WORKING PAPER 250/2023

DETERMINANTS OF EFFICIENCY OF COMMERCIAL BANKS IN INDIA AFTER GLOBAL CRISES

K. Ravirajan
K. R. Shanmugam

MSE
Mentoring Excellence

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

November 2023

Determinants of Efficiency of Commercial Banks in India after Global Crises

K. Ravirajan
Research Scholar, Madras School of Economics, Gandhi Mandapam Road,
Chennai-600 025 (India)
ravirajan@mse.ac.in, ravirajan1981@gmail.com
(Corresponding Author)

and

K. R. Shanmugam
Director and Professor, Madras School of Economics, Gandhi Mandapam Road, Chennai
shanmugam@mse.ac.in

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

November 2023

WORKING PAPER 250/2023

November 2023

Price : Rs. 35

MADRAS SCHOOL OF ECONOMICS
Gandhi Mandapam Road
Chennai 600 025
India

Phone: 2230 0304/2230 0307/2235 2157
Fax: 2235 4847/2235 2155
Email : info@mse.ac.in
Website: www.mse.ac.in

Determinants of Efficiency of Commercial Banks in India after Global Crises

K. Ravirajan and K. R. Shanmugam

Abstract

This study contributes to the bank efficiency literature by estimating the technical efficiency, pure efficiency and scale efficiency of banks in four different ownership groups in India from 2008-09 to 2019-20 utilizing the DEA method and three alternative approaches to choose inputs and outputs of banks-intermediation approach, value added approach and operating approach. It also uses the tobit estimation procedure to identify the factors determining the variations in the technical efficiency of banks. Results indicate a high degree of inefficiency of several banks during the study period and there is a greater scope for improving their performances. There exists sizable scale inefficiency and banks are likely to lose sizable output. The results also indicate that banks with larger capital adequacy ratio or young banks or larger banks or more profitable banks are more efficient. Foreign banks and nationalized banks are more efficient than private domestic banks. We hope that the findings of this study will be useful to international agencies and other stakeholders in evaluating and improving the performance of Indian banks.

Keywords: *Technical Efficiency, Pure and Scale Efficiency, Data Envelopment Analysis, Non-Performing Assets, Indian Commercial Banks, Emerging Market*

JEL Codes: *G2, G210, G280, E58, C6*

Acknowledgement

We would like to thank MSE faculty members for their valuable comments when this study was presented in the synopsis approval seminar.

K. Ravirajan
K. R. Shanmugam

INTRODUCTION

Due to globalization and overwhelmingly interdependence amongst the financial sectors of the countries, the global financial crisis had affected almost all economies and financial sectors of nations. However, the Indian banking industry had no direct exposure to the sub-prime mortgage assets and the Indian economy had quickly recovered from the slow down (Viswanathan, 2010). Many cited the foundations of the Indian financial system, particularly the banking system, as the main system for its stringent regulatory and prudent policies. Later, a few developments happened in the Indian banking sector namely, increased bade loans (NPAs), the consolidation of Information Technology based efforts since 2012, demonetization (2015-16) and covid-19 pandemic from the last quarter of 2019-20 (Ravirajan and Shanmugam, 2021).[1]

In 2008, India ranked fourth lowest among G-20 countries in non-performing assets (NPAs) ratio. But in 2020, it ranked second highest, next only to Russia.[2] According to the Reserve Bank of India (RBI) website, the NPA (Gross) of Scheduled Commercial Banks (SCBs) in India increased from Rs. 683 billion (2.3 percent) in 2008-09 to Rs. 10388 billion (11.2 percent) in 2017-18.[3] The RBI instructed all banks to clean up their balance sheets and set aside high capital in the form of provisioning before March 2017. As of March 31, 2020 the quantum of NPA (Gross) of SCBs declined to Rs. 8998 billion (8.2 percent). The NPA (Gross) amounted to Rs.6783 billion (10.3 percent) in Public Sector Banks, Rs. 2096 billion (5.5 percent) in Private Domestic Banks and Rs. 102 billion (2.3 percent) in Private Foreign Banks.[4]

---

[1] Shri Shaktikanta Das, Governor of Reserve Bank of India in his speech at the Mint's Annual Banking Conclave (on February 24, 2020) remarked that "Despite the recent decline in impaired assets and a significant improvement in provisioning, profitability of the banking sector remains fragile..the sector continues to encounter challenges from events like those around the telecom sector".

[2] As per data on world indicators available in: https://data.worldbank.org/indicator.

[3] 1 crore=10 million.

[4] In India, Public Sector Banks are the major dominant banking group. Still, this group loses on an average of 23 percent against invested money (Economic Survey, 2020) due to poor credit growth,

The high degree of NPAs and the necessity of making provisions could obviously affect the profitability/efficiency and liquidity of Indian banks. The RBI's latest Financial Stability Report warned that the NPA levels would likely to worsen again and they might reach 11.2 percent in March 2022 under severe stress scenarios. Several factors, including excessive lending, lax credit standards, poor monitoring and diversion or siphoning of funds, besides malfeasance and fraud, have contributed to the high levels of NPA (Rangarajan and Sambamurthy, 2021).

Despite the NPA stress, Indian banks deployed technology-intensive solutions to increase their revenue, enhance customer experience, optimize cost structure and manage enterprise risks due to the falling internet costs and increased awareness as a result of the initiatives of the Government of India and the RBI (Bansal, 2015). However, different banks have different technology implementing capabilities. Further, technological advancements have led to the emergence of new security risks like cyber crime, hacking, etc. The demonetization announced by the Government of India in 2016 also created a further mess in the operations of banking industry in India. The Covid-19 pandemic also affected the economy from the last quarter of 2019-20 and it could have affected the performance of banking industry.

Thus, the Indian banking industry has faced an uncertain environment for its operations due to these developments as they have brought positive as well as negative impacts. Since the Indian banking industry is the major growth engine for economic growth and stability, it is essential to ensure the efficient functioning of banking sector. India has a bank dominated financial system. The Indian banking industry has four groups of scheduled commercial banks: (i) the State Bank of India and its associate banks (SBIs), (ii) the nationalized banks (NBs), (iii) private domestic banks (PBs) and (iv) private foreign banks (FBs). SBIs and NBs are jointly called as public sector banks (PSBs). The economic

---

and NPAs draw attention and necessity to improve banking performance to support growth to seize any detrimental effects.

liberalization in the early 1990s helped the entry of many new private and foreign banks. Subsequently, the Indian banks adopted the international best practices. Several prudential and provisioning norms were introduced and the competitive environment was created.

Although handful of studies emerged in the literature to examine the performance of banking industry like Shanmugam and Das (2004), Das *et. al.*, (2005), Ray and Das (2010), Das and Kumbhakar (2012), Bhattacharya and Pal (2013), Kaur and Gupta (2015) etc., the majority of them provided the efficiency estimates of Indian banks during the pre-crisis period or initial years of post-crisis period. This study attempts to measure the technical efficiency of scheduled commercial banks in India from 2008-09 to 2019-20 using the standard DEA approach and to identify the factors determining the variations in the efficiency of banks.

The main contributions of this study are as follows. First, it uses the latest available data to measure the efficiency of Indian banks during the post crisis period. Second, almost all the existing studies on the topic employ one of three alternative approaches in choosing the set of outputs and inputs of banks, except Das and Ghosh (2006). These approaches are the production (or also called service provision or value added) approach, the intermediation (or asset) approach and the operating or income based approach (Hjalmarsson *et. al.*, 2000). This study uses all these three approaches to measure the efficiency of Indian banks and to assess how banks perform under each approach. Third, this study compares the efficiency variations across four Indian banking ownership groups in recent years (particularly after the global crisis) and identifies the factors determining efficiency variations across banks. Finally, it is the first study analysing the effect of demonetization, NPA and technology adoption on the efficiency of banks in India.

The rest of this study proceeds as follows. The next section provides a brief review of literature. Subsequent sections explain the data, model and variables used in this study, and present and discuss the empirical results of the study. The final section provides the summary and policy implications of the study.

BRIEF REVIEW OF LITERATURE

Theoretical Literature: Two performance measures widely used in the existing literature are: productivity and efficiency. While the former is measured as the ratio between output(s) and input(s), the latter is measured as the ratio between actual output and the benchmark or maximum or frontier or potential output. Although they are different, they are interrelated. Among them, the efficiency measure is more popular as it helps banks to increase their outputs to the potential or frontier level by following the best practices without additional resources.

Broadly, two alternative methodologies emerged in the literature to measure the efficiency, namely the data envelopment analysis (DEA) and stochastic frontier approach (SFA). While they have their own advantages and limitations, the DEA has been widely used in measuring the efficiency of financial institutions like banks as it is successful in handling multiple outputs and inputs (Berger and Humphrey, 1997). However, the major concern in the efficiency analysis is whether the actual outcome generated could be achieved with less inputs or whether the same inputs could produce better outcomes.

The DEA includes (i) the non-parametric deterministic model developed by Farrell (1957), later popularized by Charnes, Cooper and Rhodes (1978). It was further extended by Banker, Charnes, and Cooper (1984) by introducing variable return to scale (VRS). (ii) the parametric deterministic model by Aigner and Chu (1968), (iii) the probabilistic model by Timmer (1971), and (iv) the Corrected OLS (COLS). The deterministic model assumes that the actual output Q_i of bank i is less than or equal to its potential or frontier level of output, $Q^*(=f(X))$, i.e., $Q_i \leq Q^* = f(X)$, where X is a vector of inputs, The output gap u is the difference between the potential and actual output given by $u= Q^*-Q$. u is also called the technical (in) efficiency term and is always a non-negative quantity. Due to a non-linear relationship, this relationship can be re written as: $Q_i = f(X)\ e^{-u}$. The advantage of this form is that e^{-u} = Q/Q^*=TE, that is, it directly measures the TE.

In Farrell's (1957) model, the efficient frontier is estimated by plotting the input-output ratios of the DMUs in a space of suitable number of dimensions and forming a convex closure of the set of points. The TE of a bank is obtained by comparing a hypothetical (best practiced) bank that produces more output with the same proportion of inputs. Farrell also proposed the use of a parametric function, $Q^* = f(X;\beta)$ such as the Cobb-Douglas form. Following this suggestion, Aigner and Chu (1968) specified the following Cobb-Douglas production function (with two inputs) for the parametric estimation of a deterministic model.

$$Q_i = Q_i^* e^{-u} = A X_1^{\beta_1} X_2^{\beta_2} e^{-u} \tag{1}$$

Taking log on both sides of the equation (1), it becomes:

$$\mathrm{Ln}\ Q_i = \mathrm{Ln}\ A + \beta_1 \mathrm{Ln}\ X_1 + \beta_2 \mathrm{Ln}\ X_2 - u_i \tag{2}$$

Let Ln A = β_0 and using lower case letters to denote the log of variables, the equation (2) can be re-written as:

$$q_i = \beta_0 + \beta_1 x_1 + \beta_2 x_2 - u = \sum_j \beta_j x_{ij} - u \tag{3}$$

For efficient bank, u=0 and $q=q^*$. For inefficient banks, u > 0 and $q < q^*$. Therefore, the main objective is to locate the bank which produces the potential or frontier output for which the u term is minimum. As $u_i = \Sigma_j\ \beta_j\ x_{ij} - q_i$, the objective is to minimize u_i or alternatively minimize $\Sigma u_i = \Sigma_i\ \Sigma_j\ \beta_j\ x_{ij} - \Sigma q_i$. Dividing this equation by n throughout, the last term is mean value of log output and is a constant, which can be dropped without any loss. The linear programming (LP) formulation of this problem can be specified as:

$$\text{Min: } \beta_0(1) + \beta_1 \bar{x}_1 + \beta_2 \bar{x}_2 \tag{4}$$

Subject to the constraints:

$\beta_0(1) + \beta_1 x_{11} + \beta_2 x_{21} \geq q_1$

$\beta_0(1) + \beta_1 x_{12} + \beta_2 x_{22} \geq q_2$

$\beta_0(1) + \beta_1 x_{1n} + \beta_2 x_{2n} \geq q_n$

and all $\beta_j \geq 0$.

Timmer (1971) argues that in the Aigner and Chu Model, there could be many outliers with full (100 percent) efficiency. He suggested that a 3 percent sample with full efficiency value could be deleted as outliers as they are affected by statistical errors. Then again, solve the LP problem with the remaining 97 percent sample. Thus, he converted the parametric deterministic model into the probabilistic model. The COLS method uses a simple regression procedure to estimate the efficiency. Let the model is: $Q_i = \beta_0 + \beta_1 X_1 + u$. Apply OLS to estimate the highest positive u term (u^*) in the sample and shift the estimated regression line to that level to get a frontier line. The intercept for the frontier line is calculated as: $\beta_0^* = \beta_0 + u^*$. Using this new intercept and the estimated coefficient of X_1, the estimated value of potential output, Q_i^* for i can be computed. Dividing Q_i by Q_i^* will give us TE for bank i.

The above DEA approach has three major advantages: (i) It is very flexible (it works with a small set of samples also) and does not require any functional form; (ii) multiple inputs and outputs can be utilized in measuring efficiency values; and it does not need any assumption on inefficiency distribution. However, it has the following limitations: (i) all firms share a common frontier and any variation in bank efficiency is measured relative to this frontier, (ii) the random factors that can influence the efficiency of a bank are ignored, and (iii) results of this approach are sensitive to the number of variables and the number of observations used.

The SFA (econometric) approach for cross section data was developed independently by Aigner, Lovell and Schmidt (1977) and

Meeusen and van den Broeck (1977). This model assumes that the potential output is not deterministic, but stochastic due to random factors and so $Q_i = f(X;\beta)\ e^{-u}\ e^{v} = f(X;\beta)\ e^{\varepsilon}$, where v is regular two-sided stochastic error term and ε (=v-u) is the composite error term, consisting of the regular error term v and the one-sided inefficiency term u. For estimating the SFA model using the maximum likelihood estimation (MLE) method, the one sided error term u is assumed to follow one of the following four distributional assumptions, namely half normal, truncated normal, gamma and exponential. But the SFA for cross section data also suffers from limitations. First, the estimated inefficiency is not consistent. One can consistently estimate the (whole) error term for a given observation, but it contains statistical noise (v) as well as inefficiency term (u). The variance of the distribution of inefficiency term conditional on the composite error term does not vanish when the sample size increases (Jondrow *et. al.*, 1982). Second, the estimation of the model and separation of inefficiency from the statistical noise require specific distributional assumptions on the inefficiency term. A choice of wrong distribution will lead to biased estimates. Finally, it may be incorrect to assume that the inefficiency term is independent of regressors included in the model. In addition, this is applicable only for single output. The panel versions of SFA (time invariant as well as time-varying efficiency model) have overcome some of the limitations but not all. Since banks produce multiple outputs, most empirical studies utilized the DEA approach. After estimating the efficiency in the first stage, most studies regress the efficiency on various factors to identify the major determinants of efficiency in the second stage.

(ii) Empirical Literature: The above methodologies are widely used to measure the efficiency of financial institutions, including banks in various nations. Some studies estimate the output function to measure the technical efficiency, while many others estimate the cost or profit or revenue function to measure the cost efficiency or profit or revenue efficiency. The empirical studies measuring the efficiency of financial institutions are numerous and most of them concern developed nations such as USA, Sweden, and Finland. After reviewing 130 studies on the efficiency of financial institutions/banks from 21 countries, Berger and Humphrey (1997) remarked that 116 studies were published during 1992-1997 and most of them analysed the efficiency of US banks. They also found that the annual average technical efficiency ratios of these studies were around 77 percent (median 82 percent).

The major issue in existing studies is the selection of inputs and outputs sets. These studies employ three approaches: the production (or also called value added) approach, the intermediation (or asset) approach and the operating or income based approach (Hjalmarsson *et. al.*, 2000; Das and Ghosh, 2006). The value added approach considers banks as the providers of services to customers (Benston, 1965). It uses the number of deposits and loan accounts as outputs and physical variables (like labour, material, space or information systems) or their associated costs as inputs. The intermediation approach proposed by Sealey and Lindley (1977) views operating and interest expenses as inputs and loans and other major assets as outputs. The operating approach uses interest and non-interest income as outputs and interest expenses, capital related expenses and employee expenses as inputs.

Most bank efficiency studies measuring efficiency of banks in developed nations employ the DEA approach. For instances, Elyasiani and Mehdian (1995) utilized the intermediation approach to measure the inefficiencies of small and large US commercial banks from 1979 to 1986 and found that while the efficiency declined over the years, small banks emerged as more efficient. Fecher and Pestieau (1993) measured the average efficiency of banking and insurance for 11 OECD countries from 1971 to 1986 at 0.82 with a range of 0.67 (for Denmark) to 0.98 (for Japan). Maudos and Pastor (2001) estimated the cost and the profit efficiency of banks in 14 countries of the European Union, as well as Japan and the US and found wide differences in the profit efficiency of these countries.

Efficiency studies on Asian banks are limited. Shyu (1998) found improvement in overall efficiency of Taiwan's banking industry during 1986–89 to 1992–95. Hao, Hunter, and Yang (1999) employed the SFA approach to measure the efficiency of 19 Korean banks from 1985 to 1995 and found that banks with faster growth rates, extensive branch network and those that made extensive use of deposits in funding their assets were more efficient. On comparing the effect of deregulation on the productivity growth of banks in Indian sub-continent (including India, Pakistan and Bangladesh), Jaffry *et. al.*, (2007) showed that technical efficiency increases and converges across the Indian sub-continent in response to reforms.

In the context of Indian banking, Bhattacharya, Lovell, and Sahay (1997) used the DEA approach and found that the public sector banks were the best performing and they improved their efficiency in the deregulated environment from 1986 to 1991. Mohan and Ray (2004) showed an improvement in the revenue efficiency of Indian banks and also the convergence in performance between public and private sector banks in the post-reform period. Das *et. al.*, (2005) measured the cost efficiency, the revenue efficiency, and the profit efficiency of Indian banks from 1997 to 2003 using the DEA and showed that bank size, ownership, and stock exchange listing influenced the profit efficiency positively and to some extent, the revenue efficiency.

Das and Ghosh (2006), utilizing the intermediation approach, the value added approach, and the operating approach and DEA method, showed that medium-sized public sector banks performed reasonably well, and banks with less NPAs were technically more efficient from 1992 to 2003. Using the DEA approach, Gupta *et. al.*, (2008) showed that the productive efficiency from 1999 to 2003 increased from 0.901 to 0.925. The SBI group of banks had the highest efficiency, followed by PBs, and NBs. Ray and Das (2010) applied the DEA method to estimate the cost and the profit efficiency of Indian banks during the post reforms period and found that public sector banks were more efficient than their private counter parts, and small banks (with assets up to Rs.50 billion) were mostly operating below the efficiency frontier.

Dwivedi and Charyulu (2011) used the DEA and showed that the mean TE of all banks increased from 95.6 percent in 2005 to 97.9 percent in 2010. Other than SBIs, all remaining group banks have improved their efficiency over the years. Kaur and Gupta (2015) using the DEA approach showed that the mean efficiency score was 91 percent for all 57 banks in the sample from 2009 to 2013; 94.5 percent for SBIs; 92 percent for PBs; and 86.9 percent for NBs. Tandon *et. al.*, (2014) used DEA to measure the efficiency of Indian banks (19 NBs, 15 PBs and 10 FBs) from 2009 to 2012. Only 7 out of 44 banks operated on the efficiency frontier. The efficiency scores did not vary much across three groups of banks. Goyal *et. al.*, (2019) used the DEA approach and data for 66 banks in 2015-16 and found that the average efficiency of Indian banking sector was 73.44 percent.

Utilizing Battese and Coelli's (1992) SFA model for panel data, Shanmugam and Das (2004) observed that during the deregulation period (1992-1999), the efficiency of raising non interest-income, investments and credits of Indian banks improved. Ataullah *et. al.*, (2004) reported that overall technical efficiency of the banking industry of India and Pakistan improved following the financial liberalization. Das *et. al.*, (2005) showed that the efficiency of Indian banks, in general, and of bigger banks, in particular, improved during the post-reform period. Mahesh and Bhide (2008) found that deregulation has a significant positive impact on the cost and the profit efficiencies of commercial banks. Das and Ghosh (2009) also found that the liberalization of the banking sector in India generally produced positive results in terms of improving the cost and profit efficiencies of banks.

Das and Kumbhakar (2012) observed that the efficiency of public sector banks has surpassed the efficiency of private sector banks during the post reform period 1996-2005. Bhattacharya and Pal (2013) estimated the technical efficiency of 103 commercial banks during 1989-2009 using a multiple-output generalized stochastic production frontier and intermediation approach. They showed that the mean efficiency of Indian commercial banks was 64 percent during the study period. Public sector banks were more efficient than private and foreign banks. The review clearly indicates that the efficiency studies on the Indian banks after post financial crisis period are non-existent or cover only the initial periods of crisis.

MODEL, DATA AND ESTIMATION

This study employs the Farrell's (1957) non-parametric deterministic (DEA) model which was popularized by Charnes *et. al.*, (1978) to measure the efficiency of Indian banks from 2008-09 to 2019-20. This approach considers the constant returns to scale (CRS) assumption or technology. It is noted that the output-oriented and input-oriented models coincide when measuring TE under CRS assumption. Let banks use K inputs and produce M outputs. These are represented by the vectors X_i, and Q_i respectively for the ith bank. The CRS model considers the ratio of all outputs over all inputs for each bank (i.e., productivity) as: $u' Q_i / v' X_i$, where u is an M x 1 vector of output weights and v is a K x 1 vector of input weights. These are like shadow prices vectors used for aggregation of outputs and inputs. The following mathematical programming problem will determine the optimal weights:

$$\text{Max}_{u,v} (u'Q_i / v'X_i) \qquad (5)$$

Subject to: $u'Q_j / v'X_j \leq 1$, j = 1,2,….,N
and u, v ≥ 0

The above linear fractional programming problem is difficult to solve. Further, this has an infinite number of solutions. The remedy is the LP problem by imposing the constraint $v'X_i = 1$ as:

$$\text{Max}_{\mu,\upsilon} (\mu'Q_i,) \qquad (6)$$

Subject to: $\upsilon' X_i = 1$

$$\mu' Q_j - \upsilon' X_j \leq 0,\ j = 1,2,\ldots,N \text{ and}$$

$$\mu,\ \upsilon \geq 0$$

where the notation changed from u and v to μ and υ is due to the fact that all shadow prices are multiplied by a non-negative scalar k (>0) which does not affect the objective function or constraints. This is a multiplier form of DEA. For computation purposes, its dual version is used as:

$$\text{Min}_{\theta,\lambda}\ \ \theta \tag{7}$$

Subject to: $-q_i + Q\lambda \geq 0$,

$$\theta\, x_i - X\lambda \geq 0, \text{ and}$$

$$\lambda \geq 0.$$

where θ is a scalar and λ is a $N \times 1$ vector of constants. This involves some fewer constraints than the multiplier form and is hence preferable. The value obtained for θ is the efficiency score for the ith bank. If it is 1, the bank is fully efficient. It is noted that this LP problem must be solved for N times to get an efficiency score for each of N banks.

If imperfect competition, constraints on finance etc. may cause a bank to be not operating at an optimal scale, then CRS assumption is not valid and so VRS is relevant. Banker *et. al.*, (1984) modified the CRS model into the VRS model by adding the convexity constraint: $N1'\lambda=1$ in the CRS model (7), where N1 is an N x 1 vector of ones. The output-oriented VRS model is similar to the input-oriented CRS model with some minor changes as shown in the following output-oriented VRS model:

$$\text{Min}_{\phi,\lambda}\ \ \phi \tag{8}$$

Subject to: $-\phi q_i + Qi \geq 0$,

$$x_i - X\lambda \geq 0$$

$$N1'\lambda=1, \text{ and}$$

$$\lambda \geq 0.$$

where $1 \leq \phi < \infty$ and $1/\phi$ define the a TE score (i.e., pure technical efficiency) which lies between 0 and 1. The scale efficiency is computed as a ratio between CRS TE score and VRS TE score. The above procedures are used to measure the year wise TE under CRS, TE under VRS, and the scale efficiency for each bank in the sample in three alternative approaches of selecting inputs and outputs. Details of outputs and inputs used in these three approaches are:

Inputs/Outputs	Intermediation Approach	Value Added Approach	Operating Approach
Inputs	Demand Deposits, Saving Deposits, Fixed Deposits, Capital Related Operating Expenses, Employee Expenses	Capital Related Operating Expenses, Employee Expenses, Interest Expenses	Capital Related Operating Expenses, Employee Expenses, Interest Expenses
Outputs	Advances, Investments	Advances, Investments, Demand Deposits, Saving Deposits, Fixed Deposits	Interest Income, Non-interest Income

Obviously, technical inefficiency (TEI=1-TE) scores will be different for different banks and over the years. To find out the factors determining the inefficiency score in the second stage of the analysis, this study applies the panel version of the inefficiency model. As the inefficiency scores range between 0 and 1, and are censored in nature, the following the standard Tobit regression method for panel data is employed:

$$Tai_t = Z'\gamma + e_{at} \quad \text{If RHS is} > 0 \qquad (9)$$
$$= 0 \text{ otherwise}$$

where, Z is vector of the explanatory variables influencing TEI (obtained from CRS model) and γ is the vector of coefficients associated with Z variables. Z includes the ownership dummies for SBIs, NBs and FBs, the dummy for pre demonetization period, size of the bank which is log of real assets (SIZE), age of the bank (AGE), number of branches (BRANCH), capital adequacy ratio CAR), return on asset (ROA), net NPA ratio, and technology index (T).

This study uses the secondary data compiled from the RBI website from 2008-09 to 2019-20 (12 years). Since there are multiple indicators representing the technology, this study followed Shanmugam and Rakesh (2020) to compute a composite technology index (T_t) using the Euclidean norm formula: $T_t = \sqrt{ATM^2 + POS^2 + NEFT^2}$. ATM is the amount of Debit card transaction at ATM per transaction, POS is the amount of Point of Sale per POS transaction and NEFT is the amount of NEFT transaction per transaction. Since the annual data on technology indicator variables are not directly available, using their monthly figures from April to March, we compute the annual figures for these variables. As the data for T is available only from 2011-12, and net NPA ratio is not available for many banks, these two variables have not been included in estimating (9) initially. Then later, when we have added them in an alternative model, the number of observations reduced dramatically.

RESULTS AND DISCUSSION

(i) Efficiency Analysis Results: Table 1 presents the summary results of output oriented TE scores from CRS model, VRS model and scale efficiency from 2008-09 to 2019-20 in three alternative approaches of selecting outputs-inputs bundle. The average TE scores and scale efficiency varied widely across years and across approaches. In general, the magnitude of estimated average TE was higher in value-added approach (as it uses more number of outputs) than that in intermediation and operating approaches. Differences in mean efficiency values in various approaches are justified because in a deterministic frontier analysis, the statistical noise is not separated from inefficiency and the results are sensitive to the presence of extreme observations (Das and Ghosh, 2006).[5]

Let us consider the mean TE values in the CRS model. The intermediation approach indicates that it increased from 0.56 in 2008-09 to 0.8 in 2013-14. Then, it marginally declined to 0.79 in 2014-15. In 201-16, it suddenly came down to 0.56, due to the demonetization effect. After that, it continuously increased to 0.87 in 2019-20. It seems that the beginning of covid-19 pandemic from last quarter of 2019-20 did not affect the average efficiency.

Table 1: Average Technical Efficiency (CRS, VRS and Scale) of Indian Banks

Year	No. of Banks	CRS		VRS		Scale Efficiency	
		No. of Efficient Banks	Average Efficiency	No. of Efficient Banks	Average Efficiency	No. of Efficient Banks	Average Efficiency
Intermediation Approach							
2008-09	80	10	0.558	30	0.83	11	0.69
2009-10	81	14	0.622	31	0.861	16	0.731
2010-11	81	14	0.59	31	0.835	25	0.704
2011-12	87	18	0.634	38	0.837	21	0.718
2012-13	89	17	0.699	42	0.887	17	0.781
2013-14	90	23	0.796	49	0.93	23	0.852
2014-15	91	26	0.771	57	0.939	26	0.82
2015-16	93	15	0.558	35	0.77	15	0.728
2016-17	92	20	0.741	42	0.874	20	0.838
2017-18	87	24	0.804	47	0.906	23	0.877
2018-19	87	19	0.813	56	0.917	19	0.868
2019-20	86	37	0.867	42	0.871	27	0.896

[5] Strictly speaking, the mean score of TE is not comparable across years as it is constructed and computed in the DEA analysis to measure the relative efficiency against the frontier in each year and not an absolute efficiency.

Year	No. of Banks	CRS		VRS		Scale Efficiency	
		No. of Efficient Banks	Average Efficiency	No. of Efficient Banks	Average Efficiency	No. of Efficient Banks	Average Efficiency
Value Added Approach							
2008-09	80	29	0.898	42	0.938	29	0.952
2009-10	81	38	0.912	44	0.927	39	0.981
2010-11	81	35	0.889	38	0.91	37	0.963
2011-12	87	28	0.821	38	0.851	31	0.928
2012-13	89	31	0.834	38	0.881	31	0.932
2013-14	90	25	0.801	34	0.839	25	0.943
2014-15	91	30	0.844	40	0.869	30	0.957
2015-16	93	33	0.873	46	0.898	33	0.956
2016-17	92	26	0.822	37	0.883	27	0.92
2017-18	87	32	0.872	44	0.915	32	0.951
2018-19	87	11	0.59	30	0.714	11	0.832
2019-20	86	37	0.867	41	0.9	37	0.94
Operating Approach							
2008-09	80	6	0.66	22	0.874	6	0.758
2009-10	81	5	0.38	24	0.867	5	0.426
2010-11	81	7	0.626	29	0.883	7	0.706
2011-12	87	15	0.749	33	0.872	15	0.863
2012-13	89	13	0.734	30	0.87	13	0.846
2013-14	90	11	0.765	29	0.86	11	0.893
2014-15	91	9	0.724	30	0.859	9	0.848
2015-16	93	12	0.731	30	0.873	12	0.836
2016-17	92	11	0.724	28	0.853	11	0.848
2017-18	87	13	0.74	27	0.857	13	0.866
2018-19	87	13	0.67	24	0.8	13	0.847
2019-20	86	11	0.867	25	0.792	11	0.852

It is noticed that during the initial period of the global crisis (2008-09 to 2012-13), only less than 20 percent of banks were efficient (having above average TE value). In 2015-16 (demonetization year), only 15 percent of banks were efficient. Results of the value added approach indicate that the average TE (CRS) declined from 0.9 in 2008-09 to 0.8 in 2013-14 and it increased to 0.87 in 2015-16, indicating that the demonetization did not affect the performance of the Indian banking industry. In 2016-17, it marginally declined to 0.82. But in 2018-19 it suddenly came down to 0.59 and in 2019-20 it again increased to 0.87. Results of operating approach show that the mean TE value increased from 0.66 in 2008-09 to 0.77 in 2013-14. Then it started decreasing marginally till 2016-17. But it came down to 0.67 in 2018-19. However, in 2019-20, it again increased to 0.87. As per this approach, less than 15 percent of banks were efficient during the study period. Since there is a high degree of inefficiency during the study period, there is a greater possibility for Indian banks to improve their performance. For instance, the average efficiency was 86.7 percent in 2019-20 and so the Indian banks could improve their outputs by 13.3 percent without additional resources or they could produce the same level of outputs with 13.7 percent less inputs.

The summary results using the VRS model in table 1 indicate that in all three approaches, the average (pure) efficiency scores using the VRS model were relatively high as compared to the scores using the CRS model. In the intermediation approach, this change could be observed very clearly. For instance, the average efficiency score using the VRS model ranged between 0.77 (in 2015-16) and 0.94 (in 2014-15) as against the average score ranged between 0.56 (2015-16) and 0.87 (2019-20) using the CRS model. However, except the magnitude, the pattern of average score was more or less similar to the pattern observed using the CRS model. In the intermediation approach, in most of the years (8 out of 12), over 40 percent of banks were found to be purely technically efficient. One could observe more or less a similar pattern of average TE under VRS as in the case of TE in CRS. In the operating approach, one could find that the pattern of average TE (VRS) was similar to the pattern observed using the CRS model.

Besides, one could observe that the number of efficient banks in the CRS model and in the VRS model differ significantly, irrespective of the choices of various inputs and outputs. For instance, in the intermediation approach, 57 banks (out of 91) were efficient under VRS in 2014-15, while only 26 banks were efficient under CRS. That is, the remaining 31 banks failed to reach the CRS frontier due to scale inefficiencies. This clearly demonstrates the existence of sizable scale inefficiency among Indian banks. Thus, scale inefficiency is a serious problem of Indian banks.

Table 1 also reports the summary results of scale efficiency from 2008-09 to 2019-20. The intermediation approach indicates that the average scale efficiency increased from 0.69 in 2008-09 to 0.85 in 2013-14. It marginally declined to 0.82 in 2014-15. But in 21015-16 it suddenly came down to 0.73 and after that it started increasing. This pattern was more or less similar to the pattern observed for mean TE in the CRS method. In both the value added approach and the operating approach, one could observe that the respective pattern of average scale efficiency over the years was similar to that observed for mean TE in the CRS. Since the average scale efficiency estimates for Indian banks were below 90 percent for most of the study years in both intermediation approach and operating approach, it seems that with respect to their scale of operations, Indian commercial banks are likely to lose sizable output.

Table 2 reports the average efficiency scores in the CRS technology for four ownership groups of banks-SBIs, NBs, PBs, and FBs. As the trend for average efficiency in the CRS scheme and in the VRS scheme in Table 1 are the same, we concentrate on the former. The principal agent framework and public choice theory highlights the importance of the extent to which management is constrained by capital market discipline. The theoretical argument is that a lack of capital market discipline weakens the owners' control over management, enabling the latter to pursue their own interests, and giving fewer incentives to be efficient. Therefore, different ownership structures of banks may produce different levels of efficiency.

In the intermediation approach, the overall average efficiency score during 2008-09 to 2019-20 was 72.4 percent for foreign banks, 72.3 percent for nationalized banks, 67.6 percent for SBIs and 63.1 percent for private banks. In the operating approach, the average efficiency was 71.1 percent for foreign banks, 67.3 percent for NBs, 62.6 percent for private banks and 61.3 percent for SBIs. But in the value added approach, the average efficiency was 92.8 percent for NBs, 89.8 percent for SBIs, 80.1 percent for PBs and 79.7 percent for foreign banks. Except the nationalized banks, all other groups of banks obtained the last (fourth) rank in at least one approach in overall average score. The private banks obtained either third place or fourth place. These results suggest that the public sectors are more efficient than their private counterparts.

Year-wise results indicate that the average score in value added approach was relatively high as compared to average scores in other approaches for all groups of banks. It is noted that in the operating approach, SBIs obtained fourth rank in average score during 2013-14 to 2019-20. It also obtained either third or fourth rank in intermediation approach from 2014-15 to 2018-19 except in 2017-18. This is the concern. The demonetization effect is clearly seen in the intermediation approach. In 2015-16, the average score for all groups of banks declined significantly. This may be due to the fact that the intermediation approach considers all types deposits as inputs. Due to demonetization, all people were forced to deposits their old currencies in their bank deposits. Surprisingly, in other approaches, particularly in the value added approach, the average scores for almost all banks groups in 2015-16 increased from their respective scores in 2014-15.

Table 2: Average Efficiency (CRS) of Indian Banks by Ownership from 2008-09 to 2019-20

Year	State Bank and Its Associate Banks	Nationalized Banks	Private Sector Banks	Foreign Banks
Intermediation Approach				
2008-09	0.544	0.549	0.489	0.615
2009-10	0.592	0.618	0.53	0.694
2010-11	0.505	0.616	0.478	0.657
2011-12	0.665	0.659	0.567	0.649
2012-13	0.77	0.813	0.602	0.681
2013-14	0.821	0.906	0.687	0.787
2014-15	0.696	0.816	0.642	0.818
2015-16	0.444	0.518	0.427	0.652
2016-17	0.569	0.767	0.703	0.76
2017-18	0.799	0.773	0.787	0.8
2018-19	0.794	0.78	0.814	0.814
2019-20	0.911	0.862	0.848	0.765
Average	0.676	0.723	0.631	0.724
Value-added Approach				
2008-09	0.927	0.962	0.844	0.887
2009-10	0.943	0.955	0.828	0.936
2010-11	0.885	0.949	0.87	0.864
2011-12	0.871	0.926	0.799	0.772
2012-13	0.861	0.934	0.766	0.815
2013-14	0.83	0.929	0.749	0.756
2014-15	0.878	0.936	0.777	0.824
2015-16	0.937	0.937	0.852	0.843
2016-17	0.852	0.892	0.811	0.781
2017-18	0.966	0.963	0.884	0.776
2018-19	0.831	0.817	0.624	0.444
2019-20	1	0.94	0.811	0.863
Average	0.898	0.928	0.801	0.797
Operating Approach				
2008-09	0.654	0.665	0.617	0.689
2009-10	0.301	0.334	0.267	0.503

Year	State Bank and Its Associate Banks	Nationalized Banks	Private Sector Banks	Foreign Banks
2010-11	0.718	0.806	0.555	0.547
2011-12	0.737	0.82	0.666	0.756
2012-13	0.689	0.762	0.64	0.771
2013-14	0.722	0.812	0.728	0.765
2014-15	0.662	0.7	0.663	0.77
2015-16	0.673	0.693	0.683	0.777
2016-17	0.611	0.684	0.693	0.764
2017-18	0.627	0.695	0.707	0.751
2018-19	0.498	0.556	0.64	0.718
2019-20	0.465	0.552	0.651	0.72
Average	0.613	0.673	0.626	0.711

(ii) Inefficiency Model Results: Table 3 reports the tobit (full sample) estimation results of technical inefficiency equation (9). The dependent variable is technical inefficiency (1-TE) of jth bank in t period obtained using CRS technology from three alternative models-intermediation approach, value-added approach and operating approach. As expected, the capital adequacy ratio (CAR) has a negative and statistically significant effect at 1 percent level on inefficiency under operating approach. This highlights that the increased emphasis on the achievement of CAR helped banks to change their internal functioning, particularly in the system of credit evaluation, risk assessment and management, quality of manpower, and the quality of internal control and corporate governance and improved financial soundness in turn contributed to reduction in inefficiency. However, the CAR has positive coefficient in other models, but it is not significant in the intermediation model.

As expected, the return on assets (ROA) has a negative parameter and is statistically significant at 1 percent level in both value added approach and operating approach, indicating that more profitable banks have lower inefficiency levels. But this variable is not significant in the intermediation approach. The SIZE has a negative and significant impact on efficiency under all three models, implying that large banks appear to be relatively less inefficient compared to smaller banks. The BRANCH has a positive and significant association with inefficiency under the operating approach and a negative and significant relation under the value-added approach. But it is not significant under intermediation approach. Thus, this has had mixed results. The AGE is positively and significantly related to inefficiency in all three models, indicating that age old banks appear to be more inefficient than the younger ones. The coefficients associated with ownership dummies indicate that both foreign banks and nationalized banks are more efficient than private domestic banks. The SBIs inefficiency is more or less similar to the inefficiency of private banks. In both intermediation and operating approaches, the banks were less efficient in the pre-demonetization period than the post demonetization period. But in the value added approach, the banks were less efficient in the post demonetization period.

Table 3: Tobit Estimation Results of Technical Inefficiency (Full Sample) Model

Variables	Mean	S.D	Intermediation Approach		Value Added Approach		Operating Approach	
			Coef.	t	Coef.	T	Coef.	T
CAR	37.418	65.391	0.0001	0.14	0.0004	2.31	-0.0009	-6.83
ROA	0.764	2.223	0.0011	0.25	-0.0222	-5.2	-0.0356	-10.99
SIZE	9.846	2.514	-0.0414	-6.35	-0.0131	-2.05	-0.0266	-5.75
BRANCH	1206.563	2443.119	0.0001	0.52	-0.0001	-3.66	0.0001	2.24
AGE	67.966	54.393	0.0005	2.72	0.0006	3.59	0.0004	3.48
Dummy for SBIs	0.059	0.236	0.0027	0.06	-0.0260	-0.61	-0.0196	-0.62
Dummy for NBS	0.220	0.415	-0.0490	-1.68	-0.1361	-4.71	-0.0591	-2.85
Dummy for FBs	0.472	0.499	-0.2860	-9.99	-0.0991	-3.65	-0.1408	-7.06
Dummy for Pre-Demonetization	0.574	0.495	0.0571	2.91	-0.0644	-3.43	0.0574	4.15
Intercept			0.7411	10.05	0.3271	4.58	0.6328	12.1

Variables	Mean	S.D	Intermediation Approach		Value Added Approach		Operating Approach	
			Coef.	t	Coef.	T	Coef.	T
TIEI	0.296	0.246						
TIEV	0.164	0.209						
TIEO	0.316	0.206						
Var (e.TIE)			0.0841	18.75	0.0728	16.99	0.0020	20.78
LLH			-389.9029		-377.322		15.0083	
Pseudo R Square			0.14		0.153		0.1449	
N	1044		1044		1044		1044	

Table 4 presents the tobit model estimation of inefficiency model including two additional variables-net NPA ratio and technology Index T. As indicated earlier, these variables have not been available for many banks for many years, the number of observations reduced from 1044 to 363. The CAR has a negative impact on inefficiency as expected in the intermediation approach, but it is not significant. However, in the value added and the operating approaches, this variable has a positive and significant impact. As expected, the ROA is negatively related to inefficiency under value added approach and operating approach. The SIZE is negatively and significantly related to inefficiency under all approaches as in Table 3. The AGE is negatively and significantly associated with inefficiency in the intermediation approach. But it is not significant in other approaches. The BRANCH has a positive and significant coefficient in operating approach, but is not significant in other approaches.

Ownership dummies indicate that in the intermediation approach, both SBI group and foreign group of banks were less efficient than private banks. In the value-added approach, foreign banks were more efficient than private banks. In the operating approach, the foreign banks were more efficient than private banks and nationalized banks were less efficient than private banks. Banks had relatively less inefficiency in the pre-demonetization period. The technology index has mixed results. In the intermediation approach, it has a negative and significant effect on inefficiency. In the operating approach, it has a positive and significant effect on inefficiency. In the value added approach, it is not a significant factor in determining the in-efficiency. Unexpectedly, the net NPA ratio is not significant in all three approaches.

Table 4: Tobit Estimation Results of Technical Inefficiency Model Including NPA Ratio and Technology Index (2011-12 to 2019-20)

Variables	Mean	S.D	Intermediat-ion Approach		Value Added Approach		Operating Approach	
			Coef.	t	Coef.	t	Coef.	t
CAR	13.31	2.45	-0.0035	-0.66	0.0141	2.77	0.0152	4.96
ROA	0.45	1.23	0.0196	1.69	-0.0392	-3.58	-0.0449	-4.87
SIZE	11.91	1.18	-0.0640	-4.46	-0.0802	-5.52	-0.0730	-9.07
BRANCH	2547.54	3404.53	-0.0001	-0.49	-0.0001	-0.61	0.0001	5.28
AGE	82.02	49.17	-0.0007	-3.38	0.0001	0.31	-0.0002	-1.61
Dummy for SBIs	0.02	0.16	0.2790	2.08	0.1204	0.74	-0.1065	-1.46
Dummy for NBs	0.42	0.49	0.0277	0.91	-0.0373	-1.20	0.0346	1.97
Dummy for FBs	0.14	0.35	0.0755	2.27	-0.0965	-2.91	-0.0923	-4.74
Net NPA Ratio	3.202	3.123	0.0016	0.33	-0.0062	-1.29	0.0004	0.18
Technology Index	444.819	247.335	-0.0002	-5.10	0.0012	0.28	0.0001	2.13
Dummy for Pre-Demonetiza tion	0.46	0.50	-0.0656	-2.97	-0.0098	-0.45	-0.0344	-2.68
Intercept			1.2390	7.55	0.9488	5.78	0.9210	9.97
TIEI	0.2783	0.172						
TIEV	0.139	0.146						
TIEO	0.301	0.120						
var(e.TIE)			0.02471	20.97	0.0203	16.33	0.0085	0.72
LLH			78.383		2.469		307.173	
Pseudo R Square			-2.02		1.03		-0.43	
N	363		363		363		363	

SUMMARY AND POLICY IMPLICATIONS

This study has analyzed the technical efficiency of Indian commercial banks and its determinants during 2008-09 to 2019-20. It has employed the standard DEA methodology model to estimate year-wise efficiency under CRS technology, pure efficiency (VRS) and scale efficiency. To check the robustness of the results, it has used three alternative approaches to choose inputs and outputs of banks, namely the intermediation approach, the value-added approach and the operating approach. Then, it has employed the tobit estimation procedure to identify the factors determining the efficiency.

The results indicate that the average TE scores and scale efficiency scores varied widely across years and approaches. The magnitude of the estimated mean TE (using CRS model) was higher in the value-added approach than in the other two approaches. In the intermediation approach, the average TE increased from the initial global crisis period, but suddenly came down in 2015-16 due to the demonetization effect. After that it increased continuously till 2019-20, indicating that the covid-19 pandemic which started in the last quarter of 2019-20 did not affect the efficiency of Indian banks. In other approaches, the demonetization did not affect the mean TE values. The trends in mean TE in the VRS model and scale efficiency over the years in respective approaches are more or less the same pattern observed in the CRS model.

As there exists a high degree of inefficiency of several banks during the study period, there is a greater possibility for these banks to improve their performance. The average efficiency was 86.7 percent in 2019-20, indicating that on an average the Indian banks could improve their outputs by 13.3 percent without additional resources or they could produce the same outputs with 13.7 percent less inputs.

The number of efficient banks under the CRS model and under the VRS model differ significantly, irrespective of the choices of various inputs and outputs. In the intermediation approach, 57 banks (out of 91) were efficient in VRS in 2014-15, while only 26 banks were efficient in CRS. That is, the remaining 31 banks failed to reach the CRS frontier due to scale inefficiencies. This result is a clear indication of the existence of sizable scale inefficiency among Indian banks. Thus, scale inefficiency is a serious problem of Indian banks and they are likely to lose sizable output.

Results also indicate that banks with larger capital adequacy ratio are more efficient. More profitable banks, large banks and new banks are also more efficient. Both foreign banks and nationalized banks appear to be more efficient than private domestic banks. The technology effect is mixed. In the intermediation approach, it has a negative and significant effect on inefficiency, but in the operating approach, it has a positive and significant effect on inefficiency. It seems that Indian banks are still learning the new technology to reap the maximum possible outputs. Unexpectedly, the net NPA ratio is not significant in all three approaches.

Our results are not directly comparable with the results of past studies as most of them do not provide estimates for recent years. However, the estimates two past studies may be comparable to some extent. In Kaur and Gupta (2015), the average efficiency of Indian banks was 91.2 percent during 2009-2013. The SBI group has the highest average efficiency, followed by private banks and nationalized banks. The magnitude of average efficiency of our study in the value added approach during this period was almost closer, but relatively low (around 76 percent). In our study, both foreign and nationalized banks emerged as more efficient than both SBI and private groups. Goyal *et. al.*, (2019) shows that the average efficiency of the Indian banking industry was 73.44 percent in 2015-16. This value is closer to the value in the operating approach of our study. We hope that this study will be useful to international agencies, and other stakeholders in evaluating and improving the performance of the banking sector in India.

REFERENCES

Aigner, D.J. and S.F. Chu (1968), On Estimating the Industry Production Function, *American Economic Review 58*, 826-39.

Aigner, D., Lovell, C.A. Knox and Schmidt, Peter (1977), Formulation and Estimation of Stochastic Frontier Production Function Models, *Journal of Econometrics 6*, 21-37.

Ataullah, A., T. Cockerill and H. Le, (2004), Financial Liberalization And Bank Efficiency: A Comparative Analysis of India and Pakistan, *Applied Economics* 36, 1915-1924.

Banker, R.D., A. Charnes and W.W. Cooper (1984), Some Models For Estimating Technical and Scale Inefficiencies In Data Envelopment Analysis., *Management Science 30,* 1078-1092.

Bansal, Sanjeev (2015), The Impact of Technology on the Performance of Indian Banking Industry: An Empirical Study, Macro Research Project, Indian Institute of Banking.

Battese, G.E. and T.J. Coelli (1992), Frontier Production Functions, Technical Efficiency and Panel Data: With Application To Paddy Farmers in India, *Journal of Productivity* 3, 153–69.

Benston, G.J. (1965), Branch Banking and Economies of Scale, *Journal of Finance* 20, 312–331.

Berger, A.N. and D.B. Humphrey (1997), Efficiency of Financial Institutions: International Survey and Direction for Future Research, Working Paper No. 97-05, The Wharton Financial Institutions Centre, University of Pennsylvania.

Bhattacharya, A., C.A.K. Lovell and P. Sahay (1997), The Impact of Liberalization on the Productive Efficiency of Indian Commercial Banks, *European Journal of Operational Research* 98, 332–45.

Bhattacharyya, A. and Sudeshna Pal (2013), Financial Reforms and Technical Efficiency in Indian Commercial Banking: A Generalized Stochastic Frontier Analysis, *Review of Financial Economics* 22, 109-117.

Charnes, A., W.W. Cooper and E. Rhodes (1978), Measuring the Efficiency of Decision Making Units, *European Journal of Operational Research 2*, 429–444.

Das, A., A. Nag and S.C. Ray (2005), Liberalization, Ownership and Efficiency in Indian banking: A Nonparametric Analysis, *Economic and Political Weekly 40*, 1190-1197.

Das, A. and S. Ghosh (2006), Financial Deregulation and Efficiency: An Empirical Analysis of Indian Banks During the Post Reform Period, *Review of Financial Economics* 15(3), 193–221.

Das, A., and S. Ghosh (2009), Financial Deregulation and Profit Efficiency: A Non-Parametric Analysis of Indian Banks, Munich Personal RePEc Archive.

Das, A. and S.C. Kumbhakar (2012), Productivity and Efficiency Dynamics in Indian Banking: An Input Distance Function Approach Incorporating Quality of Inputs and Outputs, *Journal of Applied Econometrics* 27(2), 205-234.

Dwivedi, A.K. and D.K. Charyulu (2011), Efficiency of Indian Banking Industry in the Post-Reform Era, Working Paper No. 2011-03-01, IIM, Ahmedabad.

Elyasiani, E. and S. Mehdian (1995), The Comparative Efficiency Performance of Small and Large US, Commercial Banks in the Pre- and Post-Deregulation Era, *Applied Economics* 27, 1069–1079.

Farrell, M.J. (1957), Generalized Farrell Measures of Efficiency: An Application to Milk Processing in Swedish Dairy Plants", *Economic Journal* 89, 294-315.

Fecher, F. and P. Pestieau (1993), Efficiency and Competition in OECD Financial Services", in H.O. Fried and S.S. Schmidt (eds.), The Measurement of Productive Efficiency: Techniques and Applications, Oxford University Press, 374-385.

Goyal, J., M. Singh, A. Singh and A. Agarwal (2019), Efficiency and Technology Gaps In Indian Banking Sector: Application Of Meta-Frontier Directional Distance Function DEA Approach, *The Journal of Finance and Data Science* 5(3), 156-172.

Gupta, Omprakash K., Yogesh Doshit and Aneesh Chinubhai (2008). Dynamics of Productive Efficiency of Indian Banks, *International Journal of Operations Research* 5(2), 78-90.

Hao, J., W. Hunter and W. Yang (1999), Deregulation and Efficiency: The Case of Private Korean Banks, Federal Reserve Bank of Chicago Working Paper, 27.

Hjalmarsson, L., I. Andersson and A. Mlima (2000), Swedish Banking Efficiency and Productivity in an International Perspective", Estocolmo: Supplement No. 28 to the Government Inquiry on the International Competitiveness of the Swedish Financial Sector.

Jaffry, S., Y. Ghulam, S. Pascoe and J. Cox (2007), Regulatory Changes and Productivity of the Banking Sector in the Indian Sub-Continent, *Journal of Asian Economy* 18, 415-438.

Jondrow J., C.A.K. Lovell, I.S. Materov and P.Schmidt (1982), On the Estimation of Technical Inefficiency in the Stochastic Frontier Production Model, *Journal of Econometrics* 19, 233-238.

Mahesh, H.P. and S.Bhide (2008), Do Financial Sector Reforms Make Commercial Banks More Efficient? A Parametric Exploration of the Indian Case, *Margin: The Journal of Applied Economic Research* 2 (4), 415-441.

Maudos, J. and J.M. Pastor (2001), Cost and Profit Efficiency in Banking: An International Comparison of Europe, Japan and USA, *Applied Economics Letters* 8, 383–387.

Meeusen, W. and J.V.D. Broeck (1977), Efficiency Estimation From Cobb–Douglas Production Function With Composed Error, *International Economic Review* 18, 435–44.

Mohan Ram, T.T. and S.C. Ray (2004), Comparing Performance of Public and Private Sector Banks: A Revenue Maximization Efficiency Approach, *Economic and Political Weekly* 39, 1271–1275.

Kaur, Sandeep, and P.K. Gupta (2015), Productive Efficiency Mapping of Indian Banking System Using Data Envelopment Analysis, 16th Annual Conference on Finance and Accounting, ACFA Prague, May 2015, *Economics and Finance 25*, 227 – 238.

Rangarajan, C. and B. Sambamurthy (2021), Preventing the Pile of NPAs, (Business Line, August 3. Retrieved from https://www.thehindubusinessline.com/opinion/preventing-the-pile-up=of-npas-ii/article35704889.ece.

Ravirajan, K. and K.R. Shanmugam (2021), The Effect of Technology On Financial Performance of Indian Bank, *Indian Journal of Economics and Business* 20 (3), 1043-1056.

Ray, S.C. and A. Das (2010), Distribution of Cost and Profit Efficiency: Evidence from Indian Banking, *European Journal of Operational Research 201*, 297-307.

Sealy, C. W. and J. Lindley (1977), Inputs, Outputs And A Theory of Production and Cost At Depository Financial Institutions, *Journal of Finance* 32, 1252–1266.

Shanmugam, K.R. and A. Das (2004), Efficiency of Indian Commercial Banks During The Reform Period, *Applied Finance Economics* 14, 681-686.

Shanmugam, K.R. and Nigam Rakesh (2020), Impact of Technology on the Financial Performance of Indian Commercial Banks : A Clustering Based Approach. Innovation and Development 10 (3), 433-449.

Shyu, J. (1998). Deregulation and Bank Operating Efficiency: An Empirical Study of Taiwan Banks, *Journal of Emerging Markets* 3, 27–46.

Tandon, D., K. Tandon and N. Malhotra (2014), An Evaluation of the Technical, Pure Technical and Scale Efficiencies in the Indian Banking Industry Using Data Envelope Analysis, *Global Business Review* 15(3), 545–563.

Timmer, C.P. (1971), Using a probabilistic frontier production function to measure technical efficiency", *Journal of Political Economy 79*, 776-94.

Viswanathan, K.G. (2010), The Global Financial Crisis and Its Impact on India, *Journal of International Business and Law* 9(1), 1-22. Available at: http://scholarlycommons.law.hofstra.edu/jibl/vol9/iss1/2

MSE Monographs

* Monograph 34/2015
  Farm Production Diversity, Household Dietary Diversity and Women's BMI: A Study of Rural Indian Farm Households
  Brinda Viswanathan
* Monograph 35/2016
  Valuation of Coastal and Marine Ecosystem Services in India: Macro Assessment
  K. S. Kavi Kumar, Lavanya Ravikanth Anneboina, Ramachandra Bhatta, P. Naren, Megha Nath, Abhijit Sharan, Pranab Mukhopadhyay, Santadas Ghosh, Vanessa da Costa and Sulochana Pednekar
* Monograph 36/2017
  Underlying Drivers of India's Potential Growth
  C.Rangarajan and D.K. Srivastava
* Monograph 37/2018
  India: The Need for Good Macro Policies *(4th Dr. Raja J. Chelliah Memorial Lecture)*
  Ashok K. Lahiri
* Monograph 38/2018
  Finances of Tamil Nadu Government
  K R Shanmugam
* Monograph 39/2018
  Growth Dynamics of Tamil Nadu Economy
  K R Shanmugam
* Monograph 40/2018
  Goods and Services Tax: Revenue Implications and RNR for Tamil Nadu
  D.K. Srivastava, K.R. Shanmugam
* Monograph 41/2018
  Medium Term Macro Econometric Model of the Indian Economy
  D.K. Srivastava, K.R. Shanmugam
* Monograph 42/2018
  A Macro-Econometric Model of the Indian Economy Based on Quarterly Data
  D.K. Srivastava
* Monograph 43/2019
  The Evolving GST
  Indira Rajaraman

MSE Working Papers
Recent Issues

* Working Paper 241/2023
  Impact of Transfers on Elementary Education Expenditure and Measuring Equalization Transfers to Indian States
  Jyotsna Rosario and K. R. Shanmugam
* Working Paper 242/2023
  Application of Volatility-Managed Portfolios in the Context of a Volatility Index
  Abhishek Subramanian and Parthajit Kayal
* Working Paper 243/2023
  Spatial Durbin Model of Regional Incomes in India: The Role of Public, Private and Human Capital
  Vivek Jadhav & Brinda Viswanathan
* Working Paper 244/2023
  Financing Urban Services Through Cost Recoveries from Semi-Public goods – The Case of Drinking Water Supply
  J V M Sarma
* Working Paper 245/2023
  Corporate Social Responsibility of Indian Banks
  Brijesh C. Purohit
* Working Paper 246/2023
  Role of State in Food and Nutrition security: A case of Telangana
  Gummadi Sridevi, Amalendu Jyotishi, Matta Srinivas & Balaji
* Working Paper 247/2023
  The Impact of Monetary and Fiscal Stimulus on Stock Returns During the COVID-19 Pandemic
  Chinmaya Behera, Badri Narayan Rath & Pramod Kumar Mishra
* Working Paper 248/2023
  Deflecting Economic Sanctions: Do Trade and Political Alliances Matter?
  Devasmita Jena, Akash & Prachi Gupta
* Working Paper 249/2023
  The Lausanne School of Economics
  S. Pridiksha & T. Archana

---

* Working papers are downloadable from MSE website http://www.mse.ac.in

$ Restricted circulation