
Data Envelopment Analysis (DEA): New Approach to Measure Financial Efficiency of Banks

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Abstract

Data Envelopment Analysis (DEA) is a popular non-parametric test approached to measure the production frontiers of financial institutions such as Banks. DEA measures the optimal combination of inputs that help firms realise higher returns. Understanding the relative efficiency and performance of banks compared to the market over a period of time is extremely important for analysts, practitioners, and policymakers alike.

In the present case, DEA is employed to measure the financial efficiency of the banks, referred to as Decision Making Units (DMUs), and to understand how these DMUs employ their input to gain optimal outputs. The bank performance is quantified in terms of their productivity or efficiency which is given by the ratio of the total output to total inputs.

Keywords: Business Intelligence, Public sector banks, Old generation private sector banks, New generation private sector banks, Data Envelopment Analysis, Malmquist Productivity Index.

Introduction

The banking sector plays a very crucial role in the economic growth in India. The efficient banking sector is thus the fundamental requirement for smooth functioning of any economy (Arora et al.). Soundness is key for Indian financial system and soundness is synonymous for stability, profitability, efficiency, productivity and a shock free environment (A.K. Mishra et al., 2013). If banks intermediate efficiently it positively affects economic growth and banking failures result into systematic crises, so bank performances are at vital interest for depositors, regulators, customers and investors (MDuygun-Fethi, 2009). Measuring operational efficiency of financial institutions is pivotal for academic researcher and policymakers, as aim of both is to assess the impact of market structure on financial system and improve efficiency of financial system (Shaik Saleem et al., 2014). The main objective of liberalization Indian banking is stability, stand against external shocks and remain internally sound and sensible. A efficiency in Indian commercial banks increases it lead to reduction in spreads, this will stimulate industrial loan demand (lead to higher economic growth) and greater mobilization of savings (Majid Karimjade, 2012). Competition in banks and

banking system forces commercial banks to perform efficiently (I.A. Shah, 2012).

In the recent years, the burgeoning non-performing assets (NPAs) have become a matter of concern and scrutiny in India as the surge in NPAs impinge on the credit services of the banks, make the banks vulnerable to external shocks, leave them with less cushion in case of idiosyncratic shocks and thus, leading to the abrasion of their productive capital. In this backdrop, some very normative questions become inevitable. Last 25 years' Indian commercial banks have been observing deregulation, technological innovation and increased opportunities to finance Indian economy and emerging competition from private sector accompanied with foreign ownership banks. Government approach to liberalization is to spur competition which further influences to efficiency in Indian commercial banking sector.

The progress of the financial sector is deemed as sine qua non of robust economic growth and development. Additionally, banks play a critical role in the financial market hence, any management crisis would be entailed by an unprecedented degree of financial predicament, social cost, and thus has a potential for economic crisis. Banks play a very critical role in the development process of an economy (Tsolas and Charles 2015) given that they channelize the funds to their most productive uses in the economy.

McKinsey's Report (2019) has raised concerns over the banks across the world as growth decelerates and has further stressed upon the urgency to consider a 'suite of radical organic or inorganic moves'. Drawing a parallel between the banks in emerging countries and in developed nations, the report has identified waning Return On Tangible Equity (ROTE) from 20% in 2013 to 14.1% in 2018 especially, on account of digital disruption in emerging nations in contrast with the developed nations, where the banks have managed to strengthen productivity and have witnessed a surge in ROTE from 6.8 to 8.9% over the same period. Interestingly, India in this scenario is an interesting case with the World Bank anticipating India's share in global investments to almost double by 2030 and designating the nation as a "Powerhouse in global savings and investment".

With 158,373 functioning offices of commercial banks in India as on March, 2021, there are 14.1 banks and 20.95 ATMs per 1,00,000 adults in India (World Bank, 2019) making the Indian banking system one of the largest in the world. Adapting to the technological shift globally, since 2015, Indian banking sector has taken a quantum leap as the banks transformed their business models from brick-and-mortar to digital modes of transaction. But, for a well-functioning banking sector what matters apart from the deposits is the mechanism through which the savings are allocated as investments or credit. The banking sector in India is characterized by large chunks of non-performing assets which came into limelight post 2016 when the asset quality review (AQR) was conducted. The AQR basically classifies the loans into performing and non-performing. According to the central bank of the country, the RBI, the percentage of the bad loans jumped to as high as 80% in the financial year 2016 due solely to the AQR. Since bad loans greatly influence the efficiency of the banks, the AQR has shown us how better our banking system is doing and also the need to monitor and evaluate the performance of these banks. The AQR has impacted almost all of the Indian public sector banks while

Only a few major private sector banks were impacted. Therefore, post AQR the gap between the efficiencies of public and private sector banks is bound to decrease given the fact that these banks may actively deal with the bad loans in the aftermath of AQR. The burgeoning NPAs have become a matter of concern and scrutiny because it impinges on the credit services of the banks, makes them vulnerable to external shocks, leaves them with less cushion in case of idiosyncratic shocks and thus, leading to the abrasion of their productive capital.

While financial ratios indeed reflect the financial status, profitability and efficiency of individual banks, they are rendered ineffective when used to compare two or more banks that differ in size, capital and scale of operations and often lead to misleading findings. Therefore, a non-parametric approach called Data Envelopment Analysis (DEA) is popularly used to assess the efficiency of banks and other financial entities that use similar business tools and operate in the same environment (Maradin et al., 2018).

Sustainability is one of the concepts which has been associated with bank performance; therefore, assessing and predicting bank performance have become vital for managers when examining the suitability of their managerial decisions. Additionally, studying bank performance greatly facilitates measuring the success of decisions made by a bank as compared to those of its counterpart during the same period. Furthermore, it allows one to learn how to make better financial decisions that allocate financial resources in a more efficient manner. There is a substantial body of published academic research that discusses different methods of evaluating bank performance; Berger and Humphrey (1997) grouped them into two main approaches, namely, parametric and nonparametric. The most popular parametric method is known as the stochastic frontier approach (SFA), whereas the most popular nonparametric method is data envelopment analysis (DEA).

Although using these methods could help researchers determine performance level, they are not sufficient to explain inefficiency or predict performance. Therefore, several studies, like that of Fethi and Pasiouras (2010), proposed a combination of measuring and explaining bank performance using DEA or SFA in the first stage to measure performance and regression models as a second stage to explain it. Casu and Molyneux (2003); Ariff and Can (2008) and San et al. (2011) used Tobit regression in particular to explain bank performance. Other researchers used different regression models to explain bank performance; Anouze (2010); Emrouznejad and Anouze (2010) and Bou-Hamad et al. (2017) used boosted generalized linear model, and Seol et al. (2007) used decision trees, whereas Azadeh et al. (2011) used the artificial neural networks (ANNs). On the other hand, Sun and Li (2008) and Wu and Hsu (2019) used decision tree techniques to introduce a multiple criteria decision-making method to determine suitable warning mechanisms of corporate financial failure or distress. Meanwhile, Lai et al. (2011) used DEA to develop an intellectual benchmarking knowledge-based system for benchmarking, performance evaluation and process improvement.

However, no comparison of methods used in second DEA stage has been made, and most of these studies aimed only to explain the factors affecting efficiency rather than predicting future efficiency of banks. Predicting bank performance is extremely important: bad performance may lead to bankruptcy, which negatively influences the economy of a country. Thus, conceiving a powerful predictive model for bank performance would be useful in avoiding at least limiting such consequences.

Data envelopment analysis (DEA) is a linear-programming-based method for assessing the performance of homogeneous organizational units and is increasingly being used in banking. The unit of assessment is normally the bank branch. Studies are mostly centered on deriving a summary measure of the efficiency of each unit, on estimating targets of performance for the unit, and on identifying role-model units of good operating practice. Additional uses for DEA in banking include the measurement of efficiency in light of resource and output prices, the estimation of operating budgets that are conducive to efficiency, the assessment of financial risk at bank-branch level, and the measurement of the impact of managerial change initiatives on productivity.

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There are however numerous techniques that are helpful in measuring the efficiency of the banks. They range from the traditional ratio analysis to the regression based parametric methods to the new non parametric frontier based methods. While the ratio analyses are the simplest methods to analyses the efficiency scores of the banks they have various inherent limitations that make them less valuable in presence of more advanced parametric and non-parametric techniques. The most widely used regression based parametric technique is the stochastic frontier analysis (SFA) while data envelopment analysis (DEA) is the widely used non-parametric technique. The major differences between these two competing methods are the assumption that are imposed on the specification of the frontier, the existence of a random error and the distribution of the inefficiencies and the random error (Berger and Humphrey 1997). While SFA is a regression based approach and assumes an underlying functional form (Cobb Douglas, Translog, etc.) the DEA on the other hand is a non-parametric technique and does not assume any particular underlying functional form. The advantage of using non-parametric DEA technique over the deterministic SFA techniques is that the DEA is more flexible in the sense that it allows use of multiple input and output vectors while calculating the efficiency scores of the decision making units unlike SFA where we can use only a single output and single or multiple input variables. In addition, DEA also allows for accounting the undesirable outputs (inputs) which cannot be accounted for in the SFA methods.

Structure of Indian Banking System

The Indian banking industry is centrally governed by the Reserve Bank of India, which is the central bank of the country. Its major functions are to oversee the commercial banks of the country and to carry out the monetary policy besides other huge responsibilities that any central bank has in every country. At a lower level the Indian banking system is characterized by both commercial and cooperative banks, however, the commercial banks are the single largest asset holder and accounting for about 90%. The Indian commercial banks are then further categorized into scheduled and non-scheduled commercial banks. The scheduled banks are those banks that are included in the second schedule of the Reserve Bank of India Act, 1934. The scheduled commercial banks are further classified into three major categories based on the ownership status: (1) public sector banks, (2) private sector banks and (3) foreign banks. The public sector banks are largely owned by the government of India (more than 50% of the stake) and are subjected to the regulations of the government. The private sector banks on the other hand are owned privately by the individuals; however, they too are subjected to heavy regulations of the government (Banerjee et al. 2004)

Data Envelopment Analysis (DEA)

Data envelopment analysis (DEA) was first introduced in the literature in 1978 (Charnes et al. 1978). It is an empirically based methodology that eliminates the need for some of the assumptions and limitations of traditional efficiency measurement approaches. It was originally intended for use as a performance measurement tool for organizations that lacked a profit motivation, e.g., not-for-profit and governmental organizations. However, since its introduction, it has been developed and expanded for a variety of uses in for-profit as well as not-for-profit situations.

Since the initial development of DEA by Charnes, Cooper, and Rhodes in 1978, there have been several variations of the model developed in response to new and varied needs. The intent here is to describe some of these models and what they were designed to do. Additional details on the models can be found in the references. Also, see Ahn, Charnes, and Cooper (1988) for an analysis that relates results for these different DEA models in a rigorous mathematical manner.

Data Envelopment Analysis (DEA) is a methodology that has been adopted to “analyze the relative efficiency and managerial performance of productive (or response) units that have the same multiple inputs and multiple outputs” (Jemric & Vujcic, 2002, p.170). It allows for the comparison of relative efficiency of banks; thereby, determine the most efficient bank. DEA is considered a superior method for measuring the overall technical efficiency of banks. It is also a linear programming technique that evaluates the efficiency of multiple DMUs (Decision Making Units) with measurements involving multiple inputs and outputs.

Further, DEA compares individual observation with the others in order to calculate piece-wise discrete linear frontier. The most efficient units are those that lie on the linear frontier, with each having an efficiency score of one. Inefficient units are considered to be inefficient because they either use too much input and/or do not produce sufficient output.

Though there exists a number of DEA models, the most basic ones are the

CRS(*Constant Returns to Scale or CCR*) model (Charnes, Cooper & Rhodes, 1978) and the VRS(*Variable Returns to Scale or BCC*) model (Banker, Charnes and Cooper, 1984). CRS models are used when all the units are operating at an optimal scale.

The CCR and the BCC models measure different types of efficiencies. While CCR measures the overall efficiency of banks, BCC measures only pure technical efficiency. The overall efficiency can be further split into pure technical and scale efficiency. While pure technical efficiency is related to the technical process, scale efficiency is related to the scale size of the evaluated system. A bank is said to be scale efficient when its size of operations is optimal and that any modifications on its size will render it less efficient. The CCR model adopted in the study is used to measure the pure technical efficiency as well as the scale efficiency of select banks. Pure technical efficiency (PTE) refers to deviations from the efficiency frontier resulting from the inefficient use of resources, i.e., PTE supposes that the firms are operating under the supposition of CRS and scale efficiency (SE) refers to the losses due to lack of operating with CRS.

When the efficiency or the performance of the units has to be improved, either the input has to be reduced or the output has to be increased so that the unit can reach the efficient frontier. Therefore, DEA models have two orientations: input-oriented and output-oriented. Input-oriented models are applied to see whether the unit that is being evaluated can reduce its inputs while keeping the outputs at current levels. In the case of input-oriented models, the linear programming model is configured to determine how much the input use of a firm can be contracted if used efficiently to achieve the same level of output.

In contrast, in the case of output-oriented models, the linear programming model is configured to determine a firm's potential output given its inputs if it operated efficiently as the firms along the efficient frontiers. Thus, the input-oriented models use only the fixed variables used for operation/production and hence cannot be used to estimate the utilization of capacity or resources. Output-oriented models can however be used to measure capacity utilization for a given set of inputs. The output-oriented models are ideally suited to test whether the DMU under evaluation can increase its outputs while keeping the inputs at the current levels. In the present study, whether the overall efficiency of the banks can be increased with the help of business intelligence (i.e. capacity utilization) was evaluated. The inputs, which are produced as a result of adopting business intelligence, are kept constant to study whether the efficiency of banks can be increased. Therefore, *output-oriented model* was developed in the study.

DEA is an alternative to regression analysis. While the latter depends on central tendencies, the former is based on extreme observations. In a regression analysis, a single estimated regression equation is assumed to be applied to each observation vector; whereas, in DEA, each vector is analysed separately to produce individual efficiency measures relative to the entire set that is evaluated. Further, unlike regression, DEA must need a priori assumptions since it constructs the best efficiency function solely based on the observed data (Jemric & Vujcic, 2002).

Overall efficiency and productivity of banks calculated using CRS method

The performance of banks can be observed with the help of their efficiency and productivity (in terms of managing the funds). Malmquist Productivity Index (MPI) was adopted to observe the level of bank productivity based on changes in the efficiency and technology (i.e. business intelligence) adopted. MPI is a function of distance that describes a technology by defining a set of input and output indices. Consider a function F that describes a technology of production. F is given by $F(x, y) = 0$, where x is the input vector given by $X = (x_1, x_2, x_3 \dots x_M)$ and y is the output vector given by $Y = (y_1, y_2, y_3 \dots y_S)$. Caves, Christensen, and Diewert (1982) provided an alternative interpretation to production technology based on the concept of distance function. Accordingly, the output distance function is given by:

$$D_0(x, y) = D_{\mu}^{Min} \left[\begin{matrix} Y \\ \mu : F(X, \mu Y) = 0 \end{matrix} \right] \quad \text{---(1)}$$

where μ is the minimum equi-proportional change in the output vector. It measures the maximum proportional change required in the output to place (X, Y) in the efficiency frontier. That is, if the evaluated DMU (or the production unit) is efficient, $D_0(X, Y) = 1$ otherwise, it is < 1 .

In order to compare the performance of a DMU in time period t and $t+1$ with reference to period t technology, the output based Malmquist productivity index is given as follows (Galagedera & Edirisuriya, 2004):

$$M_0^t(X_{t+1}, Y_{t+1}, X_t, Y_t) = \frac{D_0^{t+1}(X_{t+1}, Y_{t+1})}{D_0^t(X_t, Y_t)} \quad \text{---(2)}$$

$M_0 > 1$ indicates higher productivity in period t than in period $t+1$. In order to avoid the choice of time period arbitrarily, Färe, Grosskopf, Norris and Zhang (1994) proposed an output-based Malmquist index (TFP index) as follows which has been adopted in the present study:

$$M^t(X_{t+1}, Y_{t+1}, X_t, Y_t) = \left[\frac{D^t(X_{t+1}, Y_{t+1})}{D^{t+1}(X_{t+1}, Y_{t+1})} \cdot \frac{D^{t+1}(X_t, Y_t)}{D^t(X_t, Y_t)} \right]^{1/2}$$

$$= \frac{D^{t+1}(X_{t+1}, Y_{t+1})}{D^t(X_t, Y_t)} \cdot \frac{D^t(X_{t+1}, Y_{t+1})}{D^{t+1}(X_t, Y_t)} \quad \text{---(3)}$$

The output orientation of the model given in (1) provides information as to how much equi-proportional increase in output is necessary while maintaining the input levels at a constant for an inefficient DMU to become an efficient DMU. From the (3) equation it can be seen that Malmquist Total Factor Productivity Index can be split into two: *relative efficiency*

$$\frac{D^{t+1}(X_{t+1}, Y_{t+1})}{D^t(X_t, Y_t)} = \frac{D^{t+1}(X_{t+1}, Y_{t+1})}{D^t(X_{t+1}, Y_{t+1})} \cdot \frac{D^t(X_{t+1}, Y_{t+1})}{D^{t+1}(X_t, Y_t)} \cdot \frac{D^{t+1}(X_t, Y_t)}{D^t(X_t, Y_t)}$$

between period t and $t+1$, given by $\frac{D^t(X_{t+1}, Y_{t+1})}{D^{t+1}(X_t, Y_t)}$ and shift in technology (i.e. *technical progress*) captured between the two time periods evaluated at (X_t, Y_t) and (X_{t+1}, Y_{t+1}) is given

$$\text{by } \left[\frac{D^t(X_{t+1}, Y_{t+1})}{D^{t+1}(X_t, Y_t)} \right]^{1/2} \cdot \frac{D^t(X_t, Y_t)}{D^{t+1}(X_t, Y_t)}$$

For each of the DMUs, five Malmquist indices were defined for period $t+1$ relative to period t , as follows.

$$\text{Total factor productivity change index (TFPCI)} = \frac{D^{t+1}(CRS)(X_{t+1}, Y_{t+1})}{D^t(CRS)(X_{t+1}, Y_{t+1})} \cdot \frac{D^t(CRS)(X_t, Y_t)}{D^{t+1}(CRS)(X_t, Y_t)}$$

$$\text{Relative efficiency or Technical efficiency change index (TECI)} = \frac{D^{t+1}(CRS)(X_{t+1}, Y_{t+1})}{D^t(CRS)(X_t, Y_t)}$$

$$\text{Technological change (or Technical progress change) index (TCI)} = \frac{D^t(CRS)(X_{t+1}, Y_{t+1})}{D^{t+1}(CRS)(X_{t+1}, Y_{t+1})} \cdot \frac{D^t(CRS)(X_t, Y_t)}{D^{t+1}(CRS)(X_t, Y_t)}$$

TECI can be further split into pure technical efficiency change (PTECI) and scale efficiency change (SECI). Pure technical efficiency is measured by the VRS (Variable Return to Scale) model. Hence, it is given by

$$\text{Pure technical efficiency change index (PTECI)} = \frac{D^{t+1}(VRS)(X_{t+1}, Y_{t+1})}{D^t(VRS)(X_t, Y_t)}$$

$$\text{Scale efficiency change index (SECI)} = \frac{\text{Technical efficiency change index (TECI)}}{\text{Pure technical efficiency change index (PTECI)}}$$

Index values of <1 indicate that there is a decline in the efficiency, value equal to 1 indicate that there is stagnation in efficiency and values >1 indicate that there is growth in the efficiency during the period between t and t+1 from the prospective of period t technology.

The indicators of bank performance were recalculated annually. The changes in performance were observed using the following metrics: TECI – Technical efficiency change index, TCI – Technological efficiency change index, PTECI – Pure technical efficiency change index, SECI – Scale efficiency change index, TFPCI – Total factor productivity change index.

Since the initial development of DEA by Charnes, Cooper, and Rhodes in 1978, there have been several variations of the model developed in response to new and varied needs. The intent here is to describe some of these models and what they were designed to do. Additional details on the models can be found in the references. Also, see Ahn, Charnes, and Cooper (1988) for an analysis that relates results for these different DEA models in a rigorous mathematical manner.

Conclusion

Banks are an integrated component in the financial system such as a nervous system in a human body, so it needs to perform with efficiency so that the entire financial system can perform efficiently. Bank efficiency is very important and a crucial issue especially in transition economies, where the banking sector faced a considerable change in ownership structure as a result of privatization, foreign bank entry and competition, liberalization, change in legislative environment and institutional rules. All these factors exerted some influence on the bank performance and efficiency. In addition, technological changes and knowledge, transferred normally with the increase in foreign ownership in the transition economies, altered significantly the operational environment for the banking institutions and the technology of banks production, which in its turn changed the bank efficiency. Efficiency can be simply defined as the ratio of output to input. More output per unit of input reflects relatively greater efficiency. If the greatest possible output per unit of input is achieved, a state of absolute optimum efficiency has been achieved and it is not possible to become more efficient without new technology or other changes in the production process. Hence, Data Envelopment Analysis (DEA) plays a crucial role in modern era to analyze and measure the financial efficiency of the banks and to know the clear financial health of the organization.

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