Determinants of Efficiency of Commercial Banks in India After Global Crises

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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 008-09 to 019-20, utilizing the DEA method and three alternative approaches to choosing 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 greater scope for improving their performances. Sizable scale inefficiency exists, and banks are likely to lose sizable output. The results also indicate that banks with a larger capital adequacy ratio, young banks, 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

INTRODUCTION

Due to globalization and overwhelming interdependence amongst the financial sectors of the countries, the global financial crisis has affected almost all economies and financial sectors of nations. However, the Indian banking industry had no direct exposure to the subprime mortgage assets, and the Indian economy had quickly recovered from the slowdown (Viswanathan, 010). 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 bad loans (NPAs), the consolidation of Information Technology based efforts since 012, demonetization (2015-16), and covid-19 pandemic from the last quarter of the 019-20 (Ravirajan and Shanmugam, 021).[1]

In 008, India ranked fourth lowest among G-20 countries in the non-performing assets (NPAs) ratio. But in 020, 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%) in 008-09 to Rs. 10388 billion (11.2%) in 017-18.[3] As of March 31, 020, the quantum of NPA (Gross) of SCBs declined to Rs. 8998 billion (8.2%). The NPA (Gross) amounted to Rs. 6783 billion

(10.3%) in Public Sector Banks, Rs. 096 billion (5.5%) in Private Domestic Banks, and Rs. 102 billion (2.3%) in Private Foreign Banks.[4]

The high degree of NPAs and the necessity of making provisions could affect the profitability/efficiency and liquidity of Indian banks. The RBI's latest Financial Stability Report warned that the NPA levels would likely worsen again, and they might reach 11.2 percent in March 022 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, 021).

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, 015). However, different banks have different technology-implementing capabilities. Further, technological advancements have led to the emergence of new security risks like cybercrime, hacking, etc. The demonetization announced by the Government of India in 016 also created a further mess in the operations of the banking industry in India. The Covid-19 pandemic also affected the economy from the last quarter of 019-20, and it could have affected the performance of the banking industry.

Thus, the Indian banking industry has faced an uncertain environment for its operations due to these developments, as they have brought positive and 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 the 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 public sector banks (PSBs). The economic liberalization in the early 1990s helped the entry of many new private and foreign banks. Subsequently, the Indian banks adopted international best practices. Several prudential and provisioning norms were introduced, and a competitive environment was created.

Although a handful of studies emerged in the literature to examine the performance of the 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 008-09 to 019-20 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 (also called service provision or value added) approach, the intermediation (or asset) approach, and the operating or income-based approach (Hjalmarsson et al., 000). 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 analyzing the effect of demonetization, NPA, and technology adoption on the efficiency of banks in India.

The rest of this study proceeds as follows. Section provides a brief review of the literature. Section 3 explains the data, model, and variables used in this study, while Section 4 presents and discusses the study's empirical results. The final Section 5 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 the ratio between output(s) and input(s), the latter is 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 efficiency: the data envelopment analysis (DEA) and the stochastic frontier approach (SFA). While they have advantages and limitations, the DEA has been widely used in measuring the efficiency of financial institutions like banks as it successfully handles 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 rewritten 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 the space of a 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 using 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.

$$Q_i = Q_i^* e^{-u} = AX_1^{\beta_1}X_2^{\beta_2}e^{-u} \tag{1}$$

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

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

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

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

For efficient banks, 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 the mean value of log output and is a constant that can be dropped without any loss. The linear programming (LP) formulation of this problem can be specified as:

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

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 there could be many outliers with full (100%) efficiency in the Aigner and Chu Model. He suggested that a 3% sample with full efficiency value can be deleted as outliers as they are affected by statistical errors. Then again, solve the LP problem with the remaining 97% 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 a 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: 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 an inefficiency term (u). The variance of the distribution of the inefficiency term conditional on the composite error term does not vanish when the sample size increases (Jondrow et al., 1982). Second, estimating the model and separating 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 the regressors included in the model. In addition, this is applicable only to 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.

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 1 countries, Berger and Humphrey (1997) remarked that 116 studies were published during 1992-1997and most of them analyzed the efficiency of US banks. They also found that these studies' annual average technical efficiency ratios were around 77% (median 82%).

The major issue in existing studies is the selection of inputs and outputs sets. These studies employ three approaches: the production (also called value-added) approach, the intermediation (or asset) approach, and the operating or income-based approach (Hjalmarsson et al., 000; Das and Ghosh, 006). 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, 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 the efficiency of banks in developed nations employ the DEA approach. For instance, 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 Taiwan’s banking industry's overall efficiency from 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 networks 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 the 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, & 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 the convergence in performance between public and private sector banks in the post-reform period. Das et al. (2005) measured the cost efficiency, revenue efficiency, and profit efficiency of Indian banks from 1997 to 003 using the DEA. They 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 fewer NPAs were technically more efficient from 1992 to 003. Using the DEA approach, Gupta et al. (2008) showed that the productive efficiency from 1999 to 003 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. They found that public sector banks were more efficient than their private counterparts, 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% in 005 to 97.9% in 010. Besides SBIs, all remaining group banks have improved their efficiency over the years. Using the DEA approach, Kaur and Gupta (2015) showed that the mean efficiency score was 91% for all 57 banks in the sample from 009 to 013; 94.5% for SBIs; 92% for PBs; and 86.9% for NBs. Tandon et al. (2014) used DEA to measure the efficiency of Indian banks (19 NBs, 15 PBs, and 10 FBs) from 009 to 012. Only 7 out of 44 banks operated on the efficiency frontier. The efficiency scores did not vary much across the three groups of banks. Goyal et al. (2019) used the DEA approach and data for 66 banks in 015-16 and found that the average efficiency of the Indian banking sector was 73.44%.

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 the overall technical efficiency of India and Pakistan's banking industry improved after 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 commercial banks' cost and profit efficiencies. Das and Ghosh (2009) also found that the liberalization of the banking sector in India generally produced positive results in improving banks' cost and profit efficiencies.

Das and Kumbhakar (2012) observed that the efficiency of public sector banks has surpassed that 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% during the study period. Public sector banks were more efficient than private and foreign banks. The review 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 Farrell's (1957) non-parametric deterministic (DEA) model, which was popularized by Charnes et al., (1978) to measure the efficiency of Indian banks from 008-09 to 019-20. 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 the 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 the aggregation of outputs and inputs. The following mathematical programming problem will determine the optimal weights:

$$Max_{u,v}(u'Q_i/v'X_i) \tag{5}$$

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

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:

$$Max_{\mu,\upsilon}(\mu'Q_i) \tag{6}$$

Subject to: $\upsilon'X_i = 1$
$\mu'Q_j - \upsilon'X_j \leq 0$, $j = 1,2,...,N$ and
$\mu, \upsilon \geq 0$

where the notation changes from u and v to μ and υ is because 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:

$$Min_{\theta,\lambda} \ \theta \tag{7}$$

Subject to: $-q_i + Q\lambda \geq 0$,
$\theta x_i - X \lambda \geq 0$, and
$\lambda \geq 0$.

where θ is a scalar and λ is a N × 1 vector of constants. This involves some fewer constraints than the multiplier form and, hence, is 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 optimal scale, then CRS assumption is not valid, so VRS is relevant. Banker et al., (1984) modified the CRS model into the VRS model by adding the convexity constraint: N1'λ=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:

$$Min_{\phi,\lambda} \ \phi \tag{8}$$

Subject to: $-\phi q_i + Qi \geq 0$,
$x_i - X \lambda \geq 0$
$N1'\lambda=1$, 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 shown in Table 1:

TABLE 1
INPUTS AND OUTPUTS OF BANKS IN DIFFERENT APPROACHES

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 standard Tobit regression method for panel data is employed:

$$Tai_t = Z'\gamma + e_{at} \qquad If\ RHS\ is\ > 0 \tag{9}$$

= 0 otherwise

Z is the 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 008-09 to 019-20 (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, we compute the annual figures for these variables using their monthly figures from April to March. As the data for T is available only from 011-12, and net NPA ratio is not available for many banks, these two variables have not been initially included in estimating (9). Then later, we have added them in an alternative model, where the number of observations reduced dramatically.

RESULTS AND DISCUSSION

Efficiency Analysis Results

Table presents the summary results of output-oriented TE scores from the CRS model, VRS model, and scale efficiency from 008-09 to 019-20 in three alternative approaches of selecting outputs-inputs bundle. The average TE scores and scale efficiency varied widely across years and approaches. In general, the magnitude of the estimated average TE was higher in the value-added approach (as it uses more outputs) than that in the 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 extreme observations (Das and Ghosh, 006).[5]

Let us consider the mean TE values in the CRS model. The intermediation approach increased from 0.56 in 008-09 to 0.8 in 013-14. Then, it marginally declined to 0.79 in 014-15. In 01-16, it suddenly came down to 0.56, due to the demonetization effect. After that, it continuously increased to 0.87 in 019-20. The beginning of the covid-19 pandemic from last quarter of 019-20 did not affect the average efficiency.

TABLE 2
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
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 global crisis (2008-09 to 012-13), only less than 0% of banks were efficient (having above-average TE value). In 015-16 (demonetization year), only 15% of banks were efficient. Results of the value-added approach indicate that the average TE (CRS) declined from 0.9 in 008-09 to 0.8 in 013-14 and it increased to 0.87 in 015-16, indicating that the demonetization did not affect the performance of the Indian banking industry. In 016-17, it marginally declined to 0.82. But in 018-19 it suddenly came down to 0.59; in 019-20 it again increased to 0.87. Results of the operating approach show that the mean TE value increased from 0.66 in 008-09 to 0.77 in 013-14. Then it started decreasing marginally till 016-17. But it came down to 0.67 in 018-19. However, in 019-20, it again increased to 0.87. As per this approach, less than 15% 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% in 019-20, so the Indian banks could improve their outputs by 13.3% without additional resources, or they could produce the same level of outputs with 13.7% fewer inputs.

The summary results using the VRS model in table indicate that in all three approaches, the average (pure) efficiency scores using the VRS model were relatively high compared to the CRS model scores. 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 015-16) and 0.94 (in 014-15) whereas the average score ranged between 0.56 (2015-16) and 0.87 (2019-20) using the CRS model. However, except for the magnitude, the pattern of the 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% 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 average TE (VRS) pattern was similar to the pattern observed using the CRS model.

Besides, one could observe that the number of efficient banks in the CRS and VRS models 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 014-15, while only 6 banks were efficient under CRS. 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 for Indian banks.

Table 2 also reports the summary results of scale efficiency from 008-09 to 019-20. The intermediation approach indicates that the average scale efficiency increased from 0.69 in 008-09 to 0.85 in 013-14. It marginally declined to 0.82 in 014-15. But in 1015-16 it suddenly came down to 0.73, and then 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% for most of the study years in both the intermediation and operating approaches, it seems that with respect to their scale of operations, Indian commercial banks are likely to lose sizable output.

Table 3 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 VRS scheme in Table 1 are the same, we concentrate on the former. The principal-agent framework and public choice theory highlight 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 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 008-09 to 019-20 was 72.4% for foreign banks, 72.3% for nationalized banks, 67.6% for SBIs, and 63.1% for private banks. In the operating approach, the average efficiency was 71.1% for foreign banks, 67.3% for NBs, 62.6% for private banks, and 61.3% for SBIs. But in the value-added approach, the average efficiency was 92.8% for NBs, 89.8% for SBIs, 80.1% for PBs, and 79.7% for foreign banks. Except for 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 rank (place) or fourth rank. These results suggest that the public sectors are more efficient than private ones.

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. In the operating approach, SBIs obtained fourth rank in average score from 013-14 to 019-20. It also obtained third or fourth rank in intermediation approach from 014-15 to 018-19 except in 017-18. This is the concern. The demonetization effect is clearly seen in the intermediation approach. In 015-16, the average score for all groups of banks declined significantly. This may be because the intermediation approach considers all types of deposits as inputs. Due to demonetization, all people were forced to deposit 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 015-16 increased from their respective scores in 014-15.

TABLE 3
AVERAGE EFFICIENCY (CRS) OF INDIAN BANKS BY OWNERSHIP FROM 008-09 TO 019-20

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
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

Inefficiency Model Results

Table 4 reports the Tobit (full sample) estimation results of technical inefficiency equation (9). The dependent variable is the technical inefficiency (1-TE) of jth bank in t period obtained using CRS technology from three alternative models-intermediation, value-added, and operating approaches. As expected, the capital adequacy ratio (CAR) has a negative and statistically significant effect at 1% level on inefficiency under the 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 a reduction in inefficiency. However, the CAR has a 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% 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 are relatively less inefficient than 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 the 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 more inefficient than the younger ones. The coefficients associated with ownership dummies indicate that foreign 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 pre-demonetization than post demonetization. But in the value-added approach, the banks were less efficient in the post-demonetization period.

TABLE 4
TOBIT ESTIMATION RESULTS OF TECHNICAL INEFFICIENCY (FULL SAMPLE) MODEL

			Intermediation Approach		Value Added Approach		Operating Approach	
Variables	**Mean**	**S.D**	**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
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 5 presents the Tobit model estimation of the inefficiency model, including two additional variables-net NPA ratio and technology Index T. As indicated earlier, these variables were not available for many banks for many years. The number of observations reduced from 1044 to 363. The CAR hurts inefficiency, as expected in the intermediation approach, but it is insignificant. However, this variable has a positive and significant impact in the value added and the operating approaches. 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 the operating approach but is not significant in other approaches.

Ownership dummies indicate that in the intermediation approach, both the SBI group and the 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, 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 5
TOBIT ESTIMATION RESULTS OF TECHNICAL INEFFICIENCY MODEL INCLUDING NPA RATIO AND TECHNOLOGY INDEX (2011-12 TO 019-20)

			Intermediation Approach		Value Added Approach		Operating Approach	
Variables	**Mean**	**S.D**	**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-Demonetization	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 008-09 to 019-20. 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 used three alternative approaches to choose banks' inputs and outputs: the intermediation approach, the value-added approach, and the operating approach. Then, it employed the Tobit estimation procedure to identify the factors determining efficiency.

The results indicate that the average TE 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 slowed in 015-16 due to the demonetization effect. After that, it increased continuously till 019-20, indicating that the covid-19 pandemic, which started in the last quarter of 019-20, 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 several banks have a high degree of inefficiency during the study period, there is a greater possibility for these banks to improve their performance. The average efficiency was 86.7% in 019-20, indicating that, on average, the Indian banks could improve their outputs by 13.3 % without additional resources or produce the same outputs with 13.7% less inputs.

The number of efficient banks under the CRS model and the VRS model differs significantly, irrespective of the choices of various inputs and outputs. In the intermediation approach, 57 banks (out of 91) were efficient in VRS in 014-15, while only 6 were efficient in CRS. 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 for Indian banks, and they are likely to lose sizable output.

Results also indicate that banks with larger capital adequacy ratios are more efficient. More profitable banks, large banks, and new banks are also more efficient. Foreign and nationalized banks appear to be more efficient than private domestic banks. The technology effect is mixed. The intermediation approach 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 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 of two past studies may be somewhat comparable. In Kaur and Gupta (2015), the average efficiency of Indian banks was 91.2 percent during 009-2013. The SBI group has the highest average efficiency, followed by private and nationalized banks. The magnitude of the 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, foreign and nationalized banks emerged as more efficient than SBI and private groups. Goyal et al. (2019) show that the average efficiency of the Indian banking industry was 73.44 percent in 015-16. This value is closer to the value in the operating approach of our study. We hope this study will be useful to international agencies and other stakeholders in evaluating and improving the performance of the banking sector in India.

ENDNOTES

1. Shri Shaktikanta Das, Governor of Reserve Bank of India in his speech at the Mint's Annual Banking Conclave (on February 4, 020) 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 3% against invested money (Economic Survey, 020) due to poor credit growth, and NPAs draw attention and necessity to improve banking performance to support growth to seize any detrimental effects.
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.

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