and technologies in the context of big data after reviewing the literature of environmental performance evaluation. In their research, they discuss problems and challenges for these related areas and summarize the latest advance in environmental management based on big data technologies. Chu, et al. (2018) apply a slack-based measure (SBM) DEA to discuss an environmental efficiency evaluation problem when discussing big data, while two publications utilizing a network DEA under the consideration of big data context (see for Mavi, et al., 2019) and Zhong, et al. (2020) in other areas. Among them, Zhong, et al. (2020) measure the technological innovation efficiency for China's strategic emerging industries in all provinces via a non-oriented SBM network DEA model. In sum, the use of DEA for big data focuses on evaluating the efficiency or performance, and few of them consider a network DEA model. Thus, the second motivation for this current study is that it constructs a set of network DEA models to deal with the "value" dimension in big data context which may help to eliminate bias if utilizing the traditional one-stage DEA model.

Last but not least, new network DEA models in this study are highly non-linear models due to the nature complexity relations among metrics under consideration. This dissertation utilizes a technique called second order cone programming (SOCP) to solve the non-linear network models without any predetermined parameters.

1.3 Research problems

In this research, it conducts both the traditional two-stage network DEA and the additive slack-based measure (ASBM) network DEA under big data context in evaluating airline's performance and providing a set of comprehensive globalization indices via integrating metrics from multi-dimensions, respectively.

The first research problem comes from what we have introduced in the above section that few publications have been found which apply DEA in the context of big data in the current existing literature. Especially, there are only two publications which utilize a network DEA in big data modeling. Zhu (2020) provides adoptions about how network DEA can be used in big data research. As limited publications which apply DEA in big data analytics have been found. It is in my interest that in addition to evaluate performance and efficiency, my dissertation seeks more possibilities to apply DEA models, in particular, network DEA models, in other areas, such as composite index under big data environment. Since it is not feasible to cover all "V" characteristics of big data, this dissertation here emphasizes the "Value" aspect in big data which focuses on how to transfer useful information from big data.

The second research problem of this dissertation is about how to measure the performance in operations management considering metrics from multi-dimensions. The majority of extant studies centering on performance and efficiency benchmarking of firms utilize only operational measures while neglecting indicators from other dimensions in their methodological frameworks, such as stock market dimension, social dimension, political dimension, and others. They may lead to erroneous or biased conclusions about performance in a firm or an organization. For example, in many competitive industries, like the airline industry, managers need to be acutely aware of not only their operational efficiency but also the sentiment, attitudes and expectations of their shareholders and the stock market at large, which may require to integrate both operational indicators and financial market indicators into the methodological framework.

The last research problem discusses how to solve the non-linear problem in network DEA models as this dissertation generalizes the network structure based upon the data structure itself. In the current existing literature, there are two ways to solve the non-linear issue in network DEA for additive performance. One is to choose a special set of weights to convert the objective function into a single linear fractional form (see for example Cook et al., 2010). On another hand, Chen and Zhu (2017) and Chen and Zhu (2020) show that for two-stage network DEA models, when the overall performance is expressed as a product of the two stages' performance scores, the network DEA model can be solved using a second order cone programming (SOCP) technique. In the current dissertation, it develops and integrates the second order cone programming (SOCP) technique introduced by Chen and Zhu (2017) and Chen and Zhu (2020) in a set of network DEA models to solve the non-linear problem under big data environment.

1.4 Organizations

The remaining chapters of this dissertation are organized as follows.

Chapter 2 provides a literature overview of DEA. A discussion of two basic DEA models has been provided in both envelopment side and multiplier side. This is followed by an introduction of the SBM DEA model and super-efficiency model, which are two extensions of basic DEA models. After that, network DEA structures and two ways of overall score decomposition in network DEA have been introduced, as well as the overview review of network DEA applications in current existing literature, especially applications in traditional two-stage DEA and SBM network DEA.

Chapter 3 builds and implements a two-stage network DEA process which integrates both operational and stock market indicators in order to evaluate the performance of eight major international airline companies from 2006 until 2016. In this chapter, it shows that there is heterogeneity in the performance of all airlines across time. Most notably, during the 2013-14 European debt crisis and United States debt-ceiling crisis, the stock market-based performance scores declined significantly for all sampled companies under consideration. It also shows that full-service carriers earn higher performance scores based on stock market indicators, while low-cost carriers generally maintain higher operational-based performance scores than their full-service counterparts. This finding lends support to the approach and the general premise which argues that performance evaluation methods can yield more comprehensive conclusions if both operational and stock market indicators are utilized.

Chapter 4 introduces a political-economic globalization index (PEGI) via constructing a two-stage SBM DEA model. It integrates indicators of globalization from both political dimension and economic dimension, as well as provides PEGI for countries around the world during a time period from 1995 to 2015. A SOCP has been implementing to solve the non-linear problem in the network DEA model. It shows that the U.S. has the highest PEGI among 79 countries under consideration in 2015, while Malawi has the lowest PEGI. Conclusions have also been introduced.

Chapter 5, which introduces an economic-social globalization index (ESGI), is similar to chapter 4. The main difference between these two chapters is that the indicators under consideration are from different dimensions. In chapter 5, it focuses on indicators of globalization which are from the economic dimension and the social dimension, while chapter 4 utilizes indicators in the political dimension and economic dimension. In this chapter, it also constructs the composite globalization performance score for countries around the world in one year time window from the total sample period 1995 to 2015. According to the results, in addition to United State, Germany also obtains a value of one (the highest score) for ESGI.

Chapter 6 discusses how a country's globalization performance via integrating indicators of globalization from the political dimension, the economic dimension, and the social dimension. In this chapter, the two-stage network structure in chapter 4 and chapter 5 has been expanded into a three-stage network structure according to the actual data inner relationship. An ASBM model with SOCP is utilized, and the same 79 countries which have been analyzed in chapter 4 and chapter 5 have been considered. The result shows that the United States and China perform best in globalization via this three-stage ASBM network DEA approach.

Chapter 7 discusses the conclusions, research contributions, and future researches.

Chapter II Literature Review: Data Envelopment Analysis

2.1 Introduction

DEA is a "data-oriented" approach for evaluating the performance of a set of peer entities, called DMUs, with multiple inputs and multiple outputs (Cooper et al., 2011). The first DEA model was introduced by Charnes et al., (1978), and it has been applied in many different areas since 1978.

NDEA is also a branch of DEA that has substantially been developed in recent years. In the NDEA structure, intermediate factors which are outputs in a stage and inputs in the next stage, have been considered. For example, Seiford et al. (1999) utilize a two-stage network structure to measure the profitability and marketability of U.S. commercial banks. In the first stage of their study, revenues and profits are used as outputs where labor, assets, and capital stock are considered as inputs, in order to measure the profitability of DMUs. The outputs in the first stage are considered as inputs to measure the marketability of DMUs in the second stage. The outputs in the second stage are selected as market value, the total return to investors, and earnings per share. Zhu (2000) also applies the same two-stage network structure to the Fortune Global 500 companies.

In addition to the development of DEA models, DEA is also a well-known and effective tool for performance evaluation and benchmarking in finance, education, banking, environment, transportation, and so forth. Liu et al. (2013) mention that five major applications of DEA can be introduced as banking, healthcare, agriculture and farm, transportation, and education, respectively. The applications of DEA in these areas include 41.09% of all DEA applications.

As DEA is the main implemented technique in this dissertation, this chapter discusses basic DEA models, NDEA models, and a summary of NDEA applications.

The rest of this chapter is organized as follows. Section 2.1 illustrates two basic DEA models in both envelopment form and multiplier form. Section 2.2 presents an extension of the SBM model. In section 3.3, the NDEA's structures and two approaches to decompose the overall efficiency scores are introduced. Section 2.4 provides an overview of DEA applications.

2.2 Basic DEA models

DEA models are generally categorized into four major production technologies on the basis of economic concept of returns to scale. These technologies are called constant returns to scale (CRS), variable returns to scale (VRS), non-increasing returns to scale, and non-decreasing returns to scale. Charnes. et al. (1978) proposed the first DEA model in CRS, also known as CCR model. Banker et al. (1984) proposed the VRS model, called the BCC model. In the next sections, these models are described.

2.2.1 The CCR model

Assume that there is a set of n DMUs where each DMU_j, $(j=1,2,...,n)$ has m inputs x_{ij} , $(i=1,2,...,m)$ and s outputs y_{rj} , $(r=1,2,...,s)$. Assume that $x_{ij} \geq 0, y_{rj} \geq 0$, and each DMU has at least one positive input and one positive output. The following CCR model measures the relative efficiency of DMU_0 .

$$
\begin{aligned}
& E^* = \max \sum_{r=1}^{s} u_r y_{r0} / \sum_{i=1}^{m} v_i x_{i0} \qquad (2.1) \\
& s.t. \quad \sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \leq 1, \qquad j=1,...,n \\
& u_r, v_i \geq \varepsilon, \qquad r=1,...,s, i=1,...,m
\end{aligned}
$$

In model (2.1), DMU_0 represents one of the n DMU_s , x_{i0} and y_{r0} are the *i*th input and *r*th output for DMU_0, respectively, and ε is a very small positive real number, called non-Archimedean epsilon. The constraints show the ratio of 'the weighted virtual outputs' to 'the weighted virtual inputs'. This ratio is exceed 1 for each DMU . The objective in model 2.1 is to maximize the ratio of the weighted outputs of DMUo to its weighted inputs. The optimal objective, E^* is at most equal to 1.

Model (2.1) provides CRS efficiency scores for DMUs. CRS says that the proportional increase (decrease) in input values affect the same proportional increase (decrease) in output values (Cooper, et al., 2004).

By applying Charnes-Cooper transformation (Charnes and Cooper, 1962) and defining $\mu_r = tu_r$ and $\upsilon_i = tv_i$, where $t = \frac{1}{\sum_{i=1}^{m} v_i x_{i0}}$, the above model (2.1) can be transformed to the following linear program model (2.2):

$$
\begin{aligned}
& E^* = \max \sum_{r=1}^{s} \mu_r y_{r0} && (2.2)\\
& s.t. \quad \sum_{i=1}^{m} \upsilon_i x_{i0} = 1 \\
& \quad \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \upsilon_i x_{ij} \le 0, \quad j = 1, \ldots, n \\
& \quad \mu_r, \upsilon_j \ge \varepsilon, \quad r = 1, \ldots, s, i = 1, \ldots, m
\end{aligned}
$$

The dual linear programming of model (2.2) is given by:

$$
\begin{aligned}
& \min \theta - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) && (2.3)\\
& s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i0}, \quad i = 1, \ldots, m \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0,} \quad r = 1, \ldots, s \\
& \quad \lambda_j, s_i^-, s_r^+ \ge 0, \quad j = 1, \ldots, n, i = 1, \ldots, m, r = 1, \ldots, s
\end{aligned}
$$

In general, model (2.2) is referred to as the multiplier CCR model, where model (2.3) is referred to as the envelopment CCR model. Here, s_i^- and s_r^+ are the input slacks and output shortfalls, respectively.

Note that model (2.1), model (2.2), and model (2.3) are in input-oriented approach, that is, determining the possible decrease in inputs at the same outputs' level. The output-oriented approach is introduced by model (2.4).

$$Q^* = \min \sum_{i=1}^{m} v_i x_{i0} / \sum_{r=1}^{s} u_r y_{r0} \qquad (2.4)$$

$$s.t. \quad \sum_{i=1}^{m} v_i x_{ij} / \sum_{r=1}^{s} u_r y_{rj} \geq 1, \qquad j = 1, \ldots, n$$

$$u_r, v_j \geq \varepsilon, \qquad r = 1, \ldots, s, i = 1, \ldots, m$$

Similarly, by applying the Charnes-Cooper transformation model (2.5) concluded.

$$Q^* = \min \sum_{i=1}^{m} \upsilon_i x_{i0} \qquad (2.5)$$

$$s.t. \quad \sum_{r=1}^{s} \mu_r y_{r0} = 1$$

$$\sum_{i=1}^{m} \upsilon_i x_{ij} - \sum_{r=1}^{s} \mu_r y_{rj} \geq 0, \qquad j = 1, \ldots, n$$

$$\mu_r, \upsilon_j \geq \varepsilon, \qquad r = 1, \ldots, s, i = 1, \ldots, m$$

The output-oriented CRS model in envelopment form is also given by:

$$\max \varphi + \varepsilon (\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+) \qquad (2.6)$$

$$s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0}, \qquad i = 1, \ldots, m$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \varphi y_{r0,} \qquad r = 1, \ldots, s$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \qquad j = 1, \ldots, n, i = 1, \ldots, m, r = 1, \ldots, s$$

From an output-oriented approach, possible increase in output values for a DMU at the same level of inputs are measured.

2.2.2 The BBC model

The input-oriented BCC model proposed by Banker et al. (1984) to evaluate efficiency score of DMU_0 in VRS. BCC differs from CCR by an additional variable u_0, as shown in model (2.7).

$$
\begin{aligned}
& E_{VRS}^{*} = \max(\sum_{r=1}^{s} u_r y_{r0} - u) / \sum_{i=1}^{m} v_i x_{i0} && (2.7)\\
& s.t. \quad (\sum_{r=1}^{s} u_r y_{rj} + u) / \sum_{i=1}^{m} v_i x_{ij} \leq 1, \quad j = 1,\ldots,n \\
& \qquad u_r, v_j \geq 0, \quad r = 1,\ldots,s, i = 1,\ldots,m \\
& \qquad u \quad free
\end{aligned}
$$

The equivalent linear programming model to model (2.7) is expressed as:

$$
\begin{aligned}
& E_{VRS}^{*} = \max \sum_{r=1}^{s} \mu_r y_{r0} - \mu && (2.8)\\
& s.t. \quad \sum_{i=1}^{m} \upsilon_i x_{i0} = 1 \\
& \qquad \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \upsilon_i x_{ij} + \mu \leq 0, \quad j = 1,\ldots,n \\
& \qquad \mu_r, \upsilon_j \geq 0, \quad r = 1,\ldots,s, i = 1,\ldots,m \\
& \qquad \mu \quad free
\end{aligned}
$$

Table 2.1 shows the multiplier and envelopment BCC models in input-oriented and output-oriented approaches.

Table 2.1 Other BCC models

Envelopment Model	Multiplier Model
Input-oriented	
$\begin{aligned} &\min \theta - \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+) \\ &s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta x_{i0}, \quad i = 1,\ldots,m \\ &\qquad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0,} \quad r = 1,\ldots,s \\ &\qquad \sum_{j=1}^{n} \lambda_j = 1 \\ &\qquad \lambda_j, s_i^-, s_r^+ \ge 0, \quad j = 1,\ldots,n, i = 1,\ldots,m, r = 1,\ldots,s \end{aligned}$	$\begin{aligned} &\max \sum_{r=1}^{s} \mu_r y_{r0} - \mu \\ &s.t. \quad \sum_{i=1}^{m} \upsilon_i x_{i0} = 1 \\ &\qquad \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \upsilon_i x_{ij} + \mu \le 0, \quad j = 1,\ldots,n \\ &\qquad \mu_r, \upsilon_j \ge \varepsilon, \quad r = 1,\ldots,s, i = 1,\ldots,m \\ &\qquad \mu \quad free \end{aligned}$
Output-oriented	
$\begin{aligned} &\max \varphi + \varepsilon(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+) \\ &s.t. \quad \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{i0}, \quad i = 1,\ldots,m \\ &\qquad \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^+ = \varphi y_{r0,} \quad r = 1,\ldots,s \\ &\qquad \sum_{j=1}^{n} \lambda_j = 1 \\ &\qquad \lambda_j, s_i^-, s_r^+ \ge 0, \quad j = 1,\ldots,n, i = 1,\ldots,m, r = 1,\ldots,s \end{aligned}$	$\begin{aligned} &\min \sum_{r=1}^{s} \upsilon_i x_{r0} + \mu \\ &s.t. \quad \sum_{i=1}^{m} \mu_r y_{r0} = 1 \\ &\qquad \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{i=1}^{m} \upsilon_i x_{ij} - \mu \le 0, \quad j = 1,\ldots,n \\ &\qquad \mu_r, \upsilon_j \ge \varepsilon, \quad r = 1,\ldots,s, i = 1,\ldots,m \\ &\qquad \mu \quad free \end{aligned}$

2.3 Extensions of basic models

2.3.1 The SBM model: non-radial model

DEA models can be categorized into two categories, such as radial and non-radial models. The CCR and BCC models are radial models, that is, a proportional decrease in inputs or a proportional increase in outputs to achieve efficiency. Using radial models, slacks may still exist in some inputs (outputs). To deal with this problem, several non-radial DEA models are developed to measure the possible reduction in inputs and the possible increase in outputs. For example, Charnes et al. (1985) proposed an additive model which combines both input and output orientations in a single model. Tone (2001) proposed a non-radial DEA model, called the Slack-Based Measure (SBM) model. The SBM model is formulated as below:

$$
\begin{aligned}
\min \quad & \rho = \frac{1-(1/m)\sum_{i=1}^{m} s_i^- / x_{io}}{1+(1/s)\sum_{r=1}^{s} s_r^+ / y_{r0}} && (2.9) \\
s.t. \quad & x_{i0} = \sum_{j=1}^{n} \lambda_j x_{ij} + s^- \quad \forall i \\
& y_{i0} = \sum_{j=1}^{n} \lambda_j y_{rj} + s^+ \quad \forall r \\
& \lambda_j, s^-, s^+ \geq 0, \forall j, i, r
\end{aligned}
$$

In the model (2.9), s_i^- and s_r^+ indicate the input excess and output shortfall, respectively. Here, λ_j is the intensity variable, and indicates the importance of DMU_j in measuring the efficient score of DMU_0 . The constraints in model (2.9) are similar to those of additive DEA model. The main difference between the additive DEA model and SBM is the objective function. The SBM measurement is unit invariant. From the unit invariant property, the unit measurement for slacks are the same as the corresponding inputs and outputs. Model (2.9) is a non-oriented model, however, it can be transformed into the input-oriented or output-oriented CCR models where $s_i^- = s^-, s_r^+ = 0, \forall i, r$ or $s_r^+ = s^+, s_i^- = 0, \forall i, r$, respectively.

In addition, model (2.9) can be transformed to a linear programming problem, using the Charnes-Cooper transformation. To show this, a scalar variable $t(t > 0)$ is multiplied to both denominator and numerator of the objective of model (2.9). Now, assuming that $S^- = ts^-, S^+ = ts^+, and \varphi = t\lambda$, results model (2.10).

$$
\begin{aligned}
Min \quad & \tau = t - (1/m)\sum_{i=1}^{m} S_i^- / x_{io} && (2.10)\\
s.t. \quad & 1 = t + (1/s)\sum_{r=1}^{s} S_r^+ / y_{ro} \\
& tx_{i0} = \sum_{j=1}^{n} \varphi_j x_{ij} + S^- \quad \forall i \\
& ty_{i0} = \sum_{j=1}^{n} \varphi_j y_{rj} + S^+ \quad \forall r \\
& \varphi_j, S^-, S^+ \geq 0, t > 0, \forall j, i, r
\end{aligned}
$$

If ($\tau^*, t^*, \varphi^*, S^{-*}, S^{+*}$) is an optimal solution for model (2.10), then ($\rho^* = \tau^*, \lambda^* = \varphi^* / t^*, s^{-*} = S^{-*} / t^*, s^{+*} = S^{+*} / t^*$) is an optimal solution for model (3.9). As shown by Tone (2001), we have the following definition:

Definition 3.1 *(SBM-efficiency):* A $DMU(x_{0,}y_0)$ is SBM-efficient if $\rho^* = 1$ or equivalently, $s^{-*} = s^{+*} = 0$, that is, there are no input excess nor output shortfalls in any optimal solution.

2.3.2 The super-efficiency model

The super-efficiency approach is used for sensitivity analysis in DEA, such as the CCR super-efficiency model, the BCC super-efficiency model, and the SBM super-efficiency model. From a super-efficiency model, in order to evaluate the performance of a DMU, the DMU is not included in the reference set. Charnes et al. (1992) develop a super-efficiency sensitivity analysis model that measures the proportional changes in all inputs and outputs for a specific DMU simultaneously. Zhu (1996) and Seiford and Zhu (1998) introduce robustness and stability of efficient DMUs, where inputs and outputs can be changed individually.

Model (2.11) illustrates the super-efficiency CCR model. Similarly, model (2.12) shows the super-efficiency BCC model.

$$\min \theta^{SUPER} - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{2.11}$$

$$\begin{aligned} s.t. \quad & \sum_{j=1,\, j\neq 0}^{n} \lambda_j x_{ij} + s_i^- = \theta^{SUPER} x_{i0}, \qquad i = 1,\ldots,m \\ & \sum_{j=1,\, j\neq 0}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0,} \qquad r = 1,\ldots,s \\ & \lambda_j, s_i^-, s_r^+ \geq 0, \qquad j = 1,\ldots,n, i = 1,\ldots,m, r = 1,\ldots,s \end{aligned}$$

$$\min \theta^{SUPER} - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \tag{2.12}$$

$$\begin{aligned} s.t. \quad & \sum_{j=1,\, j\neq 0}^{n} \lambda_j x_{ij} + s_i^- = \theta^{SUPER} x_{i0}, \qquad i = 1,\ldots,m \\ & \sum_{j=1,\, j\neq 0}^{n} \lambda_j y_{rj} - s_r^+ = y_{r0,} \qquad r = 1,\ldots,s \\ & \sum_{j=1,\, j\neq 0}^{n} \lambda_j = 1 \\ & \lambda_j, s_i^-, s_r^+ \geq 0, \qquad j = 1,\ldots,n, i = 1,\ldots,m, r = 1,\ldots,s \end{aligned}$$

Note that in the above models, the DMU under evaluation has been removed from the reference set, as shown by the constraint $j \neq 0$.

Correspondingly, the SBM super-efficiency model (Tone, 2002) can be illustrated as follows:

$$\min \qquad \rho = \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x}_i / x_{io}}{\frac{1}{s}\sum_{r=1}^{s} \bar{y}_r / y_{r0}} \tag{2.13}$$

$$\begin{aligned} s.t. \qquad & \bar{X} \geq \sum_{j=1, j\neq 0}^{n} \lambda_j X_j \\ & \bar{Y} \leq \sum_{j=1, j\neq 0}^{n} \lambda_j Y_j \\ & \bar{X} \geq X_0 \ and \quad , \bar{Y} \leq Y_0 \quad , \bar{Y} \geq 0 , \lambda \geq 0 \end{aligned}$$

The fractional program (2.13) can be transformed into a linear programming problem, given by model (2.14), where $\rho^* = \tau^*$, $\lambda^* = \varphi^*/t^*$, $\bar{X}^* = \tilde{X}^*/t^*$, and $\bar{Y}^* = \tilde{Y}^*/t^*$.

$$\min \qquad \tau = \frac{1}{m}\sum_{i=1}^{m} \tilde{x}_i / x_{io} \tag{2.14}$$

$$\begin{aligned} s.t. \qquad & 1 = \frac{1}{s}\sum_{r=1}^{s} \frac{\tilde{y}_r}{y_{r0}}, \\ & \tilde{X} \geq \sum_{j=1, j\neq 0}^{n} \varphi_j X_j \\ & \tilde{Y} \leq \sum_{j=1, j\neq 0}^{n} \varphi_j Y_j \\ & \tilde{X} \geq tX_0 \ and \quad , \tilde{Y} \leq tY_0 \quad , \tilde{Y} \geq 0 , \varphi \geq 0, t > 0 \end{aligned}$$

2.4 The NDEA

2.4.1 The NDEA structures

Charnes, et al. (1986) address the need to study the performance of a DMU and its component processes, simultaneously. For this aim, a lot of researches have been developed during the last four decades. These studies can be found in the studies of Kao and Hwang (2008), Chen (2009), Liang et al. (2008), Tone and Tsutsui (2014), and Kao (2014).

One particular network structure in DEA is to separate the whole operation process into two detailed processes that helps to identify the impact of each factor. For example, Seiford and Zhu (1999) use a two-stage network structure to measure the profitability and marketability of U.S. commercial banks. There are many complicated networks that the entire process is separated into more than two processes. Kao (2014) introduces a framework to classify network DEA structures. These structures can be classified as a) series, b) parallel, c) mixed, d) hierarchical, and e) dynamic. A brief introduction about these five structures is introduced in the following subsections.

2.4.1.1 The series structure

The series structure is the main DEA network structure that has been widely used in the DEA literature. This structure refers to a number of processes connected in sequence, where each process consumes the exogenous inputs and intermediate products produced by the preceding process and produces exogenous outputs and intermediate products for the succeeding ones to use Kao (2014). Figure 2.1 illustrates the general series structure.

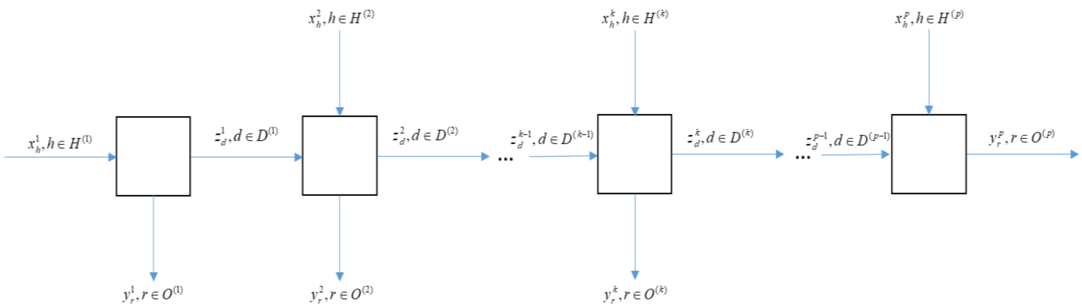

Figure 2.1 A series structure

One of the basic series structure is the two-stage structure (see for Seiford and Zhu, 1999; Zhu, 2000; Luo, 2003; Tsai and Wang, 2010; Kao and Hwang, 2008; Tajbakhsh and Hassini, 2018). All inputs from outside, x_i, are applied to the first process to produce intermediate factors, z_d. After that, all intermediate factors, z_d, are used to produce the final outputs, y_r. A basic two-stage network structure is shown in Figure 2.2.

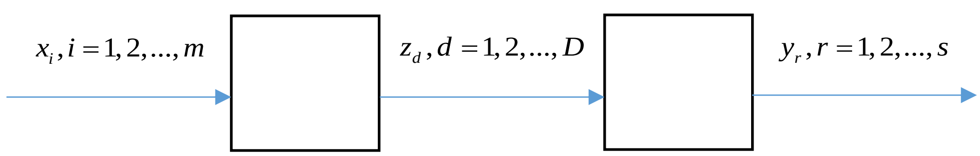

Figure 2.2 A basic two-stage structure

Another example of series structure is a generalization of the basic two-stage structure, which allows both of processes to use outside inputs and produce final outputs, This structure can be seen in the studies of Charnes, et al. (1986), Färe and Whittaker (1995), Chen, et al. (2006), Chen, et al. (2012), Zhou, et al. (2013), and

Zhang, et al. (2019). A general two-stage network structure is shown in the following Figure 2.3.

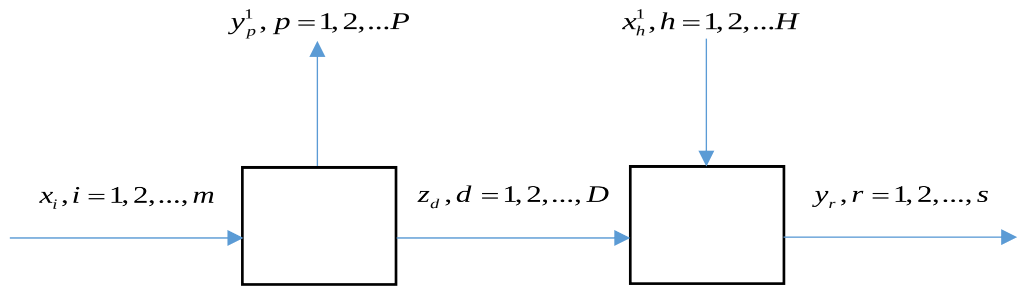

Figure 2.3 A general two-stage structure

2.4.1.2 The parallel structure

In a parallel structure, all processes operate independently, as shown in Figure 2.4. this structure is very similar to the multi-period system. The only difference between the parallel structure and the multi-period system is that the inputs and outputs of each sub-system are not the same in parallel structure, whereas the multi-period system requires that the inputs and outputs of each period be the same.

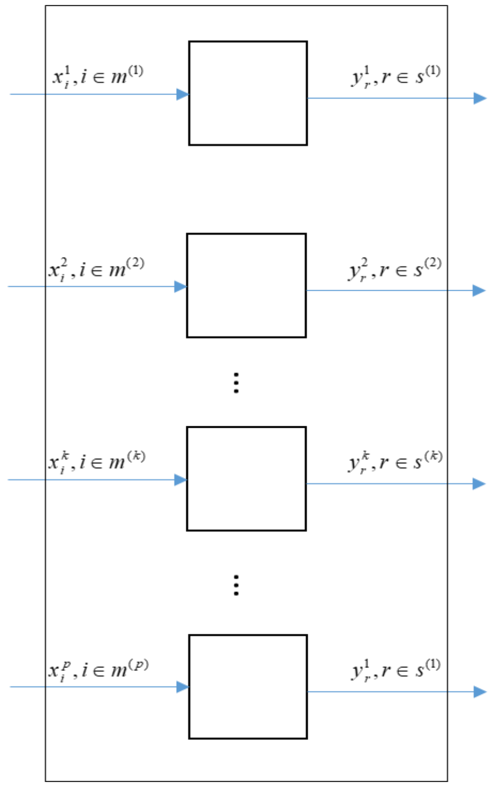

Figure 2.4 Parallel structure

2.4.1.3 The mixed structure

The mixed structure is neither a series structure nor a parallel structure, but a mix of both. Network systems with mixed structures are more relevant to depict real-world problems. The complexity to obtain the overall results in this structure is high, however, a few studies can be found in the literature.

Figure 2.5 shows an example of the mixed structure proposed by Adler, et al. (2013). They analyzed the performance of 43 airports in 13 European countries, where two stages of operations were identified. The first stage has one process of generating passengers and cargo, while the second has two processes of aeronautical and non-aeronautical activities. The two stages are evaluated independently.

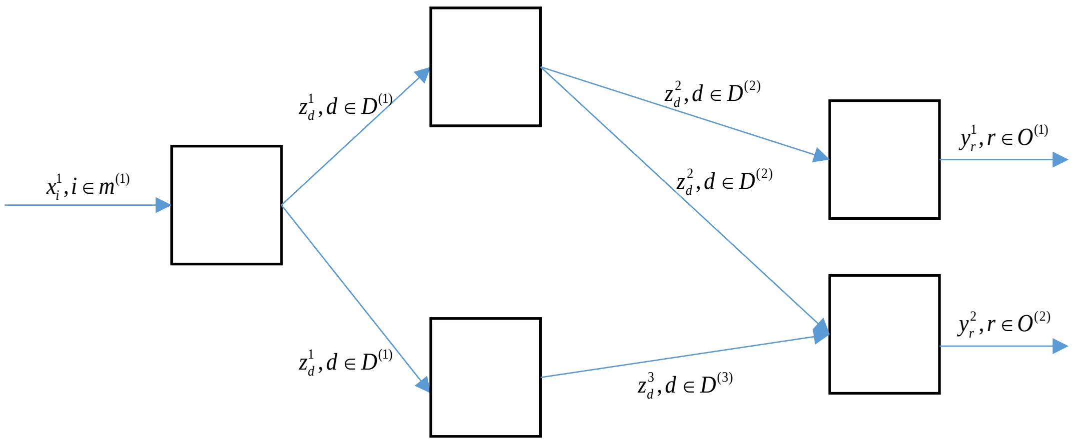

Figure 2.5 an example of mixed structure

2.3.1.4 The hierarchical structure

In the previous structures, DMUs have been evaluated under the same consideration, wherein real-life applications, the performance of a subgroup of DMUs should be measured all together to be compared with other DMUs or other groups of DMUs (Cook, et al. (1998)). In those cases, the grouping is a natural phenomenon which needs to be considered together rather than considering each individual units in one group. The hierarchical structure is applied to those cases that DMUs should be categorized into different groups and each group should be evaluated.

A hierarchical structure has also serval levels. When there is one level only and there is no interaction between the headquarters and subordinate units, the hierarchical structure is equivalent to a parallel structure. For example, Kao (2009) treats the subordinate working circles of a forest district as a set of parallel processes operating independently and uses a parallel model to measure the efficiency of forest districts.

2.4.1.5 The dynamic structure

Almost all human activities are dynamic (Färe and Grosskopf, 1997). Dynamic structures concern the repetition of a single-period system connected by carryovers. Kao (2014) mentions that dynamic structure could be considered as a special type of series structure, as the inputs, outputs, and intermediate are the same in each period.

Since a dynamic structure is adapted from the real-world application, many methodology development and application studies can be found in this area. For example, Tone and Tsutsui (2014) propose a dynamic DEA model including network structure in each period within the framework of SBM. From their model, the overall efficiency over the entire observed period, the dynamic change of period efficiency, and the dynamic change of divisional efficiency are evaluated. Sueyoshi and Sekitani (2005) incorporate the concept of returns to scale into the dynamic DEA. Chen (2009) proposes a systematic approach to incorporate the effect of efficiency measurement to solve biases that occur from the dynamic effect in production networks. In terms of dynamic structure application, Amirteimoori (2006) obtains the dynamic efficiencies of 11 gas companies in two periods along with the efficiency of the whole period. Kao (2013) applies a dynamic DEA model to measure the system and period efficiencies at the same time for multi-period systems. Lu et al. (2014) apply the dynamic SBM model to evaluate the performance of 34 Chinese life insurance companies for the period 2006–2010.

2.4.2 Measuring network DEA

In this section, two types of efficiency decomposition are discussed for two-stage network systems: a) multiplicative decomposition and b) additive decomposition. As Cook and Zhu (2014) summarize, the overall efficiency in multiplicative efficiency decomposition is defined as a product of the two individual stages' efficiency scores, whereas in additive efficiency decomposition, the overall efficiency is defined as a weighted average of the two individual stages' efficiency scores.

2.4.2.1 The multiplicative efficiency decomposition

Kao and Hwang (2008) modify the conventional DEA model for measuring the efficiency of a two-stage network by taking into account the series relationship of the two sub-processes within the whole process. According to their research, a two-stage network system is depicted in Figure 2.6.

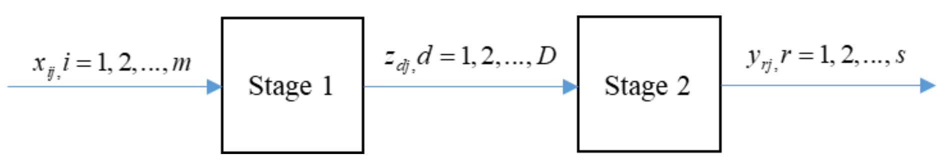

Figure 2.6 Two-stage process

Suppose there is a set of n DMUs which use multiple inputs to produce multiple outputs. Assume that each $DMU_j (j = 1, 2, \ldots, n)$, has m inputs to the first stage $x_{ij}, (i = 1, 2, \ldots, m)$, and D outputs from this stage, $z_{dj}, (d = 1, 2, \ldots, D)$. These D outputs then become the inputs for the second stage and are referred to as intermediate. The outputs from the second stage are denoted $y_{rj},(r=1,2,...,s)$. Based on the conventional two-stage DEA model (Seiford and Zhu, 1999), model (2.15), model (2.16), and model (2.17) are used to measure the overall efficiency score, the efficiency score in stage 1, and the efficiency score in stage 2, respectively.

$$\begin{aligned} E^* &= \max \sum_{r=1}^{s} u_r y_{r0} / \sum_{i=1}^{m} v_i x_{i0} \\ s.t. \quad & \sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \le 1,\ j=1,...,n \\ & u_r, v_i \ge \varepsilon, r=1,...,s; i=1,...,m \end{aligned} \tag{2.15}$$

$$\begin{aligned} E_1^* &= \max \sum_{d=1}^{D} \eta_d z_{d0} / \sum_{i=1}^{m} v_i x_{i0} \\ s.t. \quad & \sum_{r=1}^{s} \eta_d z_{dj} / \sum_{i=1}^{m} v_i x_{ij} \le 1,\ j=1,...,n \\ & \eta_d, v_i \ge \varepsilon, d=1,...,D; i=1,...,m \end{aligned} \tag{2.16}$$

$$\begin{aligned} E_2^* &= \max \sum_{r=1}^{s} u_r y_{r0} / \sum_{d=1}^{D} \eta_d z_{d0} \\ s.t. \quad & \sum_{r=1}^{s} u_r y_{rj} / \sum_{d=1}^{D} \eta_d z_{dj} \le 1,\ j=1,...,n \\ & u_r, \eta_d \ge \varepsilon, r=1,...,s; d=1,...,D \end{aligned} \tag{2.17}$$

For a DMU under evaluation, the overall efficiency score is calculated by $E^* = E_1^* \times E_2^*$. From this approach, the overall efficiency E^* can also be calculated by model (2.18):

$$
\begin{aligned}
& E^* = \max \sum_{r=1}^{s} u_r y_{r0} / \sum_{i=1}^{m} v_i x_{i0} && (2.18) \\
& s.t. \quad \sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \le 1,\ j = 1,\dots,n \\
& \qquad \sum_{r=1}^{s} \eta_d z_{dj} / \sum_{i=1}^{m} v_i x_{ij} \le 1,\ j = 1,\dots,n \\
& \qquad \sum_{r=1}^{s} u_r y_{rj} / \sum_{d=1}^{D} \eta_d z_{dj} \le 1,\ j = 1,\dots,n \\
& \qquad u_r, v_i, \eta_d \ge \varepsilon, r = 1,\dots,s; i = 1,\dots,m; d = 1,\dots,D
\end{aligned}
$$

Model (2.18) is a fractional programming and it can be transformed into the following linear programming:

$$
\begin{aligned}
& E^* = \max \sum_{r=1}^{s} u_r y_{r0} && (2.19) \\
& s.t. \quad \sum_{i=1}^{m} v_i x_{i0} = 1 \\
& \qquad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0,\ j = 1,\dots,n \\
& \qquad \sum_{r=1}^{s} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0,\ j = 1,\dots,n \\
& \qquad \sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \le 0,\ j = 1,\dots,n \\
& \qquad u_r, v_i, \eta_d \ge \varepsilon, r = 1,\dots,s; i = 1,\dots,m; d = 1,\dots,D
\end{aligned}
$$

The optimal multipliers in model (2.19) may not be unique. In order to remove this problem, the efficiency of the first sub-process is maximized in the second stage where the overall efficiency score is maintained at the same level, as shown in model (2.20).

$$E_1^* = \max \sum_{d=1}^{D} \eta_d z_{d0} \tag{2.20}$$

$$\begin{aligned}
s.t. \quad & \sum_{i=1}^{m} v_i x_{i0} = 1 \\
& \sum_{r=1}^{s} u_r y_{r0} - E^* \times \sum_{i=1}^{m} v_i x_{i0} = 0 \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \ j = 1, \dots, n \\
& \sum_{d=1}^{D} \eta_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \ j = 1, \dots, n \\
& \sum_{r=1}^{s} u_r y_{rj} - \sum_{d=1}^{D} \eta_d z_{dj} \le 0, \ j = 1, \dots, n \\
& u_r, v_i, \eta_d \ge \varepsilon, r = 1, \dots, s; i = 1, \dots, m; d = 1, \dots, D
\end{aligned}$$

After E_1^* is calculated from the above model, the efficiency of the second stage is obtained as $E_2^* = E^* / E_1^*$.

2.4.2.2 The additive efficiency decomposition

The Kao and Hwang (2008)'s approach only defines the overall efficiency of two-stages in CRS. They assume the same weights for intermediate (the outputs for the first stage and the inputs for the second stage). Chen, et al. (2009) develop an additive efficiency decomposition approach where the overall efficiency is expressed as a (weighted) sum of the efficiencies of the individual stages. The model can be applied in both CRS and VRS.

Chen et al. (2009) define the overall efficiency as $E^* = w_1 E_1^* \times w_2 E_2^*$, where w_1 and w_2 are user-specified weights and $w_1 + w_2 = 1$. This means that the overall efficiency of the entire process is the weighted sum of efficiencies of the two individual stages. Model (2.21) illustrates the proposed model by Chen et al. (2009).

$$E^{*} = \max\left[w_1 \cdot \left(\sum_{d=1}^{D} \eta_d z_{d0} / \sum_{i=1}^{m} v_i x_{i0} \right) + w_2 \cdot \left(\sum_{r=1}^{s} u_r y_{r0} / \sum_{d=1}^{D} \eta_d z_{d0} \right) \right] \tag{2.21}$$

$$\begin{aligned} s.t. \quad & \sum_{r=1}^{s} \eta_d z_{dj} / \sum_{i=1}^{m} v_i x_{ij} \le 1,\ j = 1,\ldots,n \\ & \sum_{r=1}^{s} u_r y_{rj} / \sum_{d=1}^{D} \eta_d z_{dj} \le 1,\ j = 1,\ldots,n \\ & u_r, v_i, \eta_d \ge \varepsilon, r = 1,\ldots,s; i = 1,\ldots,m; d = 1,\ldots,D \end{aligned}$$

Since model (2.21) cannot be transformed into a linear program using Charnes-Cooper transformation, Chen et al. (2009) convert model (2.21) into the following linear form. Here, $\sum_{i=1}^{m} v_i x_{i0} + \sum_{d=1}^{D} \eta_d z_{d0}$ represent the total size of (amount of resources consumed by) the two-stage process, and $\sum_{i=1}^{m} v_i x_{i0}$ and $\sum_{d=1}^{D} \eta_d z_{d0}$ represent the sizes of the stages 1 and 2 respectively.

$$w_1 = \sum_{i=1}^{m} v_i x_{i0} / \left(\sum_{i=1}^{m} v_i x_{i0} + \sum_{d=1}^{D} \eta_d z_{d0} \right) \text{ and } w_2 = \sum_{d=1}^{D} \eta_d z_{d0} / \left(\sum_{i=1}^{m} v_i x_{i0} + \sum_{d=1}^{D} \eta_d z_{d0} \right)$$

Also, $w_1 > \alpha$ and $w_2 > \alpha$, where α is a selected constant value that $0\% < \alpha < 50\%$ to avoid this problem that $w_1 = 1$ & $w_2 = 0$ or $w_1 = 0$ & $w_2 = 1$ in optimization. They show that model (2.21) is equivalent to model (2.22) using the Charnes-Cooper transformation.

$$
\begin{aligned}
E^{*} = \max & \sum_{r=1}^{s} \mu_r y_{r0} + \sum_{d=1}^{D} \pi_d z_{d0} \qquad (2.22)\\
s.t. \quad & \sum_{d=1}^{D} \pi_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0,\ j = 1,\dots,n \\
& \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{d=1}^{D} \pi_d z_{dj} \le 0,\ j = 1,\dots,n \\
& \sum_{i=1}^{m} v_i x_{i0} + \sum_{d=1}^{D} \pi_d z_{d0} = 1 \\
& \sum_{i=1}^{m} v_i x_{i0} \ge \alpha, \sum_{d=1}^{D} \pi_d z_{d0} \ge \alpha \\
& \pi_d, v_i, \mu_r \ge \varepsilon, r = 1,\dots,s; i = 1,\dots,m; d = 1,\dots,D
\end{aligned}
$$

E_1^*, E_2^* can be determined first, and then the efficiency of the other stage will be derived. For the case that pre-emptive priority is given to the first stage, the following model (2.23) is used where the overall efficiency score at E_0 is calculated from model (2.22).

$$
\begin{aligned}
E_1^{*} = \max & \sum_{d=1}^{D} \pi_d z_{d0} \qquad (2.23)\\
s.t. \quad & \sum_{d=1}^{D} \pi_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0,\ j = 1,\dots,n \\
& \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{d=1}^{D} \pi_d z_{dj} \le 0,\ j = 1,\dots,n \\
& (1 - E_0) \sum_{d=1}^{D} \pi_d z_{d0} + \sum_{r=1}^{s} \mu_r y_{r0} = E_0 \\
& \sum_{i=1}^{m} v_i x_{i0} = 1 \\
& \pi_d, v_i, \mu_r \ge \varepsilon, r = 1,\dots,s; i = 1,\dots,m; d = 1,\dots,D
\end{aligned}
$$

The efficiency for the second stage is then calculated as $E_2^* = (E^* - w_1^* \cdot E_1^*) / w_2^*$.

By the same approach, when a pre-emptive priority is given to the first stage, the following model (2.24) is applied.

$$
\begin{aligned}
& E_2^* = \max \sum_{r=1}^{s} \mu_r y_{r0} && (2.24) \\
& s.t. \quad \sum_{d=1}^{D} \pi_d z_{dj} - \sum_{i=1}^{m} v_i x_{ij} \le 0,\ j = 1,\dots,n \\
& \qquad \sum_{r=1}^{s} \mu_r y_{rj} - \sum_{d=1}^{D} \pi_d z_{dj} \le 0,\ j = 1,\dots,n \\
& \qquad \sum_{d=1}^{D} \pi_d z_{d0} + \sum_{r=1}^{s} \mu_r y_{r0} - E_0 \sum_{i=1}^{m} v_i x_{i0} = E_0 \\
& \qquad \sum_{d=1}^{D} \pi_d z_{dj} = 1 \\
& \qquad \pi_d, v_i, \mu_r \ge \varepsilon, r = 1,\dots,s; i = 1,\dots,m; d = 1,\dots,D
\end{aligned}
$$

The efficiency score for the second stage is also calculated as $E_1^* = (E^* - w_2^* \cdot E_2^*) / w_1^*$.

2.5 Studies via network DEA structures

From 1978 to 2010, two-third of DEA journal papers include empirical data analysis, where the remaining journal papers are purely-methodological articles (Liu et al., 2013). These DEA applications are in many different areas, such as healthcare, education, manufacturing, environmental protection, supply chain, banking, government, and others. Since the first paper in 1978, DEA has been proven as a useful data-oriented analytics tool in productivity analytics, performance evaluation, and benchmarking. For example, Hwang and Kao (2008) study a two-stage DEA to examine the operation of the nonlife insurance industry in Taiwan. Toloo et al. (2017)

extend a relational linear DEA model for dealing with measuring the performance score of two-stage processes with shared inputs in an additive manner.

In addition, as big data research becomes an important area of operations analytics, DEA is evolving into Data Envelopment Analytics (Zhu, 2019). DEA is a data-oriented tool for traditional productivity analytics, benchmarking, and performance evaluation. DEA can also be known as the composite index construction.

Around 44 studies from 2009 to 2020 in the web of science database specifically focus on applying SBM network models to various areas, such as energy, environmental, supply chain, airports, banks, companies, and so on.

Out of these 44 studies, seven studies are applied to the energy area. For example, Lu et al. (2020) pay more attention to energy consumption saving, environmental pollution, and health efficiency improvement. They employ the Dynamic network SBM (DNSBM) to assess the impact of the forestry area on annual and overall energy as well as health efficiency in two intertemporal stages. Chiu et al. (2020) and Li et al. (2020) also apply a dynamic two-stage SBM approach in their study, but they concentrate on measuring overall energy performance for the purpose of regional sustainable development. In addition, Hu et al. (2019) use an extended two-stage SBM network model with feedbacks variables to evaluate the oil production and wastewater treatment efficiency, while Chen et al. (2019) consider undesirable network SBM model to analyze the efficiency of China's energy, environment, health, and media communications.

A good proportion of the research studies (11 out of 44, that is, 25%) applied network SBM for performance evaluation in telecommunication companies, hi-tech zones, airlines, airports, distributors, banking branches, and regional coke production chain (Bai et al., 2015; Chiu et al., 2020; Chou et al., 2016; Mahmoudabadi and Emrouznejad, 2019; Momeni et al., 2014; Moreno, et al., 2013; Olfat et al., 2016; Olfat et al., 2019; Xia et al., 2020; Yu, 2010). For instance, Yu (2010) presents a network SBM model to analyze the airport operation performance. Their approach is decomposed into two sections, production and service performance. They suggest that efficiency in airport production may not guarantee efficiency in the service process of domestic airports in Taiwan and vice versa. Mahmoudabadi and Emrouznejad (2019) expand the traditional two-stage network SBM structure to a three-stage network SBM to measure comprehensive performance evaluation of banking branches. In their study, the network SBM model is applied to simultaneously evaluate operational efficiency, service effectiveness, and social effectiveness for 37 branches of one of the largest commercial banks in Iran.

There are 10 studies (22.7% in total) that apply network SBM to analyze problems in different areas in China, including discussion of hi-technic, production chain, energy and air pollution reduction efficiency, economic production system, public health, water use and treatment system, environmental performance evaluation, and political 2018 (Bai, et al., 2015; Li, Chiu and Lin, 2019; Li, et al., 2020; Shao and Han, 2019; Song et al., 2017; Xia, et al., 2020; Xia et al., 2016; Zhong et al., 2020; Zhou et al., 2018). For example, Xia, et al. (2020) demonstrate an empirical analysis of the dynamic performance of China's regional coke production chain from 2006 to 2011. By adopting the SBM DEA structure and a famous dynamic network DEA framework, their paper simplifies the coke production chain into a three-stage process and captures the interactions between intermediates inside each stage. Likewise, most of the above studies evaluate efficiency for companies, industries, or government, except the study of Li et al. (2019) that discusses the impact of economic growth and air pollution on public health in 31 Chinese cities. They show that the environmental efficiencies were continuing to rise in most cities where all cities are needed to improve their GDP.

Chapter III Performance Evaluation for Airline Companies: A Two-stage Network DEA Approach

3.1 Introduction

The majority of extant studies that focus on performance and efficiency benchmarking of firms utilize only operational measures while neglecting to integrate stock market indicators in their methodological frameworks. Such an approach may lead to erroneous or biased conclusions given that operational and stock measures serve to capture different dimensions and attributes of an overall firm's activities, health and prospects. Thus, in this chapter, we introduces a two-stage network DEA process and implement a SOCP technique into our two-stage DEA network model to solve non-linear DEA models without the need for calculating numerous parametric linear programs in an effort to estimate the global optimal solution. Our network structure utilizes both operational and stock market indicators in order to evaluate the performance of eight major international airline companies from 2006 until 2016.

In our analysis, we show that there is heterogeneity in the performance of all airlines across time. Most notably, during the 2013-14 European debt crisis and United States debt-ceiling crisis, we find that stock market-based performance scores declined significantly for all our sampled companies. We also show that while low cost carriers generally maintain higher operational-based performance scores than their full service counterparts, full service carriers earn higher performance scores based on stock market indicators. This finding lends support to our approach and our general premise which argues that performance evaluation methods can yield more comprehensive conclusions if both operational and stock market indicators are utilized.

The remainder of this chapter is structured as follows: the section 3.2 provides a backgrounds review. In section 3.3, a survey of the literature pertaining to the airlines industry and DEA have been introduced. In section 3.4, we build the two-stage network DEA methodology that is implemented. Section 3.5 describes the input-output variables and intermediate measures in our network DEA which consist of operational and financial market variables. It then presents the major findings that we derive from our two-stage network DEA. Finally, the section 3.6 discusses concluding remarks.

3.2 Background introduction

The airlines industry has experienced unparalleled changes in the last few decades. Liberalization and deregulatory initiatives have attracted many new firms into the industry and have facilitated the growing number of mergers and diverse collaborative schemes among firms (Barros and Couto, 2013). As a result, the level of competition within the industry has grown immensely and prompted a growing area of research into how to measure efficiency and benchmark airline performance (Mallikarjun, 2015).

Measuring efficiency is a fundamentally important task from a regulatory standpoint, which is concerned with the social impact of airline operations on issues such as the environment, health and safety (Lee, Yeo and Thai, 2014). Efficiency benchmarking is also critical from a managerial and shareholder perspective, especially since upper management compensation schemes and CEO tenures are tied to operational and financial performance and efficiency (Davila and Venkatachalam, 2004; Mellat-Parast et al., 2015). Finally, in an efficient capital market, investors are constantly scanning the marketplace and vying to find the most efficient, sustainable and healthy companies to invest in with the hopes that they will enjoy superior future capital gains (Eccles, Ioannou and Serafeim, 2014).

There is already a voluminous body of empirical research which posits various methods and conceptual frameworks for measuring and capturing airline efficiency. Research in the late 1970s and early 1980s established a conceptual framework that contains three elements pertaining to transit operations; specifically, resource inputs (e.g., number of employees, labor, fuel, etc.), service outputs (e.g., vehicle-hour, vehicle-mile, etc.), and service consumption (operating revenue, passenger-mile, etc.) (Fielding and Anderson, 1983; Fielding, Glauthier and Lave, 1978).

These three elements served as a motivation for input-output methodologies designed to benchmark performance and efficiency. In the 1990s, several cost models emerged as a method for gauging performance (Liu and Lynk, 1999; Oum and Yu, 1998; Windle, 1991) as well as factor productivity methods (Bauer, 1990; Oum and Yu, 1995). Meanwhile, contemporary research has implemented various more advanced parametric as well as non-parametric models for efficiency benchmarking such as stochastic frontier analysis (SFA) (Baltagi et al., 1995; Good, et al., 1993) and data envelopment analysis (Barros and Couto, 2013; Barros and Peypoch, 2009).

Despite the growing sophistication in modelling over the years, currently, most studies seem to focus exclusively on operational indicators while neglecting to integrate measures pertaining to firms' financial market performance which can be extracted from stock market indicators. For example, a firm's net income, capital gains and market capitalization, to name only a few, give investors great insights as to the health and stability of the firm. Analysts and traders also utilize financial market data for individual companies in order to gain insights into the future prospects of the firm and to gauge the level of investor sentiment and attitude towards a firm.

Neglecting to include firm-level financial market measures sweeps important pieces of information under the rug and can ultimately lead to misleading and biased conclusions. From a managerial point of view, financial market measures can capture investor attitudes and sentiment toward their firm's prospects and give upper management important feedback into the pulse of the market. For example, in the event shareholders and investors become pessimistic, as can be inferred from stock market indicators, this can seriously impede management's ability to raise needed capital to fund their operations and projects. In a competitive industry such as the airlines industry, managers need to be acutely aware of not only their operational efficiency but also the sentiment, attitudes and expectations of their shareholders and the stock market at large. As we discuss more rigorously later on in this chapter, these types of important financial market variables are included in our analysis.

By integrating stock market indicators into our analysis, we also align ourselves with literature in financial economics which finds that investors trade based on market sentiment and fundamental factors (Chau, Deesomsak and Koutmos, 2016; Koutmos, 2012). In light of the aforementioned, this paper thus makes a conceptual contribution to literature by integrating financial market indicators along with operational indicators into a two-stage network DEA model to study the performance of eight large and international airline companies.

Over the years, DEA has been proven an effective tool for performance evaluation and benchmarking. It allows us to integrate multiple performance measures into a single model and provide a performance index. The use of DEA is not restricted to estimating production frontiers. DEA is a technique for identifying best-practice frontiers (Cook, Tone and Zhu, 2014). For example, Chiou and Chen (2006) evaluate airline performance based on air routes. They employ a DEA approach to evaluate the performance of domestic air routes from the perspectives of cost efficiency, cost effectiveness and service effectiveness. Scheraga (2004) utilizes a sample of 38 airlines from North America, Europe, Asia and the Middle East to investigate whether relative operational efficiency implied superior financial mobility (Donaldson and Fagerlund, 1969). Other studies which successfully use DEA include, but are not limited to, Barbot, Costa, and Sochirca (2008), Siregar and Norsworthy (2001), Tavassoli, Faramarzi and Saen (2014), Bhadra (2009), Wang, Lu and Tsai (2011), among others.

This chapter also demonstrates a SOCP technique that can be used to solve non-linear network DEA models when the overall performance is defined as a weighted average of the two stages' performance scores. Our approach improves upon the work of Chen and Zhu (2017) by addressing the symmetric issue in SOCP modeling. In addition, our two-stage network DEA framework models the internal structures of airlines (or DMUs) and inner relations of performance metrics are considered. For example, Lu et al. (2012) explore the relationship between operating performance and corporate governance in 30 airline companies operating in the U.S. In their study, the DMUs consists of two stages of production performance and marketing performance.

As introduced in chapter 2, there are two types of approaches in modeling DMUs with two-stage network structures. One is called the additive approach where the overall performance is defined as a weight average of the two-stage performance scores (Chen et al., 2009). The other is called the multiplicative approach where the overall performance is aggregated or decomposed as a product of the two stage performance scores (Kao and Hwang, 2008; Liang, Cook and Zhu, 2008). The current chapter is based upon the additive network DEA approach.

3.3 Background Literature on the Airline Industry and DEA

The importance of financial market indicators for decision-making is highlighted by many studies who take various approaches in examining the airline industry. Jenatabadi and Ismail (2014) use structural equation modeling (SEM) with latent variables for estimating the financial and non-financial performance in airline companies. Their model includes independent, mediator and dependent latent variables and comprises of 214 airline companies. In a separate paper, Ismail and Jenatabadi (2014) use firm age as a moderator and aim to investigate the moderating influence of firm age on the nature of the relationship between economic conditions and internal operations and ultimately its effect on the performance of the airline industry. They select thirty airline companies from the Asia Pacific region and collect relevant data from 2006 to 2011. Their first step is to investigate the relationship among the economic situation, internal operation and airline performance. They then establish the moderating effect of firm age on the relationship between the economic conditions and internal operations. Finally, they investigate the relationships between the three variables, which are investigated again by taking into account the moderating effect of the variable (firm age).

Riley, Pearson and Trompeter (2003) examine the relative value relevance to investors of non-financial performance variables, traditional accounting variables (earnings and changes in abnormal earnings) and other financial statement information in the airline industry.

Feng and Wang (2000) construct a performance evaluation process for airlines with financial ratios taken into consideration. In their paper, they use the grey relation analysis to select the representative indicators and the technique for order preference by similarity to ideal solution (TOPSIS) method for the ranking of airlines to overcome the problems of small sample size and the unknown distribution of the samples.

Rose (1990) analyzes the relationship between financial conditions and safety performance. This chapter uses data on 35 large scheduled passenger airlines from 1957 to 1986 in order to estimate the effect of profitability and other aspects of financial health on accident and incident rates.

Tsikriktsis (2007) studies the impact of operational performance on profitability in the context of the US domestic airline industry. Their analysis demonstrates two main points. First, the relationship between operational performance and profitability is contingent on a company's operating model. Second, focused airlines outperform the rest of the industry in terms of profitability.

In addition, Goll, Johnson and Rasheed (2008) focus on top management demographic characteristics, business strategy, and firm performance in the major US airlines. They examine the relationships between management characteristics and business strategies. Finally, using a vector auto regression (VAR) - a model which has been widely implemented in financial economics literature - explore how the September 11 terror attack affected the performance of the airline industry when controlling for aggregate economic conditions.

Some researchers use non-financial data to analyze airline performance because of different accounting or taxation rules. Liedtka (2002) extends the literature on non-financial performance measures (NFPMs) by assessing the information content of a broader set of NFPMs and whether NFPMs provide information not provided by financial performance measures (FPMs) from all previously identified FPM categories, rather than just earnings and book value.

Lapré and Scudder (2004) consider airline companies' performance from an improvement aspect. Using a database on the 10 largest US airlines for a period of 11 years, they test and validate some of the models presented in the operations literature. The 10 major airlines are separated into 2 groups for analysis: geographic specialists and geographic generalists.

We now turn our attention to literature that implements DEA as a technique to measure performance of airlines. Bhadra (2009) uses DEA to examine inter-temporal and peer group airline performance. This paper indicates that airline performance is converging over time for the US for the period 1985–2006. Wang et al. (2011) explore links between the operating performance of 30 airlines in the US and corporate governance. Initially, DEA is used to assess the relative performance of airlines and to investigate the contribution of inputs and outputs that affect technical performance. Schefczyk (1993) utilizes DEA as a technique to analyze and compare operational performance characteristics of airlines, drawing on data from 15 airline companies. The study concludes with an analysis of strategic factors of high profitability and performance in the airline industry.

Prior research has attempted to utilize both DEA along with other measures (TFP, regression modelling, financial mobility, to name only a few) in order to analyze the airline performance. Barros and Peypoch (2009) use both regression and DEA to evaluate the operational performance of a sample of Association of European Airlines (AEA) from 2000 to 2005, combining operational along with financial variables. In the first stage, a DEA model ranks the airlines by their overall performance. In the second stage, a bootstrapped truncated regression is used to evaluate the drivers of performance. Barbot et al. (2008) analyze airline companies' performance and productivity using two different methodologies: DEA and TFP, and they additionally investigate which factors account for differences in efficiency. Chiou and Chen (2006) evaluate airline performance based on air routes. They employ a DEA approach to evaluate the performance of domestic air routes from the perspectives of cost efficiency, cost effectiveness and service effectiveness, and then examine a total of 15 routes operated by a Taiwanese domestic airline. Barbot et al. (2008) critique some of the shortcomings in Chiou and Chen (2006) and propose various remedies while Scheraga (2004) utilizes a sample of 38 airlines from North America, Europe, Asia and the Middle East to investigate whether relative operational performance implies superior financial mobility (as is defined by Donaldson, 1969). DEA was utilized to derive performance scores for individual airlines. Their results indicate that the traditional framework developed in the literature still provides reasonable explanatory power for realized relative operational performance. However, relative operational performance did not inherently imply superior financial mobility. Siregar and Norsworthy (2001) investigate the effects of technology and their equity market impacts for major commercial airlines and the distributions of returns before, during and after deregulation to see whether deregulation has increased or decreased risk. They also examine the relationships between stock returns and prices using DEA and TFP as measures of performance.

In recent years, two-stage network structures have been an important area of development in DEA. Under a network DEA framework, in addition to the inputs and outputs, a set of intermediate measures exist in-between the two stages. For example, Seiford and Zhu (1999) utilize a two-stage network structure to measure the profitability and marketability of US commercial banks. Zhu (2000) applies the same two-stage network structure to the Fortune Global 500 companies. Kao and Hwang (2008) study a two-stage DEA to examine the operation of the non-life insurance industry in Taiwan. Limited studies however use a two-stage network DEA model to evaluate airline performance. Zhu (2011) uses a two-stage DEA process to measure airline operations performance. In this research, resources (fuel, salaries, and other factors) are used to maintain the fleet size and load factor in the first stage. In the second stage, the fleet size and load factors generate revenue. Lu et al. (2012) explore the relationship between operating performance and corporate governance in 30 airline companies operating in the U.S. Their study applies a two-stage network DEA to evaluate the production performance and marketing performance of the airlines, and implements a truncated regression to explore whether the characteristics of corporate governance affect airline performance. Tavassoli et al. (2014) propose a slacks-based network DEA approach to measure both technical performance and service effectiveness of airlines. Their model represents both the non-storable feature of transportation service and production technologies in a unified framework in the presence of shared input.

3.4 A Two-stage Network DEA Approach

We consider a general two-stage network structure shown in Figure 3.1. Each $DMU_j (j = 1, 2, ..., n)$ has m inputs x_{ij} , $(i = 1, 2, ..., m)$ to the first stage and P outputs $y^1_{pj} (p = 1, 2, ..., P)$ that leave the system. In addition to these P outputs, stage 1 has D outputs $z_{dj} (d = 1, 2, ..., D)$ called intermediate measures that become inputs to the second stage. The second stage has its own inputs $x^2_{hj} (h = 1, 2, ..., H)$. The outputs from the second stage are $y_{rj} (r = 1, 2, ..., s)$.

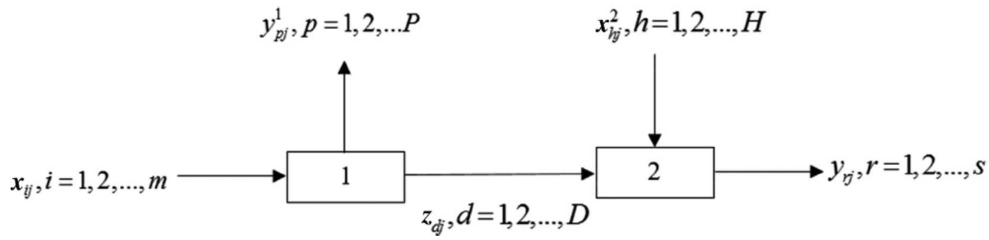

Figure 3.1 A general two-stage network structure

Our performance measures include some ratio measures that are standard metrics used by the industry. We consider the variable returns to scale (VRS) case, because the constant returns to scale (CRS) can be regarded as a special case of VRS by removing the free variables in the VRS models. In addition, our performance measures include some ratio measures that are standard metrics used by the industry. A VRS model allows us to use the ratio measure in identifying the best practices, rather than a production function (see, e.g., Cook et al. (2014)).

The efficiencies of stages 1 and 2 for a specific DMU_0 under evaluation can be expressed as follows:

$$e_o^1 = \frac{\sum_{\mathrm{d}=1}^{\mathrm{D}} \eta_{\mathrm{d}} z_{do} + \sum_{p=1}^{P} \lambda_p y_{p0}^1 + u^1}{\sum_{i=1}^{m} v_i x_{io}} \quad \text{and} \quad e_o^2 = \frac{\sum_{\mathrm{r}=1}^{\mathrm{s}} u_r y_{ro} + u^2}{\sum_{\mathrm{d}=1}^{\mathrm{D}} \eta_{\mathrm{d}} z_{do} + \sum_{h=1}^{H} Q_h x_{ho}^2}$$

where $v_i, \eta_d, \lambda_p, u_r$, and Q_h are weights which are assumed to be positive in the current chapter, by incorporating the small non-Archimedean ε in the DEA models. u^1 and u^2 are free variables associated with the VRS assumption. If we exclude u^1 and u^2, then we have a CRS model.

The VRS version of an additive performance with respect to Figure 3.1 can now be presented in the following way:

$$
\begin{aligned}
\max \quad & \alpha_1 \frac{\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1}{\sum_{i=1}^{m} v_i x_{i0}} + \alpha_2 \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 + u^2} \qquad (3.1)\\
s.t. \quad & \frac{\sum_{d=1}^{D}\eta_d z_{dj} + \sum_{p=1}^{P}\lambda_p y_{pj}^1 + u^1}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad \forall j \\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D}\eta_d z_{dj} + \sum_{h=1}^{H} Q_h x_{hj}^2 + u^2} \le 1, \quad \forall j \\
& \alpha_1 + \alpha_2 = 1 \\
& \eta_d, u_r, v_i, \lambda_p, Q_h \ge \varepsilon, \quad \forall d, r, i, p, h \\
& u^1, u^2 \text{ free in sign}
\end{aligned}
$$

where α_1 and α_2 are weights.

In the existing literature, there are two ways to solve model (3.1) which is highly non-linear. One is to choose a special set of weights (α_1 and α_2) to convert the objective function in problem (3.1) into a single linear fractional form (see for example Cook et al, 2010). These special weights are actually variables related to the input sizes of the two stages. As shown in Despotis, Koronakos and Sotiros (2016), such weights yield biased performance scores towards the second stage.

Guo and Zhu (2017) demonstrate a detailed approach to solving models similar to (3.1) by transforming problem (3.1) into a sequence of linear programming problems given different predetermined weights. Chen and Zhu (2017), on the other hand, show that for two-stage network DEA models, when the overall performance is expressed as a product of the two stages' performance scores, the network DEA model can be solved using a second order cone programming (SOCP) technique. Note that SOCP can be solved by non-heuristic algorithms such as an interior point method. In the discipline of convex optimization, SOCP has already been a mature technology (Boyd and Vandenberghe, 2004).

In this chapter, using a SOCP technique, we propose an approach to solve model (3.1) where the overall performance is expressed as a weighted average of the two stages' performance scores.

Model (3.1) is equivalent to the following:

$$
\begin{aligned}
\min \quad & -\alpha_1 \frac{\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1}{\sum_{i=1}^{m} v_i x_{i0}} - \alpha_2 \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 + u^2} \qquad (3.2)\\
s.t. \quad & \frac{\sum_{d=1}^{D}\eta_d z_{dj} + \sum_{p=1}^{P}\lambda_p y_{pj}^1 + u^1}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad \forall j\\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D}\eta_d z_{dj} + \sum_{h=1}^{H} Q_h x_{hj}^2 + u^2} \le 1, \quad \forall j\\
& \alpha_1 + \alpha_2 = 1\\
& \eta_d, u_r, v_i, \lambda_p, Q_h \ge \varepsilon, \quad \forall d, r, i, p, h\\
& u^1, u^2 \text{ free in sign}
\end{aligned}
$$

Then, by an epigraph transformation, we obtain:

$$
\begin{aligned}
\min \quad & -\theta_1 - \theta_2 \qquad (3.3)\\
s.t. \quad & -\alpha_1 \frac{\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1}{\sum_{i=1}^{m} v_i x_{i0}} \le -\theta_1\\
& -\alpha_2 \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 + u^2} \le -\theta_2\\
& \frac{\sum_{d=1}^{D}\eta_d z_{dj} + \sum_{p=1}^{P}\lambda_p y_{pj}^1 + u^1}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad \forall j\\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D}\eta_d z_{dj} + \sum_{h=1}^{H} Q_h x_{hj}^2 + u^2} \le 1, \quad \forall j\\
& \alpha_1 + \alpha_2 = 1\\
& \eta_d, u_r, v_i, \lambda_p, Q_h, \theta_1, \theta_2 \ge \varepsilon, \quad \forall d, r, i, p, h\\
& u^1, u^2 \text{ free in sign}
\end{aligned}
$$

Above model (3.3) is a highly non-linear model. Now we provide the mathematics in deriving model (3.3) into our SOCP model. Note that while our approach is based upon SOCP as in Chen and Zhu (2017), the underlying network DEA modeling (in particular, the overall efficiency construct) is different. The following provides more detailed discussion and shows an improvement to the Chen and Zhu (2017) approach by addressing the symmetric issue of the SOCP model developed in Chen and Zhu (2017).

Chen and Zhu (2017) develop a SOCP model for a two-stage network structure where the overall efficiency is defined as the product of $e_o^1 = \frac{\sum_{\mathrm{d}=1}^{\mathrm{D}} \eta_{\mathrm{d}} z_{do} + \sum_{p=1}^{P} \lambda_p y_{p0}^1 + u^1}{\sum_{i=1}^{m} v_i x_{io}}$ and $e_o^2 = \frac{\sum_{\mathrm{r}=1}^{\mathrm{s}} u_r y_{ro} + u^2}{\sum_{\mathrm{d}=1}^{\mathrm{D}} \eta_{\mathrm{d}} z_{do} + \sum_{h=1}^{H} Q_h x_{ho}^2}$. Namely, their approach is a multiplicative two-stage DEA network model. Intuitively, one could use the same technique to develop a SOCP model when the overall efficiency is defined as a weighted average of e_o^1 and e_o^2 as in model (3.1). However, after careful examination, we find that the positive semi-definite matrix to deal with multiplicative two-stage DEA shown as follows may not be positive semi-definite since it is not symmetric.

$$\begin{bmatrix} \theta\left(\sum_{d=1}^{D} \eta_d z_{d0} + \sum_{p=1}^{P} \lambda_p y_{p0}^1 + u^1\right) & \sum_{d=1}^{D} \eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 \\ \sum_{i=1}^{m} v_i x_{i0} & \sum_{r=1}^{s} u_r y_{r0} + u^2 \end{bmatrix} \succ= 0 \qquad (A1)$$

Nevertheless, the symmetric problem of Chen and Zhu (2017) can be fixed by letting $\sum_{d=1}^{D} \eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 = k \sum_{i=1}^{m} v_i x_{i0}$ where k is a parameter which can be incorporated into other terms by algebraic manipulations and can be located by a bisection search method.

However, in the current chapter which addresses additive two-stage network DEA, we have to develop a different technique to the symmetric problem since the numerator of stage efficiency in an additive two-stage DEA includes only one linear combination. The new technique is summarized as follows.

Note that in model (3.3) since $\alpha_1 \frac{\sum_{d=1}^{D} \eta_d z_{d0} + \sum_{p=1}^{P} \lambda_p y_{p0}^1 + u^1}{\sum_{i=1}^{m} v_i x_{i0}} \geq \theta_1$ is equivalent to the following model (A2):

$$\alpha_1^{\,2} \frac{\left(\sum_{d=1}^{D} \eta_d z_{d0} + \sum_{p=1}^{P} \lambda_p y_{p0}^1 + u^1\right)^2}{\left(\sum_{i=1}^{m} v_i x_{i0}\right)^2} \geq \theta_1^{\,2} \qquad (A2)$$

Then, we have

$$\begin{bmatrix} \frac{1}{\theta_1^{\,2}}\left(\sum_{d=1}^{D} \eta_d z_{d0} + \sum_{p=1}^{P} \lambda_p y_{p0}^1 + u^1\right) & \sum_{i=1}^{m} v_i x_{i0} \\ \sum_{i=1}^{m} v_i x_{i0} & \alpha_1^{\,2}\left(\sum_{d=1}^{D} \eta_d z_{d0} + \sum_{p=1}^{P} \lambda_p y_{p0}^1 + u^1\right) \end{bmatrix} \succ= 0 \qquad (A3)$$

Note that the symmetric matrix in (A3) is positive semi-definite since all of its principal minors are nonnegative. Similarly, $\alpha_2 \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{d=1}^{D} \eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 + u^2} \geq \theta_2$ is equivalent to the following model (A4):

$$\begin{bmatrix} \frac{1}{\theta_2^{\,2}}\sum_{r=1}^{s} u_r y_{r0} & \sum_{d=1}^{D} \eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 + u^2 \\ \sum_{d=1}^{D} \eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 + u^2 & \alpha_2^{\,2}\sum_{r=1}^{s} u_r y_{r0} \end{bmatrix} \succ= 0 \qquad (A4)$$

Note that α_1 in (A3) and α_2 in (A4) can be provided by the decision maker, or searched for the optimal weight that yields the largest overall efficiency as in Guo and Zhu (2017). Thus, if we can locate the true values of parameter θ_1 in (A3) and parameter θ_2 in (A4), (A3) and (A4) correspond to the following two conic constraints respectively.

$$\left\| \begin{matrix} \sum_{i=1}^{m} v_i x_{i0} \\ \frac{1}{2}\left[\frac{1}{\theta_1^2}\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1\right) - \alpha_1^2\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1\right)\right] \end{matrix} \right\|_2$$

$$\leq \frac{1}{2}\left[\frac{1}{\theta_1^2}\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1\right) + \alpha_1^2\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1\right)\right] \qquad (A5)$$

$$\left\| \begin{matrix} \sum_{d=1}^{D}\eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 + u^2 \\ \frac{1}{2}\left[\frac{1}{\theta_2^2}\sum_{r=1}^{s} u_r y_{r0} - \alpha_2^2 \sum_{r=1}^{s} u_r y_{r0}\right] \end{matrix} \right\|_2 \leq \frac{1}{2}\left[\frac{1}{\theta_2^2}\sum_{r=1}^{s} u_r y_{r0} + \alpha_2^2 \sum_{r=1}^{s} u_r y_{r0}\right] \qquad (A6)$$

The above transformation is based on a simple fact that $AC - B^2 \geq 0$ is equivalent to $\sqrt{B^2 + \left[\frac{1}{2}(A-C)\right]^2} \leq \frac{1}{2}(A+C)$, where $A, B, C \in R$. Finally, we can have the following SOCP problem (3.4):

$$\begin{aligned}
\min \quad & -\theta_1 - \theta_2 \qquad\qquad (3.4) \\
s.t. \quad & \left\| \begin{matrix} \sum_{i=1}^{m} v_i x_{i0} \\ \frac{1}{2}\left[\frac{1}{\theta_1^2}\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1\right) - \alpha_1^2\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1\right)\right] \end{matrix} \right\|_2 \\
& \leq \frac{1}{2}\left[\frac{1}{\theta_1^2}\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1\right) + \alpha_1^2\left(\sum_{d=1}^{D}\eta_d z_{d0} + \sum_{p=1}^{P}\lambda_p y_{p0}^1 + u^1\right)\right] \\
& \left\| \begin{matrix} \sum_{d=1}^{D}\eta_d z_{d0} + \sum_{h=1}^{H} Q_h x_{h0}^2 + u^2 \\ \frac{1}{2}\left[\frac{1}{\theta_2^2}\sum_{r=1}^{s} u_r y_{r0} - \alpha_2^2 \sum_{r=1}^{s} u_r y_{r0}\right] \end{matrix} \right\|_2 \leq \frac{1}{2}\left[\frac{1}{\theta_2^2}\sum_{r=1}^{s} u_r y_{r0} + \alpha_2^2 \sum_{r=1}^{s} u_r y_{r0}\right] \\
& \frac{\sum_{d=1}^{D}\eta_d z_{dj} + \sum_{p=1}^{P}\lambda_p y_{pj}^1 + u^1}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \quad \forall j \\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D}\eta_d z_{dj} + \sum_{h=1}^{H} Q_h x_{hj}^2 + u^2} \leq 1, \quad \forall j \\
& \alpha_1 + \alpha_2 = 1, \\
& \eta_d, u_r, v_i, \lambda_p, Q_h, \theta_1, \theta_2 \geq \varepsilon, \quad \forall d, r, i, p, h \\
& u^1, u^2 \ \text{free in sign}
\end{aligned}$$

In above model (3.4), we can search for the values of θ_1 and θ_2 in a convergent manner. Note that we can always find initial values of θ_1 and θ_2, denoted as θ_1^0 and θ_2^0 respectively, to satisfy the constraints of model (3.4). Otherwise, the original problem (3.1) is infeasible. Then, without loss of generality, we can fix θ_1^0 and increase the value of θ_2 from θ_2^0 to θ_2^1 by bisection method. Further, fixing θ_2^1, we can adopt a bisection method again to increase the value of θ_1 from θ_1^0 to θ_1^1. Repeatedly, the maximal values of θ_1 and θ_2 can be obtained since the searching sequence is monotonic in a compact set.

Thus, by solving model (3.4), we can determine stage efficiencies for a specific DMU under evaluation. We will demonstrate this in our empirical application in the following section.

3.5 Empirical Implementation and Major Findings

The majority of extant studies that focus on performance and efficiency benchmarking of firms utilize only operational measures while neglecting to integrate stock market indicators in their methodological frameworks. Such an approach may lead to erroneous or biased conclusions given that operational and stock measures serve to capture different dimensions and attributes of an overall firm's activities, health and prospects. In a contribution to existing literature, we show that integrating operational along with stock market indicators, which represent the financial prospects of a firm, into our two-stage network DEA framework can provide new insights into performance rankings and performance benchmarking for airline companies.

To empirically implement model (3.4), we utilize five key operational indicators and six financial market indicators. Our operational indicators are as follows: fuel cost per available seat miles (*Fuel*), number of employees (*Employees*), operation costs per available seat miles (excluding fuel costs) (*Operation Cost*), sales revenue (*Sales*) and revenue passenger kilometers (*RPKs*), respectively.[1]

Fuel is a unit of cost measurement that is derived by dividing fuel costs by available seat miles (ASM). ASM is a measure of airline companies' passenger carrying capacity that is equivalent to the number of seats available to passengers multiplied by the number of miles (or kilometers) flown. Generally speaking, the lower *Fuel* is, the lower the costs are for the airline company and, ceteris paribus, the higher the probability that the company will be profitable.

Employees denotes the number of individuals that are employed by the airline. *Operation Cost* is another unit of cost measurement. It is computed by dividing operating costs by ASM. In general, the lower *Operation Cost* is, the lower the operational costs are for the airline company and, ceteris paribus, the higher the probability that the company will be profitable. The reason why *Operation Costs* here is estimated excluding fuel costs, and the reason why this measure is important for airline companies, are because management is, among other methods, evaluated on company performance while isolating for macroeconomic factors that are beyond their direct control - such as oil price volatility, which is the result of a broad range of market forces. *Sales* captures income which an airlines company generates for its services. Positive sales growth over time is a sign of rising market share and consumer demand. Finally, *RPKs* is a measure of traffic for an airline. The *RPKs* of

[1]The Bureau of Transportation Statistics (BTS) provides a comprehensive description some of the operational indicators we use in this chapter along with other commonly cited operations indicators. These can be accessed publicly on-line at this URL address:
http://www.transtats.bts.gov/Glossary.asp?index=A.

an airline is the sum of the products obtained by multiplying the number of revenue passengers carried on each flight stage by the distance travelled. It can be regarded as airline "production."

In terms of stock market and financial indicators, we use the following six indicators: market capitalization (*Market Cap*), the weighted average cost of capital (*WACC*), the short interest ratio (*Short Interest Ratio*), net income (*Net Income*), capital gains yield (*Capital Gains Yield*) and return on equity (*ROE*), respectively.

Market Cap is the total market value of a company's outstanding shares and is computed by multiplying the number of outstanding shares by the market price for one of those shares. Market participants generally view this indicator as a measure for firm size whereby the larger *Market Cap* is, the larger the company is. Using *Market Cap* is a market indicator of size which serves as an alternative to accounting measures of size such as total assets or sales figures. *WACC* reflects investors' required rate of return on their investment.[2] It is the rate of return that a company is expected to pay its security holders and is regarded as a useful proxy for the required rate of return in finance because it is determined by the market and not by a company's management. *Short Interest Ratio* is a stock market indicator that reflects investor sentiment. It is computed by dividing short interest, or the quantity of shares sold short but not yet covered, by the average trading volume for a stock over a given period. When short interest rises, and therefore the *Short Interest Ratio* rises, it reflects investor pessimism and bearishness regarding the prospects of the company.

[2] Assuming that the company is financed with only debt and equity, the equation for WACC is as follows: $WACC = \frac{D}{D+E}K_D + \frac{E}{D+E}K_E$ whereby *D* and *E* represent total debt and total shareholder's equity, respectively. K_D is the cost of debt while K_E is the cost of equity. When computing WACC, market values for debt and equity are conventionally used. We use market values in this chapter as well for each of the airline companies.

Net Income is the company's total profit and computed by subtracting costs of doing business (taxes, interest expenses, depreciation, employee salaries) from revenues. *Capital Gains Yield* is the percent change in a company's stock price from one period to the next. This indicator excludes dividends paid on the stock by the company to its shareholders. Finally, the *ROE* is the amount of net income returned as a percentage of shareholder's equity. This measure reflects profitability by showing profits that the company generated with money which shareholders invested.

All operations and financial market indicators are quarterly - since they are extracted from quarterly disclosed statements and 10-Q filings with the Securities and Exchange Commission (SEC). Thus our sample frequency consists of quarterly observations for each of the aforementioned operational and financial market indicators for each of the eight respective airlines, which consists of Alaska Airlines, Air Canada, Delta, Hawaiian Airlines, Jet Blue, Southwest Airlines, Spirit Airlines and United Continental Holdings, respectively.

With respect to the two-stage structure in Figure 3.1, this chapter considers the operational and stock market performance in a unified way, as shown in Figure 3.2, x_i represents *Fuel*, *Employees*, and *Operation Cost*. y_p^1 refers to *Sales*. z_d refers to *RPKs*. x_h^2 corresponds to *Short Interest Ratio*, *Market Cap*, and *WACC*. y_r refers to *Net Income*, *Capital Gains Yield*, and *ROE*.

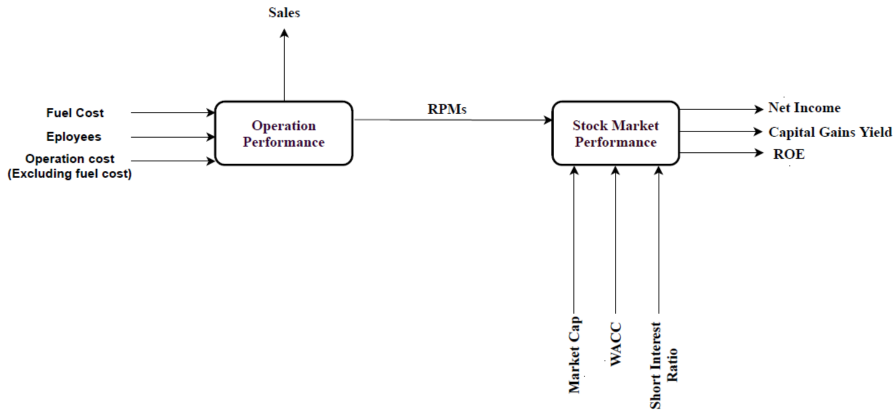

Figure 3.2 Two-stage network DEA structure of airline performance

Thus, the inputs in the first stage of the two-stage DEA network, as is illustrated in figure 3.2, are *Fuel*, *Employees*, and *Operation Cost*. The output in the first stage is *Sales*. Our intermediate measure is *Revenue Passenger Kilometers* while inputs for the second stage are *Short Interest Ratio*, *Market Cap*, and *WACC*. The outputs in the second stage are *Net Income*, *Capital Gains Yield*, and *ROE*.

Our rationale for using the respective variables in the first and second stages, respectively, is as follows. Airline companies utilize *Fuel*, *Employee*, and *Operation Cost* as inputs in order to generate *Sales* and *Revenue Passenger Kilometers*. *Sales* is also one of the final outputs from the first stage, while *Revenue Passenger Kilometers* is regarded as the intermediate measure which is an output in the first stage and also used as an input in the second stage. Outside investors, traders and other market participants then trade shares depending on how they feel about the future prospects of the firm. Thus, in the second stage, *Short Interest Ratio*, *Market Cap*, and *WACC* are used as inputs because they are what investors demand prior to a company undertaking a project. WACC is regarded as a proxy for the required rate of return in finance. Finally, *Net Income*, *Capital Gains Yield*, and *ROE* are regarded as outputs in the second stage because they can be viewed as the result of financial operations.

Using the two-stage DEA network and the aforementioned inputs, outputs, and intermediate measure (Figure 3.2), we focuses on evaluating eight airline companies (Alaska Airlines, Air Canada, Delta Airlines, Hawaiian Airlines, Jet Blue, Southwest Airlines, United Continental Holdings and Spirit Airlines respectively) in ten rolling 1-year time windows for the total sample period of 1/1/2006 to 9/30/2016. Thus, the first time window is 1/1/2006 – 12/31/2007 while the next time window is 1/1/2007 – 12/31/2008, and so on. A data set example for this rolling window approach is shown in table 3.1

Table 3.1 Data for one time window (1/1/2015-09/30/2016)

Airlines Companies	Date (Quarterly)	Cost per ASM (excluding fuel)	Employees (thousands)	Fuel Cost per ASM (cents)	Sales	Revenue Passenger Kilometers	WACC	Short Interest Ratio	Market Capitalization	Net Income (millions)	Capital Gains Yield (%)	ROE
Alaska	12/31/2015	8.48	14.36	2.05	1377	8526.00	8.47	10.35	10154614784	1651.00	131.33	357.37
Alaska	3/31/2016	8.51	14.36	1.60	1347	8571.00	9.87	9.88	10230277120	1644.00	131.86	358.22
Alaska	6/30/2016	7.91	14.47	1.82	1494	9397.00	10.06	4.10	7184391680	1720.00	95.85	357.52
Alaska	9/30/2016	8.39	14.67	2.01	1566	9601.00	9.88	6.52	8106905088	1716.00	142.21	354.08
Air Canada	3/31/2015	9.60	24.50	2.60	3249	14937.00	8.08	0.59	2800421888	1209.90	134.29	332.08
Air Canada	6/30/2015	9.19	24.80	2.62	3414	16845.00	9.54	0.20	3035396352	1699.92	136.41	332.60
Air Canada	9/30/2015	7.65	25.00	2.26	4023	20462.00	10.28	5.00	2288377856	1792.56	109.21	333.20
Air Canada	12/31/2015	9.14	25.10	2.41	3182	15301.00	11.12	8.28	2093185408	1372.39	125.03	332.17
Air Canada	3/31/2016	8.97	25.40	1.64	3343	16092.00	12.44	6.22	1944739072	1533.66	116.94	340.33
Air Canada	6/30/2016	8.69	26.10	1.83	3458	18418.00	12.72	6.13	1894500224	1604.33	129.22	336.49
Air Canada	9/30/2016	7.21	26.50	1.91	4451	24328.00	11.24	2.92	2231885056	2048.74	147.59	339.34
Delta	3/31/2015	10.41	81.06	3.24	9388	46221.00	11.11	1.38	37059252224	2206.00	121.01	331.04
Delta	6/30/2015	10.14	83.25	2.74	10707	54755.00	11.03	2.31	33533681664	2945.00	120.97	338.07
Delta	9/30/2015	10.02	83.03	3.05	11107	59076.00	10.47	2.52	35689521152	2775.00	138.82	348.30
Delta	12/31/2015	10.54	82.95	2.84	9502	49573.00	10.22	2.05	39866347520	2440.00	142.20	366.55
Delta	3/31/2016	10.86	83.82	2.40	9251	47725.00	10.99	2.71	37897797632	2406.00	125.95	366.28
Delta	6/30/2016	9.97	84.79	2.19	10447	56415.00	10.60	1.40	28109109248	3006.00	101.01	364.47
Delta	9/30/2016	9.94	84.08	2.39	10483	58973.00	10.46	1.13	29477005312	2719.00	137.74	361.67
Hawaiian	3/31/2015	8.46	5.37	2.63	540	3345.38	11.64	3.38	1199819648	1485.88	113.22	348.84
Hawaiian	6/30/2015	8.27	5.44	2.53	571	3588.25	13.37	4.57	1299513984	1508.83	137.54	352.60

Table 3.1 Data for one time window (1/1/2015-09/30/2016) (Continued)

Airlines Companies	Date (Quarterly)	Cost per ASM (excluding fuel)	Employees (thousands)	Fuel Cost per ASM (cents)	Sales	Revenue Passenger Kilometers	WACC	Short Interest Ratio	Market Capitalization	Net Income (millions)	Capital Gains Yield (%)	ROE
Hawaiian	9/30/2015	7.97	5.48	2.26	632	3882.90	12.79	2.71	1354105472	1530.03	133.84	357.20
Hawaiian	12/31/2015	10.94	5.55	2.02	574	3634.03	13.19	3.42	1880058368	1497.90	165.87	364.92
Hawaiian	3/31/2016	10.52	5.72	1.60	551	3541.07	14.00	3.35	2520013824	1511.47	158.94	372.72
Hawaiian	6/30/2016	10.45	5.95	1.84	595	3846.97	13.59	2.90	2034248064	1539.57	108.24	373.41
Hawaiian	9/30/2016	10.17	6.07	1.94	672	4166.49	13.39	4.11	2596129792	1562.45	154.71	372.05
Jet Blue	3/31/2015	8.19	14.05	2.93	1523	9622.00	9.34	7.12	6015743488	1597.00	149.37	342.04
Jet Blue	6/30/2015	7.83	14.22	3.03	1612	10472.00	9.78	3.83	6503353856	1612.00	137.55	337.85
Jet Blue	9/30/2015	7.67	14.42	2.64	1687	11063.00	9.93	3.75	8112769024	1658.00	151.62	341.28
Jet Blue	12/31/2015	7.64	14.54	2.38	1594	10554.00	9.68	4.66	7136120832	1650.00	117.09	343.59
Jet Blue	3/31/2016	8.08	15.20	1.65	1616	10976.00	10.17	3.68	6801623552	1659.00	123.01	344.14
Jet Blue	6/30/2016	7.76	15.30	2.02	1643	11553.00	10.16	2.00	5334882304	1640.00	105.68	343.83
Jet Blue	9/30/2016	7.86	15.52	2.12	1732	11905.00	9.98	2.29	5579465728	1659.00	134.02	342.38
Southwest	3/31/2015	8.53	47.01	2.72	4414	25860.87	9.58	1.92	29946529792	1913.00	134.57	340.39
Southwest	6/30/2015	8.29	47.65	2.76	5111	30858.38	10.34	1.71	22113935360	2068.00	100.82	341.53
Southwest	9/30/2015	8.68	48.64	2.57	5318	31052.66	9.43	2.49	25081884672	2044.00	143.94	345.49
Southwest	12/31/2015	8.91	49.58	2.26	4977	29727.97	9.93	2.98	28004290560	1996.00	142.40	350.86
Southwest	3/31/2016	8.59	50.91	2.42	4826	28408.16	10.32	2.49	28585535488	1971.00	133.96	351.10
Southwest	6/30/2016	8.38	52.30	2.36	5384	32707.69	10.02	1.15	25042911232	2280.00	116.67	352.73
Southwest	9/30/2016	9.25	53.07	2.48	5139	32315.95	9.62	1.42	24120848384	1848.00	129.18	350.04

Table 3.1 Data for one time window (1/1/2015-09/30/2016) (Continued)

Airlines Companies	Date (Quarterly)	Cost per ASM (excluding fuel)	Employees (thousands)	Fuel Cost per ASM (cents)	Sales	Revenue Passenger Kilometers	WACC	Short Interest Ratio	Market Capitalization	Net Income (millions)	Capital Gains Yield (%)	ROE
United Continental	3/31/2015	10.49	81.70	3.25	8608	46444.00	10.73	2.52	25839224832	1968.00	130.54	400.51
United Continental	6/30/2015	9.84	82.30	3.26	9914	54289.00	10.46	1.38	20249896960	2653.00	106.21	391.04
United Continental	9/30/2015	9.70	82.40	2.90	10306	57160.00	9.37	1.72	20265177088	6276.00	130.08	425.40
United Continental	12/31/2015	10.34	82.10	2.64	9036	50718.00	9.84	1.75	21888684032	2283.00	137.71	449.20
United Continental	3/31/2016	10.86	82.50	2.09	8195	46582.00	11.12	2.36	21518759936	1773.00	134.37	451.73
United Continental	6/30/2016	10.66	83.20	2.22	9396	54017.00	10.59	3.08	13777115136	2048.00	92.25	429.86
United Continental	9/30/2016	9.83	85.10	2.35	9913	58172.00	10.64	1.86	16916763648	2425.00	154.57	351.65
Spirit	3/31/2015	5.72	3.72	2.38	493	4017.56	14.30	2.25	5629944832	1529.00	132.33	347.33
Spirit	6/30/2015	5.80	3.72	2.45	553	4481.06	15.79	3.33	4532477952	1536.70	108.03	347.44
Spirit	9/30/2015	5.39	3.72	2.07	575	4768.69	13.91	3.56	3448730624	1557.11	102.78	348.53
Spirit	12/31/2015	5.15	4.33	1.84	520	4728.00	12.55	3.10	2850854144	1534.40	112.86	348.47
Spirit	3/31/2016	5.59	4.33	1.44	538	5070.31	12.35	3.90	3432809472	1521.92	148.57	346.43
Spirit	6/30/2016	5.30	4.33	1.76	584	5549.41	12.37	5.12	3195075584	1533.08	123.30	345.74
Spirit	9/30/2016	5.48	4.33	1.87	621	5599.37	12.21	2.85	2977989632	1541.38	124.64	343.33

We use our two-stage network DEA model to examine the data and to gauge airline performance. Table 3.1 reports results for the time window 1/1/2015 - 09/30/2016 of the overall performance and its decomposition.

While the weights α_1 and α_2 can be viewed as the relative importance of the two stages, the current chapter is not able to use such information in this application for the following reasons. Since the overall performance is defined as the weighted average of the two stages' performance scores, one would hope that different sets of stage weights lead to different individual stage performance scores. In the current chapter, we discover that multiple sets of stage weights lead to the identical individual stage performance scores; namely, each pair of stage performance scores can correspond to multiple stage weight combinations. Such a situation has already been observed in the literature Guo and Zhu (2017). In fact, Guo and Zhu (2017) discover that sometimes the changes in the overall performance is due to the varying stage weights while the individual stage performance scores remain unchanged. In such cases, a larger overall performance from one set of stage weights does not necessarily mean a better overall performance. This is because the larger overall score is caused by the stage weights, not the individual stage scores which remain the same. We can perform sensitivity analysis to determine the exact range of stage weights that maintain the identical stage performance scores. Our analysis indicates that the current data set yields a unique pair of individual stage performance scores for each DMU. Such scenarios have also been observed in the literature for other data sets and network DEA models (see, e.g., Chen et al. (2009), Chen and Guan (2012), and Guo and Zhu (2017)). In such a case, one can use any weight combinations to yield the overall performance scores. In the current chapter, we use average, indicating the two stages are viewed equally; namely, α_1 and α_2 are 0.5 in this current chapter.

Table 3.2 Examples results for time window (1/1/2015-09/30/2016)

Airlines Companies	Date (Quarterly)	α_1	Operation Efficiency	α_2	Stock Market Efficiency	Overall Efficiency
Alaska	3/31/2015	0.50	0.6642	0.50	0.9620	0.8131
Alaska	6/30/2015	0.50	0.6997	0.50	0.9246	0.8121
Alaska	9/30/2015	0.50	0.7225	0.50	1.0000	0.8612
Alaska	12/31/2015	0.50	0.7347	0.50	1.0000	0.8673
Alaska	3/31/2016	0.50	0.9368	0.50	0.9241	0.9304
Alaska	6/30/2016	0.50	0.8300	0.50	1.0000	0.9150
Alaska	9/30/2016	0.50	0.7644	0.50	0.9574	0.8609
Air Canada	3/31/2015	0.50	0.7933	0.50	1.0000	0.8967
Air Canada	6/30/2015	0.50	0.8228	0.50	1.0000	0.9114
Air Canada	9/30/2015	0.50	0.9594	0.50	1.0000	0.9797
Air Canada	12/31/2015	0.50	0.7646	0.50	0.9174	0.8410
Air Canada	3/31/2016	0.50	1.0000	0.50	0.8715	0.9358
Air Canada	6/30/2016	0.50	0.9333	0.50	0.8914	0.9124
Air Canada	9/30/2016	0.50	1.0000	0.50	1.0000	1.0000
Delta	3/31/2015	0.50	0.8866	0.50	0.7504	0.8185
Delta	6/30/2015	0.50	0.9890	0.50	0.7730	0.8810
Delta	9/30/2015	0.50	1.0000	0.50	0.8466	0.9233
Delta	12/31/2015	0.50	0.8911	0.50	0.9128	0.9020
Delta	3/31/2016	0.50	0.8832	0.50	0.7785	0.8309
Delta	6/30/2016	0.50	1.0000	0.50	0.8054	0.9027
Delta	9/30/2016	0.50	1.0000	0.50	0.8896	0.9448
Hawaiian	3/31/2015	0.50	0.7227	0.50	1.0000	0.8613
Hawaiian	6/30/2015	0.50	0.7317	0.50	1.0000	0.8659
Hawaiian	9/30/2015	0.50	0.8010	0.50	1.0000	0.9005
Hawaiian	12/31/2015	0.50	0.7840	0.50	1.0000	0.8920
Hawaiian	3/31/2016	0.50	0.8984	0.50	1.0000	0.9492
Hawaiian	6/30/2016	0.50	0.7840	0.50	1.0000	0.8920
Hawaiian	9/30/2016	0.50	0.8113	0.50	1.0000	0.9056
Jet Blue	3/31/2015	0.50	0.6979	0.50	1.0000	0.8490
Jet Blue	6/30/2015	0.50	0.7376	0.50	0.9647	0.8512
Jet Blue	9/30/2015	0.50	0.7625	0.50	1.0000	0.8813
Jet Blue	12/31/2015	0.50	0.7581	0.50	0.9551	0.8566
Jet Blue	3/31/2016	0.50	0.9236	0.50	0.9441	0.9338
Jet Blue	6/30/2016	0.50	0.7898	0.50	0.9898	0.8898
Jet Blue	9/30/2016	0.50	0.7798	0.50	0.9936	0.8867

Table 3.2 Examples results for time window (1/1/2015-09/30/2016) (continued)

Airlines Companies	Date (Quarterly)	α_1	Operation Efficiency	α_2	Stock Market Efficiency	Overall Efficiency
Southwest	3/31/2015	0.50	0.8191	0.50	0.8657	0.8424
Southwest	6/30/2015	0.50	0.8976	0.50	0.8030	0.8503
Southwest	9/30/2015	0.50	0.8654	0.50	0.9648	0.9151
Southwest	12/31/2015	0.50	0.8450	0.50	0.8903	0.8676
Southwest	3/31/2016	0.50	0.8467	0.50	0.8095	0.8281
Southwest	6/30/2016	0.50	0.9067	0.50	0.8348	0.8707
Southwest	9/30/2016	0.50	0.8281	0.50	0.8656	0.8468
United Continental	3/31/2015	0.50	0.8462	0.50	0.8454	0.8458
United Continental	6/30/2015	0.50	0.9655	0.50	0.8628	0.9141
United Continental	9/30/2015	0.50	1.0000	0.50	1.0000	1.0000
United Continental	12/31/2015	0.50	0.8925	0.50	1.0000	0.9462
United Continental	3/31/2016	0.50	0.9800	0.50	1.0000	0.9900
United Continental	6/30/2016	0.50	0.9729	0.50	1.0000	0.9864
United Continental	9/30/2016	0.50	1.0000	0.50	1.0000	1.0000
Spirit	3/31/2015	0.50	1.0000	0.50	1.0000	1.0000
Spirit	6/30/2015	0.50	1.0000	0.50	0.8579	0.9289
Spirit	9/30/2015	0.50	1.0000	0.50	0.8712	0.9356
Spirit	12/31/2015	0.50	1.0000	0.50	0.9518	0.9759
Spirit	3/31/2016	0.50	1.0000	0.50	0.9607	0.9803
Spirit	6/30/2016	0.50	1.0000	0.50	0.8911	0.9455
Spirit	9/30/2016	0.50	1.0000	0.50	0.9654	0.9827

For the overall performance, there are seventy-one airline units which are best practices (or efficient) out of total 518 airline units. There are twenty units from Hawaiian Airlines, fourteen units from Spirit Airlines, nine units from Southwest Airlines, nine units from Air Canada, seven units from Jet Blue, five units from Delta Airline, five units from United Continental Holding and two units from Alaska Airlines, respectively.

In addition, airlines perform better in the second stage (stock market performance stage) than they do in the first stage (operation performance stage). In the second stage, we have 222 DMUs whose performance score is equal to one.

However, there are only 126 DMUs in the first stage whose performance are aligned with best practices. Among them, Hawaiian Airlines has the vast majority of efficient units in the second stage, while Spirit Airlines has the vast majority of efficient units in the first stage.

We also conduct a comparison of the results between low-cost and the full-service carriers. A low-cost carrier is an airline that generally has lower fares and fewer comforts while full-service airlines are usually regarded as having a higher level of customer service and more features. Table 3.3 summarizes the performance score for these two different airline carrier types.

Table 3.3 Performance score by carrier type

Carrier Type	Operation Performance	Stock Market Performance	Overall Performance
Lower Cost Carrier	0.9258	0.8652	0.8955
Full Service Carrier	0.8954	0.9195	0.9075

According to Table 3.3, the full-service carriers perform better in the stock market stage than they perform in the operation stage, while the low-cost carriers perform better in the first stage than they do in the second stage. In addition, the low-cost carriers have a higher performance score in the operational performance stage than the full-service carriers have. On the contrary, full-service carriers perform better in the second stage relative to their low-cost counterparts. In terms of overall performance, full-service carriers appear to be more efficient with an average score of 0.9075.

Tables 3.4 reports the results across all ten time-windows while Table 3.5 reports final results and overall rankings for the airline companies for the entire sample period, 1/1/2006 to 9/30/2016.

Table 3.4 Performance scores across all time windows

Time Window	Operation Performance	Stock Market Performance	Overall Performance
2006-2007	0.9641	0.988	0.976
2007-2008	0.9544	0.9562	0.9553
2008-2009	0.9468	0.9125	0.9297
2009-2010	0.934	0.9154	0.9247
2010-2011	0.9479	0.8822	0.9151
2011-2012	0.8957	0.9055	0.9006
2012-2013	0.8929	0.8913	0.8921
2013-2014	0.8811	0.7630	0.822
2014-2015	0.8661	0.7906	0.8284
2015-2016	0.8736	0.9338	0.9037

Table 3.5 Performance scores for all airline companies

Airline Companies	Operation Performance	Stock Market Performance	Overall Performance	Rank
Alaska	0.8394	0.9112	0.8753	6
Air Canada	0.9007	0.9335	0.9171	3
Delta	0.9404	0.8155	0.878	5
Hawaiian	0.9098	0.9986	0.9542	2
Jet Blue	0.9188	0.8261	0.8725	7
Southwest	0.9046	0.8654	0.885	4
United Continental	0.9181	0.7197	0.8189	8
Spirit	0.9952	0.9596	0.9774	1

The 2008/09 financial crisis and the European debt crisis and United States debt-ceiling crisis, which both respectively transpired during the 2013/14 period, are associated with declines in overall airline performance. Note that the crisis during 2013/14 has a greater impact on the airline industry where the average performance score for the stock market stage reduces to 0.7630. Following 2015/16, however, the airlines appear to be recovering and performing better.

The overall rank in Table 3.5 is constructed according to the value of overall performance of each airline. It appears that Spirit Airlines performs the best while United Continental Holdings performs the worst. More than half of the airline companies perform better in terms of their operational performance relative to their stock market performance. Alaska Airlines and Air Canada perform worse in terms of their operational performance - this is an important finding considering that both of these companies are considered full-service carriers. In addition, Hawaiian Airlines performs best in the stock market performance stage and Spirit performs best in terms of operational performance.

Our results also indicate that there is no relationship between performance scores and capital gains. This finding lends support to a growing branch of behavioral finance literature which shows that stock prices can behave in ways that do not reflect fundamental aspects of a firm, such as its operational performance, and can deviate from 'fair' values indefinitely (Koutmos, 2015). They are prone to such deviations as a result of speculative buying and selling decisions that take place in the market and as a result of traders with heterogeneous trading styles.

3.6 Conclusions

There have been significant methodological advances in efficiency and performance benchmarking. Despite this, the majority of extant studies, albeit with some exceptions, focus exclusively on operational indicators when drafting their conceptual and empirical frameworks. Stock market indicators are almost absent from empirical considerations. Such an approach may lead to biased or erroneous conclusions.

This chapter makes a conceptual contribution to the literature by integrating operational with financial market data. Neglecting to include stock market and financial indicators into any empirical framework can lead to biased conclusions. From a managerial point of view, stock market measures can capture investor attitudes and give upper management important feedback into the pulse of the market. Given that the airlines industry is so competitive, managers need to be acutely aware of not only their operational efficiency but also the sentiment, attitudes and expectations of their shareholders and the stock market at large. By integrating financial market indicators into our two-stage DEA framework, we also align ourselves with financial economics literature which finds that investors trade on sentiment and various market indicators.

This chapter also makes a methodological contribution because it implements a two-stage network DEA with SOCP. Such a technique is novel in operations literature and is advantageous because it enables us to solve non-linear DEA models without the need for calculating numerous parametric linear programs in an effort to estimate the global optimal solution.

Overall, we provide performance rankings of all the eight major airlines in our sample for the period 1/1/2006 to 9/30/2016. These performance rankings are unique in that they include both operational and financial stock market indicators. We also uncover some important findings regarding our full- and sub-sample analyses. Low-cost carriers generate higher performance scores in the operational performance stage than their full-service counterparts. On the contrary, full-service carriers perform better in the financial market stage relative to low-cost airlines.

The 2008/09 financial crisis and the European debt crisis and United States debt-ceiling crisis, which both respectively transpired during the 2013/14 period, are associated with declines in overall airline performance. Following 2013/14, however, the airlines appear to be performing better.

The current chapter shows that there is no relationship between performance scores and capital gains. This finding lends support to an emerging body of behavioral finance literature which shows that stock prices can behave in ways that do not reflect fundamental and objective aspects pertaining to a firm's operations or growth prospects.

Chapter IV Globalization Index from Political Dimension and Economic Dimension — A ASBM Network DEA Approach

4.1 Introduction

In the previous chapter, we implement a ratio from a two-stage network DEA with SOCP which enables us to solve non-linear DEA models without the need for calculating numerous parametric linear programs to estimate the global optimal solution. In this chapter, we start to discuss how to implement an additive slaked-based measure (ASBM) structure which was first introduced by Tone and Tsutsui (2009) with SOCP to measure globalization performance for countries around the world.

In current existing literature, the two most widely known and most frequently used globalization indices are the A. T. Kearney/Foreign Political Magazine (2002) and the KOF globalization index (Dreher, 2006), which bring together indicators from different dimensions. Kearney's globalization index, however, has been criticized for its ad hoc procedure of determining the weights of its components and a lack of robustness to alternative weighting schemes (Lockwood, 2004). Dreher (2006) introduces a KOF index which improved Kearney's index-creation methodology and expanded the number of indicators. The overall KOF for each country is based on a set of weights for sub-indicators from three dimensions (economic dimension, political dimension, and social dimension).

In addition to the above most frequently discussed globalization index which considers metrics of globalization from political, social, and economic dimensions, a great portion of researchers focus on only how globalization performs in firms, organizations, or countries due to different situations of economic and political. At the same time, they also care about how globalization has an impact on a country's economic situation and political making. For example, Soejachmoen (2016) addresses the determinants of a country's participation in the global production network and reveals that foreign investment policies are one of the reasons why Indonesia is being left behind in global automotive production networks.

This chapter applies a non-parametric data-oriented method called DEA, to measure the globalization performance via integrating the indicators of globalization of political aspects and economic aspects in each country under consideration.

The remainder of this chapter is structured as follows: section 4.2 develops a two-stage network DEA structure and describes the input-output variables and intermediate measures in our model. In section 4.3, we implement the two-stage DEA network structure proposed in section 4.2 into our SBM-SOCP network model. In section 4.4, we provide the political-economic globalization index (PEGI) of countries in our sample for the period from 1995 to 2015 and present major findings. Finally, conclusions are given in section 4.5.

4.2 Globalization indicators in political and economic dimensions

To describe how to measure the globalization performance from both the economic dimension and political dimension, we develop the following network structure considering the inner relations among indicators under consideration as shown in figure 4.1.

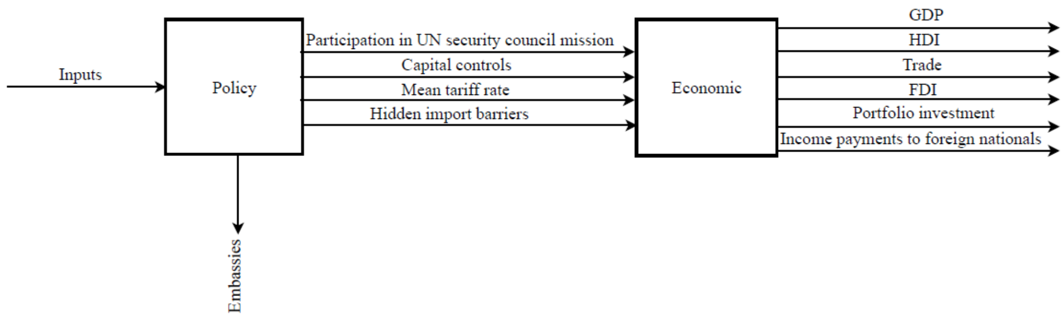

Figure 4.1 Two-stage network DEA structure of Political-Economic Globalization Index

As shown in Figure 4.1, it utilizes five key indicators of globalization in the political dimension and six indicators of globalization in the economic dimension. Political indicator are: (i) the number of embassies, (ii) participation in UN Security Council mission, (iii) capital controls, (iv) mean tariff rate, and (v) hidden import barriers

i. *Embassies* is the indicator only in political dimension and denotes the total number of embassies in each country. Generally speaking, the more the number of embassies in each country, the higher connections with other countries that the country has soft policies for globalization.

ii. *Participation in UN Security Council missions is* the absolute number of missions a country participated. In the political stage, it stands for the social power of a country. However, in the economic stage, it consumes the budgets of a country.

iii. *Capital Controls* are residency-based measures such as transaction taxes, other limits, or outright prohibitions that a nation's government can use to regulate flows from capital markets into and out of the country's capital account. These measures may be economy-wide, usually in the financial sector.

iv. *Mean tariff rate* illustrates the average of effectively applied rates weighted by the product import shares corresponding to each partner country, while *Hidden import barriers* are any obstacle to international trade that is not an import or export duty. They may take the form of import quotas, subsidies, customs delays, technical barriers, or other systems preventing or impeding trade.

v. *Hidden import barriers* are any obstacle to international trade that is not an import or export duty. They may take the form of import quotas, subsidies, customs delays, technical barriers, or other systems preventing or impeding trade.

In terms of economic indicators in globalization, this research uses the following six indicators: (i) gross domestic product (GDP), (ii) human development index (HDI), (iii) trade, (iv) foreign direct investment (FDI), (v) portfolio investment, and (vi) income payments to foreign nationals, respectively.

i. *GDP* is the monetary value of all finished goods and services produced by a country in a given period, and is used to estimate the size of a country's economy. It could be seen as the outputs from the growth of economy, and the inputs for the social stage.

ii. *HDI* reveals the imbalance between economic growth and social development. There are three dimensions: long and healthy life, knowledge, and a decent standard of living which is also considered as one of the indexes of poverty. It is one of the outcomes from the economic, and the cost of the social stage.

iii. *Trades* are the sum of exports and imports of goods and services as a share of GDP.

iv. *FDI is s*um of the absolute values of inflows and outflows of foreign direct investment. It is an investment in the form of controlling ownership in a business in one country by an entity based in another country. It is thus distinguished from a foreign portfolio investment by a notion of direct control.

v. *Portfolio investment* covers transactions in equity securities and debt securities. They are investments in the form of a group (portfolio) of assets, including transactions in equity securities, such as common stock, and debt securities, such as banknotes, bonds, and debentures.

vi. *Income payments to foreign nationals* are referred to employee compensation paid to nonresident workers and investment income.

4.3 PEGI with an ASBM two-stage network approach

According to figure 4.1, we consider a two-stage network structure shown in Figure 4.2. Each $DMU_j \, (j = 1, 2, ..., n)$ has m inputs x_{ij} , $(i = 1, 2, ..., m)$ to the first stage and E outputs $y_{ej}^1 (e = 1, 2, ..., E)$ that leave the system. In addition to these E outputs, stage 1 has D outputs $z_{dj} (d = 1, 2, ..., D)$ called intermediate measures that become inputs to the second stage. The outputs from the second stage are $y_{rj} (r = 1, 2, ..., s)$.

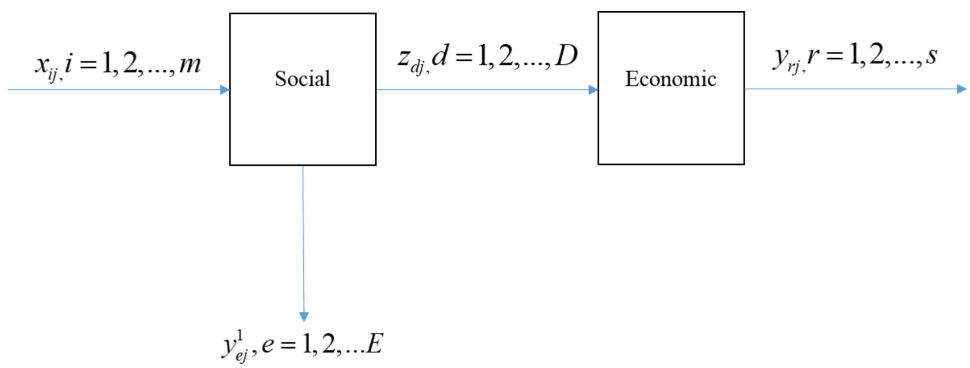

Figure 4.2 a two-stage SBM network DEA structure

We still consider the variable returns to scale (VRS) case, but note that we do not study the issue of returns-to-scale and VRS and CRS here are used to distinguish the two different types of DEA best-practice frontiers (not production frontiers). The DEA score here is treated as a composite index, we name it as the Political-Economic Globalization Index (PEGI), not an efficiency score from a production technology. In current chapter, DEA is used as a data analytics (benchmarking) tool.

Chapter 3 uses traditional ratio DEA models to define the performance of airline companies. This chapter, however, it will apply an ASBM approach which has been introduced by Chen and Zhu (2020).

First, based on the production possibility set (PPS) proposed by Fare and Grosskopf (1997), Tone and Tsuisui (2014), and Kao (2013), the following two-stage network DEA model is adapted for the proposed network structure in figure 4.2:

$$\sum_{j=1}^{n} x_{ij}\lambda_j^1 + s_i^- = x_{i0}, \forall i; \sum_{j=1}^{n} y_{ej}^1\lambda_j^1 - s_e^+ = y_{e0}^1, \forall e \qquad (C1)$$

$$\sum_{j=1}^{n} \lambda_j^2 z_{dj} + t_d^- = z_{d0}, \forall d; \sum_{j=1}^{n} \lambda_j^1 z_{dj} - t_d^+ = z_{d0}, \forall d;$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j^2 - s_r^+ = y_{r0}, \forall r;$$

$$\sum_{j=1}^{n} \lambda_j^1 = 1, \sum_{j=1}^{n} \lambda_j^2 = 1$$

$$\sum_{j=1}^{n} \lambda_j^1 z_{dj} = \sum_{j=1}^{n} \lambda_j^2 z_{dj}, \forall d$$

$$s_i^-, s_e^+, s_q^+, \lambda_j^1, \lambda_j^2 \geq 0$$

The constraint $\sum_{j=1}^{n} \lambda_j^1 z_{dj} = \sum_{j=1}^{n} \lambda_j^2 z_{dj}, \forall d$ in model (*C1*) on intermediate measures is reviewed as a cooperation on quantity that all intermediate measures from the first division has been, and at the same time are exactly the measures involved in the second division.

Then, based upon ASBM (Chen and Zhu (2020)), the divisional efficiencies are defined as follows:

$$E^1 = \frac{1}{P+m+D}\left(\sum_{e=1}^{E} \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} + \sum_{i=1}^{m} \frac{x_{i0} - s_i^-}{x_{i0}} + \sum_{d=1}^{D} \frac{z_{d0}}{z_{d0} + t_d^+}\right) \qquad (4.1)$$

$$E^2 = \frac{1}{S+D}\left(\sum_{r=1}^{s} \frac{y_{r0}}{y_{r0} + s_r^+} + \sum_{d=1}^{D} \frac{z_{d0} - t_d^-}{z_{d0}}\right) \qquad (4.2)$$

Further, the internal evaluation based on network DEA is defined as follows:

$$\min w^{(1)} \frac{1}{E+m+D}\left(\sum_{e=1}^{E}\frac{y_{e0}^{1}}{y_{e0}^{1}+s_e^{+}}+\sum_{i=1}^{m}\frac{x_{i0}-s_i^{-}}{x_{i0}}+\sum_{d=1}^{D}\frac{z_{d0}}{z_{d0}+t_d^{+}}\right) \tag{4.3}$$

$$+w^{(2)} \quad \frac{1}{S+D}\left(\sum_{r=1}^{S}\frac{y_{r0}}{y_{r0}+s_r^{+}}+\sum_{d=1}^{D}\frac{z_{d0}-t_d^{-}}{z_{d0}}\right)$$

$$s.t. \quad w^{(1)}+w^{(2)}=1$$

$$constra\operatorname{int}s \quad (C1)$$

where $w^{(1)}$ and $w^{(2)}$ ($w^{(2)}=1-w^{(1)}$) are weights. Here, weights can be user-specified weights or exogenous weights satisfying $0<w^{(1)}<1$.

Above model (4.3) is highly nonlinear, and can be rewritten as:

$$\frac{w^{(1)}}{E+m+D}*\frac{y_{e0}^{1}}{y_{e0}^{1}+s_e^{+}}+\frac{w^{(2)}}{S+D}*\frac{y_{r0}}{y_{r0}+s_r^{+}}+\frac{w^{(1)}}{E+m+D}*\frac{z_{d0}}{z_{d0}+t_d^{+}}+$$
$$\left(\frac{w^{(1)}}{E+m+D}*\sum_{i=1}^{m}\frac{x_{i0}-s_i^{-}}{x_{i0}}+\frac{w^{(2)}}{S+D}*\sum_{d=1}^{D}\frac{z_{d0}-t_d^{-}}{z_{d0}}\right)$$

Then, for each term, we introduce its upper bounds as $\xi_e^1, \xi_d^1, \xi_r^2$ and ξ_3 respectively. Consequently, by an epigraph transformation which replaces the nonlinear objective function of model (4.3) with sum of those upper bounds, model (4.3) is equivalent to the following optimization model (4.4).

$$\min \sum_{e}^{E} \xi_e^1 + \sum_{d}^{D} \xi_d^1 + \sum_{r}^{S} \xi_r^2 + \xi^3 \tag{4.4}$$

$$\begin{aligned}
s.t. \quad & \frac{w^{(1)}}{E+m+D} * \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} \le \xi_e^1 \\
& \frac{w^{(1)}}{E+m+D} * \frac{z_{d0}}{z_{d0} + t_d^+} \le \xi_d^1 \\
& \frac{w^{(2)}}{S+D} * \frac{y_{r0}}{y_{r0} + s_r^+} \le \xi_r^2 \\
& \frac{w^{(1)}}{E+m+D} * \frac{x_{i0} - s_i^-}{x_{i0}} + \frac{w^{(2)}}{S+D} * \frac{z_{d0} - t_d^-}{z_{d0}} \le \xi^3 \\
& w^{(1)} + w^{(2)} = 1 \\
& \text{constraints } (C1)
\end{aligned}$$

Evidently, model (4.4) is a quadratic optimization problem which can be convex or nonconvex. Then, model (4.4) can be converted into a SOCP problem whose global optimal solution is ensured and can be obtained by solvers such as CVX in MATLAB since SOCP is a special form of convex optimization (Boyd and Vandenberghe, 2004). Obviously, above constraints $\frac{w^{(1)}}{E+m+D} * \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} \le \xi_e^1$ is equivalent to $(E+m+D)(y_{e0}^1 + s_e^+)\xi_e^1 \ge (\sqrt{w^{(1)} * y_{e0}^1})^2$. Then, according to the transformation utilized in Chen and Zhu (2017), we know that $(E+m+D)(y_{e0}^1 + s_e^+)\xi_e^1 \ge (\sqrt{w^{(1)} y_{e0}^1})^2$ can be converted into

$$\sqrt{(\sqrt{w^{(1)} y_{e0}^1})^2 + \left(\frac{1}{2}\left((E+m+D)(y_{e0}^1 + s_e^+) - \xi_e^1\right)\right)^2} \le \frac{1}{2}(E+m+D)(y_{e0}^1 + s_e^+) + \xi_e^1) \tag{4.5}$$

.

Similarity, $\frac{w^{(1)}}{E+m+D}*\frac{z_{d0}}{z_{d0}+t_d^+}\le \xi_d^1$ is equivalent to $(E+m+D)(z_{d0}+t_d^+)\xi_d^1 \ge (\sqrt{w^{(1)}*z_{d0}})^2$, and then can be transformed into the following model (4.6):

$$\sqrt{(\sqrt{w^{(1)}z_{e0}})^2+\left(\frac{1}{2}\left((E+m+D)(z_{e0}+t_d^+)-\xi_d^1)\right)\right)^2} \le \frac{1}{2}(E+m+D)(z_{e0}+t_d^+)+\xi_d^1) \qquad (4.6)$$

And $\frac{w^{(2)}}{S+D}*\frac{y_{r0}}{y_{r0}+s_r^+}\le \xi_r^2$ is equivalent to $(S+D)(y_{r0}+s_r^+)\xi_r^2 \ge (\sqrt{w^{(2)}*y_{r0}})^2$, and can be transformed into model (4.7) as the following:

$$\sqrt{(\sqrt{w^{(2)}y_{r0}})^2+\left(\frac{1}{2}\left((S+D)(y_{r0}+s_r^+)-\xi_r^2)\right)\right)^2} \le \frac{1}{2}(S+D)(y_{r0}+s_r^+)+\xi_r^2) \qquad (4.7)$$

Base on (Boyd and Vandenberghe (2004)), above model (4.5), (4.6), and (4.7) are second order cone constraints and can be further converted into SOCP problem in the following model (4.8):

$$
\begin{aligned}
\min \quad & \sum_{e=1}^{E}\xi_e^1+\sum_{d=1}^{D}\xi_d^1+\sum_{r=1}^{S}\xi_r^2+\xi^3 \qquad (4.8)\\
s.t. \quad & \left\| \begin{matrix} \sqrt{w^{(1)}y_{e0}^1} \\ \frac{1}{2}\left(\left(E+m+D\right)\left(y_{e0}^1+s_e^+\right)-\xi_e^1\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left(\left(E+m+D\right)\left(y_{e0}^1+s_e^+\right)+\xi_e^1\right),\ \forall e\\
& \left\| \begin{matrix} \sqrt{w^{(1)}z_{d0}} \\ \frac{1}{2}\left(\left(E+m+D\right)\left(z_{d0}+t_d^+\right)-\xi_d^1\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left(\left(E+m+D\right)\left(z_{d0}+t_d^+\right)+\xi_d^1\right),\ \forall d\\
& \left\| \begin{matrix} \sqrt{w^{(2)}y_{r0}} \\ \frac{1}{2}\left(\left(S+D\right)\left(y_{r0}+s_r^+\right)-\xi_r^2\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left(\left(S+D\right)\left(y_{r0}+s_r^+\right)+\xi_r^2\right),\forall r\\
& w^{(1)}\frac{1}{E+m+D}\left(\sum_{i=1}^{m}\frac{x_{i0}-s_i^-}{x_{i0}}\right)+w^{(2)}\frac{1}{S+D}\left(\sum_{d=1}^{D}\frac{z_{d0}-t_d^-}{z_{d0}}\right)\le\xi^3\\
& w^{(1)}+w^{(2)}=1\\
& \quad \text{constraints } (C1)
\end{aligned}
$$

4.4 Results of PEGI and major findings

Using the two-stage ASBM network in section 4.3 and the aforementioned inputs, outputs, and intermediate measures (figure 4.1), we construct a composite globalization index for countries around the world in one-year time window from the total sample period from 1995 to 2015. A data set example for PEGI for countries in 2015 is shown in table 4.1.

Table 4.1 PEGI in 2015

Countries	PEGI	Political Globalization Index	Economic Globalization Index
Argentina	0.7139	0.7325	0.6949
Armenia	0.6587	0.7854	0.5316
Australia	0.8227	0.8508	0.7940
Austria	0.7079	0.8234	0.5894
Belgium	0.8512	0.8400	0.8622
Benin	0.6437	0.6991	0.5875
Bulgaria	0.7419	0.8732	0.6104
Bosnia and Herzegovina	0.6505	0.7102	0.5901
Bolivia	0.6603	0.7342	0.5854
Brazil	0.7344	0.8053	0.6622
Brunei Darussalam	0.6705	0.7902	0.5506
Canada	0.8033	0.9669	0.6383
Switzerland	0.7862	0.7339	0.8356
Chile	0.6829	0.8012	0.5628
China	0.9648	0.9085	1.0000
Cote d'Ivoire	0.6744	0.7183	0.6304
Czech Republic	0.7141	0.7746	0.6535
Germany	0.9726	0.9451	1.0000
Denmark	0.7297	0.8655	0.5937
Ecuador	0.6864	0.6830	0.6895
Egypt, Arab Rep.	0.6871	0.7941	0.5794
Spain	0.7290	0.8454	0.6126
Estonia	0.6711	0.8019	0.5398
Finland	0.6900	0.8154	0.5635
France	0.8326	1.0000	0.6619
United Kingdom	0.9515	0.9029	1.0000
Georgia	0.7147	0.8565	0.5729
Ghana	0.6633	0.7919	0.5342
Greece	0.7354	0.7722	0.6984
Guatemala	0.6661	0.8337	0.4980
Honduras	0.6497	0.7475	0.5514
Croatia	0.6856	0.8164	0.5541
Hungary	0.6796	0.7502	0.6060
Indonesia	0.7138	0.8596	0.5678

Table 4.1 PEGI in 2015 (continued)

Countries	PEGI	Political Globalization Index	Economic Globalization Index
Ireland	0.8519	0.9605	0.7432
Italy	0.8485	1.0000	0.6426
Jamaica	0.7222	0.7519	0.6925
Japan	0.8774	0.7536	1.0000
Kazakhstan	0.7125	0.6956	0.7293
Kenya	0.6478	0.7403	0.5550
Kyrgyz Republic	0.6551	0.7190	0.5906
Cambodia	0.6404	0.7395	0.5411
Lesotho	0.6489	0.6883	0.6095
Lithuania	0.7770	0.8272	0.7267
Morocco	0.6822	0.7647	0.5964
Moldova	0.6738	0.7429	0.6046
Madagascar	0.6509	0.6756	0.6254
Myanmar	0.7003	0.7515	0.6491
Montenegro	0.6795	0.8368	0.5218
Mongolia	0.6546	0.7680	0.5411
Malawi	0.6403	0.7409	0.5390
Malaysia	0.7135	0.8114	0.6148
Namibia	0.6591	0.7583	0.5593
Nigeria	0.6763	0.8475	0.5049
Netherlands	0.8888	1.0000	0.7586
Norway	0.9365	0.8734	0.9995
Peru	0.6864	0.8556	0.5170
Philippines	0.6915	0.7730	0.6098
Poland	0.7390	0.7328	0.7445
Portugal	0.7721	0.8733	0.6709
Paraguay	0.6484	0.7351	0.5609
Qatar	0.8008	0.8025	0.7990
Russian Federation	0.7299	0.8219	0.6372
Rwanda	0.6798	0.8890	0.4705
El Salvador	0.6491	0.7364	0.5613
Serbia	0.6610	0.7329	0.5875
Slovenia	0.6817	0.7600	0.6025
Sweden	0.7091	0.8287	0.5873

Table 4.1 PEGI in 2015 (continued)

Countries	PEGI	Political Globalization Index	Economic Globalization Index
Thailand	0.7212	0.6948	0.7450
Timor-Leste	0.6687	0.8205	0.5168
Tunisia	0.6604	0.7047	0.6153
Turkey	0.6897	0.7566	0.6226
Uganda	0.6551	0.8061	0.5040
Uruguay	0.6841	0.8492	0.5186
United States	1.0000	1.0000	1.0000
Vietnam	0.7669	0.7467	0.7870
Yemen, Rep.	0.6406	0.7521	0.5290
South Africa	0.7165	0.8457	0.5855
Zambia	0.6619	0.8167	0.5071

We construct PEGI for 79 countries in total in 2015 which have a completely data set for all metrics under consideration in figure 4.1. Among them, we find the United States is the only country which has a value of one for PEGI, and so do its sub-political globalization index and sub-economic globalization index. According to the DEA approach, the indices here (PEGI, sub-political globalization index, and sub-economic globalization index) are with a zero to one scale, whereas higher values denote more globalization. Malawi has the lowest PEGI score as 0.6403 because its economic globalization score is sixth from the bottom and its political globalization score is lower intermediate.

Also, except for United State, France, Italy, and Netherland have a value of one (the highest value) in political globalization performance, while China, United Kingdom, Germany, and Japan rank the first in the economic dimension. Note that Germany, China, United Kingdom ranks the second, third, and fourth in overall PEGI with a score of 0.9726, 0.9648, and 0.9515, respectively. However, Japan only has a PEGI score of 0.8774 due to its lower political integration index (0.7356). Italy only has a PEGI score of 0.8485, mainly because of its low economic integration index (0.6426) compared with the rest of the world.

The lowest score of political globalization (0.6756) is obtained from Madagascar. One of the reasons is because there were only 45 embassies in Madagascar in 2015, while the average number of embassies in countries was 145. The lowest points of globalization performance in the economic dimension is from Rwanda as 0.4705. It is worth mentioning that the ranking of GDP for Rwanda's is also the lowest among the total seventy-nine countries in 2015 under consideration. Considering GDP may play an important role in PEGI, the followings we will discuss what kind of relationship it may exist between GDP and our PEGI.

As Dreher (2006) mentions in his study, countries with the lowest growth rates are countries that do not globalize. According to both our PEGI and his KOF globalization index, Rwanda has the lowest score for globalization, and at the same time, its GDP ranks the lowest in countries which are under consideration. The following table 4.2 shows the comparison between GDP and our PEGI in countries whose GDP rank top 15 around the whole world for a period from 2005 to 2015.

Table 4.2 PEGI from top 15 largest economies in the world by GDP nominal

Countries	GDP (billion, USD)	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
United States	21482	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
China	14172	0.965	0.9587	0.968	0.954	N/A	N/A	N/A	N/A	N/A	N/A	0.8743
Japan	5221	0.877	0.8094	1.000	1.000	0.779	0.75	0.9353	0.7799	0.863	0.9	0.8854
Germany	4117	0.973	0.9856	0.975	0.971	0.842	0.849	0.9795	0.808	0.869	0.857	0.818
India	2958	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
France	2845	0.833	0.8299	0.867	0.844	0.994	0.844	1.000	0.8472	0.832	0.84	0.8144
United Kingdom	2810	0.952	0.7779	0.957	0.978	0.859	0.836	1.000	0.878	0.825	0.817	1.000
Italy	2113	0.849	0.7975	0.808	0.786	0.803	0.816	0.8482	0.8242	0.812	0.814	0.8035
Brazil	1930	0.734	0.7599	0.767	0.757	0.752	0.737	0.7336	0.7036	0.699	0.697	0.705
Canada	1820	0.803	0.7991	0.785	0.783	0.794	0.777	0.8077	0.7473	0.761	0.767	0.7466
Korea, Rep.	1700	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Russian Federation	1649	0.73	0.7479	0.74	0.739	0.73	0.72	0.7127	0.7103	0.698	0.693	0.6933
Spain	1474	0.729	0.7308	0.774	0.765	0.746	0.741	0.7717	0.7464	0.75	0.762	0.7506
Australia	1464	0.823	0.8162	0.84	0.842	0.806	0.82	N/A	0.7976	N/A	0.795	0.8517
Mexico	1242	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Note that considering the table size, we only shows an average score of GDP from 2005 to 2015 for countries. Detailed comparison analysis examples can be found in the following table 4.3 and table 4.4. Besides, we don't have PEGI for India, Korea Rep, and Mexico for the years we considered above, and no result for China from 2006 to 2011 because of incomplete data information. According to table 4.2, under most of situations, countries which experience a higher PEGI are those who also have a higher GDP value. But exceptions exist, such as the relationship between PEGI and GDP in Japan and Germany. We'll illustrate this in detail in the next table

(table 4.3) as it shows all data for GDP and PEGI instead of an average value for GDP from 2005 to 2015 for countries.

In order to provide a detailed analysis of the relationship between PEGI and GDP, we show both GDP and PEGI for ten years since 2005 for three countries who are the most developed economic countries around the world, and the other three countries whose economic situation are in the medium around the world, respectively.

Table 4.3 Comparison between GDP and PEGI in United States, Japan, and Germany from 2005 to 2015

Year	**United States**		**Japan**		**Germany**	
	GDP ($Billion)	PEGI	GDP ($Billion)	PEGI	GDP ($Billion)	PEGI
2005	13093.7260	1.0000	4755.4106	0.8601	2861.4103	0.8493
2006	13855.8880	1.0000	4530.3772	0.8134	3002.4464	1.0000
2007	14477.6350	1.0000	4515.2645	0.7885	3439.9535	1.0000
2008	14718.5820	1.0000	5037.9085	0.6994	3752.3656	0.8715
2009	14418.7390	1.0000	5231.3827	0.8151	3418.0050	0.9587
2010	14964.3720	1.0000	5700.0981	0.8243	3417.0946	0.9499
2011	15517.9260	1.0000	6157.4596	0.8060	3757.6983	0.9486
2012	16155.2550	1.0000	6203.2131	0.9999	3543.9839	0.9412
2013	16691.5170	1.0000	5155.7171	1.0000	3752.5135	0.9501
2014	17427.6090	1.0000	4850.4135	0.9370	3890.6069	0.9708
2015	18120.7140	1.0000	4394.9778	0.8774	3375.6111	0.9726

Table 4.4 Comparison between GDP and PEGI in Tunisia, Uganda, and Estonia from 2005 to 2015

Year	Tunisia		Uganda		Estonia	
	GDP ($Billion)	PEGI	GDP ($Billion)	PEGI	GDP ($Billion)	PEGI
2005	32.2730	0.6797	9.0138	0.6452	14.0061	0.7737
2006	34.3784	0.6887	9.9426	0.6499	16.9636	0.7974
2007	38.9081	0.6884	12.2928	0.6404	22.2371	0.8110
2008	44.8566	0.6889	14.2390	0.6387	24.1940	0.7092
2009	43.4549	0.6817	18.1689	0.6441	19.6525	0.8140
2010	44.0509	0.6802	20.1865	0.6438	19.4909	0.7981
2011	45.8106	0.6852	20.1768	0.6441	23.1702	0.7572
2012	45.0441	0.6861	23.1321	0.6432	23.0439	0.7972
2013	46.2511	0.6839	24.5996	0.6456	25.1372	0.7048
2014	47.5879	0.6850	27.2952	0.6564	26.2246	0.6995
2015	43.1567	0.6604	27.0594	0.6551	22.5670	0.6711

Above 4.3 shows three countries whose GDP rank first, third, and fourth around the world in 2015, respectively, while table 4.4 shows three countries whose GDP rank 98 out of 211, 99 out of 211, and 100 out of 211 around the world in 2015, respectively. China's GDP ranks second. However, it isn't been involved here because its information is insufficient from 2006 to 2011. Comparing these two tables, first, there is a positive correlation between the globalization index and the economic situation. The range of PEGI for U.S., Japan, and Germany is 0.7885 to 1.0039, while the range of PEGI for Tunisia, Uganda, and Estonia is from 0.6387 to 0.8140. Among them, only two PEGI from Japan are lower than 0.8 for all three countries which rank the top in GDP. In terms of three countries that rank in the

medium in GDP, only two values of PEGI which are from Estonia are higher than 0.8. Especially, all PEGI values in Tunisia and Uganda are lower than 0.7. Second, the PEGI for each country is stable. For example, from 2005 to 2015, the GDP of U.S. increases from $13093.8880 billion to $18120.7140 billion, while the PEGI of U.S. changes from 1.0004 to 1.0001. Another example is from Uganda, its GDP increases from 9.0138 billion to 27.0594 billion, increasing around 200%. However, the PEGI keeps stable ranging from 0.6387 to 0.6564.

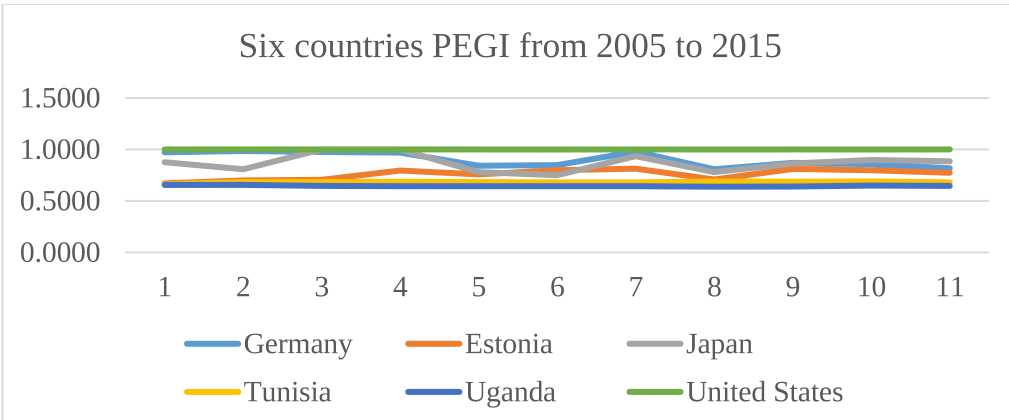

Figure 4.3 A line chart of six countries' PEGI in 2005 - 2015

Figure 4.3 illustrates the change of PEGI for the six countries we mentioned above. In figure 4.3, the y-axis stands for the value of PEGI, and the x-axis stands for years from 2005 to 2015 where 2005 is on the far left. Lines with different color shows the value of PEGI for different countries from 2005 to 2015. In detail, the green line stands for the change of PEGI for U.S., the grey line stands for the Japan's, the light-blue line stands for Germany's, the yellow line is for Tunisia, the dark-blue line is for Uganda, and the orange line is for the PEGI change of Estonia. According to figure 4.3, lines of the U.S., Tunisia, and Uganda are almost straight lines, while the lines for Japan, Germany, and Estonia are broken lines. The different shapes of lines are highly coincidental with countries' GDP change differently. For countries, such as the U.S. or Uganda, whose GDP keeps increasing with an constant rate, the PEGI lines in figure 4.3 are almost horizontal straight. On the contrary, if GDP don't keep a continuously constant increasing or decreasing, such as Japan, Germany, and Estonia, the PEGI lines are broken lines. In addition to the different shape of PEGI lines, the chart shows the range of Japan's EPGI has the most dramatic change. The minimum PEGI for Japan is 0.7885 in 2007, while the maximum PEGI is 1.000 in 2013. This change also illustrates a highly coincidence with the change of GDP.

The following table 4.5 shows PEGI for 81 countries from 2005 to 2015. We collected complete data set for more than 120 countries. However, for some countries, they don't have complete data set for all years we considered that we cannot obtain their PEGI for that specific year. Thus, in table 4.5, we include countries which have PEGI for three years at least. Thus, there are 81 countries in total in table 4.5.

Table 4.5 Countries PEGI from 2005 to 2015

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Argentina	0.7139	0.7227	0.7249	0.7328	0.7366	0.7337	N/A	0.6858	0.6848	N/A	N/A
Armenia	0.6587	0.6595	0.7011	0.7019	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Australia	0.8227	0.8162	0.8399	0.8422	0.8058	0.8195	N/A	0.7976	N/A	0.7952	0.8517
Austria	0.7141	0.7141	N/A	0.7084	0.7177	0.7065	N/A	0.7184	0.7236	0.7159	0.7507
Belgium	0.7079	0.9307	0.7370	0.7349	0.7427	0.7387	0.7642	0.7452	0.7211	0.7202	0.8658
Benin	0.8512	0.6479	0.6446	0.6397	0.6405	0.6384	0.6415	0.6458	0.6454	0.6431	N/A
Burkina Faso	N/A	0.6418	0.6436	0.6373	0.6351	0.6335	0.6423	0.6430	0.6426	0.6421	0.6470
Bulgaria	0.7419	0.7438	0.7626	0.7560	0.7804	0.7814	0.8341	0.6904	0.6890	0.6823	0.6666
Bosnia and Herzegovina	0.6505	0.6528	0.6511	0.6530	0.6534	0.6551	0.6538	0.6585	0.6668	0.6653	0.6537
Bolivia	0.6603	0.6586	0.6514	0.6527	0.6518	0.6516	0.6521	0.6554	0.6550	0.6563	0.6585
Brazil	0.7344	0.7599	0.7673	0.7573	0.7522	0.7368	0.7336	0.7036	0.6993	0.6970	0.7050
Canada	0.8033	0.7991	0.7853	0.7833	0.7937	0.7772	0.8077	0.7473	0.7614	0.7673	0.7466
Switzerland	0.7862	0.7376	0.7426	0.7964	0.7619	0.7279	0.7574	0.7361	0.7982	0.8239	0.8078
Chile	0.6829	0.7058	0.6882	0.6875	0.6994	0.7009	0.7039	0.7062	0.7038	0.7051	0.6920
China	0.9648	0.9587	0.9681	0.9541	N/A	N/A	N/A	N/A	N/A	N/A	0.8743
Cote d'Ivoire	0.6744	0.6557	0.6546	0.6535	N/A	N/A	0.6522	0.6559	0.6571	N/A	N/A
Cameroon	N/A	0.6530	0.6449	0.6456	0.6442	0.6387	0.6464	N/A	N/A	0.6402	0.6645
Colombia	N/A	0.7193	0.7145	0.7707	0.6818	0.7139	0.7133	0.7613	0.8656	0.8571	N/A
Czech Republic	0.7141	0.7340	0.7546	0.8257	0.7438	0.7528	0.7515	0.7118	0.7178	0.7194	0.7117
Germany	0.9726	0.9856	0.9753	0.9707	0.8415	0.8488	0.9795	0.8080	0.8693	0.8572	0.8180
Denmark	0.7297	0.7410	0.7528	0.7528	0.7342	0.7167	0.7197	0.7098	0.7385	0.7122	0.7386
Ecuador	0.6864	0.6705	0.6568	0.6578	0.6586	0.6562	0.6750	0.6765	0.6728	0.6711	0.6734
Egypt, Arab Rep.	0.6871	0.6851	0.6933	0.6938	0.7006	0.7097	0.6995	0.6794	0.6649	0.6654	0.6670
Spain	0.7290	0.7308	0.7743	0.7649	0.7463	0.7406	0.7717	0.7464	0.7496	0.7621	0.7506
Estonia	0.6711	0.6995	0.7048	0.7972	0.7572	0.7981	0.8140	0.7092	0.8110	0.7974	0.7737
Finland	0.6900	0.6993	0.6926	0.7084	0.7278	0.7151	0.7020	0.7160	0.6966	0.6949	0.7315
France	0.8326	0.8299	0.8670	0.8441	0.9942	0.8437	1.0001	0.8472	0.8324	0.8398	0.8144
United Kingdom	0.9515	0.7779	0.9572	0.9776	0.8587	0.8356	1.0003	0.8780	0.8246	0.8173	1.0001
Ghana	0.6633	0.6706	0.6628	0.6513	0.6534	0.6541	0.6549	0.6521	0.6589	N/A	N/A
Greece	0.7354	0.7013	0.6974	0.7008	0.7046	0.6903	0.7096	0.6914	0.6929	0.6914	0.7464
Guatemala	0.6661	0.6602	0.6631	0.6616	N/A	0.6606	0.6619	0.6579	0.6560	0.6562	0.6558
Honduras	0.6497	0.6521	0.6659	0.6708	0.6711	0.6675	N/A	N/A	N/A	N/A	N/A
Croatia	0.6856	0.6940	0.6782	0.6672	0.6620	0.6655	0.6657	0.6699	0.6843	0.6912	0.6877
Hungary	0.6796	0.6803	0.6808	0.6789	0.6827	0.6916	0.6936	0.6961	0.6985	0.6880	0.6894
Indonesia	0.7138	0.7184	0.7021	0.6999	0.6918	0.6863	N/A	N/A	N/A	N/A	N/A

Table 4.5 Countries PEGI from 2005 to 2015 (Continued)

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Ireland	0.8519	0.7566	0.7747	0.7540	0.7392	0.7531	0.7906	0.7339	0.7261	0.7246	0.7671
Italy	0.8485	0.7975	0.8078	0.7855	0.8034	0.8157	0.8482	0.8242	0.8116	0.8144	0.8035
Japan	0.8774	0.8094	1.0000	1.0000	0.7794	0.7501	0.9353	0.7799	0.8629	0.8998	0.8854
Kenya	N/A	0.6485	0.6465	0.6469	0.6441	0.6461	0.6455	0.6412	0.6415	0.6416	0.6445
Kyrgyz Republic	0.7125	0.6529	0.6534	0.6560	0.6548	0.6528	0.6495	0.6512	0.6646	0.6628	0.6550
Cambodia	0.6404	0.6433	0.6421	0.6428	0.6398	N/A	N/A	N/A	N/A	N/A	N/A
Lesotho	0.6489	0.6418	0.6546	0.6422	N/A	0.6661	N/A	N/A	N/A	N/A	N/A
Lithuania	0.7770	0.6825	0.6896	N/A	0.7490	0.7511	N/A	0.6950	0.7118	0.7120	0.6860
Luxembourg	N/A	N/A	0.9384	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Morocco	0.6822	0.6916	0.6871	0.6860	0.6859	0.6822	N/A	N/A	N/A	0.6955	0.6798
Mali	0.6738	0.6469	0.6569	0.6501	0.6466	0.6395	0.6428	0.6465	0.6448	0.6446	N/A
Montenegro	0.6795	0.6827	0.6709	0.6700	0.6670	0.6745	0.6796	0.6675	0.7017	N/A	N/A
Mongolia	0.6546	0.6554	0.6607	0.6593	0.6526	0.6515	0.6508	0.6508	0.6563	N/A	0.6694
Malawi	0.6403	0.6348	0.6397	0.6332	0.6335	0.6302	0.6297	0.6405	0.6414	N/A	N/A
Malaysia	0.7135	0.7208	0.7210	0.7229	0.7390	0.7341	0.7236	0.7540	0.7446	0.7447	N/A
Namibia	0.6591	0.6731	0.6574	0.6567	0.6703	0.6571	0.6663	0.6728	0.6795	N/A	N/A
Nigeria	0.6763	N/A	0.7352	N/A	N/A	0.7010	N/A	0.6830	0.6599	N/A	0.6564
Netherlands	0.8888	0/8836	1.0001	0.8576	0.9982	0.8213	0.8327	0.8130	1.0000	1.0000	1.0000
Norway	0.9365	0.9642	0.9482	0.9548	0.9528	0.9471	0.9427	0.9467	0.9683	0.9446	0.9874
New Zealand	N/A	N/A	0.7526	0.7617	0.7253	0.7225	N/A	0.7047	0.7420	0.7355	0.7470
Pakistan	N/A	N/A	N/A	N/A	N/A	0.7174	0.7229	0.7327	0.7311	0.7316	0.7310
Peru	0.6864	0.6860	0.6887	0.6841	0.6813	0.6861	0.6820	0.6769	0.6712	0.6709	0.6713
Philippines	0.6915	0.7106	0.6986	0.7008	0.7021	N/A	0.7089	0.7165	0.7156	0.7160	0.7068
Poland	0.7390	0.7514	0.7599	0.7898	0.7773	0.7598	0.7234	0.6979	0.6968	0.7144	0.7145
Portugal	0.7721	0.7850	0.8428	0.9117	0.6956	0.6959	0.7074	0.6864	0.6828	0.6876	0.7337
Paraguay	0.6484	0.6486	0.6500	0.6464	0.6489	N/A	N/A	N/A	N/A	N/A	N/A
Qatar	0.8008	0.7939	0.7707	0.8596	0.8326	N/A	N/A	N/A	N/A	N/A	N/A
Russian Federation	0.7299	0.7479	0.7395	0.7394	0.7297	0.7195	0.7127	0.7103	0.6984	0.6932	0.6933
Rwanda	0.6798	0.6814	0.6799	0.6771	0.6680	0.6630	N/A	N/A	N/A	N/A	N/A
Senegal	N/A	0.6756	0.6797	0.6537	0.6548	0.6515	0.6573	0.6579	0.6573	0.6559	N/A
Singapore	N/A	N/A	N/A	N/A	0.7862	0.7693	0.7806	0.7335	0.8255	0.8182	N/A
El Salvador	0.6491	0.6508	0.6475	0.6505	0.6492	0.6484	0.6514	0.6551	0.6642	0.6722	0.6577
Serbia	0.6610	0.6649	0.6676	0.6906	0.6892	0.6845	0.6810	0.6654	0.6803	N/A	N/A
Slovenia	0.6817	0.6838	0.6796	0.6950	0.6877	0.6845	0.6849	0.6790	0.7181	0.6973	0.6883
Sweden	0.7091	0.7146	0.7332	0.7359	0.7244	0.7156	0.7559	0.7226	0.7328	0.7187	0.7242

Table 4.5 Countries PEGI from 2005 to 2015 (Continued)

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Thailand	0.7211	0.7240	0.7182	0.7361	0.6861	0.6836	0.6880	0.7015	0.7104	0.7160	0.6975
Tajikistan	N/A	N/A	0.6437	0.6537	0.6512	0.6625	N/A	N/A	N/A	N/A	N/A
Timor-Leste	0.6687	N/A	0.6780	0.6898	0.7099	N/A	N/A	N/A	N/A	N/A	N/A
Tunisia	0.6604	0.6850	0.6839	0.6861	0.6852	0.6802	0.6817	0.6889	0.6884	0.6887	0.6797
Turkey	0.6897	0.6929	0.6968	0.6969	0.6876	0.6801	0.6829	0.7231	0.7207	0.7209	0.7251
Uganda	0.6551	0.6564	0.6456	0.6432	0.6441	0.6438	0.6441	0.6387	0.6404	0.6499	0.6452
Ukraine	N/A	N/A	N/A	N/A	N/A	N/A	0.7059	0.7258	0.7179	0.7144	0.7009
Uruguay	0.6841	0.6824	0.6971	0.6899	0.6960	0.6925	0.6855	0.6774	0.6788	0.6761	N/A
United States	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
South Africa	0.7165	0.7224	0.7294	0.7249	0.7317	0.7270	0.7500	0.7540	0.7512	0.7531	0.7381
Zambia	0.6619	0.6606	0.6562	0.6540	0.6536	0.6557	0.6560	0.6508	0.6506	0.6478	0.6486

In table 4.5, it shows that the change of PEGI is less than 0.1 for most of countries. As a benchmarking tool, DEA provides the comprehensive globalization index for each country while considering all other countries in the same year. Even if a country has a positive impact on the growth of globalization, such as having a higher GDP and less barriers for international trades, its PEGI may not increase greatly as other countries at the same time also have higher volume of GDP or less volume of international trade barriers. In addition, the result also shows that most of developed counties' PEGI are above 0.7, while the PEGIs are below 0.7 for most of developing countries, except for China.

4.5 Conclusions

In this chapter, we build a two-stage ASBM network DEA model to construct the performance index for globalization via integrating indicators from the political dimension and the economic dimension. Due to the complex inner structure among indicators, we implement SOCP to solve the non-leaner problem in our network DEA under the big data modeling.

According to the results, the globalization performances of the U.S. are the best from 1995 to 2005 due to a large number of embassies, the highest value of GDP, and others. France, Italy, and Netherland perform best in the sub-political dimension for globalization performance, while China, United Kingdom, Germany, and Japan perform best in the sub economic dimension of globalization.

Also, the result shows there is the positive relationship between the GDP and PEGI, which leads support to the KOF globalization index that globalization affects economic growth. It also shows that only two PEGI from Japan are lower than 0.8 for all three developed countries under consideration, while only two PEGI are higher than 0.8 from Estonia.

Chapter V Globalization Index from Economic Dimension and Social Dimension — A ASBM Network DEA Approach

5.1 Introduction

From the existing literature, globalization measurement can be categorized into three dimensions: policy dimension, economic dimension, and social dimension. In the previous chapter, policy dimension and economic dimension of Economic-Social Globalization Index via an ASBM (Chen and Zhu, 2020) network approach are illustrated. In this chapter, the impact of social indicators on globalization is discussed.

The gross domestic product (GDP) and human developing index (HDI) are the indicators for economic dimension and have great impact on the social aspects. They also influence the globalization situation in countries. In order to evaluate the globalization index via integrating indicators from both economic dimension and social dimension, a two-stage data network structure is proposed in this chapter.

The rest of this chapter is organized as follows. Section 5.1 develops a two-stage data network structure and describes the input-output variables and intermediate measures in the proposed network model. In section 5.2, a two-stage additive slack-base model is introduced. The model is then used with SOCP to solve a non-linear problem and composite the Economic-Social Globalization Index (ESGI). Section 5.3 provides ESGI for the selected sample including findings. Section 5.4 concludes this chapter with several remarks.

5.2 Globalization indicators in economic dimension and social dimension

In this section, a network structure is developed to measure the both economic dimension and social dimension of globalization. Figure 5.1 represents the proposed network structure. The indicators in this figure are introduced in chapter 4.

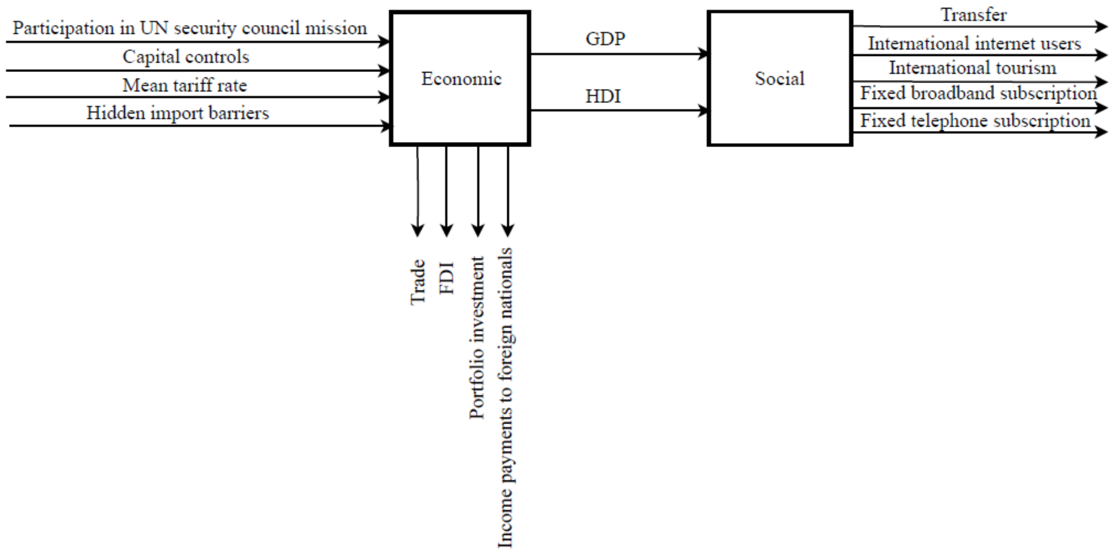

Figure 5.1 Two-stage network DEA structure of ESGI

In Figure 5.1, there are two indicators from both economic and social dimensions, and five indicators from social dimension. The economic indicators are: (1) participation in UN security council mission, (2) capital controls, (3) mean tariff rate, (4) hidden import barriers, trade, (5) foreign direct investment (FDI), (6) portfolio investment, and (7) income payments. The first four indicators, are used as policy and economic dimensions in chapter 4. Here, these indicators are intermediates and considered as economic indicators.

The indicators in both economic and social dimension are (a) gross domestic product (GDP) and (b) human development index (HDI).

The indicators in social dimension are: (i) international internet users, (ii) international tourism, (iii) fixed broadband subscription, and (iv) fixed telephone subscription. There indicators are described as follows:

i. *International internet users is the a*bsolute number of international internet users.
ii. *International tourism refers to the* international inbound and outbound tourists (overnight visitors) are the number of tourists who travel to a country other than their home country for a period not exceeding 12 months. The main purpose of visiting is other than an activity remunerated from within the visited country.
iii. *Fixed broadband subscription* refers to fixed subscriptions to high-speed access to the public Internet (a TCP/IP connection), at downstream speeds equal to, or greater than, 256 kbit/s. It includes both residential subscriptions and subscriptions for organizations.
iv. *Fixed telephone subscription* refers to the sum of active number of analogue fixed telephone lines, voice-over-IP (VoIP) subscriptions, fixed wireless local loop (WLL) subscriptions, ISDN voice-channel equivalents and fixed public payphones.

5.3 ESGI with an ASBM two-stage network approach

According to figure 5.1, we consider the same two-stage network model shown in figure 5.2 which has been proposed in the previous chapter. As shown in figure 5.2, each $DMU_j\,(j = 1, 2, ..., n)$ has m inputs x_{ij}, $(i = 1, 2, ..., m)$ to the first stage and E outputs $y^1_{ej}\,(e = 1, 2, ..., E)$ that leave the system. In addition to these E outputs, stage 1 has D outputs $z_{dj}(d=1,2,...,D)$ called intermediate measures that become inputs to the second stage. The outputs from the second stage are $y_{rj}(r=1,2,...,s)$.

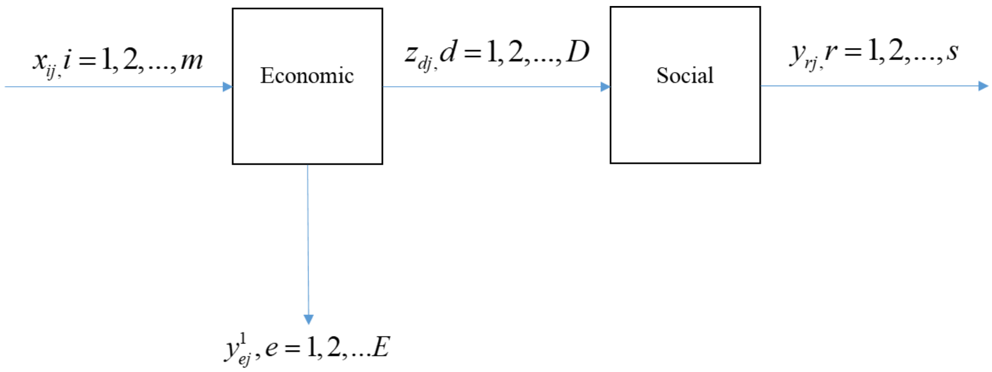

Figure 5.2 a two-stage SBM network DEA structure

Similarly, variable returns to scale (VRS) is considered to distinguish the two different types of DEA best-practice frontiers. Here, the DEA score here is treated as a composite index, and it is called in this dissertation as the Economic-Social Globalization Index (ESGI).

According to Fare and Grosskopf (1997), Tone and Tsuisui (2014), and Kao (2013), the following two-stage network DEA model is adapted for the proposed network structure in Figure 5.2:

$$\sum_{j=1}^{n} x_{ij}\lambda_j^1 + s_i^- = x_{i0}, \forall i; \sum_{j=1}^{n} y_{ej}^1\lambda_j^1 - s_e^+ = y_{e0}^1, \forall e \qquad (C2)$$
$$\sum_{j=1}^{n} \lambda_j^2 z_{dj} + t_d^- = z_{d0}, \forall d; \sum_{j=1}^{n} \lambda_j^1 z_{dj} - t_d^+ = z_{d0}, \forall d;$$
$$\sum_{j=1}^{n} y_{rj}\lambda_j^2 - s_r^+ = y_{r0}, \forall r;$$
$$\sum_{j=1}^{n} \lambda_j^1 = 1, \sum_{j=1}^{n} \lambda_j^2 = 1$$
$$\sum_{j=1}^{n} \lambda_j^1 z_{dj} = \sum_{j=1}^{n} \lambda_j^2 z_{dj}, \forall d$$
$$s_i^-, s_e^+, s_q^+, \lambda_j^1, \lambda_j^2 \geq 0$$

The constraint $\sum_{j=1}^{n} \lambda_j^1 z_{dj} = \sum_{j=1}^{n} \lambda_j^2 z_{dj}, \forall d$ in model (C2) are related to the intermediates and guarantee that the quantity of all intermediates remain the same in the both stages.

Using ASBM (Chen and Zhu 2020), the divisional efficiencies are defined as follows:

$$E^1 = \frac{1}{P+m+D}\left(\sum_{e=1}^{E} \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} + \sum_{i=1}^{m} \frac{x_{i0} - s_i^-}{x_{i0}} + \sum_{d=1}^{D} \frac{z_{d0}}{z_{d0} + t_d^+}\right) \qquad (5.1)$$

$$E^2 = \frac{1}{S+D}\left(\sum_{r=1}^{s} \frac{y_{r0}}{y_{r0} + s_r^+} + \sum_{d=1}^{D} \frac{z_{d0} - t_d^-}{z_{d0}}\right) \qquad (5.2)$$

The NDEA internal evaluation is now defined as follows:

$$\min w^{(1)} \frac{1}{E+m+D}\left(\sum_{e=1}^{E}\frac{y_{e0}^{1}}{y_{e0}^{1}+s_e^{+}}+\sum_{i=1}^{m}\frac{x_{i0}-s_i^{-}}{x_{i0}}+\sum_{d=1}^{D}\frac{z_{d0}}{z_{d0}+t_d^{+}}\right) \tag{5.3}$$

$$+w^{(2)} \quad \frac{1}{S+D}\left(\sum_{r=1}^{S}\frac{y_{r0}}{y_{r0}+s_r^{+}}+\sum_{d=1}^{D}\frac{z_{d0}-t_d^{-}}{z_{d0}}\right)$$

$$s.t. \quad w^{(1)}+w^{(2)}=1$$

$$constra\,\mathrm{int}\,s \quad (C2)$$

In model (5.3), $w^{(1)}$ and $w^{(2)}$ ($w^{(2)}=1-w^{(1)}$) are the weights thatcan be specified by decision makers or using the following constraint $0<w^{(1)}<1$.

Model (5.3) is nonlinear and can be rewritten as:

$$\frac{w^{(1)}}{E+m+D}*\frac{y_{e0}^{1}}{y_{e0}^{1}+s_e^{+}}+\frac{w^{(2)}}{S+D}*\frac{y_{r0}}{y_{r0}+s_r^{+}}+\frac{w^{(1)}}{E+m+D}*\frac{z_{d0}}{z_{d0}+t_d^{+}}+$$

$$(\frac{w^{(1)}}{E+m+D}*\sum_{i=1}^{m}\frac{x_{i0}-s_i^{-}}{x_{i0}}+\frac{w^{(2)}}{S+D}*\sum_{d=1}^{D}\frac{z_{d0}-t_d^{-}}{z_{d0}})$$

For each term, the upper bound are introduced as $\xi_e^1, \xi_d^1, \xi_r^2$ and ξ_3 , respectively. Consequently, by an epigraph transformation which replaces the nonlinear objective function of model (5.3) with sum of those upper bounds, model (5.3) is equivalent to the following optimization model (5.4).

$$\min \sum_{e}^{E} \xi_e^1 + \sum_{d}^{D} \xi_d^1 + \sum_{r}^{S} \xi_r^2 + \xi^3 \tag{5.4}$$

$$
\begin{aligned}
s.t. \quad & \frac{w^{(1)}}{E+m+D} * \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} \leq \xi_e^1 \\
& \frac{w^{(1)}}{E+m+D} * \frac{z_{d0}}{z_{d0} + t_d^+} \leq \xi_d^1 \\
& \frac{w^{(2)}}{S+D} * \frac{y_{r0}}{y_{r0} + s_r^+} \leq \xi_r^2 \\
& \frac{w^{(1)}}{E+m+D} * \frac{x_{i0} - s_i^-}{x_{i0}} + \frac{w^{(2)}}{S+D} * \frac{z_{d0} - t_d^-}{z_{d0}} \leq \xi^3 \\
& w^{(1)} + w^{(2)} = 1 \\
& \text{constraints } (C1)
\end{aligned}
$$

Model (5.4) is a quadratic optimization problem which can be convex or nonconvex. A quadratic optimization problem can be converted into a SOCP problem whose global optimal solution is ensured and can be obtained by solvers such as CVX in MATLAB. SOCP is a special form of convex optimization (Boyd and Vandenberghe 2004).

Note that the constraint $\frac{w^{(1)}}{E+m+D} * \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} \leq \xi_e^1$ is equivalent to $(E+m+D)(y_{e0}^1 + s_e^+)\xi_e^1 \geq (\sqrt{w^{(1)} * y_{e0}^1})^2$. Thus, according to the transformation utilized in Chen and Zhu (2017), that the inequality $(E+m+D)(y_{e0}^1 + s_e^+)\xi_e^1 \geq (\sqrt{w^{(1)} y_{e0}^1})^2$ can be converted into the following inequality:

$$\sqrt{(\sqrt{w^{(1)} y_{e0}^1})^2 + \left(\frac{1}{2}\Big((E+m+D)(y_{e0}^1 + s_e^+) - \xi_e^1)\Big)\right)^2} \leq \frac{1}{2}(E+m+D)(y_{e0}^1 + s_e^+) + \xi_e^1) \tag{5.5}$$

Similarity, the inequality $\frac{w^{(1)}}{E+m+D} * \frac{z_{d0}}{z_{d0}+t_d^+} \leq \xi_d^1$ is equivalent to $(E+m+D)(z_{d0}+t_d^+)\xi_d^1 \geq (\sqrt{w^{(1)} * z_{d0}})^2$, and can be transformed into the following inequality:

$$\sqrt{(\sqrt{w^{(1)} z_{e0}})^2 + \left(\frac{1}{2}\left((E+m+D)(z_{e0}+t_d^+)-\xi_d^1)\right)\right)^2} \leq \frac{1}{2}(E+m+D)(z_{e0}+t_d^+)+\xi_d^1) \qquad (5.6)$$

Correspondingly, the constraint $\frac{w^{(2)}}{S+D} * \frac{y_{r0}}{y_{r0}+s_r^+} \leq \xi_r^2$ is equivalent to $(S+D)(y_{r0}+s_r^+)\xi_r^2 \geq (\sqrt{w^{(2)} * y_{r0}})^2$, and can be transformed to the following inequality:

$$\sqrt{(\sqrt{w^{(2)} y_{r0}})^2 + \left(\frac{1}{2}\left((S+D)(y_{r0}+s_r^+)-\xi_r^2)\right)\right)^2} \leq \frac{1}{2}(S+D)(y_{r0}+s_r^+)+\xi_r^2) \qquad (5.7)$$

According to Boyd and Vandenberghe (2004), the above inequalities (5.5), (5.6), and (5.7) are second order cone constraints and can be further converted into SOCP problem as shown in the following model (5.8):

$$
\begin{aligned}
\min \quad & \sum_{e=1}^{E}\xi_e^1+\sum_{d=1}^{D}\xi_d^1+\sum_{r=1}^{S}\xi_r^2+\xi^3 \qquad (5.8)\\
s.t. \quad & \left\| \begin{matrix} \sqrt{w^{(1)}y_{e0}^1} \\ \frac{1}{2}\left(\left(E+m+D\right)\left(y_{e0}^1+s_e^+\right)-\xi_e^1\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left(\left(E+m+D\right)\left(y_{e0}^1+s_e^+\right)+\xi_e^1\right),\ \forall e\\
& \left\| \begin{matrix} \sqrt{w^{(1)}z_{d0}} \\ \frac{1}{2}\left(\left(E+m+D\right)\left(z_{d0}+t_d^+\right)-\xi_d^1\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left(\left(E+m+D\right)\left(z_{d0}+t_d^+\right)+\xi_d^1\right),\ \forall d\\
& \left\| \begin{matrix} \sqrt{w^{(2)}y_{r0}} \\ \frac{1}{2}\left(\left(S+D\right)\left(y_{r0}+s_r^+\right)-\xi_r^2\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left(\left(S+D\right)\left(y_{r0}+s_r^+\right)+\xi_r^2\right),\forall r\\
& w^{(1)}\frac{1}{E+m+D}\left(\sum_{i=1}^{m}\frac{x_{i0}-s_i^-}{x_{i0}}\right)+w^{(2)}\frac{1}{S+D}\left(\sum_{d=1}^{D}\frac{z_{d0}-t_d^-}{z_{d0}}\right)\le\xi^3\\
& w^{(1)}+w^{(2)}=1\\
& \qquad \text{constraints } (C2)
\end{aligned}
$$

5.4 Results of Political-Economic Globalization Index and Major Findings

In this section, the proposed two-stage SBM network in section 5.2 is applied to construct composite globalization index for a sample of countries in each year from 1995 to 2015. Table 5.1 selected dataset for policy-economic globalization index in 2015.

Table 5.1 Economic-Social globalization index in 2015

Countries	Economic-Social Globalization Index	Economic Globalization Index	Social Globalization Index
	2015	2015	2015
Argentina	0.8314	0.9999	0.6629
Armenia	0.6262	0.4865	0.7659
Australia	0.6588	0.7506	0.5657
Austria	0.6766	0.5360	0.8168
Belgium	0.9249	0.9993	0.8499
Benin	0.6346	0.5961	0.6732
Bulgaria	0.7511	0.6253	0.8769
Bosnia and Herzegovina	0.6945	0.5057	0.8832
Bolivia	0.5973	0.4942	0.7004
Brazil	0.9994	1.0000	0.9982
Brunei Darussalam	0.5816	0.6109	0.5522
Canada	0.7230	0.7120	0.7323
Switzerland	0.9989	0.9992	0.9963
Chile	0.6054	0.5181	0.6927
China	0.9994	1.0000	0.9952
Cote d'Ivoire	0.9996	0.9997	0.9991
Czech Republic	0.7047	0.6427	0.7666
Germany	1.0000	1.0000	1.0000
Denmark	0.9874	0.9793	0.9849
Ecuador	0.8382	0.9999	0.6765
Egypt, Arab Rep.	0.9998	0.9996	0.9996
Spain	0.7343	0.6076	0.8592
Estonia	0.6837	0.5320	0.8353
Finland	0.6150	0.5051	0.7245
France	0.8272	0.6286	1.0000
United Kingdom	0.9972	1.0000	0.9924
Georgia	0.8043	0.6044	1.0000
Ghana	0.5158	0.4354	0.5963
Greece	0.7814	0.6563	0.9065
Guatemala	0.5721	0.3782	0.7657
Honduras	0.6251	0.4612	0.7890
Croatia	0.6999	0.4658	0.9340
Hungary	0.7813	0.6047	0.9574
Indonesia	0.5897	0.5845	0.5944

Table 5.1 Economic-Social globalization index in 2015 (Continued)

Countries	Economic-Social Globalization Index	Economic Globalization Index	Social Globalization Index
Ireland	0.8360	0.9238	0.7476
Italy	0.6542	0.5767	0.7294
Jamaica	0.9999	1.0000	0.9998
Japan	0.9773	1.0000	0.9343
Kazakhstan	0.7200	0.6937	0.7463
Kenya	0.4701	0.4100	0.5302
Kyrgyz Republic	0.8068	0.5927	1.0000
Cambodia	0.5718	0.4281	0.7155
Lesotho	0.9999	0.9999	0.9998
Lithuania	0.9084	0.9931	0.8227
Morocco	0.7720	0.5887	0.9552
Moldova	0.8296	0.6602	0.9990
Madagascar	0.7573	0.9999	0.5147
Myanmar	0.8056	0.9930	0.6173
Montenegro	0.7221	0.6138	0.8304
Mongolia	0.4771	0.4589	0.4952
Malawi	0.5546	0.4098	0.6994
Malaysia	0.7880	0.6773	0.8981
Namibia	0.7365	0.7610	0.7119
Nigeria	0.4867	0.4244	0.5488
Netherlands	0.8626	0.9083	0.8150
Norway	0.9895	0.9948	0.9769
Peru	0.5570	0.4411	0.6728
Philippines	0.6530	0.6053	0.7006
Poland	0.7725	0.6940	0.8507
Portugal	0.7377	0.6852	0.7899
Paraguay	0.5667	0.4838	0.6497
Qatar	0.9902	0.9967	0.9758
Russian Federation	0.7561	0.6286	0.8822
Rwanda	0.5091	0.3823	0.6358
El Salvador	0.6338	0.4297	0.8378
Serbia	0.7463	0.5394	0.9531
Slovenia	0.7021	0.6543	0.7497
Sweden	0.6515	0.5939	0.7085

Table 5.1 Economic-Social globalization index in 2015 (Continued)

Countries	Economic-Social Globalization Index	Economic Globalization Index	Social Globalization Index
Thailand	0.7761	0.7097	0.8419
Timor-Leste	0.5646	0.5863	0.5429
Tunisia	0.8836	0.9999	0.7673
Turkey	0.6315	0.5493	0.7136
Uganda	0.5589	0.4438	0.6740
Uruguay	0.5529	0.4243	0.6816
United States	1.0000	1.0000	1.0000
Vietnam	0.9998	0.9996	0.9997
Yemen, Rep.	0.5566	0.3743	0.7389
South Africa	0.6609	0.6154	0.7063
Zambia	0.4759	0.4202	0.5317

The dataset for year 2015 includes 79 countries and with 10 inputs-intermediates-outputs indicators. The results show that the United States and Germany are the two countries that their ESGI and economic globalization indexes are equal to 1. Kenya has the lowest ESGI score as 0.4701. Yemen Rep has the lowest economic globalization index as 0.3743, but its medium social globalization score is 0.7389. Mongolia has also the lowest social globalization score as o.4952.

The globalization index in economic for seven countries, such as Brazil, China, Germany, United Kingdom, Jamaica, Japan, and United States, are equal to 1. In addition, the globalization index in social dimension for five countries, such as Germany, France, Georgia, Kyrgyz Republic, and United States are equal to 1.

Overall, countries perform better in social globalization index than their economic globalization index. There are 19 countries who have the economic globalization less than 0.5. These countries and their economic globalization indexes are Armenia (0.4865), Bolivia (0.4942), Ghana (0.4354), Guatemala (0.3782), Honduras (0.4612), Croatia (0.4658), Kenya (0.4100), Cambodia (0.4281), Mongolia (0.4589), Malawi (0.4098), Nigeria (0.4244), Peru (0.4411), Paraguay (0.4838), Rwanda (0.3823), El Salvador (0.4297), Uganda (0.4438), Uruguay (0.4243), Yemen, Rep. (0.3743), and Zambia (0.4202). In contrast, only one of the 79 countries has the social globalization index smaller than 0.5, which is Mongolia.

Table 5.2 ESGI from top 15 largest economies in the world by GDP nominal

Countries	**GDP (billion, USD)**	**2015**	**2014**	**2013**	**2012**	**2011**	**2010**	**2009**	**2008**	**2007**	**2006**	**2005**
United States	21482	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
China	14172	1.0000	1.0000	1.0000	1.0000	N/A	N/A	N/A	N/A	N/A	N/A	0.9380
Japan	5221	0.9773	0.6804	0.9999	0.9999	0.7497	0.6741	1.0542	0.8580	0.9364	0.9834	0.9099
Germany	4117	1.0000	1.0000	1.0000	1.0000	0.7340	0.7471	0.9999	0.7439	0.7382	0.7105	0.7856
India	2958	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
France	2845	0.8272	0.8965	0.8854	0.8598	1.0000	0.8044	1.0000	0.8292	0.8198	0.8319	0.8952
United Kingdom	2810	0.9972	0.8664	1.0000	1.0000	0.7303	0.8581	0.9997	0.8274	0.7321	0.7074	0.9999
Italy	2113	0.6542	0.5422	0.5611	0.5511	0.5749	0.5581	0.6050	0.5840	0.5709	0.5695	0.7115
Brazil	1930	0.9994	0.9599	0.9673	0.9573	0.9522	0.9368	0.9336	0.9036	0.8993	0.9970	0.9050
Canada	1820	0.7230	0.7014	0.6771	0.6712	0.6338	0.6244	0.6935	0.6483	0.6399	0.5944	0.5676
Korea, Rep.	1700	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Russian Federation	1649	0.7561	0.7038	0.6516	0.6874	0.6561	0.6417	0.6460	0.7347	0.7008	0.6797	0.7006
Spain	1474	0.7343	0.6042	0.6886	0.6813	0.5939	0.5869	0.6939	0.6790	0.7043	0.7101	0.7276
Australia	1464	0.6588	0.7230	0.7902	0.7645	0.6808	0.7758	N/A	0.7387	N/A	0.8036	0.8715
Mexico	1242	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A

Table 5.2 shows the comparison between GDP and the proposed ESGI for 15 countries that have the highest GDP in the world. The shown GDP in Table 5.2 illustrates the average GDP of each country from 2005 to 2015.

Note that the PEGI for India, Korea Rep, and Mexico for all years as well as the PEGI for China from 2006 to 2011 are not calculated as data were not available for these countries. According to Table 5.2, the higher the GDP value, the higher the ECGI. The top three countries with the highest GDP are the top three countries with highest ESGI in 2015. There is also a noticeable change in ESGI for Japan from 2013 and 2015, as its GDP is changed. Japan's GDP starts to decrease from 2013 to 2015, whereas the GDP for other countries increase.

The relationship between ESGI and GDP of the mentioned countries are illustrated in table 5.3 and 5.4. In these two tables, a comparison between GDP and PEGI for ten years since 2005 for three countries whose GDP are in top and three countries whose GDP in the medium around the world, respectively.

Table 5.3 Comparison between GDP and ESGI in United States, Japan and Germany from 2005 to 2015

Year	**United States**		**Japan**		**Germany**	
	GDP ($Billion)	ESGI	GDP ($Billion)	ESGI	GDP ($Billion)	ESGI
2005	13093.7260	1.0000	4755.4106	0.9914	2861.4103	0.9992
2006	13855.8880	1.0000	4530.3772	0.9999	3002.4464	0.9996
2007	14477.6350	1.0000	4515.2645	0.9996	3439.9535	0.9999
2008	14718.5820	1.0000	5037.9085	0.7773	3752.3656	1.0000
2009	14418.7390	1.0000	5231.3827	0.8836	3418.0050	0.9998
2010	14964.3720	1.0000	5700.0981	0.6949	3417.0946	0.9541
2011	15517.9260	1.0000	6157.4596	0.8744	3757.6983	0.9360
2012	16155.2550	1.0000	6203.2131	0.8529	3543.9839	0.9999
2013	16691.5170	1.0000	5155.7171	0.9571	3752.5135	1.0000
2014	17427.6090	1.0000	4850.4135	0.8417	3890.6069	1.0000
2015	18120.7140	1.0000	4394.9778	0.9773	3375.6111	1.0000

Table 5.4 Comparison between GDP and ESGI in Tunisia, Uganda, and Estonia from 2005 to 2015

Year	**Tunisia**		**Uganda**		**Estonia**	
	GDP ($Billion)	ESGI	GDP ($Billion)	ESGI	GDP ($Billion)	ESGI
2005	32.2730	0.8283	9.0138	0.8350	14.0061	0.9981
2006	34.3784	0.8502	9.9426	0.8090	16.9636	0.9998
2007	38.9081	0.8810	12.2928	0.5806	22.2371	0.7871
2008	44.8566	0.9260	14.2390	0.5624	24.1940	0.7268
2009	43.4549	0.9199	18.1689	0.5345	19.6525	0.9985
2010	44.0509	0.9986	20.1865	0.5100	19.4909	0.9989
2011	45.8106	0.9490	20.1768	0.5960	23.1702	0.9994
2012	45.0441	0.9999	23.1321	0.8552	23.0439	0.9993
2013	46.2511	0.9998	24.5996	0.5561	25.1372	0.6688
2014	47.5879	0.9431	27.2952	0.8277	26.2246	0.7768
2015	43.1567	0.8836	27.0594	0.5589	22.5670	0.6837

Table 5.3 shows the results for three countries such as United States, Japan, and Germany. The ranks of these countries according to their GDP are the first, third, and fourth among other countries in 2015, respectively. Table 5.4 shows the outcomes for three countries such as Tunisia, Uganda, and Estonia with the GDP's rank of 98, 99, and 100 among 211 countries around the world in 2015, respectively.

There is a positive correlation between ESGI and economic situation from the outcomes in this chapter and the outcomes in Chapter 4. The range of ESGI for United States, Japan, and Germany is 0.6949 to 1.0024, while the range of ESGI for Tunisia, Uganda, and Estonia is from 0.5100 to 0.9998. Among the developed countries, the lowest score for Japan, United State, and Germany are 0.6949, 0.9360, and 0.9360, respectively.   From the above tables, the PEGI for United State, Japan, Germany, Tunisia, and Estonia are stable. For example, from 2005 to 2015, the United States's GDP increases from $13093.8880 billion to $18120.7140 billion, whereas the PEGI's range for the United States is from 1.0003 to 1.0027. The ESGI for Uganda is not stable as the Uganda's GDP increases from 9.0138 billion to 27.0594 billion, that is, 200% increase, whereas its PEGI's range changes from 0.5100 to 0.8552. Note that, according to outcomes in Chapter 4, from 2005 to 2015, the Uganda's PEGI is stable and its range is from 0.6387 to 0.6564 . As a result, the change in GDP has more impact on social indicators than policy indicators. It also influences the ESGI.

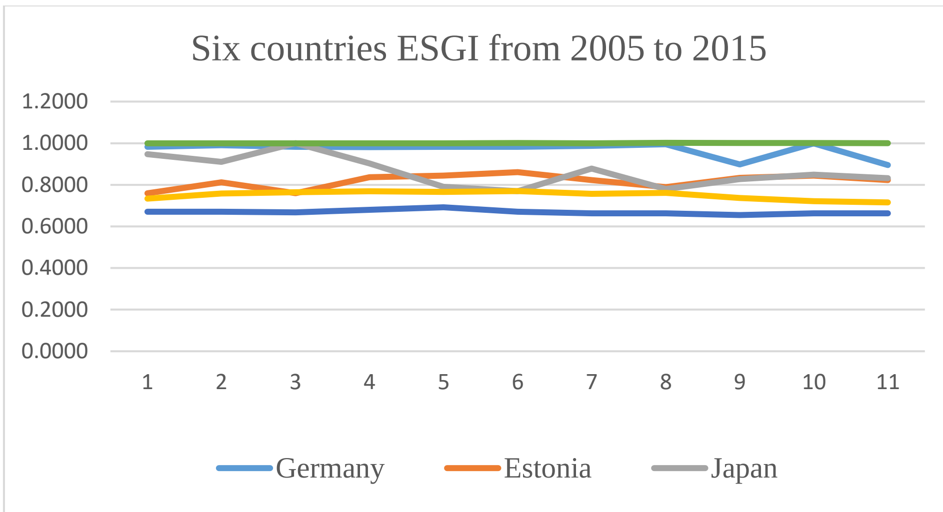

Figure 5.3 A line chart of six countries' ESGI from 2005 to 2015

Figure 5.3 illustrates the change of ESGI for six countries we mentioned above. In Figure 5.3, the y-axis shows the value of ESGI, and the x-axis displays the years from 2005 to 2015. The corresponding ESGI for each country during time period 2005 to 2015 are shown by different colors. The green, grey, light-blue, yellow, ark blue, and orange piecewise lines illustrate the change of PEGI for United States, Japan's, Germany, Tunisia, Uganda, and the Estonia, respectively. According to Figure 5.3, the ESGI for United States, Germany, and Uganda are almost constant, whereas there are fluctuations in the ESGI values for the other three countries. The

GDP of the Untied State increases uniformly during 2005-2015. Similarly, the ESGI of the United States in Figure 5.3 are almost constant. In contrast, , the GDPs for Japan and Estonia change from a year to another and similarly the PEGI for these two countries increasing for some period and decreasing for another. Among the countries in Figure 5.3, Japan's ESGI changes the most. The minimum ESGI for Japan occurs in 2008 as 0.7773 and its maximum PEGI achieves in 2006 as 0.9999. It is also highly coincidence with the changes of GDP.

Table 5.5 shows ESGI for 81 countries from 2005 to 2015. The dataset included more than 120 countries; however, for some countries, no data was available. Thus, these countries are removed from the dataset. Table 5.5 shows the remaining 81 countries that their data were available for at least three years.

Table 5.5 Countries ESGI from 2005 to 2015

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Argentina	0.8314	0.8501	0.8452	0.8261	0.8633	0.8561	N/A	0.6523	0.8582	0.8441	N/A
Armenia	0.6262	0.6804	0.9363	0.9333	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Australia	0.6588	0.6597	0.6719	0.6923	0.6638	N/A	N/A	0.6559	N/A	0.7025	0.8085
Austria	0.6766	0.6790	N/A	0.6883	0.7351	0.7012	N/A	0.6895	0.7277	0.7059	0.7723
Belgium	0.9249	0.9285	0.7362	0.7394	0.7826	0.7650	0.7790	0.8193	0.7366	0.7136	0.8652
Benin	0.6346	0.5791	0.6286	0.6823	0.6641	0.5835	0.5392	0.5221	0.5379	0.5302	N/A
Burkina Faso	N/A	0.5858	0.5924	0.5649	0.5687	0.5619	0.5276	0.6524	0.6506	0.5594	0.5841
Bulgaria	0.7511	0.9986	0.7859	0.9999	0.9998	0.8488	0.9983	0.6942	0.6771	0.7241	0.7099
Bosnia and Herzegovina	0.6945	0.7013	0.7041	0.7407	0.6927	0.6565	0.6357	0.7049	0.6741	0.6601	0.6308
Bolivia	0.5973	0.6342	0.5987	0.6746	0.6628	0.6138	0.5869	0.6674	0.8366	0.5796	0.8052
Brazil	0.9994	0.8268	0.6558	0.6851	0.7599	0.7122	0.8188	0.6968	0.6693	0.6495	0.5584
Canada	0.7230	0.7310	0.7106	0.6961	0.7577	0.7087	0.7478	0.6992	0.7273	0.7409	0.7064
Switzerland	0.9989	0.9817	0.9987	0.9983	0.9996	0.8468	0.8848	0.8174	0.9996	0.9998	0.9969
Chile	0.6054	0.6297	0.6059	0.6240	0.6470	0.6329	0.6366	0.6000	0.6139	0.6184	0.5550
China	0.9994	0.9991	0.9988	0.9998	N/A	N/A	N/A	N/A	N/A	N/A	0.9889
Cote d'Ivoire	0.9996	0.5928	0.5753	0.5789	N/A	N/A	0.5682	0.5755	0.6278	N/A	N/A
Cameroon	N/A	0.7915	0.7597	0.7527	0.7365	0.7262	0.7131	N/A	N/A	0.6908	0.6784
Colombia	N/A	0.8747	0.8757	0.8614	0.9013	0.8827	0.8918	0.9000	0.8957	0.8721	N/A
Czech Republic	0.7047	0.7116	0.9318	0.9285	0.7333	0.7881	0.7476	0.6747	0.6828	0.6775	0.6206
Germany	1.0000	1.0000	1.0000	0.9999	0.9360	0.9541	0.9998	1.0000	0.9999	0.9996	0.9992
Denmark	0.9874	0.9786	0.7697	0.7620	0.7058	0.6805	0.6902	0.6904	0.7443	0.7481	0.7069
Ecuador	0.8382	0.8358	0.6215	0.6214	0.8423	0.8045	0.8115	0.8236	0.8122	0.7968	0.7817
Egypt, Arab Rep.	0.9998	0.9998	0.7351	1.0000	1.0000	0.7715	0.7101	0.9999	0.7561	1.0000	0.9999
Spain	0.7343	0.7260	0.7442	0.7210	0.7577	0.7264	0.7463	0.7501	0.7949	0.8396	0.7678
Estonia	0.6837	0.7768	0.6688	0.9993	0.9994	0.9989	0.9985	0.7268	0.7871	0.9998	0.9981
Finland	0.6150	0.6376	0.6422	0.6254	0.6794	0.7030	0.6616	0.6761	0.6637	0.6791	0.6551
France	0.8272	0.8169	0.8146	0.8285	0.9996	0.8093	0.9997	0.7847	0.8180	0.8118	0.7777
United Kingdom	0.9972	0.9807	0.9976	0.9979	0.9894	0.9529	0.9999	0.9996	0.8667	0.8633	0.9499
Ghana	0.5158	0.5215	0.4824	0.5060	0.4971	0.4988	0.5022	0.4798	0.4746	N/A	N/A
Greece	0.7814	0.7000	0.6662	0.6552	0.7158	0.6672	0.6744	0.6224	0.6116	0.5659	0.5756
Guatemala	0.5721	0.5793	0.5744	0.5764	N/A	0.5526	0.5457	0.5672	0.5686	0.5708	0.5500
Honduras	0.6251	0.6262	0.7075	0.7564	0.7054	0.6333	0.6421	0.6530	0.6419	N/A	N/A
Croatia	0.6999	0.7561	0.6884	0.7031	0.6790	0.6596	0.7097	0.7659	0.7384	0.6863	0.7422
Hungary	0.7813	0.7753	0.7169	0.7658	0.7721	0.7383	0.7794	0.7466	0.6796	0.7293	0.6672
Indonesia	0.5897	0.6431	0.6239	0.6273	0.6385	0.6410	0.9998	0.9994	0.6777	N/A	N/A

Table 5.5 Countries ESGI from 2005 to 2015 Continued

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Ireland	0.8360	0.8319	0.7040	0.7859	0.7502	0.8355	0.6778	0.6760	0.7285	0.6637	0.7360
Italy	0.6542	0.6297	0.6346	0.6311	0.6921	0.6737	0.6467	0.6724	0.6723	0.6946	0.6892
Japan	0.9773	0.8417	0.9571	0.8529	0.8744	0.6949	0.8836	0.7773	0.9996	0.9999	0.9914
Kenya	0.4701	0.5499	0.4779	0.5069	0.4943	0.8300	N/A	0.7598	0.7811	0.5342	0.8030
Kyrgyz Republic	0.8068	0.8216	0.7470	0.7748	0.8006	0.4714	0.4916	0.5102	0.5267	0.9996	0.9998
Cambodia	0.5718	0.5950	0.5606	0.5874	0.5757	0.9989	0.7974	0.7801	0.7633	N/A	N/A
Lesotho	0.9999	0.9998	0.9990	0.9999	N/A	0.9995	N/A	N/A	N/A	N/A	N/A
Lithuania	0.9084	0.7180	0.6996	N/A	0.9194	0.8092	N/A	0.6474	0.6692	0.7335	0.6306
Luxembourg	N/A	N/A	0.9975	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Morocco	0.7720	0.7937	0.7604	0.7618	0.7787	0.9999	N/A	N/A	N/A	0.9999	0.9993
Mali	N/A	0.9999	0.9994	0.7805	0.6154	0.6699	0.6475	0.6486	0.7644	0.7916	N/A
Montenegro	N/A	0.7440	0.6890	0.7514	0.7016	0.7112	0.7223	0.7289	0.7302	N/A	N/A
Mongolia	0.4771	0.5033	0.4896	0.5463	0.5593	0.5492	0.5452	0.6058	0.6209	N/A	N/A
Malawi	0.5546	0.5864	0.5858	0.5957	0.5710	0.5988	0.5849	0.6079	0.6035	N/A	N/A
Malaysia	0.7880	0.8410	0.7931	0.8183	0.9961	0.9998	0.9994	0.9997	0.9995	0.9995	N/A
Namibia	0.7365	0.6563	0.6074	0.6809	0.6448	0.6624	0.6601	0.7213	0.7657	N/A	N/A
Nigeria	0.4867	N/A	0.5149	N/A	N/A	0.5667	N/A	0.5840	0.5805	N/A	0.5322
Netherlands	0.8626	0.8636	0.9945	0.9914	0.9992	0.9946	0.9510	0.9943	0.9999	1.0000	1.0000
Norway	0.9895	0.9674	0.9926	0.9841	0.9856	0.9885	0.9863	0.8688	0.9808	0.7433	0.7463
New Zealand	N/A	N/A	0.5683	0.6120	0.6250	0.6182	N/A	0.5847	0.6182	0.6043	0.5637
Pakistan	N/A	N/A	N/A	0.6423	0.7821	0.8348	0.9999	0.9981	0.8134	0.9993	0.7468
Peru	0.5570	0.5653	0.5658	0.5826	0.5712	0.5784	0.5916	0.5712	0.5947	0.5933	0.5518
Philippines	0.6530	0.6930	0.6486	0.6463	0.6831	N/A	0.6489	0.6029	0.6410	0.6168	0.6646
Poland	0.7725	0.7774	0.9972	0.9977	0.9997	0.9523	0.8201	0.7074	0.7390	0.7930	0.7638
Portugal	0.7377	0.7284	0.8408	0.8922	0.6279	0.6226	0.6195	0.6104	0.6434	0.6303	0.6386
Paraguay	0.5667	0.5793	0.5329	0.5606	0.5264	N/A	N/A	N/A	N/A	N/A	N/A
Qatar	0.9902	0.9957	0.9910	0.9985	0.9988	N/A	N/A	N/A	N/A	N/A	N/A
Russian Federation	0.7561	0.8046	0.7793	0.9030	0.8178	0.7884	0.7927	0.8204	0.7986	0.8063	0.7211
Rwanda	0.5091	0.4997	0.5094	0.5183	0.5528	0.5471	N/A	N/A	N/A	N/A	N/A
Senegal	N/A	0.6635	0.6468	0.6269	0.6835	0.6246	0.5995	0.6316	0.6514	0.6783	N/A
Singapore	N/A	N/A	N/A	N/A	0.9962	0.8563	0.8681	0.8127	0.9818	0.8420	N/A
El Salvador	0.6338	0.6489	0.6528	0.9999	0.6381	0.6149	0.5933	0.5966	0.6124	0.6194	0.5791
Serbia	0.7463	0.7360	0.7343	0.9995	1.0000	0.8430	0.7707	0.6710	0.6871	N/A	N/A
Slovenia	0.7021	0.7027	0.6560	0.7207	0.6909	0.6709	0.6491	0.6077	0.6350	0.6573	0.6141
Sweden	0.6515	0.6916	0.9858	0.9599	0.9869	0.7839	0.9215	0.9702	0.7530	0.9918	0.8740

Table 5.5 Countries ESGI from 2005 to 2015 Continued

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Thailand	0.7761	0.9444	0.9403	0.9394	0.7205	0.7088	0.7361	0.7411	0.7456	0.7532	0.7545
Tajikistan	N/A	N/A	0.6151	0.6191	0.8061	0.7962	N/A	N/A	N/A	N/A	N/A
Timor-Leste	0.5646	N/A	0.5727	0.9998	0.9999	N/A	N/A	N/A	N/A	N/A	N/A
Tunisia	0.8836	0.9431	0.9998	0.9999	0.9490	0.9986	0.9199	0.9260	0.8810	0.8502	0.8283
Turkey	0.6315	0.6731	0.6420	0.6391	0.6845	0.6353	0.6349	0.6674	0.6646	0.6574	0.6350
Uganda	0.5589	0.8277	0.5561	0.8552	0.5960	0.5100	0.5345	0.5624	0.5806	0.8090	0.8350
Ukranine	N/A	N/A	N/A	N/A	N/A	N/A	0.8692	0.9997	0.9995	0.9992	0.9989
Uruguay	0.5529	0.5746	0.5507	0.5800	0.5707	0.5461	0.5248	0.5557	0.5645	0.5802	N/A
United States	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
South Africa	0.6609	0.6995	0.7327	0.7122	0.7944	0.6790	0.7588	0.6574	0.7662	0.7691	0.7333
Zambia	0.4759	0.5750	0.4872	0.4871	0.4807	0.4841	0.4697	0.4782	0.4905	0.4779	0.5042

Table 5.5 illustrates that, most of the countries' ESGI keep stable to some extent. It is reasonable. As shown in Table 5.5., DEA provides a comprehensive globalization relative performance score for each country per year. From the DEA results, a country with higher GDP and less barriers for international trades, does not necessarily has a higher ESGI

5.5 Conclusion

Applying the same two-stage ASBM network model, we evaluate the performance index for globalization via integrating indicators from economic dimension and social dimension. The non-linear problem is also solved via implementing SOCP to our network DEA.

According to the results, United States and Germany has highest ESGI, which means compared with other countries in 2015 under consideration, their globalization performs best. Kenya has the lowest ESGI score as 0.4701. Yemen, Rep has the lowest economic globalization with 0.3743, but a medium social globalization score 0.7389. Mongolia has the lowest social globalization score as o.4952. There are seven countries (Brazil, China, Germany, United Kingdom, Jamaica, Japan and United States) which have globalization index in economic as one, while three countries (France, Georgia, and Kyrgyz Republic) which have globalization index in social dimension as one.

In addition, countries perform better in social globalization index than their economic globalization index. There are 19 out of 79 countries who have the economic globalization less than 0.5.

Chapter VI Globalization Index via Indicators from Political, Economic and Social Dimensions — A SBM Network DEA Approach

6.1 Introduction

There are two most widely known globalization indices: the A. T. Kearney/Foreign Political Magazine (2002) and the KOF globalization index (Dreher, 2006), which bring together indicator groups of different areas of globalization. Dreher expanded Kearney's indicators which were from political, economic and social dimensions. In chapter 4 and chapter 5, this study develops a two-stage ASBM network structure to introduce PEGI which focuses on metrics of globalization from political aspect and economic aspect and ESGI which concentrates on indicators of globalization in economic and social aspect, respectively.

This chapter, it discusses how globalization performance of countries are via integrating indicators of globalization from political dimension, economic dimension, and social dimension. Compared with these two most widely known globalization indices, this work provides an alternative with a data-oriented method called DEA. As traditional DEA models are not sufficient to deal with information and value that are hidden within data under a big data modeling, the network DEA approach to construct the composite globalization performance index has been considered. In addition, the SOCP has also been implemented to solve the non-linear problem in network DEA models.

The remainder of this chapter is structured as follows: the section 6.2 provides an overview literature review of globalization in the existing literature. In section 6.3, a three-stage network DEA structure has been developed. In addition, it describes the input-output variables and intermediate measures which have been involved. Section 6.4 implements the three-stage DEA network structure with SOCP to solve the non-linear problem and composite the globalization index via our SBM network DEA approach. In section 6.5, it provides an alternative of globalization index for countries around the world during a time period from 1995 to 2015 and present major findings. Finally, section 6.6 provides concluding remarks.

6.2 Background literature on the globalization index

The phenomenon of globalization has become a subject of academic research for more than twenty years. Kearney globalization index and the Dreher (KOF) globalization index which bring together indicator groups of different areas of globalization - economic, political, and social, are most popular and widely used. Kearney was the first to attempt to combine aspects such as personal contacts, technological and political integration together with measurements of economic globalization. The compilers of the index look for correlations between the globalization level of a state and economic, social, political and other characteristics of the country, but do not address the question of positive or negative effects of globalization. Dreher improved Kearney's index-creation methodology, expanding the number of indicators. In his study, the overall KOF for each countries is obtained from a weighted average of three sub-globalization index. It also do a robustness analysis for the overall index, actual economic flows, capital and trade restrictions in developed countries, and flows of information.

Like Dreher, there are other researchers develop their globalization index based on the Kearney/Foreign Political. For example, Heshmati (2006) presents two composite indices of globalization which the first is based on the Kearney/Foreign Political magazine. Their indices are composed of four components: economic integration, personal contact, technology and political engagement, and indicate countries which have become most global and show how globalization has developed over time. Martens and Zywietz (2006) suggested index is based upon the A.T. Kearney/Foreign Political Globalization Index, but is improved both conceptually and operationally. In their study, they use data for 117 countries from a variety of resources to test the robustness of the suggested index. Zhou, Biswas, Bowles, and Saunders (2011) use Kearney's (2002, 2003 and 2004) data and principal component analysis (PCA), to create wo globalization indices. One of these indices is the equally weighted index investigates the impact of globalization on income inequality distribution in 60 developed, transitional, and developing countries, while the other index is derived from the principal component analysis.

In addition to above globalization indices which are developed based on Kearney/Foreign Political Globalization Index, many researchers proposed other methods to measure globalization. Andersen and Herbertsson (2005) introduce a single measure or index of globalization based on several indicators of economic integration combined by use of the multivariate technique of factor analysis. Martens et al. (2015) discusses the measurement of globalization with a view to advancing the construction of globalization indices. Fisch and Oesterle (2003) present a new quantitative measurement concept that integrates multiple dimensions of internationalization in a complex number and tries to measure globalization instead of simple internationalization. Raab, et al. (2008) suggests a multidimensional globalization measure, encompassing economic, social, cultural and political dimensions of global change. Andersen and Herbertsson (2003)'s index is an alternative to the simple measure of openness based on trade, and it produces a ranking of countries over time for 23 OECD countries.

Some researchers view current globalization indices and discuss measurements. Caselli (2013) justify in any case the use of instruments that seek to measure globalization on the basis of states, and, on the other, to propose alternative approaches to such measurement. Axel et al. (2010) discusses the measurement of globalization with a view to advancing the understanding of globalization indices, and critically analyze the types of index that can contribute to the debate on globalization.

6.3 A three-stage network DEA approach

To describe how to measure the globalization from three indicator groups of globalization: the political dimension, economic dimension and social dimension, we develop the following DEA network structure with all indicators as shown in figure 6.1.

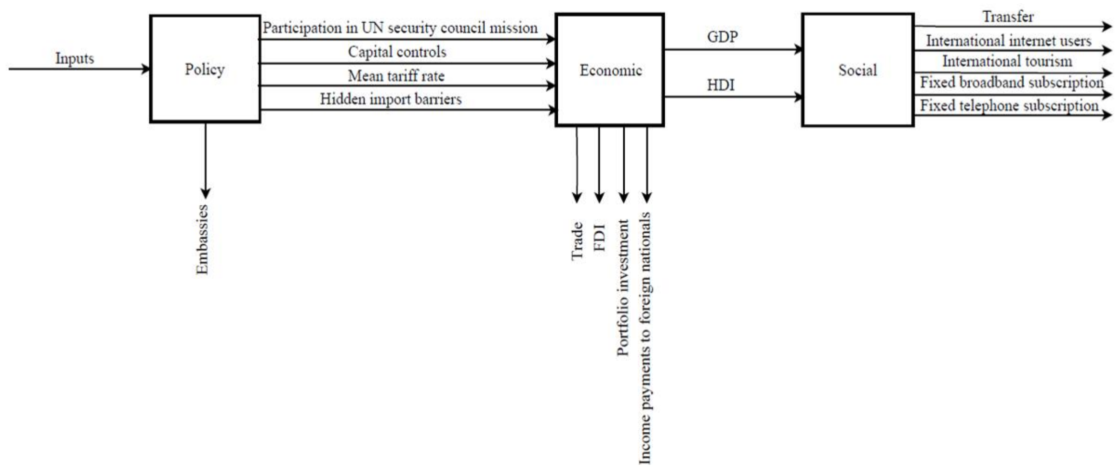

Figure 6.1 a three-stage DEA network structure of globalization index

In this three-stage structure, we utilize five key indicator in political dimension, six key indicators in economic dimension, and five indicators only in social dimension. Introduction for all measures shown in figure 6.1 can be found in chapter 4 and chapter 5.

DEA requires measures or metrics to be classified into inputs and outputs. In general, it minimizes “inputs” and maximizes “outputs”. Under some situation, measures should be minimized in one stage, and be maximized in another stage that we have the intermediate measures. Intermediate measures are those indicators which could be regarded as the “inputs” at one stage, and then be regarded as the “outputs” in the following stage. Our rationale for using the respective variables in three stages, respectively, is as follows. The number of “Participation in UN Security Council mission”, “capital controls”, “mean tariff rate”, and “hidden import barriers” are policies making by each countries. From the countries aspects, the more “capital controls”, “mean tariff rate”, and “hidden import barriers”, the less export and import goods which decrease the investments and trades for a country. At the same time, the more number of “Participation in UN Security Council mission”, a country needs to spend more money and human resources where the total wealth decreases. All of them are the measures which are the less, the better that they are treated as the inputs in economic dimension.

Similar, “GDP” and “HDI” could be regarded as the “inputs” in the social dimension as they are measures a country want to spend the least and enjoy the highest social globalization level. It likes a production process where organizations want to spend the least materials to produce the most products or provided most services. At the same time, in economic dimension, they are should be regarded as the outputs as countries always want have a higher GDP and HDI value. Thus, we treat the GDP and HDI as the intermediate measures in economic stage and social stage.

6.4 Globalization index with an ASBM three-stage network approach

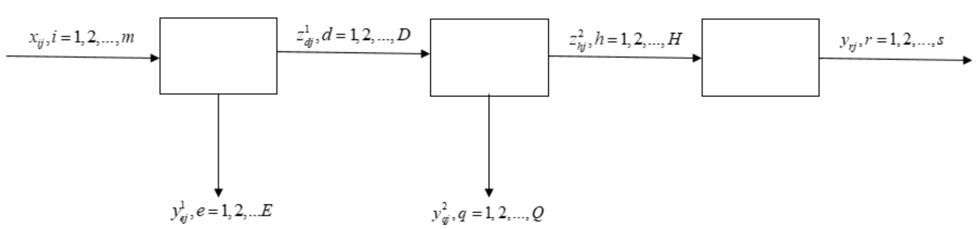

Figure 6.2 a two-stage SBM network DEA structure

The two-stage ASBM network model in chapter 4 and chapter 5 has been expanded to a three-stage network structure shown in above figure 6.2. Each DMU$_j$ (j=1, 2, … , n) has m inputs x_{ij} , (i=1, 2, … , m) to the first stage and E outputs y^1_{ej}

(e=1, 2, … , E) that leave the system. In addition to these E outputs, stage 1 has D outputs z_{dj}^1 (d=1, 2, … , D) called intermediate measures that become inputs to the second stage. The second stage has its own outputs y_{qj}^2 (q=1, 2, … , Q) that leaves system, and has H outputs z_{hj}^2 ($h = 1,2,...,H$) which are used in the third stages as the inputs. The outputs from the third stage are y_{rj} (r=1, 2, … , s).

The constraints based on slacks variables are as follows.

$$\begin{aligned}
&\sum_{j=1}^{n} x_{ij}\lambda_j^1 + s_i^- = x_{i0}, \forall i; \sum_{j=1}^{n} y_{ej}^1\lambda_j^1 - s_e^+ = y_{e0}^1, \forall e \qquad (6.1)\\
&\sum_{j=1}^{n} y_{qj}^2\lambda_j^2 - s_q^+ = y_{q0}^2, \forall q; \sum_{j=1}^{n} y_{rj}\lambda_j^3 - s_r^+ = y_{r0}, \forall r\\
&\sum_{j=1}^{n} \lambda_j^2 z_{dj}^1 + t_d^{1-} = z_{d0}^1, \forall d; \sum_{j=1}^{n} \lambda_j^1 z_{dj}^1 - t_d^{1+} = z_{d0}^1, \forall d\\
&\sum_{j=1}^{n} \lambda_j^3 z_{hj}^2 + t_h^{2-} = z_{h0}^2, \forall h; \sum_{j=1}^{n} \lambda_j^2 z_{hj}^2 - t_h^{2+} = z_{h0}^2, \forall h\\
&\sum_{j=1}^{n} \lambda_j^2 z_{dj}^1 = \sum_{j=1}^{n} \lambda_j^1 z_{dj}^1, \forall d; \sum_{j=1}^{n} \lambda_j^3 z_{hj}^2 = \sum_{j=1}^{n} \lambda_j^2 z_{hj}^2, \forall h\\
&\sum_{j=1}^{n} \lambda_j^1 = 1, \sum_{j=1}^{n} \lambda_j^2 = 1, \sum_{j=1}^{n} \lambda_j^3 = 1\\
&s_i^-, s_e^+, s_q^+, s_r^+, \lambda_j^1, \lambda_j^2, \lambda_j^3 \geq 0
\end{aligned}$$

Then, based upon ASBM (Chen and Zhu, 2018), divisional efficiencies are defined as follows.

$$E^1 = \frac{1}{E+m+D}\left(\sum_{e=1}^{E} \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} + \sum_{i=1}^{m} \frac{x_{i0} - s_i^-}{x_{i0}} + \sum_{d=1}^{D} \frac{z_{d0}^1}{z_{d0}^1 + t_d^{1+}}\right) \qquad (6.2)$$

$$E^2 = \frac{1}{Q+H+D}\left(\sum_{q=1}^{Q} \frac{y_{q0}^2}{y_{q0}^2 + s_q^+} + \sum_{h=1}^{H} \frac{z_{h0}^2}{z_{h0}^2 + t_h^{2+}} + \sum_{d=1}^{D} \frac{z_{d0}^1 - t_d^{1-}}{z_{d0}^1}\right) \qquad (6.3)$$

$$E^3 = \frac{1}{S+D}\left(\sum_{r=1}^{s} \frac{y_{r0}}{y_{r0} + s_r^+} + \sum_{d=1}^{D} \frac{z_{h0}^2 - t_h^{2-}}{z_{h0}^2}\right) \qquad (6.4)$$

Further, the internal evaluation based on network DEA is defined as follows.

$$
\begin{aligned}
\min \quad & w^{(1)} \frac{1}{E+m+D}\left(\sum_{e=1}^{E}\frac{y_{e0}^{1}}{y_{e0}^{1}+s_{e}^{+}}+\sum_{i=1}^{m}\frac{x_{i0}-s_{i}^{-}}{x_{i0}}+\sum_{d=1}^{D}\frac{z_{d0}^{1}}{z_{d0}^{1}+t_{d}^{1+}}\right) \qquad (6.5)\\
& + w^{(2)} \frac{1}{Q+H+D}\left(\sum_{q=1}^{Q}\frac{y_{q0}^{2}}{y_{q0}^{2}+s_{q}^{+}}+\sum_{h=1}^{H}\frac{z_{h0}^{2}}{z_{h0}^{2}+t_{h}^{2+}}+\sum_{d=1}^{D}\frac{z_{d0}^{1}-t_{d}^{1-}}{z_{d0}^{1}}\right)\\
& + w^{(3)} \frac{1}{S+D}\left(\sum_{r=1}^{s}\frac{y_{r0}}{y_{r0}+s_{r}^{+}}+\sum_{d=1}^{D}\frac{z_{h0}^{2}-t_{h}^{2-}}{z_{h0}^{2}}\right)\\
s.t. \quad & w^{(1)}+w^{(2)}+w^{(3)}=1\\
& \text{constraints (6.1)}
\end{aligned}
$$

Above model (6.5) is highly nonlinear, and can be rewritten as the followings:

$$
\begin{aligned}
& \frac{w^{(1)}}{E+m+D} * \frac{y_{e0}^{1}}{y_{e0}^{1}+s_{e}^{+}} + \frac{w^{(2)}}{Q+H+D} * \frac{y_{q0}^{2}}{y_{q0}^{2}+s_{q}^{+}} + \frac{w^{(3)}}{S+D} * \frac{y_{r0}}{y_{r0}+s_{r}^{+}} + \\
& + \frac{w^{(1)}}{E+m+D} * \frac{z_{d0}}{z_{d0}+t_{d}^{+}} + \frac{w^{(2)}}{Q+H+D} * \frac{z_{h0}^{2}}{z_{h0}^{2}+t_{h}^{2+}} + \\
& +\left(\frac{w^{(1)}}{E+m+D} * \sum_{i=1}^{m}\frac{x_{i0}-s_{i}^{-}}{x_{i0}} + \frac{w^{(2)}}{Q+H+D} * \sum_{d=1}^{D}\frac{z_{d0}^{1}-t_{d}^{1-}}{z_{d0}^{1}} + \frac{w^{(3)}}{S+D} * \sum_{d=1}^{D}\frac{z_{h0}^{2}-t_{h}^{2-}}{z_{h0}^{2}}\right)
\end{aligned}
$$

Then, for each term, we introduce its upper bounds as $\xi_e^1, \xi_q^2, \xi_r^3, \xi_d^1, \xi_h^2$ and ξ_4 respectively. Consequently, by an epigraph transformation which replaces the nonlinear objective function of model (6.5) with sum of those upper bounds, model (6.5) is equivalent to the following optimization model (6.6).

$$\min \sum_{e}^{E} \xi_e^1 + \sum_{q}^{Q} \xi_q^2 + \sum_{r}^{S} \xi_r^3 + \sum_{d}^{D} \xi_d^1 + \sum_{h}^{H} \xi_h^2 + \xi_4 \tag{6.6}$$

$$\begin{aligned}
s.t.\quad & \frac{w^{(1)}}{E+m+D} * \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} \le \xi_e^1 \\
& \frac{w^{(2)}}{Q+H+D} * \frac{y_{q0}^2}{y_{q0}^2 + s_q^+} \le \xi_q^2 \\
& \frac{w^{(3)}}{S+D} * \frac{y_{r0}}{y_{r0} + s_r^+} \le \xi_r^3 \\
& \frac{w^{(1)}}{E+m+D} * \frac{z_{d0}}{z_{d0} + t_d^+} \le \xi_d^1 \\
& \frac{w^{(2)}}{Q+H+D} * \frac{z_{h0}^2}{z_{h0}^2 + t_h^{2+}} \le \xi_h^2 \\
& \frac{w^{(1)}}{E+m+D} * \sum_{i=1}^{m} \frac{x_{i0} - s_i^-}{x_{i0}} + \frac{w^{(2)}}{Q+H+D} * \sum_{d=1}^{D} \frac{z_{d0}^1 - t_d^{1-}}{z_{d0}^1} + \frac{w^{(3)}}{S+D} * \sum_{d=1}^{D} \frac{z_{h0}^2 - t_h^{2-}}{z_{h0}^2} \le \xi_4 \\
& w^{(1)} + w^{(2)} + w^{(3)} = 1 \\
& \text{constraints (6.1)}
\end{aligned}$$

Evidently, model (6.6) is a quadratic optimization problem which can be convex or nonconvex. Then, model 6.6) can be converted into a SOCP problem whose global optimal solution is ensured and can be obtained by solvers such as CVX in MATLAB since SOCP is a special form of convex optimization (Boyd and Vandenberghe (2004)). Obviously, above constraints $\frac{w^{(1)}}{E+m+D} * \frac{y_{e0}^1}{y_{e0}^1 + s_e^+} \le \xi_e^1$ is equivalent to $(E+m+D)(y_{e0}^1 + s_e^+)\xi_e^1 \ge (\sqrt{w^{(1)} * y_{e0}^1})^2$. Then, according to the transformation utilized in Chen and Zhu (2017), we know that $(E+m+D)(y_{e0}^1 + s_e^+)\xi_e^1 \ge (\sqrt{w^{(1)} y_{e0}^1})^2$ can be converted into

$$\sqrt{(\sqrt{w^{(1)} y_{e0}^1})^2 + \left(\frac{1}{2}\Big((E+m+D)(y_{e0}^1 + s_e^+) - \xi_e^1\Big)\right)^2} \le \frac{1}{2}(E+m+D)(y_{e0}^1 + s_e^+) + \xi_e^1) \tag{6.7}$$

Similarity, other constraints can be transferred as the following (1), (2), (3), and (4):

(1) $\frac{w^{(2)}}{Q+H+D} * \frac{y_{q0}^2}{y_{q0}^2 + s_q^+} \le \xi_q^2$ is equivalent to $(Q+H+D)(y_{q0}^2 + s_q^+)\xi_q^2 \ge (\sqrt{w^{(2)} * y_{q0}^2})^2$, and then can be transformed into the following model (6.8):

$$\sqrt{(\sqrt{w^{(2)} y_{q0}^2})^2 + \left(\frac{1}{2}\left((Q+H+D)(y_{q0}^2 + s_q^+) - \xi_q^2)\right)\right)^2} \le \frac{1}{2}\left((Q+H+D)(y_{q0}^2 + s_q^+) + \xi_q^2)\right) \quad (6.8)$$

(2) $\frac{w^{(3)}}{S+D} * \frac{y_{r0}}{y_{r0} + s_r^+} \le \xi_r^3$ is equivalent to $(S+D)(y_{r0} + s_r^+)\xi_r^3 \ge (\sqrt{w^{(3)} y_{r0}})^2$, and then can be transformed into the following model (6.9):

$$\sqrt{(\sqrt{w^{(3)} y_{r0}})^2 + \left(\frac{1}{2}\left((S+D)(y_{r0} + s_r^+) - \xi_r^3)\right)\right)^2} \le \frac{1}{2}\left((S+D)(y_{r0} + s_r^+) + \xi_r^3)\right) \quad (6.9)$$

(3) $\frac{w^{(1)}}{E+m+D} * \frac{z_{d0}}{z_{d0} + t_d^+} \le \xi_d^1$ is equivalent to $(E+m+D)(z_{d0} + t_d^+)\xi_d^1 \ge (\sqrt{w^{(1)} * z_{d0}})^2$, and then can be transformed into the following model (6.10):

$$\sqrt{(\sqrt{w^{(1)} z_{e0}})^2 + \left(\frac{1}{2}\left((E+m+D)(z_{e0} + t_d^+) - \xi_d^1)\right)\right)^2} \le \frac{1}{2}(E+m+D)(z_{e0} + t_d^+) + \xi_d^1) \quad (6.10)$$

And (4) $\frac{w^{(2)}}{Q+H+D} * \frac{z_{h0}^2}{z_{h0}^2 + t_h^{2+}} \le \xi_h^2$ is equivalent to $(Q+H+D)(z_{h0}^2 + t_h^{2+})\xi_h^2 \ge (\sqrt{w^{(2)} z_{h0}^2})^2$, and then can be transformed into the following model (6.8):

$$\sqrt{\left(\sqrt{w^{(2)}z_{h0}^2}\right)^2+\left(\frac{1}{2}\left((Q+H+D)(z_{h0}^2+t_h^{2+})-\xi_h^2\right)\right)^2} \le \frac{1}{2}\left((Q+H+D)(z_{h0}^2+t_h^{2+})+\xi_h^2\right) \tag{6.11}$$

Base on (Boyd and Vandenberghe (2004)), above model (6.7), (6.8), (6.9), (6.10), and (6.11) are second order cone constraints and can be further converted into SOCP problem in the following model (6.12):

$$\min \quad \sum_{e}^{E}\xi_e^1+\sum_{q}^{Q}\xi_q^2+\sum_{r}^{S}\xi_r^3+\sum_{d}^{D}\xi_d^1+\sum_{h}^{H}\xi_h^2+\xi_4 \tag{6.12}$$

$$s.t. \quad \left\| \begin{matrix} \sqrt{w^{(1)}y_{e0}^1} \\ \frac{1}{2}\left((E+m+D)\left(y_{e0}^1+s_e^+\right)-\xi_e^1\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left((E+m+D)\left(y_{e0}^1+s_e^+\right)+\xi_e^1\right),\ \forall e$$

$$\left\| \begin{matrix} \sqrt{w^{(2)}y_{q0}^2} \\ \frac{1}{2}\left((Q+H+D)(y_{q0}^2+s_q^+)-\xi_q^2)\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left((Q+H+D)(y_{q0}^2+s_q^+)+\xi_q^2)\right),\ \forall q$$

$$\left\| \begin{matrix} \sqrt{w^{(3)}y_{r0}} \\ \frac{1}{2}\left((S+D)(y_{r0}+s_r^+)-\xi_r^3)\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left((S+D)(y_{r0}+s_r^+)+\xi_r^3)\right),\ \forall r$$

$$\left\| \begin{matrix} \sqrt{w^{(1)}z_{e0}} \\ \frac{1}{2}\left((E+m+D)(z_{e0}+t_d^+)-\xi_d^1)\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left((E+m+D)(z_{e0}+t_d^+)+\xi_d^1)\right),\ \forall d$$

$$\left\| \begin{matrix} \sqrt{w^{(2)}z_{h0}^2} \\ \frac{1}{2}\left((Q+H+D)\left(z_{h0}^2+t_h^{2+}\right)-\xi_h^2\right) \end{matrix} \right\|_2 \le \frac{1}{2}\left((Q+H+D)\left(z_{h0}^2+t_h^{2+}\right)+\xi_h^2\right),\forall h$$

$$w^{(1)}\frac{1}{E+m+D}\left(\sum_{i=1}^{m}\frac{x_{i0}-s_i^-}{x_{i0}}\right)+w^{(2)}\frac{1}{Q+H+D}\left(\sum_{d=1}^{D}\frac{z_{d0}^1-t_d^{1-}}{z_{d0}^1}\right)+w^{(3)}\frac{1}{S+D}\left(\sum_{d=1}^{D}\frac{z_{h0}^2-t_h^{2-}}{z_{h0}^2}\right)$$

$$w^{(1)}+w^{(2)}+w^{(3)}=1$$

constraints (6.1)

6.5 Results of globalization index and major findings via a three-stage network approach

Using the three-stage SBM network in section 6.3 and the aforementioned inputs, outputs, and intermediate measures (figure 6.1), we construct composite globalization index for countries around the world in one year time window from the total sample period 1995 to 2015. A data set example for political-economic globalization index is shown in table 6.1.

Table 6.1 SBMGI in 2015

Countries	SBMGI	Political Globalization Performance	Economic Globalization Performance	Social Globalization Performance
Argentina	0.7353	0.7216	0.8212	0.6631
Armenia	0.7305	0.7915	0.6391	0.7607
Australia	0.7567	0.8674	0.8198	0.5825
Austria	0.7711	0.7963	0.7194	0.7976
Belgium	0.8563	0.9011	0.9033	0.7642
Benin	0.6748	0.7655	0.6980	0.5608
Bulgaria	0.8176	0.8851	0.6868	0.8808
Bosnia and Herzegovina	0.7428	0.7288	0.6641	0.8356
Bolivia	0.6799	0.7324	0.7017	0.6056
Brazil	0.7570	0.7780	0.7760	0.7170
Brunei Darussalam	0.6728	0.7904	0.6792	0.5487
Canada	0.8193	0.9328	0.7888	0.7362
Switzerland	0.8777	0.7869	0.9984	0.8479
Chile	0.7201	0.7898	0.6842	0.6864
China	1.0000	1.0000	1.0000	1.0000
Cote d'Ivoire	0.6792	0.6775	0.8079	0.5523
Czech Republic	0.7694	0.7894	0.7433	0.7753
Germany	0.9818	0.9453	1.0000	1.0000
Denmark	0.8555	0.8424	0.8105	0.9136
Ecuador	0.7207	0.6922	0.7794	0.6905
Egypt, Arab Rep.	0.7635	0.7952	0.6377	0.8578
Spain	0.8049	0.8245	0.7387	0.8514
Estonia	0.7593	0.7884	0.6561	0.8334
Finland	0.7232	0.8013	0.6843	0.6840
France	0.9056	0.9483	0.7438	1.0000
United Kingdom	0.9677	0.9030	1.0000	1.0000
Georgia	0.8474	0.8574	0.6872	0.9975
Ghana	0.6796	0.7755	0.6669	0.5964
Greece	0.8101	0.7940	0.7700	0.8663
Guatemala	0.7302	0.8410	0.5858	0.7638
Honduras	0.7260	0.7576	0.6486	0.7718
Croatia	0.7896	0.7976	0.6512	0.9199
Hungary	0.7936	0.7302	0.7389	0.9116
Indonesia	0.7287	0.8502	0.7402	0.5957

Table 6.1 SBMGI in 2015 (Continued)

Countries	SBMGI	Political Globalization Performance	Economic Globalization Performance	Social Globalization Performance
Ireland	0.8748	0.9527	0.9154	0.7563
Italy	0.8129	0.9957	0.7135	0.7293
Jamaica	0.7877	0.7734	0.7947	0.7949
Japan	0.9466	0.7622	1.0000	1.0000
Kazakhstan	0.7481	0.7294	0.7601	0.7546
Kenya	0.6444	0.7440	0.6617	0.5273
Kyrgyz Republic	0.7794	0.7283	0.6925	0.9175
Cambodia	0.6915	0.7380	0.6761	0.6603
Lesotho	0.7265	0.6907	0.7669	0.7219
Lithuania	0.7896	0.8456	0.7870	0.7362
Morocco	0.8084	0.8017	0.6988	0.9247
Moldova	0.8001	0.7376	0.7138	0.9490
Madagascar	0.6405	0.6857	0.7486	0.4872
Myanmar	0.6989	0.7450	0.7525	0.5992
Montenegro	0.7618	0.8009	0.6812	0.8033
Mongolia	0.6482	0.7690	0.6870	0.4885
Malawi	0.6476	0.7673	0.6628	0.5129
Malaysia	0.8168	0.7877	0.8126	0.8501
Namibia	0.7032	0.7660	0.6998	0.6437
Nigeria	0.6697	0.8415	0.6160	0.5515
Netherlands	0.8963	0.9339	0.9191	0.8360
Norway	0.9577	0.8731	0.9999	1.0000
Peru	0.7116	0.8529	0.6121	0.6699
Philippines	0.7330	0.7639	0.7605	0.6746
Poland	0.8002	0.7674	0.7933	0.8399
Portugal	0.7960	0.8916	0.6912	0.8051
Paraguay	0.6758	0.7354	0.6774	0.6145
Qatar	0.8021	0.8257	0.8113	0.7690
Russian Federation	0.8082	0.8054	0.7393	0.8798
Rwanda	0.6755	0.9094	0.5738	0.5432
El Salvador	0.7355	0.7342	0.6499	0.8224
Serbia	0.7842	0.7254	0.6966	0.9306
Slovenia	0.7472	0.7353	0.7772	0.7290
Sweden	0.7414	0.7992	0.7368	0.6880

Table 6.1 SBMGI in 2015 (Continued)

Countries	SBMGI	Political Globalization Performance	Economic Globalization Performance	Social Globalization Performance
Thailand	0.7868	0.7029	0.8244	0.8329
Timor-Leste	0.6804	0.8209	0.6480	0.5721
Tunisia	0.7330	0.6870	0.7484	0.7636
Turkey	0.7304	0.7658	0.7112	0.7140
Uganda	0.6706	0.8054	0.6105	0.5960
Uruguay	0.7120	0.8511	0.6067	0.6781
United States	1.0000	1.0000	1.0000	1.0000
Vietnam	0.8551	0.7432	0.8691	0.9528
Yemen, Rep.	0.6960	0.7492	0.6182	0.7205
South Africa	0.7587	0.8535	0.7550	0.6676
Zambia	0.6442	0.8254	0.6435	0.4638

As shown in table 6.1, the same 79 countries in 2015 which have completely data set for all indicators are under consideration as the countries we mentioned in the previous chapter. Among them, we find the United States and China are countries which has globalization index as one (the highest globalization index) via our three-stage ASBM DEA network approach. The sub-dimension globalization (political globalization, economic globalization, and social globalization) index are also the highest. Madagascar has the lowest SBM-DEA globalization index (SBMGI) score as 0.6405. Cote d'Ivoire has the lowest political globalization with 0.6775, Rwanda has the lowest economic globalization with 0.5738, and Zambia has the lowest social globalization score as o.4638.

There are two countries (China and United States) have globalization in political are one, five countries (China, Germany, United Kingdom, Japan and United States) which have globalization index in economic as one, and seven countries

(China, Germany, France, United Kingdom, Japan, Norway, and United States) which have globalization index in social dimension as one when we consider all three dimensions at the same time. Among them, Germany, Japan, and United Kingdom have the highest globalization score in economic and social. But because their social globalization are not the best, their SBM globalization index (SBMGI) is not one.

Table 6.2 SBMGI for 15 countries which rank top 15 in GDP

Countries	GDP (billion, USD)	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
United States	21482	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
China	14172	1.0000	1.0000	1.0000	1.0000	N/A	N/A	N/A	N/A	N/A	N/A	1.0000
Japan	5221	0.9466	0.9098	1.0000	0.9018	0.7909	0.7694	0.8773	0.7802	0.8275	0.8487	0.8321
Germany	4117	0.9818	0.9906	0.9831	0.9807	0.9823	0.9817	0.9864	0.9942	0.8980	0.9990	0.8948
France	2845	0.9056	0.9356	0.9236	0.9258	0.9962	0.9150	1.0000	0.8949	0.9052	0.9083	0.8532
United Kingdom	2810	0.9677	0.9314	0.9713	0.9852	1.0000	1.0000	1.0000	0.9176	0.8863	0.8885	0.9686
Italy	2113	0.8129	0.7911	0.7974	0.7912	0.8227	0.8360	0.8393	0.8250	0.8208	0.8390	0.7935
Brazil	1930	0.7570	0.7625	0.7426	0.7363	0.7729	0.7667	0.7566	0.7426	0.7420	0.7410	0.6847
Canada	1820	0.8193	0.8252	0.7904	0.7935	0.8242	0.8118	0.8314	0.7918	0.8040	0.8115	0.7992
Russian Federation	1649	0.8082	0.8150	0.7847	0.7725	0.7910	0.7899	0.7948	0.7754	0.7619	0.7591	0.7119
Spain	1474	0.8049	0.8075	0.8159	0.8053	0.8213	0.8139	0.8179	0.8134	0.8233	0.8507	0.8044
Australia	1464	0.7567	0.7657	0.7474	0.7473	0.7619	0.7853	N/A	0.7546	N/A	0.7904	0.7691

Table 6.2 shows SBMGI for 12 countries who rank top 15 of GDP. India, South Korea, and Mexico haven't been involved in figure 6.2 as there are less than 3 SBMGI for them during the time period from 2005 to 2015. Among them, United Stated has the highest SBMGI for all year we considered above. Though we do not have complete data information for China from 2006 to 2011, it performs best in globalization for rest of years. In addition, Japan has the highest value of SBMGI in 2013. Its SBMGI changes most. For the ten year time window shown in table 6.2, its lowest value of SBMGI is 0.7694 in 2010, while the highest value of SBMGI is one in 2013. The main reason is due to the change of GDP as stating in the following

figure 6.3 that GDP in most of other countries increase constantly, while Japan's GDP decreased in some years.

Figure 6.3 illustrates the relationship between the GDP and SBMGI via providing a comparison in GDP and SBMGI between developed countries and developing countries.

Table 6.3 GDP and SBMGI of United States, Japan, and Germany from 2005 to 2015

Year	**United States**		**Japan**		**Germany**	
	GDP ($Billion)	SBMGI	GDP ($Billion)	SBMGI	GDP ($Billion)	SBMGI
2005	13093.7260	1.0000	4755.4106	0.8321	2861.4103	0.8948
2006	13855.8880	1.0000	4530.3772	0.8487	3002.4464	0.9990
2007	14477.6350	1.0000	4515.2645	0.8275	3439.9535	0.8980
2008	14718.5820	1.0000	5037.9085	0.7802	3752.3656	0.9942
2009	14418.7390	1.0000	5231.3827	0.8773	3418.0050	0.9864
2010	14964.3720	1.0000	5700.0981	0.7694	3417.0946	0.9817
2011	15517.9260	1.0000	6157.4596	0.7909	3757.6983	0.9823
2012	16155.2550	1.0000	6203.2131	0.9018	3543.9839	0.9807
2013	16691.5170	1.0000	5155.7171	1.0000	3752.5135	0.9831
2014	17427.6090	1.0000	4850.4135	0.9098	3890.6069	0.9906
2015	18120.7140	1.0000	4394.9778	0.9466	3375.6111	0.9818

Above table 6.3 shows three countries whose GDP rank first, third, and fourth around the world in 2015, respectively, while the following table 6.4 shows three countries whose GDP rank 98 out of 211, 99 out of 211, and 100 out of 211 around the world in 2015, respectively. China's GDP ranks the second. However, it isn't been involved here because its information is insufficient from 2006 to 2011

Table 6.4 GDP and SBMGI of Tunisia, Uganda, and Estonia from 2005 to 2015

Year	Tunisia		Uganda		Estonia	
	GDP ($Billion)	SBMGI	GDP ($Billion)	SBMGI	GDP ($Billion)	SBMGI
2005	32.2730	0.7154	9.0138	0.6634	14.0061	0.8232
2006	34.3784	0.7213	9.9426	0.6634	16.9636	0.8449
2007	38.9081	0.7364	12.2928	0.6546	22.2371	0.8330
2008	44.8566	0.7619	14.2390	0.6622	24.1940	0.7892
2009	43.4549	0.7566	18.1689	0.6630	19.6525	0.8224
2010	44.0509	0.7699	20.1865	0.6704	19.4909	0.8608
2011	45.8106	0.7656	20.1768	0.6919	23.1702	0.8441
2012	45.0441	0.7691	23.1321	0.6796	23.0439	0.8359
2013	46.2511	0.7643	24.5996	0.6677	25.1372	0.7594
2014	47.5879	0.7588	27.2952	0.6711	26.2246	0.8116
2015	43.1567	0.7330	27.0594	0.6706	22.5670	0.7593

Comparing these two tables, first, there is a positive correlation between globalization index and economic level. The range of SBMGI for United States, Japan, and Germany is 0.7694 to 1.0000, while the range of SBMGI for Tunisia, Uganda, and Estonia is from 0.6546 to 0.8608. Among them, only Japan have SBMGI which is lower than 0.89 for all three developed countries. As mentioned before, it is main because the sudden change of GDP in Japan. From 2005 to 2015, Japan's GDP decreased from $4755 billion to $4515 billion from 2005 to 2007, then increased from $4515 billion in 2005 to $6203 billion in 2012, and finally decreased to $4395 billion in 2015. In terms of three developing countries, on the contrast, SBMGI for all countries are below 0.89. Especially, SBMGI for Tunisia and Uganda are below 0.8. Second, ranges of SBMGI for each country across the ten years are very small. For example, from 2005 to 2015, U.S. GDP increases from $13093.8880 billion to $18120.7140 billion, but its SBMGI doesn't change. Another example is Uganda, its GDP increases from 9.0138 billion to 27.0594 billion, which has been increased around 200%. However, the SBMGI is kind of stable, changing from 0.6546 to 0.6919.

The following table 6.5 shows SBMGI for 81 countries from 2005 to 2015. The same, this study collects data set for more than 120 countries. However, for some countries, they don't have complete data set for all years under consideration that it is not able to obtain their SBMGI for that specific year. Thus, in table 6.5, it includes countries who have SBMGI for three years at least. Finally, there are 81 countries in total in table 6.5.

Table 6.5 Countries SBMGI from 2005 to 2015

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Argentina	0.7353	0.7472	0.7436	0.7453	0.7622	0.7604	N/A	0.7197	0.7208	0.7179	N/A
Armenia	0.7305	0.7448	0.7617	0.7854	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Australia	0.7567	0.7657	0.7474	0.7473	0.7619	0.7853	N/A	0.7546	N/A	0.7904	0.7691
Austria	0.7711	0.7785	N/A	0.7833	0.7991	0.7875	N/A	0.7865	0.7900	0.7825	0.7858
Belgium	0.8563	0.8845	0.7983	0.8053	0.8209	0.8179	0.8296	0.8199	0.7894	0.7864	0.8290
Benin	0.6748	0.6565	0.6419	0.6662	0.6680	0.6560	0.6493	0.6477	0.6451	0.6440	N/A
Burkina Faso	N/A	0.6671	0.6673	0.6646	0.6630	0.6649	0.6519	0.6444	0.6477	0.6403	0.6500
Bulgaria	0.8176	0.8276	0.8430	0.8407	0.8483	0.8614	0.8517	0.7850	0.7804	0.7724	0.7481
Bosnia and Herzegovina	0.7428	0.7506	0.7501	0.7566	0.7520	0.7422	0.7304	0.7518	0.7461	0.7412	0.7315
Bolivia	0.6799	0.6905	0.6860	0.6981	0.6988	0.6915	0.6865	0.6986	0.6934	0.6809	0.6808
Brazil	0.7570	0.7625	0.7426	0.7363	0.7729	0.7667	0.7566	0.7426	0.7420	0.7410	0.6847
Canada	0.8193	0.8252	0.7904	0.7935	0.8242	0.8118	0.8314	0.7918	0.8040	0.8115	0.7992
Switzerland	0.8777	0.8477	0.8204	0.8366	0.8301	0.8377	0.8557	0.8261	0.8526	0.8759	0.8321
Chile	0.7201	0.7389	0.7234	0.7326	0.7538	0.7536	0.7523	0.7573	0.7561	0.7557	0.7124
China	1.0000	1.0000	1.0000	1.0000	N/A	N/A	N/A	N/A	N/A	N/A	1.0000
Cote d'Ivoire	0.6792	0.6562	0.6428	0.6496	N/A	N/A	0.6219	0.6316	0.6300	N/A	N/A
Cameroon	N/A	0.6619	0.6336	0.6390	0.6327	0.6284	0.6231	N/A	N/A	0.6057	0.6214
Colombia	N/A	0.7740	0.7550	0.7757	0.7459	0.7608	0.7724	0.7988	0.8399	0.8279	N/A
Czech Republic	0.7694	0.7893	0.7787	0.8136	0.7752	0.8012	0.7920	0.7607	0.7612	0.7548	0.7330
Germany	0.9818	0.9906	0.9831	0.9807	0.9823	0.9817	0.9864	0.9942	0.8980	0.9990	0.8948
Denmark	0.8555	0.8977	0.8169	0.8080	0.7887	0.7875	0.7895	0.7809	0.8027	0.8034	0.7948
Ecuador	0.7207	0.7128	0.7029	0.6988	0.7006	0.6817	0.7012	0.6942	0.6876	0.6836	0.6792
Egypt, Arab Rep.	0.7635	0.7879	0.7861	0.7860	0.8039	0.8108	0.7896	0.7985	0.7776	0.7758	0.7607
Spain	0.8049	0.8075	0.8159	0.8053	0.8213	0.8139	0.8179	0.8134	0.8233	0.8507	0.8044
Estonia	0.7593	0.8116	0.7594	0.8359	0.8441	0.8608	0.8224	0.7892	0.8330	0.8449	0.8232
Finland	0.7232	0.7394	0.7511	0.7533	0.7723	0.7705	0.7523	0.7601	0.7524	0.7581	0.7541
France	0.9056	0.9356	0.9236	0.9258	0.9962	0.9150	1.0000	0.8949	0.9052	0.9083	0.8532
United Kingdom	0.9677	0.9314	0.9713	0.9852	1.0000	1.0000	1.0000	0.9176	0.8863	0.8885	0.9686
Ghana	0.6796	0.6755	0.6528	0.6653	0.6678	0.6705	0.6757	0.6643	0.6679	N/A	N/A
Greece	0.8101	0.7831	0.7673	0.7572	0.7772	0.7549	0.7502	0.7230	0.7189	0.6929	0.7069
Guatemala	0.7302	0.7213	0.7247	0.7224	N/A	0.7120	0.7040	0.7147	0.7149	0.7141	0.7121
Honduras	0.7260	0.7234	0.7196	0.7484	0.7350	0.7209	N/A	0.7409	N/A	N/A	N/A
Croatia	0.7896	0.8076	0.7807	0.7743	0.7702	0.7591	0.7401	0.8148	0.7453	0.7526	0.7583
Hungary	0.7936	0.8100	0.7870	0.8043	0.8078	0.7993	0.7835	0.8067	0.7945	0.7886	0.7631
Indonesia	0.7287	0.7517	0.7248	0.7249	0.7366	0.7362	N/A	0.9542	N/A	N/A	N/A

Table 6.5 Continued

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Ireland	0.8748	0.8239	0.8203	0.8309	0.8220	0.8627	0.8407	0.8861	0.7663	0.7631	0.8054
Italy	0.8129	0.7911	0.7974	0.7912	0.8227	0.8360	0.8393	0.8250	0.8208	0.8390	0.7935
Japan	0.9466	0.9098	1.0001	0.9018	0.7909	0.7694	0.8773	0.7802	0.8275	0.8487	0.8321
Kenya	0.6444	0.6565	0.6444	0.6466	0.6548	0.6398	0.6468	0.6458	0.6521	0.6483	0.6630
Kyrgyz Republic	0.7794	0.7936	0.7899	0.7916	0.7966	0.7786	0.7622	0.7791	0.7745	0.7700	0.7613
Cambodia	0.6915	0.7004	0.6803	0.7012	0.6935	N/A	N/A	N/A	N/A	N/A	N/A
Lesotho	0.7265	0.7320	0.7108	0.7073	N/A	0.7029	N/A	N/A	N/A	N/A	N/A
Lithuania	0.7896	0.7609	0.7456	N/A	0.7954	0.8036	N/A	0.7496	0.7748	0.7761	0.7522
Luxembourg	N/A	N/A	0.8813	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Morocco	0.8084	0.8259	0.8049	0.8106	0.8093	0.8067	N/A	N/A	N/A	0.7862	0.7616
Mali	N/A	0.6556	0.6643	0.6528	0.6490	0.6472	0.6437	0.6425	0.6314	0.6401	N/A
Montenegro	0.7618	0.7751	0.7567	0.7798	0.7540	0.7695	0.7624	0.7664	0.7732	N/A	N/A
Mongolia	0.6482	0.6604	0.6515	0.6816	0.6846	0.6927	0.6953	0.6803	0.6718	N/A	N/A
Malawi	0.6476	0.6503	0.6418	0.6650	0.6609	0.6428	0.6308	0.6420	0.6443	N/A	N/A
Malaysia	0.8168	0.8226	0.8081	0.8194	0.8424	0.8455	0.8287	0.8392	0.8339	0.8350	N/A
Namibia	0.7032	0.6984	0.6754	0.6941	0.6914	0.6965	0.6998	0.6997	0.6915	N/A	N/A
Nigeria	0.6697	N/A	0.7147	N/A	N/A	0.7147	N/A	0.7325	0.7215	N/A	0.6512
Netherlands	0.8963	0.8991	1.0000	1.0001	0.9947	0.9555	0.9322	0.9013	1.0000	1.0000	1.0002
Norway	0.9577	0.9640	0.9653	0.9699	0.9685	0.9647	0.9614	0.9641	0.9788	0.7493	0.7259
New Zealand	N/A	N/A	0.7398	0.7505	0.7572	0.7473	N/A	0.7375	0.7571	0.7438	0.7256
Pakistan	N/A	N/A	N/A	0.7173	0.7095	0.7294	0.7577	0.7530	0.7285	0.7345	0.6978
Peru	0.7116	0.7209	0.7226	0.7218	0.7246	0.7332	0.7287	0.7226	0.7197	0.7155	0.6933
Philippines	0.7330	0.7347	0.7185	0.7140	0.7247	N/A	0.7149	0.7010	0.6956	0.6989	0.6881
Poland	0.8002	0.8075	0.8023	0.8125	0.8389	0.8363	0.8232	0.7875	0.7937	0.8077	0.7847
Portugal	0.7960	0.8092	0.8242	0.8615	0.7514	0.7453	0.7418	0.7394	0.7501	0.7467	0.7396
Paraguay	0.6758	0.6719	0.6598	0.6723	0.6639	N/A	N/A	N/A	N/A	N/A	N/A
Qatar	0.8021	0.8026	0.7680	0.8216	0.8218	N/A	N/A	N/A	N/A	N/A	N/A
Russian Federation	0.8082	0.8150	0.7847	0.7725	0.7910	0.7899	0.7948	0.7754	0.7619	0.7591	0.7119
Rwanda	0.6755	0.6689	0.6672	0.6768	0.6918	0.6908	N/A	N/A	N/A	N/A	N/A
Senegal	N/A	0.7383	0.7292	0.7354	0.7505	0.7290	0.7165	0.7295	0.7267	0.7254	N/A
Singapore	N/A	N/A	N/A	N/A	0.8384	0.8390	0.8559	0.8144	0.8536	0.8357	N/A
El Salvador	0.7355	0.7466	0.7354	0.7381	0.7384	0.7299	0.7197	0.7287	0.7351	0.7438	0.7260
Serbia	0.7842	0.7797	0.7825	0.8101	0.8140	0.7946	0.7869	0.7457	0.7704	N/A	N/A
Slovenia	0.7472	0.7586	0.7333	0.7611	0.7503	0.7464	0.7312	0.7164	0.7541	0.7467	0.7342
Sweden	0.7414	0.7657	0.8945	0.8526	0.9047	0.8105	0.8934	0.8942	0.8030	0.8905	0.8843

Table 6.5 Continued

Countries	2015	2014	2013	2012	2011	2010	2009	2008	2007	2006	2005
Thailand	0.7868	0.7989	0.7923	0.8047	0.7811	0.7664	0.7662	0.7764	0.7766	0.7804	0.7499
Tajikistan	N/A	N/A	0.6615	0.6808	0.6779	0.6867	N/A	N/A	N/A	N/A	N/A
Timor-Leste	0.6804	N/A	0.6906	0.7361	0.7576	N/A	N/A	N/A	N/A	N/A	N/A
Tunisia	0.7330	0.7588	0.7643	0.7691	0.7656	0.7699	0.7566	0.7619	0.7364	0.7213	0.7154
Turkey	0.7304	0.7415	0.7323	0.7345	0.7531	0.7444	0.7512	0.7720	0.7619	0.7547	0.7251
Uganda	0.6706	0.6711	0.6677	0.6796	0.6919	0.6704	0.6630	0.6622	0.6546	0.6634	0.6634
Ukraine	N/A	N/A	N/A	N/A	N/A	N/A	0.8422	0.8229	0.8173	0.8099	0.7885
Uruguay	0.7120	0.7152	0.7266	0.7320	0.7379	0.7226	0.7021	0.7205	0.7184	0.7261	N/A
United States	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
South Africa	0.7587	0.8638	0.7614	0.7471	0.7329	0.7236	0.7277	0.7290	0.7275	0.7326	0.7205
Zambia	0.6442	0.8184	0.6377	0.6484	0.6450	0.6554	0.6483	0.6447	0.6552	0.6525	0.6483

In table 6.5, the change for most of countries is small, comparing with other globalization index such as the KOF globalization index. As a benchmarking tool, DEA provides the comprehensive globalization index for each country while considering all other countries in the same year. Even if a country create more GDP and has less barriers for international trades, its SBMGI may not increase greatly as other countries at the same time also have higher volume of GDP or less volume of international trade barriers. In addition, we can also find that most of developed counties' SBMGI are above 0.7, while most of developing countries' SBMGI are below 0.7 for most years. China is the exception.

Chapter VII Conclusions and Future Research

7.1 Introduction

Performance evaluation plays an important role for firms or organizations that they can follow their strategic objectives and be continuously improvement, however, the critical review of existing literatures illustrates most of performance evaluation only focuses on measures from one aspect which may lead to biased or erroneous conclusions. Thus, this dissertation focuses on constructing composite index in performance evaluation from multi dimensions via a network DEA approach as the traditional DEA models cannot dig into useful information and value from a mess of data in the context of big data.

7.2 Summary of Research

In this study, we apply network DEA systems to evaluate performance for eight airline companies via integrating metrics from operations and stock market, and extend the same method into construct composite index for globalization of countries around the world from multi dimensions: political, economic, and social dimension. SOCP has been implementing to solve the non-linear problem in network DEA.

In Chapter 3, the proposed two-stage network DEA model has been applied to evaluate performance for airline companies via capturing both operational metrics and stock market financial metrics. By integrating stock market indicators with operational indicators, the biased can be avoided that the measures in financial aspect also serve to provide different dimensions and information of an overall firm's activities and processes. In addition, this chapter implements a two-stage network DEA with SOCP, which enables us to solve non-linear DEA models without the need for calculating numerous parametric linear programs in an effort to estimate the global optimal solution. We evaluate the performance of eight major international airline companies from 2006 until 2016. According to results, the stock market-based performance scores declined significantly for all our sampled companies because of the 2013-14 European debt crisis and United States debt-ceiling crisis. It is also shown that while low cost carriers generally maintain higher operational-based performance scores than their full service counterparts, full service carriers earn higher performance scores based on stock market indicators. This finding lends support to network DEA approach applied in this chapter and the general premise which argues that performance evaluation methods can yield more comprehensive conclusions if both operational and stock market indicators are utilized.

In chapter 4, we develops a new ASBM network DEA model to measure globalization index via integrating indicators of globalization from political dimension and economic dimension for countries around the world during a time period from 1995 to 2015. Eleven indicators in total have been considered. We find the United States is the only country which has PEGI with one, and so do its sub-political globalization index and sub-economic globalization index, while Malawi has the lowest PEGI score as 0.6403 with the economic globalization score in sixth from the bottom and lower intermediate political globalization score. According to DEA approach, the globalization index ranges from zero to one for each country, whereas higher values denote more globalization. Notice that the higher globalization performance index does not mean the better the comprehensive strength of a country has. However, by comparing the GDP and our globalization index which consider political dimension and economic dimension, we can find there is a positive relation between them. In addition, for countries, such as the Untied State and Uganda whose GDP keeps increasing at a same rate, the political-economic globalization index (PEGI) we obtained from this chapter are stable. On the contrary, if GDP value don't keep a continuously increasing or decreasing, such as Japan, Germany, and Estonia, the PEGI shocks.

In chapter 5, we apply the same model in chapter 4 to measure globalization via integrating metrics from economic dimension and social dimension for same 79 countries during same time period. Except for the same metrics in economic dimension, the economic-social globalization index (ESGI) in this chapter includes other five indicators in social dimension. They are transfer, international internet users, international tourism, fixed broadband subscription, and fixed telephone subscription. The result shows that the United States and Germany have value of one for ESGI and economic globalization. Kenya has the lowest ESGI score as 0.4701. Yemen, Rep has the lowest economic globalization with 0.3743, but social globalization performance score as 0.7389 which is at the medium level among all countries. Mongolia has the lowest social globalization score as o.4952. In addition, we can find that countries perform better in social globalization index than their economic globalization index. There are 19 out of 79 countries who have the economic globalization less than 0.5, but only one country's social globalization index bellows 0.5.

Chapter 6 discusses how countries performs in globalization via integrating indicators of globalization from all three dimensions: political dimension, economic dimension, and social dimension. It considers a three-stage network DEA approach to construct the composite globalization performance index as it is more sufficient to deal with information and value that are hidden within data under a big data modeling than traditional DEA models. We also implement SOCP to solve the non-linear problem in network DEA model. According to results, the United States and China have value of one for an overall SBM globalization index via the three-stage SBM DEA network approach in this chapter. Madagascar has the lowest SBM globalization score as 0.6405. Cote d'Ivoire has the lowest political globalization with 0.6775, Rwanda has the lowest economic globalization with 0.5738, and Zambia has the lowest social globalization score as o.4952. Germany, Japan, and United Kingdom have the highest globalization score in economic and social. But because their political globalization are not the best, their SBM globalization index is not one.

7.3 Contributions

7.3.1 Methodological Contribution

This dissertation makes a methodological contribution. First, it develops a new two-stage ASBM network DEA structure and a new three-stage ASBM network DEA structure respectively, according to the general two-stage ASBM model introduced by Chen and Zhu (2020). Compared with the general two-stage ASBM, there isn't any extra input in the second stage in our new two-stage ASBM network model due to the nature relations among metrics of globalization under consideration. In Chen and Zhu (2020)'s study, they introduce an example of three-stage network structure for electricity industry chain where all the outputs in the first stage have been utilized to the second stage, while we develop our three-stage network structure where a portion of outputs in the first stage are also the final outputs. Those outputs are not used as the inputs for the second stage, but leaving the systems. We have this three-stage structure according to the relationship among indicators of globalization from political, economic, and social dimension.

7.3.2 Conceptual Contribution to the Literature

There are three main conceptual contributions to the literature. First, we apply DEA, in particular, the network DEA in the context of big data. DEA has been regarded as an efficient data-oriented technique for performance evaluation, benchmarking, composite index construction and other uses, since it was first coined by Charles (1978). One of characteristics in DEA is to let the data speak for themselves (Zhu, (2014)), which is also an important aspect in big data. Under the context of big data consideration, except for the general "3Vs", it is necessary to evaluate the "value" dimension which focuses on how to transfer the data into useful information that DEA can be a help alternative big data-related analytics technique. However, in current existing literatures, few publications have been found which apply DEA within a big data modeling. Especially, in terms of network DEA, there are only two publications which utilize network DEA system under the consideration of big data context. This dissertation focuses on applying new DEA network models in the context of big data. In addition, most of publication which utilize DEA in big data analytics, they emphasize evaluate the efficiency or performance for firms or organizations. This study, however, also seek more possibilities to apply network DEA models in other areas, such as composite index under big data environment.

Second, this dissertation evaluates performance for airlines via integrating both operational and stock market metrics. Biased conclusions can be occurred when neglecting to include stock market and financial indicators into any empirical performance evaluation application for airline companies. From both organizational-level and operational-level points of view, stock market measures help firms or organizations to improve themselves continuously via capturing investor attitudes and giving upper management important feedback into the pulse of the market. For industries which are so competitive, such as the airline industry, it is important for managers to be acutely aware of not only metrics from operational aspects, but also metrics from their financial aspect, such as the sentiment, attitudes and expectations of their shareholders and the stock market at large. By integrating financial market indicators into our two-stage DEA framework, it is possible to align this study with financial economics literature about how sentiment and various market indicators have impact on investor trades.

Third, measuring globalization for countries around the world has been a subject of intense scholarly debate. A great portion of researchers who focus on how globalization performs according to metrics from multi-dimensions. For example, the two most frequently utilized globalization indices, the Kearney globalization index and the KOF, measure globalization via indicators from political, economic, and social dimensions. However, most of publications which construct globalization index via indicators from different dimensions utilize the simple weighted average method to combine the sub-index from each dimension. They are contingent on pre-determined weights. The current study, however, shows that by applying ASBM network DEA models, there is no need to pre-determine weights for constructing globalization index from multi dimensions, because the divisional index can be combined without any specify weight when we apply ASBM under the network DEA models. It makes a conceptual contribution to literature that provide an alternative method to construct composite globalization index from multi dimensions while weights are not pre-determined.

7.4 Future Research

First, the study does not include a sensitivity analysis, which can be done via the super-efficiency approach introduced in Chapter 2. In general, DEA determines how DMUs perform. The situation exists often that there is more than one DMU with the value of one (the maximum value). Thus, it is useful to apply the super-efficiency DEA model to rank all the DMUs which are value of one. For example, the overall globalization index for United States and China are on in 2015. By utilizing super-efficiency, we can know which country is more globalization.

Second, we integrate metrics from both operations and stock market aspects to evaluate the performance for airline companies. As we live in an internet world today, for some firms, such as Amazon, metrics in Information Systems aspect should be considered into overall performance evaluation as a great portion of their revenues are from online. The high technologies play a vital roles in performance. The same situation for the globalization index construction that the indicators from high technologies should be involved.

Third, in this dissertation, we only introduced two types of areas that network DEA systems can be applied under consideration of big data. One is to evaluate the performance for firms via integrating operational metrics and stock market metrics, and the other is to obtain a composite index from multi dimensions. As proposed by Zhu (2020), the general characteristics "3Vs" in big data can be found in DEA, and both of them focus on how to obtain useful information from data. It is possible to implement network DEA systems in different areas for different uses under big data analytics.

Bibliography

A. T. Kearney/Foreign Policy Magazine (2002) Globalization Index, http://www. foreignpolicy.com

Addo-Tenkorang, R., and Helo, P. T. (2016). Big data applications in operations/supply-chain management: A literature review. Computers and Industrial Engineering, 101, 528-543.

Adler, N., Liebert, V., and Yazhemsky, E. (2013). Benchmarking airports from a managerial perspective. Omega, 41, 442-458.

Amirteimoori, A. (2006). Data envelopment analysis in dynamic framework. Applied mathematics and computation, 181, 21-28.

An, Q., Wen, Y., Xiong, B., Yang, M., and Chen, X. (2017). Allocation of carbon dioxide emission permits with the minimum cost for Chinese provinces in big data environment. Journal of cleaner production, 142, 886-893.

Andersen, T. M., and Herbertsson, T. T. (2003). Measuring globalization.

Andersen, T. M., and Herbertsson, T. T. (2005). Quantifying globalization. Applied economics, 37, 1089-1098.

Axel, D., Noel, G., and Pim, M. (2010). Measuring globalization opening the black box. A critical analysis of globalization indices. Journal of Globalization Studies, 1.

Bai, X.-J., Yan, W.-K., and Chiu, Y.-H. (2015). Performance evaluation of China's Hi-tech zones in the post financial crisis era—Analysis based on the dynamic network SBM model. China Economic Review, 34, 122-134.

Baltagi, B. H., Griffin, J. M., and Rich, D. P. (1995). Airline deregulation: The cost pieces of the puzzle. International Economic Review, 245-258.

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

Barbot, C., Costa, Á., and Sochirca, E. (2008). Airlines performance in the new market context: A comparative productivity and efficiency analysis. Journal of Air Transport Management, 14, 270-274.

Barros, C. P., and Couto, E. (2013). Productivity analysis of European airlines, 2000–2011. Journal of Air Transport Management, 31, 11-13.

Barros, C. P., and Peypoch, N. (2009). An evaluation of European airlines' operational performance. International Journal of Production Economics, 122, 525-533.

Bauer, P. W. (1990). Recent developments in the econometric estimation of frontiers. Journal of econometrics, 46, 39-56.

Bhadra, D. (2009). Race to the bottom or swimming upstream: performance analysis of US airlines. Journal of Air Transport Management, 15, 227-235.

Boyd, S., and Vandenberghe, L. (2004). Convex optimization: Cambridge university press.

Caselli, M. (2013). Nation states, cities, and people: Alternative ways to measure globalization. SAGE Open, 3, 2158244013508417.

Charnes, A., and Cooper, W. (1962). Chance constraints and normal deviates. Journal of the American statistical association, 57, 134-148.

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

Charnes, A., Cooper, W., Golany, B., Halek, R., Klopp, G., Schmitz, E., and Thomas, D. (1986). Two-phase data envelopment analysis approaches to political evaluation and management of army recruiting activities: tradeoffs between joint services and army advertising. Center for Cybernetic Studies. University of Texas-Austin Austin, Texas, USA.

Charnes, A., Cooper, W. W., Golany, B., Seiford, L., and Stutz, J. (1985). Foundations of Data Envelopment Analysis for Pareto-Koopmans Efficient Empirical Productions Functions. In: TEXAS UNIV AT AUSTIN CENTER FOR CYBERNETIC STUDIES.

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

Charnes, A., Haag, S., Jaska, P., and Semple, J. (1992). Sensitivity of efficiency classifications in the additive model of data envelopment analysis. International Journal of Systems Science, 23, 789-798.

Chau, F., Deesomsak, R., and Koutmos, D. (2016). Does investor sentiment really matter? International Review of Financial Analysis, 48, 221-232.

Chen, C.-M. (2009). A network-DEA model with new efficiency measures to incorporate the dynamic effect in production networks. European Journal of Operational Research, 194, 687-699.

Chen, H., Liu, J., Li, Y., Chiu, Y.-H., and Lin, T.-Y. (2019). A two-stage dynamic undesirable data envelopment analysis model focused on media reports and the impact on energy and health efficiency. International journal of environmental research and public health, 16, 1535.

Chen, K., and Guan, J. (2012). Measuring the efficiency of China's regional innovation systems: application of network data envelopment analysis (DEA). Regional Studies, 46, 355-377.

Chen, K., and Zhu, J. (2017). Second order cone programming approach to two-stage network data envelopment analysis. European Journal of Operational Research, 262, 231-238.

Chen, K., and Zhu, J. (2020). Additive slacks-based measure: Computational strategy and extension to network DEA. Omega, 91, 102022.

Chen, L., and Jia, G. (2017). Environmental efficiency analysis of China's regional industry: a data envelopment analysis (DEA) based approach. Journal of cleaner production, 142, 846-853.

Chen, P.-C., Chang, C.-C., Yu, M.-M., and Hsu, S.-H. (2012). Performance measurement for incineration plants using multi-activity network data envelopment analysis: The case of Taiwan. Journal of environmental management, 93, 95-103.

Chen, Y., Cook, W. D., Li, N., and Zhu, J. (2009). Additive efficiency decomposition in two-stage DEA. European Journal of Operational Research, 196, 1170-1176.

Chen, Y., Liang, L., Yang, F., and Zhu, J. (2006). Evaluation of information technology investment: a data envelopment analysis approach. Computers and Operations Research, 33, 1368-1379.

Chiou, Y.-C., and Chen, Y.-H. (2006). Route-based performance evaluation of Taiwanese domestic airlines using data envelopment analysis. Transportation Research Part E: Logistics and Transportation Review, 42, 116-127.

Chiu, S.-H., Lin, T.-Y., and Yang, H.-L. (2020). Measuring Energy Performance for Regional Sustainable Development in China: A New Framework based on a Dynamic Two-Stage SBM Approach. Sustainability, 12, 2851.

Choi, T. M., Wallace, S. W., and Wang, Y. (2018). Big data analytics in operations management. Production and Operations Management, 27, 1868-1883.

Chou, H. W., Lee, C. Y., Chen, H. K., and Tsai, M. Y. (2016). Evaluating airlines with slack-based measures and meta-frontiers. Journal of Advanced Transportation, 50, 1061-1089.

Chu, J.-F., Wu, J., and Song, M.-L. (2018). An SBM-DEA model with parallel computing design for environmental efficiency evaluation in the big data context: A transportation system application. Annals of Operations Research, 270, 105-124.

Cook, W. D., Chai, D., Doyle, J., and Green, R. (1998). Hierarchies and groups in DEA. Journal of productivity analysis, 10, 177-198.

Cook, W. D., and Zhu, J. (2014). Data envelopment analysis: A handbook of modeling internal structure and network (Vol. 208): Springer.

Cook, W. D., Zhu, J., Bi, G., and Yang, F. (2010). Network DEA: Additive efficiency decomposition. European Journal of Operational Research, 207, 1122-1129.

Cooper, W. W., Seiford, L. M., and Zhu, J. (2004) . Data Envelopment Analysis: Models and Interpretations-Handbook on Data Envelopment Analysis. In: Kluwer, Academic Publisher, Boston.

Cooper, W. W., Seiford, L. M., and Zhu, J. (2011). Handbook on data envelopment analysis (Vol. 164): Springer Science and Business Media.

Davila, A., and Venkatachalam, M. (2004). The relevance of non-financial performance measures for CEO compensation: Evidence from the airline industry. Review of Accounting Studies, 9, 443-464.

De Mateo, F., Coelli, T., and O'Donnell, C. (2006). Optimal paths and costs of adjustment in dynamic DEA models: with application to Chilean department stores. Annals of Operations Research, 145, 211-227.

Despotis, D. K., Koronakos, G., and Sotiros, D. (2016). Composition versus decomposition in two-stage network DEA: a reverse approach. Journal of Productivity Analysis, 45, 71-87.

Doidge, C., Karolyi, G. A., and Stulz, R. M. (2007). Why do countries matter so much for corporate governance? Journal of financial economics, 86, 1-39.

Donaldson, E. M., and Fagerlund, U. H. (1969). Cortisol secretion rate in gonadectomized female sockeye salmon (Oncorhynchus nerka): Effects of estrogen and cortisol treatment. Journal of the Fisheries Board of Canada, 26, 1789-1799.

Dreher, A. (2006). Does globalization affect growth? Evidence from a new index of globalization. Applied economics, 38, 1091-1110.

Eccles, R. G., Ioannou, I., and Serafeim, G. (2014). The impact of corporate sustainability on organizational processes and performance. Management science, 60, 2835-2857.

Färe, R., and Grosskopf, S. (1997). Intertemporal production frontiers: with dynamic DEA. Journal of the Operational Research Society, 48, 656-656.

Färe, R., and Whittaker, G. (1995). An intermediate input model of dairy production using complex survey data. Journal of Agricultural Economics, 46, 201-213.

Feng, C.-M., and Wang, R.-T. (2000). Performance evaluation for airlines including the consideration of financial ratios. Journal of Air Transport Management, 6, 133-142.

Fielding, G. J., and Anderson, S. C. (1983). Public transit performance evaluation: application to Section 15 Data. Transportation Research Record, 947, 1-6.

Fielding, G. J., Glauthier, R. E., and Lave, C. A. (1978). Performance indicators for transit management. Transportation, 7, 365-379.

Fisch, J. H., and Oesterle, M.-J. (2003). Exploring the globalization of German MNCs with the complex spread and diversity measure. Schmalenbach Business Review, 55, 2-21.

Goll, I., Brown Johnson, N., and Rasheed, A. A. (2008). Top management team demographic characteristics, business strategy, and firm performance in the US airline industry: The role of managerial discretion. Management Decision, 46, 201-222.

Good, D. H., Nadiri, M. I., Röller, L.-H., and Sickles, R. C. (1993). Efficiency and productivity growth comparisons of European and US air carriers: a first look at the data. Journal of productivity analysis, 4, 115-125.

Guo, C., and Zhu, J. (2017). Non-cooperative two-stage network DEA model: Linear vs. parametric linear. European Journal of Operational Research, 258, 398-400.

Heshmati, A. (2006). Measurement of a multidimensional index of globalization. Global Economy Journal, 6, 1850087.

Hu, Z., Yan, S., Li, X., Yao, L., and Luo, Z. (2019). Evaluating the oil production and wastewater treatment efficiency by an extended two-stage network structure model with feedback variables. Journal of environmental management, 251, 109578.

Hwang, S.-N., and Kao, T.-L. (2008). Using two-stage DEA to measure managerial efficiency change of non-life insurance companies in Taiwan. International Journal of Management and Decision Making, 9, 377-401.

Ismail, N. A., and Jenatabadi, H. S. (2014). The influence of firm age on the relationships of airline performance, economic situation and internal operation. Transportation Research Part A: Policy and Practice, 67, 212-224.

Jenatabadi, H. S., and Ismail, N. A. (2014). Application of structural equation modelling for estimating airline performance. Journal of Air Transport Management, 40, 25-33.

Kao, C. (2009). Efficiency measurement for parallel production systems. European Journal of Operational Research, 196, 1107-1112.

Kao, C. (2013). Dynamic data envelopment analysis: A relational analysis. European Journal of Operational Research, 227, 325-330.

Kao, C. (2014). Network data envelopment analysis: A review. European Journal of Operational Research, 239, 1-16.

Kao, C., and Hwang, S.-N. (2008). Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. European Journal of Operational Research, 185, 418-429.

Koutmos, D. (2012). An intertemporal capital asset pricing model with heterogeneous expectations. Journal of International Financial Markets, Institutions and Money, 22, 1176-1187.

Koutmos, D. (2015). Is there a positive risk-return tradeoff? A forward-looking approach to measuring the equity premium. European Financial Management, 21, 974-1013.

Lapré, M. A., and Scudder, G. D. (2004). Performance improvement paths in the US airline industry: linking trade‐offs to asset frontiers. Production and Operations Management, 13, 123-134.

Lee, T., Yeo, G.-T., and Thai, V. V. (2014). Environmental efficiency analysis of port cities: Slacks-based measure data envelopment analysis approach. Transport Policy, 33, 82-88.

Li, Y., Chiu, Y.-h., and Lin, T.-Y. (2019). The impact of economic growth and air pollution on public health in 31 Chinese cities. International journal of environmental research and public health, 16, 393.

Li, Y., Chiu, Y.-h., Wang, L., Zhou, Y., and Lin, T.-Y. (2020). Dynamic and network slack-based measure analysis of China's regional energy and air pollution reduction efficiencies. Journal of cleaner production, 251, 119546.

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

Liedtka, S. L. (2002). The information content of nonfinancial performance measures in the airline industry. Journal of Business Finance and Accounting, 29, 1105-1121.

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

Liu, Z., and Lynk, E. L. (1999). Evidence on market structure of the deregulated US airline industry. Applied economics, 31, 1083-1092.

Lockwood, B. (2004). How robust is the Kearney/foreign policy globalisation index? World Economy, 27, 507-523.

Lu, C.-C., Wu, X., Chen, X., and Yang, C.-Y. (2020). The Energy Efficiency and Public Health in the ASEAN Plus Three Cooperation. INQUIRY: The Journal of Health Care Organization, Provision, and Financing, 57, 0046958020935664.

Lu, W.-M., Wang, W.-K., and Kweh, Q. L. (2014). Intellectual capital and performance in the Chinese life insurance industry. Omega, 42, 65-74.

Luo, X. (2003). Evaluating the profitability and marketability efficiency of large banks: An application of data envelopment analysis. Journal of Business research, 56, 627-635.

Mahmoudabadi, M. Z., and Emrouznejad, A. (2019). Comprehensive performance evaluation of banking branches: A three-stage slacks-based measure (SBM) data envelopment analysis. International Review of Economics and Finance, 64, 359-376.

Mallikarjun, S. (2015). Efficiency of US airlines: A strategic operating model. Journal of Air Transport Management, 43, 46-56.

Martens, P., Caselli, M., De Lombaerde, P., Figge, L., and Scholte, J. A. (2015). New directions in globalization indices. Globalizations, 12, 217-228.

Martens, P., and Zywietz, D. (2006). Rethinking globalization: a modified globalization index. Journal of International Development, 18, 331-350.

Mavi, R. K., Saen, R. F., and Goh, M. (2019). Joint analysis of eco-efficiency and eco-innovation with common weights in two-stage network DEA: A big data approach. Technological Forecasting and Social Change, 144, 553-562.

Mellat-Parast, M., Golmohammadi, D., McFadden, K. L., and Miller, J. W. (2015). Linking business strategy to service failures and financial performance: Empirical evidence from the US domestic airline industry. Journal of Operations Management, 38, 14-24.

Momeni, E., Tavana, M., Mirzagoltabar, H., and Mirhedayatian, S. M. (2014). A new fuzzy network slacks-based DEA model for evaluating performance of supply chains with reverse logistics. Journal of intelligent and fuzzy systems, 27, 793-804.

Moreno, P., Lozano, S., and Gutiérrez, E. (2013). Dynamic performance analysis of US wireline telecommunication companies. Telecommunications Political, 37, 469-482.

Olfat, L., Amiri, M., Soufi, J. B., and Pishdar, M. (2016). A dynamic network efficiency measurement of airports performance considering sustainable development concept: A fuzzy dynamic network-DEA approach. Journal of Air Transport Management, 57, 272-290.

Olfat, L., Pishdar, M., and Ghasemzadeh, F. (2019). A TYPE-2 FUZZY NETWORK DATA ENVELOPMENT ANALYSIS FOR FMCG DISTRIBUTORS'PERFORMANCE EVALUATION WITH SUSTAINABILITY APPROACH. International Journal of Industrial Engineering, 26.

Oum, T. H., and Yu, C. (1995). A productivity comparison of the world's major airlines. Journal of Air Transport Management, 2, 181-195.

Oum, T. H., and Yu, C. (1998). An analysis of profitability of the world’s major airlines. Journal of Air Transport Management, 4, 229-237.

Raab, M., Ruland, M., Schönberger, B., Blossfeld, H.-P., Hofäcker, D., Buchholz, S., and Schmelzer, P. (2008). GlobalIndex: A sociological approach to globalization measurement. International Sociology, 23, 596-631.

Riley, R. A., Pearson, T. A., and Trompeter, G. (2003). The value relevance of non-financial performance variables and accounting information: the case of the airline industry. Journal of accounting and public policy, 22, 231-254.

Rose, N. L. (1990). Profitability and product quality: Economic determinants of airline safety performance. Journal of Political Economy, 944-964.

Schefczyk, M. (1993). Operational performance of airlines: an extension of traditional measurement paradigms. Strategic Management Journal, 14, 301-317.

Scheraga, C. A. (2004). Operational efficiency versus financial mobility in the global airline industry: a data envelopment and Tobit analysis. Transportation Research Part A: Policy and Practice, 38, 383-404.

Seiford, L. M., and Zhu, J. (1998). Stability regions for maintaining efficiency in data envelopment analysis. European Journal of Operational Research, 108, 127-139.

Seiford, L. M., and Zhu, J. (1999). Profitability and marketability of the top 55 US commercial banks. Management science, 45, 1270-1288.

Shao, Y., and Han, S. (2019). The synergy in the economic production system: an empirical study with Chinese Industry. Sustainability, 11, 980.

Soejachmoen, M. P. (2016). Globalization of the Automotive Industry: Is Indonesia Missing Out? Asian Economic Papers, 15, 1-19.

Song, M.-L., Fisher, R., Wang, J.-L., and Cui, L.-B. (2018). Environmental performance evaluation with big data: Theories and methods. Annals of Operations Research, 270, 459-472.

Song, W., Bi, G.-b., Wu, J., and Yang, F. (2017). What are the effects of different tax policies on China's coal-fired power generation industry? An empirical research from a network slacks-based measure perspective. Journal of cleaner production, 142, 2816-2827.

Sueyoshi, T., and Sekitani, K. (2005). Returns to scale in dynamic DEA. European Journal of Operational Research, 161, 536-544.

Tajbakhsh, A., and Hassini, E. (2018). Evaluating sustainability performance in fossil-fuel power plants using a two-stage data envelopment analysis. Energy Economics, 74, 154-178.

Tavassoli, M., Faramarzi, G. R., and Saen, R. F. (2014). Efficiency and effectiveness in airline performance using a SBM-NDEA model in the presence of shared input. Journal of Air Transport Management, 34, 146-153.

Toloo, M., Emrouznejad, A., and Moreno, P. (2017). A linear relational DEA model to evaluate two-stage processes with shared inputs. Computational and Applied Mathematics, 36, 45-61.

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

Tone, K. (2002). A strange case of the cost and allocative efficiencies in DEA. Journal of the Operational Research Society, 53, 1225-1231.

Tone, K., and Tsutsui, M. (2009). Network DEA: A slacks-based measure approach. European Journal of Operational Research, 197, 243-252.

Tone, K., and Tsutsui, M. (2014). Dynamic DEA with network structure: A slacks-based measure approach. Omega, 42, 124-131.

Tsai, H.-Y., and Wang, A. S. (2010). The efficiency analysis of life insurance company in Taiwan: Two-stage data envelopment analysis. Journal of Testing and Evaluation, 38, 283-290.

Tsikriktsis, N. (2007). The effect of operational performance and focus on profitability: A longitudinal study of the US airline industry. Manufacturing and Service Operations Management, 9, 506-517.

Wang, C. H., Gopal, R. D., and Zionts, S. (1997). Use of data envelopment analysis in assessing information technology impact on firm performance. Annals of Operations Research, 73, 191-213.

Wang, W.-K., Lu, W.-M., and Tsai, C.-J. (2011). The relationship between airline performance and corporate governance amongst US Listed companies. Journal of Air Transport Management, 17, 148-152.

Windle, R. J. (1991). The world's airlines: a cost and productivity comparison. Journal of Transport Economics and Policy, 31-49.

Xia, P., Wu, J., Ji, X., and Xi, P. (2020). A DEA-based empirical analysis for dynamic performance of China's regional coke production chain. Science of The Total Environment, 717, 136890.

Xia, Q., Li, M., Wu, H., and Lu, Z. (2016). Does the Central Government's Environmental Political Work? Evidence from the Provincial-Level Environment Efficiency in China. Sustainability, 8, 1241.

Yu, M.-M. (2010). Assessment of airport performance using the SBM-NDEA model. Omega, 38, 440-452.

Zhang, Q., Koutmos, D., Chen, K., and Zhu, J. (2019). Using Operational and Stock Analytics to Measure Airline Performance: A Network DEA Approach. Decision Sciences.

Zhong, Z., Meng, F., Zhu, Y., and Wang, G. (2020). Research on the Technological Innovation Efficiency of China's Strategic Emerging Industries Based on SBM: NDEA Model and Big Data. Mathematical Problems in Engineering, 2020.

Zhou, L., Biswas, B., Bowles, T., and Saunders, P. J. (2011). Impact of globalization on income distribution inequality in 60 countries. Global Economy Journal, 11, 1850216.

Zhou, X., Luo, R., Yao, L., Cao, S., Wang, S., and Lev, B. (2018). Assessing integrated water use and wastewater treatment systems in China: A mixed network structure two-stage SBM DEA model. Journal of cleaner production, 185, 533-546.

Zhou, Z., Sun, L., Yang, W., Liu, W., and Ma, C. (2013). A bargaining game model for efficiency decomposition in the centralized model of two-stage systems. Computers and Industrial Engineering, 64, 103-108.

Zhu, J. (1996). Robustness of the efficient DMUs in data envelopment analysis. European Journal of Operational Research, 90, 451-460.

Zhu, J. (2000). Multi-factor performance measure model with an application to Fortune 500 companies. European Journal of Operational Research, 123, 105-124.

Zhu, J. (2011). Airlines performance via two-stage network DEA approach. Journal of CENTRUM Cathedra: The Business and Economics Research Journal, 4, 260-269.

Zhu, J. (2020). DEA under big data: data enabled analytics and network data envelopment analysis. Annals of Operations Research, 1-23.

Zhu, Q., Wu, J., Li, X., and Xiong, B. (2017). China's regional natural resource allocation and utilization: a DEA-based approach in a big data environment. Journal of cleaner production, 142, 809-818.

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