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Impact of International Trade on Central Bank Efficiency: An Application of DEA and Tobit Regression Analysis

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Abstract The purpose of this study is to introduces a novel methodology to measure the central bank efficiency. The data envelopment analysis (DEA) applies in the combination of three input and two output variables characterizing the economic balance in international trade. Super-efficiency DEA model is applied for ranking & comparing the efficiency of different central banks. In contrast, the Malmquist productivity index (MPI) is used to measure the productivity change over the period of time. Further, the study is extended to quantify the impact of international trade dimension on the efficiency of the central bank by using Tobit regression analysis. Finally, based on our data analysis, we reported that the efficiency changes over the period of time and the total productivity changes significantly due to the technology shift as compared to efficiency change. Additionally, it is also observed that the central bank efficiency is impacted dramatically by the export level of the country as compared to import level, average exchange rate and GDP. It implies that the export level of the country significantly influences the performances of the central bank.

Keywords Data Envelopments Analysis, Super-Efficiency, Malmquist Productivity Index, Central Bank Efficiency, International Trade, Tobit Analysis

AMS 2010 subject classifications 90C15, 68C05

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1. Introduction

International trade is the exchange of good, service and capital across the international territories (borders). The sound international trade indicates a healthy economy and development of the country. The central bank or central financial institution of a country can be considered as the engine of the economy, like an engine it has the power to control and regulate the economic and development functions, any malfunction in the engine creates a risk for the financial system of the country. The central bank plays a vital role in the economic system of the country by doing different functions, like currency regulation, securing the stability of exchange rate, supervisor of commercial and other financial institutions, controller of credit/money supply and balance on international trade. It is an only legal and autonomous financial institution that is allowed to print money as a legal tender [1], by printing money the central bank has opportunities to control the money supply, the total amount of funds available in the economy. The central bank of the country functions is dynamic because these are profoundly

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impacted by export and import level of the country. The intervention of foreign exchange and currencies affects the international trade of the nation [2]. Central bank intervention and trading rule profits in the foreign exchange market are also crucial for a healthy economic environment of the nation [3]. The cross-national dynamic diffusion of central bank independence by examining the impact of cohesive and role-equivalent trade relation between countries given by [4]. It was also observed that central bank efficiency is effecting by economic variables [5]. The job of central bankers is to conduct monetary policy to promote price stability, sustainable growth, and a stable financial system of the country [6].

There has not been extensive work and research done, especially on the evaluation of central bank efficiency and impact of international trade on central bank efficiency. The evaluation of central bank productivity and efficiency is not only complicated but also challenging aspect of research in the field of management, economics, statistics and applied operation research. It is because the policy of every central bank is not unique. In this study, we have selected the identical type input and output variables for the efficiency evaluation of each central bank. Central bank efficiency is a reasonably abstract concept that encapsulates several areas ranging from the roles that are appropriate for central banks to perform and to cost-effectiveness in a narrower sense proposed by [7]. Although research on the impact of international trade on the central bank has not reported in the literature, the central bank efficiency is already published in [8, 6, 9]. The econometric analysis was conducted on the market efficiency and transparency of the central bank in the case of the United States given by [10]. The technical efficiency analysis and effectiveness of the central bank intervention given in [11]. DEA and stochastic frontier regression (SFR) applied for the measurement of operational efficiency in a sample of 32 central banks [12] for the year 2001. Effect of non-bank financial intermediation on bank efficiency in the eight EU jurisdictions individually monitored under the Financial Stability Board (FSB) Global Shadow Banking Monitoring Report in the period 2014-2016.The efficiency analysis is conducted by applying a profit-based input-oriented DEA variable returns-to-scale model in a two-stage procedure given in [13] and analysis provides unique initial evidence in favour of the hypothesis that increased non-bank financial intermediation might result into a reduction of bank profitability.

It is essential to present the main approaches of efficiency evaluation as they reveal the foundation for the methodological framework. The term efficiency as a definition and measurement was first introduced by [14]. There are broadly three approaches to efficiency measurement: ratio analysis approach, which is considered to be easiest among all three methods. However, it provides a partial measure of efficiency and sometimes it gives misleading results given by [15]. It is also challenging to rank Decision-Making Units (DMUs) based on these partial ratios in multi-input multi-output case, as one ratio will better for one DMU and other for another DMU. However, the overall measure of efficiency can be measured by calculating several ratios simultaneously. Another one is regression analysis approaches, exploration of the association between independent variables (inputs) and at most two dependent variables (outputs). The relationships between these two variables are usually represented by fixed structural forms such as multiple linear regression forms [16], whose estimation in our context aims to identify the efficiency. This method examines the average expected quantity of output for each amount of inputs used, and the main advantage of regression analysis over the ratio analysis is that it can accommodate multiple inputs data responsible for the production of particular output, which is not possible in case of ratio analysis.

Frontier Analysis is another approach of efficiency evaluation given by [17]. The frontier analysis is a robust analysis which can adapt several inputs and several outputs in a single measurement. Furthermore, the frontier analysis evaluates the maximum efficiency rather than average efficiency. The frontier analysis approach is further divided into two classes parametric and non-parametric. DEA is a non-parametric optimization and analytical methodology used for efficiency evaluation. The advantage of DEA is to evaluate efficiency without knowing the shape of the production of DMUs and to provide enough knowledge about the benchmark information [18]. The main objective of this study is to evaluate the efficiency of central's banks of the 17 Asian countries and explore the impact and connection of central bank efficiency with international trade.

2. Literature review

The concept of efficiency evaluation was first proposed by [17]. He considered ratio in the form of input and outputs to measure the efficiency, which in turn have mathematical limitations for handling in the context of multiple inputs and multiple outputs. Almost after twenty years, [18] propose a CCR model based on Farrell's idea to assess the relative efficiency of DMU in case of multi-input and multi-output, titled it as DEA. The basic idea behind the DEA model is to formulate the optimization problem to identify the best-practised DMU, which makes an efficient frontier. Furthermore, it finds the efficiency of non-frontier DMUs and identifies benchmarks against which such inefficient DMUs can be compared. As this model was based on constant returns to scale (CRS) assumption, it was further extended by [19] in case of variable returns to scale (VRS) assumption by introducing convexity constraint in CCR-DEA model. Since the advent of DEA in 1978, there is an impressive growth in both theoretical and applied aspects. In theoretical aspects, various models were proposed to estimate different efficiency measures wherein the latter case. The proposed models were used as a performance assessment tools in a variety of organizations like banking, education, health-care, agriculture, production companies, airports and many more profit as well as non-profit organizations as reported in a survey and analysis of the first 40 years of scholarly literature in DEA [20].

DEA is a linear programming based technique for measuring the relative efficiency of DMUs, and therefore hypothesis testing is considered to be a difficult task. Sensitivity analysis will be used to verify and to estimate the robustness of efficiency scores obtained by DEA [21]. The CCR and BBC model of DEA are categorized as radial measure efficiency because both are dealing directly with the inputs and outputs of a DUM [22]. These models can solve by using either input orientation at a fixed level of output or output orientation at a fixed level of input or mixed-orientation varying both input and outputs at an optimal level [23]. A non-oriented and non-radial measure of efficiency was proposed by [24], which is not dealing with the inputs and outputs of DMU directly but dealing with input excesses and output shortfall called slack based measure (SBM) of efficiency. SBM also introduces the concept of weak and strong theory of efficiency.

DEA classifies the DMUs into two diverse, efficient and inefficient groups. Unlike the inefficient DMUs, the efficient ones cannot be ranked based on their efficiencies score because of having the same efficiency score of unity. It is not, however, reasonable to claim that efficient DMUs have the same performance in actual practice [25]. To overcome this drawback from the DEA methodology concept super-efficiency was introduced by [25, 26, 27], which is the most powerful approach for rank the DMUs. The same methodology was applied in case of the SBM approach given by [28].

Productivity and efficiency of an organization are interconnected. However, the effectiveness of DMU is static as it does not consider the time for production, whereas productivity is based on time. DEA window analysis is a suitable approach to estimate the efficiency change over time given by [29, 30]. However, it neglects the effect of technological change over time and assigns any technological change as of technical efficiency change. Several methods could be used to evaluate productivity change, which includes Fisher index, Tornqvist index and the Malmquist Index. Among the three, Malmquist Total Factor Productivity (TFP) index is used most often to evaluate productive change given by [31] and use of MPI is based on distance function in DEA proposed by [32]. Evaluation and analyse of the efficiency and productivity of 3 public, 6 private and 6 foreign deposit banks operating in the Turkish banking sector given in [33], with the help of DEA and MPI. Performance of non-banking finance companies (NBFC) in the Indian context using two stage DEA was given by [34], and Multi-period performance evaluation of Indian commercial banks by using DEA and MPI given by [35]. Bias-corrected network DEA is used to measure the efficiency of total National Innovation Systems (NIS) and the efficiency of the other sub-processes within the system given by [36]. Whereas, in case of input and output variables are not known with absolute precision in DEA we can use Fuzzy DEA as shown in [37] with different approaches.

Tobit model also called a censored regression model to estimate linear relationships between variables and first time introduced in DEA by [38]. The Tobit regression analysis was also used to identify the main influencing factors in banking efficiency [39]. It was shown that the capital adequacy ratio has a statistically significant adverse impact on the performance of banks [40] and which may reflect a risk-return trade-off in the banking sector. The DEA can be used in every aspect of research where the input and outputs are to be considered for the productivity and efficiency of DMU. There is a continuous and exponential growth of publication related to the application of DEA [20] from the last four decades (1978-2016).

In this study, we are using a non-parametric deterministic frontier DEA approach for estimating the efficiency of different central banks in case of 17 Asian countries. The study is further extended to quantify the cause and impact on the relationship between the efficiency of the central bank and international trade dimension by using the Tobit regression model.The existing literature of efficiency technique DEA are used with different application. The impact of international trade on central bank efficiency was derive from existing literature of DEA and Tobit regression. The paper structure includes, section first is on the overview of international trade, central bank and approaches of efficiency evaluation techniques. The second section is based on the brief literature review about DEA, MPI, Tobit regression analysis and its application in banking. DEA, MPI and Tobit regression analysis methodology are discussed in the third section. The fourth section is based on empirical analysis, including data description and selection of input & output variables. Significant development of studies where discussed with empirical data, results, and conclusion is in the final section.

3. Material and methods

This study based on the evaluation and estimation of central bank efficiency by using a non-parametric approach called DEA. It is a linear programming based technique for estimating the relative efficiency of organizational units together with multiple inputs and outputs. The mathematical formulations of DEA are based on two orientations (input and output). In this study, we are using input orientation in case of both constant and variable returns to scale. The non-oriented and non-radial measure of efficiency called SBM approach and super efficiency SBM approach is used for the ranking of DMUs. Apart from this, Tobit analysis is used to identify the main influencing factors of international trade on central bank efficiency.

3.1. Radial measures of DEA in case of CRS and VRS

The mathematical formulation of DEA with the assumption of CRS was given by [18]. Let x_{ij} and y_{rj} denote the $i^{th}; (i = 1, 2, 3, ..., m)$ input and $r^{th}; (r = 1, 2, 3, ..., s)$ output of j^{th} DMU $(j = 1, 2, 3, ..., n)$ respectively. The efficiency of k^{th} DMU is denoted by and standard envelopment form of input-orientation CCR-DEA model as;

$$
\begin{aligned}
&\theta_k^* = Minimise\ \theta_k \\
&Subject\ to \\
&\sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{rk}\ ;\ \forall r = 1, 2, 3, ...s \qquad (3.1.1)\\
&\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = \theta_k x_{ik}\ ;\ \forall i = 1, 2, 3...m \\
&s_r^+ \geq 0\ , s_i^- \geq 0\ and\ \lambda_j \geq 0\ ; \forall j = 1, ...n.
\end{aligned}
$$

To get valid returns on the scale, Banker, Charnes and Cooper in 1984 have extended DEA to the case of VRS by adding one more constraint known as convexity constraint in CRR envelopment model given by [19]. The purpose of this envelopment form is to point out the most efficient scale size for each DMU and at the same time to identify its technical efficiency. Following is the envelopment form of BCC-DEA model with input-orientation.

$$
\begin{aligned}
&\theta_k^* = Minimise\ \theta_k \\
&Subject\ to \\
&\quad \sum_{j=1}^{n} y_{rj}\lambda_j \ - \ s_r^+ \ = \ y_{rk}\ ; \forall\ r = 1,2,3...s \qquad (3.1.2)\\
&\quad \sum_{j=1}^{n} x_{ij}\lambda_j \ + \ s_i^- \ = \ \theta_k x_{ik}\ ;\ \forall i = 1,2,3...m \\
&\quad \sum_{j=1}^{n} \lambda_j \ = \ 1\ ;\ \forall j = 1,2,3...n \\
&\quad s_r^+ \ \geq \ 0\ , s_i^- \ \geq \ 0\ and\ \lambda_j \ \geq \ 0
\end{aligned}
$$

Where x_{ik} and y_{rk} are the inputs and outputs of k^{th} DMU (which is under evaluation).

The input excesses and output shortfalls are denoted by $s_i^-; (i = 1,2,3,...,m)$ and $s_r^+; (r = 1,2,3,...,s)$ are also known as input and output slacks. The DMU which is under evaluation is said to be efficient if and only if $\theta_k^* = 1$ and all the slacks must be zero i.e., $s_r^+ = 0$ and $s_i^- = 0$. If $\theta_k^* = 1$, but one the slack is non zero. Then DMU under evaluation is said to be week efficient otherwise if $\theta_k^* < 1$, then the DMU which is under evaluation is said to be inefficient.

CCR efficiency is the combination of purely technical and scale efficiencies and whereas BCC efficiency is only pure technical efficiency excluding scale efficiency. Thus, the radial difference between the CCR frontier and BCC frontier is called as scale inefficiency. Thus, we have an equation for scale efficiency of k^{th} DMU as;

$$
Slale\ Efficienc(SE) = \frac{CCR\ Efficiecy(\theta_{k-CCR}^*)}{BCC\ Efficiency(\theta_{k-BCC}^*)} \qquad (I)
$$

Thus any DMU with both CCR and BCC efficiency can be scale efficient and are called as most productive scale size (MPSS).

3.2. *SBM Efficiency Model in DEA*

A non-oriented and non-radial measure of efficiency, which deals with input excesses and output shortfall of DMU is called the slack-based measure of efficiency was given by [24]. The mathematical formulation is defined as: Let x_{ij} and y_{rj} denote the $i^{th}; (i = 1,2,3,...,m)$ input and $r^{th}; (r = 1,2,3,...,s)$ output of j^{th} DMU $(j = 1,2,3,...,n)$ respectively. It is assumed that the data set is known and strictly positive. The production possibility set P of DMU_k is defined as:

$$
P = \{(x_{ik}\ ,\ y_{rk})/\ x_{ik} \geq \lambda_j x_{ij}\ ;\ y_{rk} \leq \lambda_j y_{rj}\ \forall \lambda_j \geq 0\ ; j = 1,2,3,...n\} \forall i, r \qquad (II)
$$

P is closed and convex set with boundary points as the efficient production frontier. The relative reduction rate of i^{th} input and j^{th} output for the k^{th} DMU is defined as:

$$(x_{ik} - s_i^-)/x_{ik} \Rightarrow\ Relative\ Reduction\ Rate\ of\ i^{th}\ input\ in\ k^{th} DMU.$$

$$(y_{rk} + s_i^+)/y_{rk} \Rightarrow\ Relative\ Reduction\ Rate\ of\ r^{th}\ output\ in\ k^{th} DMU.$$

Where s_i^- and s_r^+ is the input and output slacks of DMU_k respectively.

Let ρ_k be the inefficiency rate of DMU_k assessing the m-inputs and s-outputs is defined as:

$$\rho_k = \left[\frac{1}{m}\sum_{i=1}^{m}(\frac{x_{ik}-s_i^-}{x_{ik}})\right] * \left[\frac{1}{s}\sum_{r=1}^{s}(\frac{y_{rk}+s_r^+}{y_{rk}})\right]^{-1}$$

The interpretation of non-oriented and non-radial DEA technique SBM is minimizing the above inefficiency rate directly on the base of slacks, subject to production possibility set P and standard mathematical form is given below:

$$Min\rho_k^* = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_i^-}{x_{ik}}}{1+\frac{1}{s}\sum_{r=1}^{s}\frac{s_r^+}{y_{rk}}}$$

Subject to

$$\sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{ik}; \forall i = 1,2,3,...,m. \qquad (3.2.2)$$
$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = y_{rk}; \forall r = 1,2,3,...,s$$
$$\lambda_j \geq 0\,; s_i^- \geq 0\,;\; s_r^+ \geq 0; \forall j = 1,2,3,...,n.$$

Where x_{ik} and y_{rk} are the inputs and outputs of the DMU_k under evaluation. $s_i^- \geq 0; (i = 1\,,2\,,3\,,\ldots m)$ and $s_r^+ \geq 0; (r = 1\,,2\,,3\,,\ldots s)$ are the input excess and output shortfalls, also referred to as slacks. The converted linear form of SMB-model by Charnes-Cooper transformation is as given below;

$$Min\ \tau_k^* = t - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{ik}}$$

Subject to

$$t + \frac{1}{s}\sum_{r=1}^{s}\frac{S_r^+}{y_{rk}} = 1$$
$$\sum_{j=1}^{n}\Lambda_j x_{ij} + S_i^- = tx_{ik}; \forall i = 1,,3,...,m. \qquad (3.2.2)$$
$$\sum_{j=1}^{n}\Lambda_j y_{rj} - s_r^+ = ty_{rk}; \forall r = 1,2,3,...,s.$$
$$S_i^- \geq 0\,;\; S_r^+ \geq 0\,; t \geq 0\ and\ \Lambda_j \geq 0; \forall j = 1,2,3,...,n.$$

Let an optimal solution of the mathematical model (3.2.2) be $(\tau_k^*, t^*, \Lambda^*, S^{-*}, S^{+*})$. Then we have an optimal solution of SBM- model is defined as:

$$\rho^* = \tau^*,\ \lambda^* = \frac{\Lambda^*}{t^*},\ s^{-*} = \frac{S^{-*}}{t^*}\ \ and\ \ s^{+*} = \frac{S^{+*}}{t^*} \qquad (III)$$

On the base of an optimal solution given in equation (III), we decide whether DMU_k which is under evaluation is efficient or inefficient. Where,in the case of SBM modal of VRS, can be expressed by adding the convexity constraint into the linear programming problem (3.2.2).

3.3. *SBM Super-Efficiency DEA Model*

Generally speaking, multiple DMUs can have the "full efficient status" with a DEA score of one in conventional DEA models. Thus, it is difficult to rank the DMUs as many of them are of having the same efficiency of value one. In order to discriminate these DMUs, another model will be used through the super efficiency of a specific DMU [24, 27, 41] which discriminates between these efficient DMUs and ranks them by assigning the efficiency score greater than1. Super efficiency refers to an amended DEA score in which the DMU can obtain a score of technical efficiency more excellent than one because each DMU is not permitted to use itself as a peer. In this section, we are discussing the super efficiency which is an extension of DEA efficiency in which efficient DMUs can obtain the efficiency scores greater than unity and each DMU is not allowed to use itself as a peer. Let us assume k^{th} DMU is SBM-efficient, i.e. $\rho_k^* = 1$ are using $x_i; (i = 1, 2, 3, ..., m)$ and $y_r; (r = 1, 2, 3, ..., s)$ respectively. Then the mathematical formulation of slack-based super-efficiency of (x_k, y_k) as the optimal objective function value ρ_k^* of the following model:

$$
\begin{aligned}
& Min\ \tau_k^* = t - \frac{1}{m}\sum_{i=1}^{m}\frac{S_i^-}{x_{ik}} \\
& Subject\ to \\
& \qquad t + \frac{1}{s}\sum_{r=1}^{s}\frac{S_r^+}{y_{rk}} = 1 \\
& \qquad \sum_{j=1, j\neq 1}^{n} \Lambda_j x_{ij} + S_i^- = t x_{ik}; \forall i = 1, 2, 3, ..., m. \qquad (3.3.1) \\
& \qquad \sum_{j=1, j\neq 1}^{n} \Lambda_j y_{rj} - s_r^+ = t y_{rk}; \forall = 1, 2, 3, ..., s. \\
& \qquad \sum_{j=1, j\neq 1}^{n} \Lambda_j = t; \forall\ t \geq 0; \forall j = 1, 2, 3, ..., n. \\
& \qquad S_i^- \geq 0\ ;\ S_r^+ \geq 0\ ; t \geq 0\ and\ \Lambda_j \geq 0
\end{aligned}
$$

The super-efficiency in powerful approach for rank DMUs efficiency obtained SMB DEA model. We can rank efficient DMUs by solving the model (3.3.1) for each efficient DMU. For efficient DMUs have super-efficiency score greater than or equal to unity, while inefficient DMUs have super-efficiency score less than unity.

3.4. *Malmquist Productivity Index (MPI) in DEA*

In this section, we are discussing the MPI to measure the productivity change over the period of time. MPI is based on the two distance function with respect time periods, and the main advantage is to decompose the total productivity change into two mutually exclusive and exhaustive components by [32]. These two components can be identified as catching up and innovation, respectively. MPI is defined as the ratio of two distance function of k^{th} DMU $(k = 1, 2, 3, ..., n)$ with reference to the period t and (t+1) is as follows:

$$
M_k(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\left(\frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)} \right) \times \left(\frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_t, y_t)} \right) \right]^{\frac{1}{2}} \qquad (3.4.1)
$$

Where x_t, x_{t+1}, y_t and y_{t+1} denotes input and output levels at the time period t and $(t+1)$. The equation (3.4.1) can be decomposing into two components, as follows:

$$M_k(x_t, y_t, x_{t+1}, y_{t+1}) = \underbrace{\frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)}}\times\underbrace{\left[\left(\frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_{t+1}, y_{t+1})}\right)\times\left(\frac{D_0^t(x_t, y_t)}{D_0^{t+1}(x_t, y_t)}\right)\right]^{\frac{1}{2}}} \quad (3.4.2)$$

This index represents two types of efficiencies. One which is outside the brackets measures the change in relative efficiency (i.e., the radial difference between the observed production and expected production) between years' t and $(t+1)$, while the other within the brackets represents a shift in technology between the years' t and $(t+1)$. That is;

$$\textit{Efficiency change} = \frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)} \quad (a)$$

$$\textit{Technical change} = \left[\left(\frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_{t+1}, y_{t+1})}\right)\times\left(\frac{D_0^t(x_t, y_t)}{D_0^{t+1}(x_t, y_t)}\right)\right]^{\frac{1}{2}} \quad (b)$$

The value of M_k lies greater than unity, i.e. $M_k \geq 1$ implies that the total factor productivity has increased or decreased over the time period t and $(t+1)$. $M_k = 1$ main that there is no change in productivity where $M_k \geq 1$ implies the percentage change of productivity over the time period t and $t+1$. Improvement in productivity yield MI greater than unity, and any impairment in performance yields MI less than unity. At times it may happen that efficiency change and technical change are moving in opposite directions.

To sum up, this [32] define productivity growth as a product of efficiency change and technical change. They interpreted the components of productivity growth as improvements in efficiency change are considered to be catching up, while improvements in technical change are considered to be evidence of innovation. This decomposition thus provides a way for testing the source of change in productivity. To know the source, it is necessary to measure the MPI, and various approaches are known to calculate this index. Herein we apply linear programming approach as given by [22]. Suppose we have x_{ij}^t and y_{rj}^t that are inputs and outputs of j^{th} DMU $(j = 1, 2, 3, ..., n)$ at point time t. The reference technology for the time period t can be obtained from the data set as follows:

$$\begin{aligned} s^t &= \{(x^t, y^t) \\ x_i^t &\geq \sum_{j=1}^n \lambda_j^t x_{ij}^t \forall i = 1, 2, 3...m \\ y_r^t &\leq \sum_{j=1}^n \lambda_j^t y_{rj}^t \forall r = 1, 2, 3...s \\ \sum_{j=1}^n \lambda_j^t &= 1 \forall \lambda_j^t \geq 0; \forall j = 1, 2, 3...n\} \end{aligned} \quad (3.4.3)$$

Thus to calculate Malmquist productivity of a DMU between time period t and $t+1$, we need to solve four linear programming problems with four different maximize objective functions $D_0^t(x_t, y_t), D_0^{t+1}(x_t, y_t), D_0^t(x_{t+1}, y_{t+})$ and $D_0^{t+1}(x_{t+1}, y_{t+})$ under the same set of constraints as shown in the model (3.4.3) on same time period t and $(t+1)$.

3.5. *Tobit Regression Analysis in DEA*

In this section, we are discussing Tobit regression analysis, to estimate the linear relationship between efficiency (dependent variable) and set of independent variables. Tobit analysis is also called a censored regression and the efficiency score estimated by (0 and 1). The standard form of the Tobit model for i^{th} DMU is given as follows:

$$\left.\begin{array}{c} y_j^* = \beta' x_j + \varepsilon_j \\ y_j = y_j^*; if y_j^* \geq 0 \\ y_j = 0; if y_j^* < 0 \end{array}\right\} \forall j = 1, 2, 3, ..., n \tag{3.5.1}$$

Where x_i and β are the vectors of explanatory variables and unknown parameters and y_i^* is an efficiency score of the DEA model treated as the latent independent variable. The error term ε_j fellows' normal distribution with mean 0 and variance σ^2 i.e. $\varepsilon_j \sim N(0, \sigma^2) \forall j = 1, 2, 3, ..., n$.

4. Data Collection and Statistical Analysis

In this section, DEA methodology is applied to the 17 central banks of top Asian exporter countries for the three financial years 2016-18. The data structure has been collected from Bloomberg, central banks annual reports and other national and international economic magazines where data was compiled in Excel, DEA Frontier, PIM-DEA and Stata software.

In this study, we have used three inputs operating expenses (million \$), total investment (million \$), and total deposits (million \$) where total assets (million \$) and net income (million \$) are considered as two outputs for the efficiency evaluation by using DEA methodology. Where for the Tobit analysis super-efficiency score is used as dependent variable (which is censored) and total exports (million \$), total imports (million \$), GDP and exchange rate (AER) are used as independent variables. Summary statistics of all inputs and output variables are given in table 1.

Table 1. Summary Statistics of all Inputs and outputs (in Million U.S. \$).

Variables	Year 2016 Mean ± S.D	Year 2017 Mean ± S.D	Year 2018 Mean ± S.D
Operating Expenses	212014±630554	1235198±4617164	15989±23617
Total Investment	440036±1229393	477378±1151894	289903±989764
Total Deposits	767908±1341411	2897261±9270686	466346±1020088
Total Assets	67398943±164099793	70552843±171047884	1365420±2780353
Net Income	904871±2539354	2341541±7643911	12355±22946
Exports	272763041±315114113	275511338±316082408	400386006±580387767
Import	317253092±527502246	363979486±554889152	326320588±406611282
GDP	1435771±2786927	1525107±2963841	1657784±3287730

The Central Intelligence Agency, Population Statistics by Country and International Trade Centre, Trade Map Accessed on August 16, 2019, has reported the top Asian exporter countries, as shown in table 2. China is the largest exporter, not only in the Asian economy but also in the world economy too. China exported \$2.41T and imported \$1.54T, resulting in a positive trade balance of \$873B, which is about 36% of total Asian export. The export of Japan is about \$738.18B, and South Korea is about \$605.17B pursue on 2nd and 3rd place in the ranking, which is about 10.7% and 8.7% of total Asia export. The total export of Kazakhstan (\$ 60.95B), Bangladesh (\$43.53B), Pakistan (\$23.63B), and Sri Lanka (\$11.97B) pursue 14th, 15th, 16th and 17th position in the Asian export economy see [42]. In this study, we have taken the central bank (as DMUs) data of the top 17 Asian exporter countries, as listed in the below table 2.

Table 2. List of top 17 Asian exporter countries.

Rank	Name Country	Name of Central Bank	DMUs
1	China	People's Bank of China	DMU1
2	Japan	Bank of Japan	DMU2
3	South Korea	Bank of Korea	DMU3
4	Hong Kong	Hong Kong Monetary Authority	DMU4
5	Singapore	Monetary Authority of Singapore	DMU5
6	Taiwan	Central Bank of the Republic of China (Taiwan)	DMU6
7	India	Reserve Bank of India	DMU7
8	Vietnam	State Bank of Vietnam	DMU8
9	Thailand	Bank of Thailand	DMU9
10	Malaysia	Central Bank of Malaysia	DMU10
11	Indonesia	Bank of Indonesia	DMU11
12	Turkey	Central Bank of the Republic of Turkey	DMU12
13	Philippines	Central Bank of the Philippines	DMU13
14	Kazakhstan	National Bank of Kazakhstan	DMU14
15	Bangladesh	Bangladesh Bank	DMU15
16	Pakistan	State Bank of Pakistan	DMU16
17	Sri Lanka	Central Bank of Sri Lanka	DMU17

5. Results and Discussion

This section analyses the central bank efficiency and results obtained by using the proposed DEA methodology. We use both radial and non-radial measures of efficiency to obtain pure technical, scale and super efficiency of top 17 Asia central banks listed in table 2 for 2016-18. The slack-based super-

Table 3. Radial, non-radial, Super-efficiency and ranking of DMUs in the year 2016.

DMUs	Radial Efficiency			Non-Radial Efficiency			SBM Super-efficiency			
	CRS	***VRS***	***SE***	***CRS***	***VRS***	**SE**	**CRS**	**Rank**	**VRS**	**Rank**
DMU1	0.0121	0.0141	0.8597	0.0080	0.0080	0.9988	0.0080	12	0.0080	13
DMU2	0.8415	0.9241	0.9106	0.0656	0.0710	0.9238	0.0656	7	0.0710	8
DMU3	0.0355	0.0749	0.4736	0.0153	0.0159	0.9676	0.0153	10	0.0159	12
DMU4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	36.8930	1	35.1489	1
DMU5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.5854	3	2.0084	5
DMU6	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	4.0676	2	4.1778	4
DMU7	0.0077	1.0000	0.0077	0.0014	1.0000	0.0014	0.0014	15	4.3089	3
DMU8	0.2335	0.8819	0.2648	0.1404	0.4444	0.3159	0.1404	4	0.4444	6
DMU9	0.0226	0.0714	0.3166	0.0156	0.0165	0.9476	0.0156	9	0.0165	11
DMU10	0.1810	0.6416	0.2821	0.1129	0.2166	0.5214	0.1129	5	0.2166	7
DMU11	0.0880	0.8493	0.1036	0.0390	0.0537	0.7264	0.0390	8	0.0537	9
DMU12	0.0027	0.3568	0.0074	0.0014	0.0019	0.7634	0.0014	14	0.0019	15
DMU13	0.3198	0.3221	0.9930	0.0062	0.0062	0.9991	0.0062	13	0.0062	14
DMU14	0.1714	1.0000	0.1714	0.0891	1.0000	0.0891	0.0891	6	5.2030	2
DMU15	0.0448	0.6268	0.0715	0.0128	0.0268	0.4774	0.0128	11	0.0268	10
DMU16	0.0153	0.0154	0.9914	0.0001	0.0002	0.2832	0.0001	17	0.0002	17
DMU17	0.1030	0.1086	0.9488	0.0011	0.0011	0.9959	0.0011	16	0.0011	16

efficiency model is applied for rank the DMUs. MPI is used to measure the productivity changes, efficiency change and technical change over a period of time. This study is further expanded to find the impact of exports, imports, GDP and average exchange rate on the central bank efficiency by using a Tobit analysis model.

The result of radial DEA model (3.1.1), (3.1.2) and non-radial DEA model (3.2.2) reveals the mixed and pure technical efficiency where the ratio of the pure technical efficiency and mixed efficiency is the scale efficiency obtained by using the equation (I). The efficiency score equal to unity has denoted the efficiency, and less than unity is deemed to be relatively inefficient. It is shown from the table 3 that four DMUs are technically efficient and only three DMUs are pure technical efficient (score=1) out of 17 DMUs. The radial and non-radial efficiency scores reveal the DMU4, DMU5, and DMU6 are technically and optimal scale efficient for the year 2016, as shown in table 3. At the same time, DMU7 is technical efficient but havening scale inefficiency 0.00771 in case of radial measures and 0.00143 in case of non-radial measure. The DMU4 is most efficient DMU and having rank 1 with super efficiency score (36.893 in CRS) and (35.1489 in VRS. On the other hand, DMU16 is most inefficient in CSR, as well as in VRS. Overall rakings based on super-efficiency are shown in table 3.

In years 2017, DMU13 have improved the both technical as well as scale efficiency 0.00616 to 1.57527 in case of CRS and 0.00617 to 1.57578 in case of VRS from 2016 to 2017. Thus out of 17 DMUs, seven DMUs are performing technically efficient, and among seven two are having scale efficiency, as shown in table 4. As per the super efficiency DMU4 retain the position at the top with a super-efficiency score (30.65587 in CRS and 77.81029 in VRS). Whereas in the case of DMU7 is the second most efficient with a super-efficiency score (29.86088) in case of VRS but have scale inefficiency. This means DMU7 and DMU14 can improve efficiency by increasing the scale of inputs and outputs. On the other side DMU 1, 2, and 3 are improving the technical as well as scale efficiency, as shown in table 4.

Table 4. Radial, non-radial, Super-efficiency and ranking of DMUs in the year 2017.

DMUs	**Radial Efficiency**			***Non-Radial Efficiency***			**SBM Super-Efficiency**			
	CRS	***VRS***	**SE**	***CSR***	***VRS***	**SE**	**CRS**	**Rank**	**VRS**	**Rank**
DMU1	0.1028	0.1133	0.9073	0.0285	0.0288	0.9874	0.0285	8	0.0289	11
DMU2	0.0224	0.0695	0.3228	0.0008	0.0009	0.9545	0.0009	13	0.0009	14
DMU3	0.1045	0.1473	0.7095	0.0181	0.0200	0.9050	0.0182	9	0.0201	12
DMU4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	77.8102	1	30.6558	1
DMU5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.1882	3	1.1898	6
DMU6	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0466	4	1.0466	7
DMU7	0.0019	1.0000	0.0019	0.0001	1.0000	0.0001	0.0001	17	29.8608	2
DMU8	0.0381	1.0000	0.0381	0.0047	1.0000	0.0047	0.0048	11	1.3555	4
DMU9	0.2092	0.5874	0.3562	0.0848	0.2115	0.4010	0.0849	6	0.2116	9
DMU10	0.1697	0.6247	0.2716	0.1322	0.2492	0.5306	0.1323	5	0.2493	8
DMU11	0.1109	0.3650	0.3039	0.0063	0.0008	0.7257	0.0006	14	0.0009	15
DMU12	0.0338	0.7112	0.0475	0.0054	0.0194	0.2798	0.0055	10	0.0195	13
DMU13	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.5753	2	1.5758	3
DMU14	0.0161	1.0000	0.0161	0.0037	1.0000	0.0037	0.0037	12	1.2043	5
DMU15	0.0856	0.7288	0.1174	0.0502	0.2032	0.2474	0.0503	7	0.2033	10
DMU16	0.1566	0.1575	0.9947	0.0003	0.0003	0.9988	0.0004	16	0.0004	17
DMU17	0.1437	0.1481	0.9697	0.0005	0.0005	0.9942	0.0005	15	0.0005	16

The technical, purely technical, scale and super-efficiency score of 17 DMUs for the year 2018 is present in table 5. It was revealed from the results the DMU1, 2, 3, 10 and 12 improves the technical and scale efficiency and become the efficient DMUs. Thus from the out of 17 DMUs, 7 DMUs are technically and optimal scale efficient. The DMU6 and DMU7 were performing efficiently there function but unable to maintain the efficiency for the year 2018 and become inefficient. Thus out of 17, 10 DMUs remain efficient in the year 2018, as shown in table 5. The inefficient DMUs can improve the efficiency either by reducing the equivalent level of inputs without altering the output quantity produced or increasing the output quantity produced without altering the level of input.

The super-efficiency results given in table 5 for the year 2018, indicates the DMU12 is most efficient DMU in case of CRS where in case of VRS, DMU2 is most efficient and is the benchmark for the other DMUs. The DMU2 which was the most efficient for the 2016 and 2017 are maintaining the rank also at the top in 2018. Where the ranking of other DMUs improve dramatically over the period of time, especially DMU1, DMU2, and DMU3 become the efficient DMUs in the year 2018. The efficiency score and rank of DMU 16 has not altered significantly over the period of time and remain the 16th position in the year 2018.

Table 5. Radial, non-radial, Super-efficiency and ranking of DMUs in the year 2018.

DMUs	Radial Efficiency			Non-Radial Efficiency			SBM Super-Efficiency			
	CRS	*VSR*	SE	*CRS*	*VRS*	SE	CRS	Rank	VRS	Rank
DMU1	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.6320	5	1.8840	6
DMU2	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	5.3181	3	22.9424	2
DMU3	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.3979	6	1.4605	9
DMU4	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	10.3103	1	23.7936	1
DMU5	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.1824	7	1.1915	10
DMU6	0.9516	0.9640	0.9871	0.9292	0.9436	0.9848	0.9292	8	0.9436	11
DMU7	0.0458	0.1497	0.3060	0.0003	0.0003	0.9695	0.0002	17	0.0002	17
DMU8	0.0424	1.0000	0.0424	0.0284	1.0000	0.0284	0.0284	14	10.2050	4
DMU9	0.4435	0.5588	0.7936	0.0069	0.0067	1.0430	0.0069	15	0.0067	15
DMU10	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	2.1614	4	1.7492	7
DMU11	0.2334	0.2699	0.8648	0.2403	0.2430	0.9890	0.2403	9	0.2430	12
DMU12	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	9.5102	2	13.0923	3
DMU13	0.5974	1.0000	0.5974	0.2262	1.0000	0.2262	0.2262	10	7.2871	5
DMU14	0.1842	0.2152	0.8561	0.0866	0.0904	0.9584	0.0866	11	0.0904	13
DMU15	0.8784	0.8834	0.9944	0.0812	0.0833	0.9752	0.0812	12	0.0833	14
DMU16	0.0296	0.0307	0.9656	0.0031	0.0031	0.9882	0.0031	16	0.0032	16
DMU17	0.1641	1.0000	0.1641	0.0289	1.0000	0.0288	0.0289	13	1.4621	8

The efficiency may change over the period of time, for example, the DMU1 (People's Bank of China), DMU2 (Bank of Japan), DMU4 (Bank of Korea), DMU10 (Central Bank of Malaysia) and DMU12 (Central Bank of the Republic of Turkey) are performing inefficiently during 2016 and 2017, but in 2018 these DMUs performing efficiently and benchmark of the other inefficiency DMUs. The statement was also cleared by DMU6 (Central Bank of the Republic of China (Taiwan)) which was the benchmark for the inefficiency DMUs during the year 2016 and 2017 but became inefficient during the year 2018. DMU13 (Central Bank of the Philippines) was inefficient in the year 2016 and 2018, improved efficiency during the year 2016 and became efficient. On the other side, DMU7 (Reserve Bank of India), DMU8 (State Bank of Vietnam), DMU9 (Bank of Thailand), DMU11 (Bank of Indonesia), DMU14 (National Bank of Kazakhstan), DMU15 (Bangladesh Bank), DMU16 (State Bank of Pakistan) and DMU17 (Central Bank of Sri Lanka) remain inefficient but change the value of efficiency over the period of time. Whereas, DMU4 (Hong Kong Monetary Authority) and DMU5 (Monetary Authority of Singapore) maintain efficiency over the period of time and remain the benchmark for the inefficient during 2016-18.

Table 6 presents the results of the MPI of 17 top Asian central banks. As mentioned in the model (3.4.2) MPI can be decomposed total productivity change into two components: technical change and efficiency change. We have estimated the total productivity change separately and analyzed the results

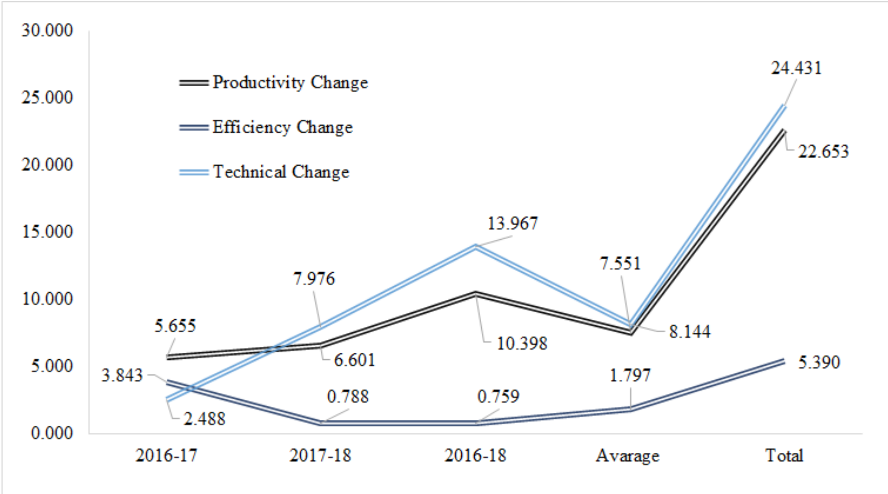

Figure 1. The productivity trend of DMUs during the period of 2016-18.

based on these separate components. Figure 1 shows the average shift of productivity, efficiency and technology over the period of time 2016-18. Overall, the productivity remains insignificant during 2016-18 where efficiency has decline trade, and the technological shift has significant positive trade over the time period.

Table 6. Productivity, Efficiency and Technical Change from 2016-18.

DMUs	Productivity Change			Efficiency Change			Technical Change		
	2016-17	2017-18	2016-18	2016-17	2017-18	2016-18	2016-17	2017-18	2016-18
DMU1	0.9817	0.1434	0.0842	0.1180	0.1029	0.0121	8.3184	1.3936	6.9333
DMU2	23.5067	0.0127	0.7477	37.4732	0.0225	0.8415	0.6273	0.5673	0.8885
DMU3	0.4992	0.8526	0.2208	0.3392	0.1046	0.0355	1.4718	8.1533	6.2247
DMU4	1.6492	4.6151	24.4527	1.0000	1.0000	1.0000	1.6492	4.6151	24.4527
DMU5	2.7571	14.9108	10.8480	1.0000	1.0000	1.0000	2.7571	14.9108	10.8480
DMU6	4.3646	3.2100	11.5113	1.0000	1.0509	1.0509	4.3646	3.0546	10.9544
DMU7	4.9107	0.2973	1.2050	3.9858	0.0423	0.1684	1.2321	7.0369	7.1560
DMU8	10.8717	4.2898	78.4714	6.1145	0.9019	5.5146	1.7780	4.7564	14.2297
DMU9	0.3238	4.7874	2.4908	0.1081	0.4718	0.0510	2.9966	10.1471	48.8575
DMU10	1.8884	1.8617	3.2777	1.0664	0.1697	0.1810	1.7709	10.9705	18.1127
DMU11	0.9410	3.2247	3.5903	0.7932	0.4755	0.3772	1.1862	6.7817	9.5185
DMU12	0.1386	0.1086	0.0138	0.0785	0.0338	0.0027	1.7671	3.2083	5.1884
DMU13	1.1148	32.2313	19.7224	0.3198	1.6739	0.5354	3.4856	19.2549	36.8387
DMU14	39.8849	2.4221	6.0391	10.6034	0.0878	0.9304	3.7615	27.6029	6.4908
DMU15	1.3076	0.3111	0.3226	0.5232	0.0975	0.0510	2.4992	3.1915	6.3260
DMU16	0.1408	36.2361	7.0959	0.0975	5.2786	0.5148	1.4440	6.8647	13.7849
DMU17	0.8491	2.6951	6.6712	0.7168	0.8754	0.6275	1.1846	3.0786	10.6313
Average	*5.6547*	*6.6006*	*10.3979*	*3.8434*	*0.7876*	*0.7585*	*2.4879*	*7.9758*	*13.9668*

Furthermore, it can be seen from the figure 1 that the productivity almost remains the same in the year 2016-17 and 2017-18. Where efficiency decreases from 3.845 in the year 2016-17 as compared to 0.788 in the year 2017-18 on the other side, there is a technological shift towards up from 2.485 in the year 2016-17 vs 7.974 in the year 2017-18. The overall productivity change, efficiency change and technical shift for each DMU over the period of time are given in table 6. The first part shows the total productivity shown the productivity change between 2016-17, 2017-18 and 2016-18. In contrast, the second and third part showed the efficiency change and technological shift throughout studied time. It is revealed from table 6 that total productivity change is in influenced much heavily by technical change than the efficiency change.

It should be noted that index value higher than one means increase of total productivity, less than one means decrease and equal to one means no change in total productivity between the respective periods. The results show that DMU 2, 4, 5, 6, 8, 10, 13, 14, and 15 have increasing trend during the year 2016-17, whereas DMU 4, 5, 6, 8, 9, 10, 11, 13, 14, 16, and 17 has increasing trend over the period 2017-18. The remaining DMUs has decreased trend over the period 2016-17 and 2017-18. The productivity change, efficiency change and technical shift are also in figure 2, 3, and 4 in the Appendix-A.

Table 7 describes the results of Tobit regression analysis since Tobit analysis is designed to estimate linear relationships between variables when there is either left- or right-censoring in the dependent variable. As we noted, the efficiency score lies between 0 and 1, which implies the efficiency score is censored variable from the left as well from right between 0 and 1. Thus in this part, we are showing a linear relationship between the efficiency score of the central bank with total export level, total import level, average exchange rate and gross domestic product of the country.

It figures out that by taking all the four predictors (total export level, total import level, average exchange rate and gross domestic product of the country) together with the super-efficiency score as dependent variable (censor variable) in the model (3.5.1). The overall goodness of fitted value of the model for all three years is significantly based on the Log-Likelihood Ratio test ($LR = -2.535, \chi^2_{(4)} = 19.830; P_{value} = 0.0002$) for the year 2016, ($LR = -8.0965, \chi^2_{(4)} = 13.720$ with $P_{value} = 0.0033$) for the year 2017 whereas the $LR = -7.0705$ for the year 2018 with ($\chi^2_{(4)}; P_{value} = 0.0006$) as shown in the table7. The pseudo R^2 has been observed to be 0.796, 0.458 and 0.583 for the year 2016, 2017 and 2018 respectively, which indicates that approximately 79.64% for the year 2016, 45.86% for the year 2017 and 58.32% variation in whether or not DMU is efficient can be predicted from the linear combination of four independent predictors. The results of the model (3.5.1) turned to statistically significant by considering all the four together.

Table 7. Estimation results of Tobit regression model during 2016-18.

Year	**2016**		**2017**		**2018**	
Variable	β	**P value**	β	**P value**	β	**P-value**
Total Export Level	5.54E-09	0.003	4.63E-09	0.026	4.65E-09	0.050
Total Import Level	-1.87E-09	0.058	-1.17E-09	0.330	-1.79E-09	0.535
Average exchange rate	-1.51E-07	0.224	-0.000230	0.141	-0.000036	0.053
Gross domestic product	-2.28E-09	0.013	-3.07E-07	0.017	-1.80E-07	0.359
Constant	-0.184093	0.157	-0.023306	0.892	-0.0769082	0.663
Modal fitted Value	2016		2017		2018	
Log likelihood / $\chi^2_{(4)}$	-2.535072 / 19.83		-8.0904675 / 13.72		-7.0705116 / 19.79	
P Value / Pseudo R^2	0.0002 / 0.7964		0.0033 / 0.4586		0.0006 / 0.5832	

Further, it was observed from the results of Tobit analysis that only total export level of country has a significant positive impact on the efficiency of the central bank. The predictor's total import level and the average exchange rate have been found negative but statistically insignificant impact on the central bank efficiency (as P value ≥ 0.05). The gross domestic products of the country are showing a significant negative impact on the central bank efficacy for the year 2016 and 2017. They have an insignificant negative impact for the year 2018, as shown in table 7.

Table 8. Correlation results between Central bank efficiency during 2016-18.

Year	**2016**		**2017**		**2018**	
Variable	**r**	**P-value**	**r**	**P-value**	**r**	**P-value**
Total Export Level	0.9596	0.000	0.3658	0.036	0.3321	0.024
Total Imports Level	-0.818	0.003	-0.129	0.050	-0.079	0.079
Exchange rate	-0.246	0.395	-0.217	0.457	-0.166	0.571
GDP	-0.378	0.182	-0.765	0.001	-0.321	0.264

Table 8 describes the results of correlation results between the central bank efficiency with total export level, total import level, GDP and average exchange rate. It was observed from the results of Pearson correlation that the total export level has found a statistically positive significant correlation with the central efficiency. Whereas, the total import, average exchange rate and GDP have a negative correlation with the central bank efficiency.

6. Summary, Conclusion and Recommendations

Performance evaluation of central banks is beneficial for the international trade, development of banking system and other financial institutions of the nation. This study endeavours to evaluate the extent of technical, pure technical and scale efficiencies of top 17 Asian exporter country central banks using time series data during 2016-18 by using DEA and its extensions. DEA proved to be a fantastic technique of performance assessment inefficiency. DEA provides a measure of relative efficiency where the performance of DMUs is evaluated concerning others and helps to identify the strength and weakness of the DMUs. It also provides the possible direction of improvement and benchmarks for comparison purposes. Besides this, an attempt has been made to explain the ranking as per the performance central banks using the concept of super-efficiency. The productivity change, efficiency change and technological shift during 2016-18 were also attempted in this study. Further, the study was extended to find out the impact of total exports, total imports, GDP and exchange rate on the efficiency of the country central banks.

From the practical point of view, the conclusions can be drawn in three different ways as per the objectives of the study. First one is about the efficiency, it was concluded that the efficiencies of DMUs changes over a period of time except for DMU4 (Hong Kong Monetary Authority) remain super-efficient and benchmark of all the DMUs throughout the study time. The central bank of China, Japan, South Korea, Hong Kong, Singapore, Taiwan, Malaysia and Turkey are operating the inputs and outputs efficiently as compared to the central bank of India, Vietnam, Thailand, Indonesia, Philippines, Kazakhstan, Bangladesh, Pakistan and Sri Lanka. However, the Hong Kong Monetary Authority is superior (super-efficient) in terms of efficiency, whereas Pakistan and Sri Lanka are inferior (lower rank) in terms of efficiency. It is observed the sources of overall technical inefficiency have been noticed due to reduced input and output utilization (i.e., managerial inefficiency) and failure to operate at most productive scale size (i.e., scale inefficiency). However, the overall inefficiency of most inefficient central banks is mainly attributed by pure technical inefficiency rather than scale inefficiency. The second one is about the change of productivity, efficiency and technology shift, and overall, the productivity remains insignificant during 2016-18 where efficiency has decline trade. The technical shift has significant positive trade over a period of time. Thus it was concluded that the overall productivity changes are because of a significant shift of technology rather than the efficiency change. It was also observed that there a significant positive correlation between the export level and the central bank efficiency. Thus finally, it was concluded that there is a positive impact of the export level of country and efficiency of the central bank as compared to import level, exchange rate and GDP.

The inefficient central bank can improve the efficiency by either reducing the level of the input without altering the output level or extended the output level without altering the input level and selecting appropriate scale size of the central bank. The efficiency of the central bank may improve by exploring the export level rather than import level in international trade. The future work could extend our research in various directions not considered in this study. First, we could examine the variations in the technical, purely technical, scale and super efficiency by using longitudinal data. Second, explore the same concept in the top exporter countries of the world.

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Appendix A

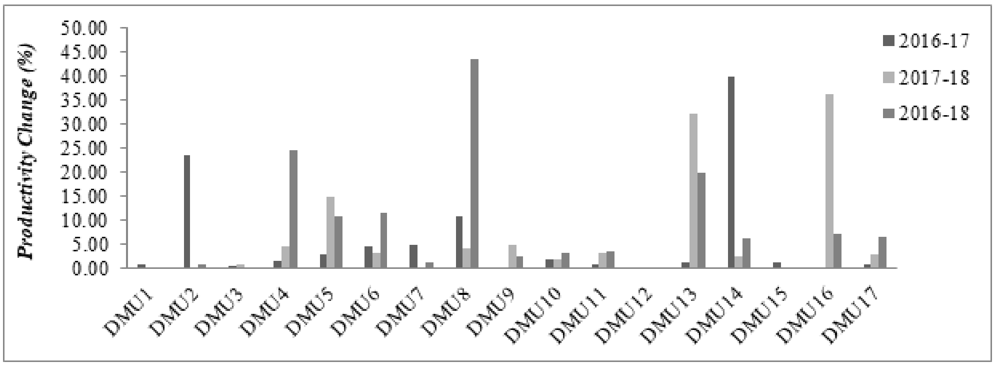

Figure 2. Productivity Change over a period of time.

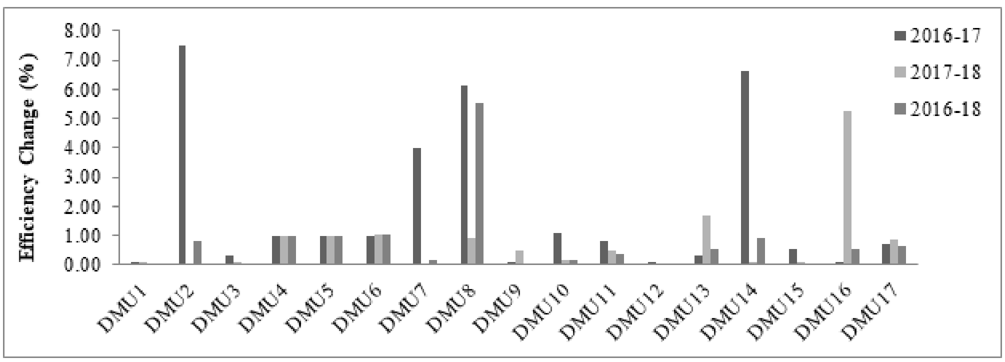

Figure 3. Efficiency Change over a period of time.

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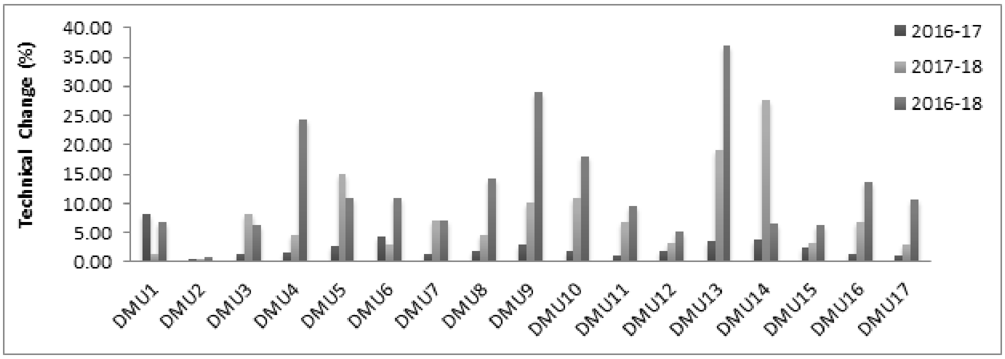

Figure 4. Technical shift over the period of time.

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