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ORIGINAL ARTICLE

The Efficiency of Indian Banks: A DEA, Malmquist and SFA Analysis with Bad Output

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Abstract
In the recent years, the burgeoning non-performing assets (NPAs) have become a matter of concern and scrutiny in India as the surge in NPAs impinge on the credit services of the banks, make the banks vulnerable to external shocks, leave them with less cushion in case of idiosyncratic shocks and thus, leading to the abrasion of their productive capital. In this backdrop, some very normative questions become inevitable. How has the technical efficiency of the banks in India changed over time especially after the asset quality review, 2016? How does undesirable output like non-performing assets (NPA) impact the technical efficiency of banks in India? Does technical efficiency have anything to do with the ownership of banks? These are some of the questions we endeavour to answer through our study by employing three cornerstone methodologies namely DEA, Malmquist productivity index and SFA in the banking sector for the period 2014–2020.The results obtained from employing DEA and SFA both points toward the heterogeneity in the technical efficiency of public sector banks and private sectors banks operating in India. The results obtained from DEA are majorly three-fold. Firstly, private sector banks have fared better than the public sector banks, while the SFA scores show that the public sector ownership promotes efficiency. Secondly, the technical efficiency of public sector banks has consistently been falling from 2014 to 2017 only to rise in the later years, evidence corroborated by the SFA scores also. This trend is in line with the slew of measures adopted by the government and RBI like AQR and mergers of banks subsequently. Although according to the Malmquist productivity decomposition results, we find that productivity of banks have been falling for the period 2014–2020. Thirdly, the non-performing assets are detrimental for the efficiency of the banks. Like DEA, the SFA results also shows the presence of technical inefficiency in the Indian banking sector and a similar trend in the technical efficiency wherein the scores decline from 2014 through 2017 and then they rise subsequently.

Keywords Bank efficiency · Frontier · Panel data · Bad output · DEA · SFA · Malmquist Index · TOBIT · Time-varying parameter · NPA · India

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JEL Classification G21 · G20 · C14 · D24

Introduction

The progress of the financial sector is deemed as sine qua non of robust economic growth and development. Additionally, banks play a critical role in the financial market hence, any management crisis would be entailed by an unprecedented degree of financial predicament, social cost, and thus has a potential for economic crisis. Banks play a very critical role in the development process of an economy (Tsolas and Charles 2015) given that they channelize the funds to their most productive uses in the economy. McKinsey's Report (2019) has raised concerns over the banks across the world as growth decelerates and has further stressed upon the urgency to consider a 'suite of radical organic or inorganic moves'. Drawing a parallel between the banks in emerging countries and in developed nations, the report has identified waning Return On Tangible Equity (ROTE) from 20% in 2013 to 14.1% in 2018 especially, on account of digital disruption in emerging nations in contrast with the developed nations, where the banks have managed to strengthen productivity and have witnessed a surge in ROTE from 6.8 to 8.9% over the same period. Interestingly, India in this scenario is an interesting case with the World Bank anticipating India's share in global investments to almost double by 2030 and designating the nation as a "Powerhouse in global savings and investment".

With 158,373 functioning offices of commercial banks in India as on March, 2021, there are 14.1 banks and 20.95 ATMs per 1,00,000 adults in India (World Bank, 2019) making the Indian banking system one of the largest in the world. Adapting to the technological shift globally, since 2015, Indian banking sector has taken a quantum leap as the banks transformed their business models from brick-and-mortar to digital modes of transaction. But, for a well-functioning banking sector what matters apart from the deposits is the mechanism through which the savings are allocated as investments or credit. The banking sector in India is characterized by large chunks of non-performing assets which came into limelight post 2016 when the asset quality review (AQR) was conducted. The AQR basically classifies the loans into performing and non-performing. According to the central bank of the country, the RBI, the percentage of the bad loans jumped to as high as 80% in the financial year 2016 due solely to the AQR. Since bad loans greatly influence the efficiency of the banks, the AQR has shown us how better our banking system is doing and also the need to monitor and evaluate the performance of these banks. The AQR has impacted almost all of the Indian public sector banks while only a few major private sector banks were impacted. Therefore, post AQR the gap between the efficiencies of public and private sectors banks is bound to decrease given the fact that these banks may actively deal with the bad loans in the aftermath of AQR. The burgeoning NPAs have become a matter of concern and scrutiny because it impinges on the credit services of the banks, make them vulnerable to external shocks, leaves them with less cushion in case of idiosyncratic shocks and thus, leading to the abrasion of their productive capital. Ghosh et al. (2016) by developing a baseline regression model have provided corroborative evidence on the vulnerability of the banks due to soaring non-performing loans. The vicious cycle demands urgent measures to gauge the bank's financial health, necessitating the adoption of a cocktail-based approach as chalked out by the RBI.

In the recent past, there has been a shift in policy toward the privatization of the publically owned banks. There is thus a need to analyse the relative performance of the nationalized banks as well as the privately owned banks so as to evaluate the recent policy change. The bank is considered as efficient if there is no way it can produce more outputs with the given level of the inputs or vice versa. In the economics jargon such an efficiency concept is called the technical efficiency. Since India has been growing rapidly post the economic liberalization and is currently one of the fastest growing economies, the importance of robust and efficient banking system is evident. An efficient and vibrant banking system in addition to generating huge positive externalities also enhances the overall efficiency of all the financial system in a country. In line with this some normative questions become inevitable. How technically efficient are banks in India? How does undesirable output like non-performing assets (NPA) impact the technical efficiency of banks in India? Does technical efficiency have anything to do with the ownership of banks? And what is the degree of heterogeneity in the banks in India based on the ownership? These are some of the questions we endeavour to answer through our study. The reason stems from the fact that following the slowing domestic and global activity the studies assessing the impact of non-performing loans on profitability and size of the banks have gained traction among scholars. Measurement of the performance of banks has the potential to gauge the relative efficiency and recognize the main factors underpinning the inefficiency. Among other techniques, by using data envelopment analysis (DEA), stochastic frontier approaches (SFA) and financial ratio analysis, performance of the banking sector could be evaluated (Chiu et al. 2016). Emrouznejad and Yang (2018) have presented a survey of the first 40 years of scholarly literature in DEA and have reported that there has been an 'exponential growth' in the number of publications related to theory and applications of Data Envelopment Analysis (DEA).

Economic efficiency of a bank comprises allocative and technical efficiency. Technical efficiency on the one hand measures the potential of a bank to derive maximum output from the limited input; allocative efficiency on the other hand takes into consideration the prices of inputs and gauges the ability of the firm to produce the output optimally. Estimation of these efficiency demands the determination of an unknown production frontier. DEA determines this production frontier non-parametrically and SFA estimates the same parametrically (Coelli et al., 2005). Taking a cue from the literature we strive to corroborate our findings with the help of DEA, Malmquist productivity index and SFA. Furthermore, through two different techniques, parametric and nonparametric, our findings have important implications for the policymakers in improving the performance and technical efficiency of India's banking sector. Our purpose is not to comment on the validity and efficacy of the models but to underscore the inconsistencies in the result obtained from both these methodologies in the current context. We have employed the dataset extracted from RBI for the period 2014–2020. For the analysis we used STATA and the MaxDEA software.

The rest of this paper proceeds as follows. In "Background" we provide a brief background of the study following which we briefly review the earlier studies concerning the efficiency of banks in India with special emphasis on accounting for NPAs in "Literature Survey". In "Objectives and Contribution of the Current Study" we present the objectives of the current study. Data and methodology in "Data and Methodology" is followed by the results in "Empirical Results". We end the paper with the conclusions and policy implication in "Conclusion and Policy Implications".

Background

Structure of the Indian Banking System

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

Techniques of Measuring Bank Efficiency

Measuring the efficiency of a bank is not a very straight forward problem. This is due to the fact that not all banks are the same in terms of the environments they are

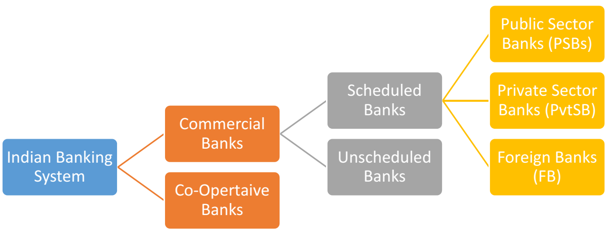


Fig. 1 Structure of Indian Banking System

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

Literature Survey

The concept of economic efficiency indicates the best attainable operation of a commodity or service. Thus, it is a sum and outcome of static and dynamic efficiency (Petrou 2014; Cabral 2000; Church and Ware 2000; Holmstrom and Tirole 1989; Schmalensee 1989). While the static efficiency operates under allocative and productive efficiency, dynamic efficiency occurs with the introduction of new products and improvisation of the existing production techniques in the market (Petrou 2014). In a nutshell, economic efficiency stems from the process of curtailing waste and augmenting the efficiency. The application of static efficiency, especially the productive efficiency has gained traction among researchers in the recent past. The literature suggests two main approaches for determining the technical efficiency of banks: parametric techniques, like stochastic frontier analysis (SFA), and non-parametric techniques, like data envelopment analysis (DEA) (Bayeh et al. 2018). Stochastic frontier analysis (SFA) was proposed by Aigner et al. (1977) and Meeusen and Van den Broeck (1977) independently which involves an econometric method (Coelli et al. 2005). Data envelopment analysis (DEA) on the other hand was first used in Charnes and Cooper (1984). It involves mathematical programming methods to construct a frontier by using the data. The efficient frontier of the production set is typically represented by the technically efficient combinations of input and output. This frontier depicts the maximal outputs that can be produced for some given underlying inputs (Bogetoft 2012). A standard DEA follows some assumptions like-free disposability (producing less with more), returns to scale; convexity (averages are preferred over extreme); additivity and replicability (Bogetoft and Otto 2010). Thus, DEA assumes weak disposability according to which there is no possibility for the reduction of undesired outputs freely. Furthermore, this safe assumption has less power. “In other words, desirable and undesirable outputs are null joint which means that good output production inevitably involves bad output generation” (Shirazi and Mohammadi 2019). Contrary to this safe assumption of weak disposability which has less power, is the strong disposability (Scheel 2001). However, in reality, decision making units experience some undesirable outputs that are ought to be curtailed. Fare et al. (1989) was the first paper to treat the matter of desirable and undesirable outputs asymmetrically wherein the authors had developed a directional-vector approach in output-orientation (Tone 2004).

To buttress the research on an alternative methodology, Scheel (2001) in their study has classified the approaches to incorporate undesirable output into direct and indirect approaches. In order to treat the undesirable output, in the direct approach, original output data is employed on which further modifications of the assumptions pertaining to the structure of technology are made. On the other hand, in the indirect approach the values of the undesirable outputs are transformed into monotonically decreasing functions which are further included as desirable output in the technology set. The underlying rationale behind transforming the undesirable output is the analogy that the values of the transformed function are indirectly proportional to the undesirable output (Scheel 2001). Indirect method has been a popular method among researchers (Cherchye et al. 2015). However, the method is also subject to certain limitations which have been clearly pointed out by Cecchini et al. (2018). Firstly, the indirect method doesn’t incorporate the reduction in input and increment in output simultaneously i.e. the models are either output-oriented or input-oriented and does not allow us to estimate input and output slacks concomitantly. Secondly, the results of indirect approach are highly sensitive to the type of transformation being made. Taking a cue from the limitation stated above a non-radial parametric approach proposed by Chung et al. (1997) is employed by researchers. A non-radial parametric method allows for the expansion of output along with reduction of inputs. Unlike the indirect method, the model illustrated in Chung et al. (1997) makes use of directional distance function as a component in the new productivity index modeling the production of both good and bad output. Barros et al. (2012) have categorized the literature on the non-radial models into three groups—Russell measure (Fare and Lovell) with an input-oriented form, Additive model (Charnes et al.) and Slacks-based model (Tone 2004).

Among the non-radial and non-oriented measures, Slack-Based Measure has gained popularity among the researchers. This model does away with the assumption of proportionate changes in inputs and outputs, and has directly dealt with slacks (Tone 2011). Furthermore, it has been designed to meet three conditions—unit invariance (measure is unwavering in the unit of data), monotone (monotone decreasing in each slack in inputs and output) and translation invariance (invariant under the parallel translation of coordinate systems (Tone 2001). Additionally, in Tone (2001) the author has put-forward a slack-based measure with data envelopment analysis which has been further extended in Tone (2004) to handle the non-separable desirable and undesirable output (SBM-NS output model) (Table 1).

Table 1 Categorization of DEA models based on the findings of Tone (2004)

	Radial	Non-radial
Oriented	Radial and oriented	Non-radial and oriented
Non-oriented	Radial and non-oriented	Non-radial and non-oriented (captures all the aspect of efficiency)

Radial model: a model wherein proportional increase or decrease of outputs/inputs is the primary concern in the measurement of efficiency. This model does not take into account slacks. Oriented model: input and output oriented model. In the input oriented model, output is inconsiderable and in the output-oriented model, input is held trivial

Halkos and Petrou (2019) have provided a critical review of four possible ways followed in the literature to treat undesirable output in data envelopment analysis. These methods are prima facie ignoring the undesirable output from the production function, treating them as regular inputs, treating the undesirable output as normal outputs and performing necessary transformations to take the undesirable output into account. Yang and Pollitt (2007) have also proposed a model wherein they have incorporated weak and strong disposability features among various undesirable outputs based on the technical nature of the undesirable outputs.

In pursuit of establishing a pragmatic model where the production process also generates undesirable output, several attempts have been made in the past. The efficiency of banks is a matter of deep concern among bank managers and regulators (Bayeh et al. 2018). Given the uncertainty, an efficient bank supports credit growth, and provides the best possible products and services at the lowest cost. Accordingly, any proposed strategic policy and bank regulation should consider potential bank outputs in relation to invested inputs (Bayeh et al. 2018). Literature provides enough evidence that the development of the banking sector positively predicts growth, capital accumulation, and productivity improvements (Levine and Zervos 1998a, b).

The literature suggests primarily two main approaches used for measuring bank efficiency: parametric techniques (stochastic frontier analysis—SFA), and non-parametric techniques (data envelopment analysis—DEA) (Bayeh et al. 2018). Some selected studies employing DEA and SFA are Berg et al. 1993; Bhattacharyya et al. 1997; Charles and Kumar 2012; Chatterjee 1997; Fall et al. 2018; Favero and Papi 1995; Goyal et al. 2019; Kohers et al. 2000; Kumar et al. 2010, 2016; Kumbhakar and Sarkar 2003; Mester 1996; Miller and Noulas 1996; Mohan and Ray 2004; Rangrajan and Mempilly 1972; Resti 1997; Saha and Ravisankar 2000; Sahoo et al. 2007; Sathye 2003; Silva et al. 2017; Stewart et al. 2016; Subrahmanyam 1993; Thoraneenitiyan and Avkiran 2009; Thyagarajan 1975; Wanke et al. 2020; Wheelock and Wilson 1995; Yue 1992) among others.

A plethora of researchers in the past have attempted to evaluate the efficiency of Indian commercial banks using the data envelopment analysis (DEA). The average efficiency scores of the Indian banks are comparable with the mean efficiency score of the banks in other parts of the world (Sathye 2003) despite the fact that the banks in India face surmounting non-performing assets compared to the other emerging economies like China, Mexico and Brazil (Hafsal et al. 2020). While most of the earlier studies have conclude that the public sector banks have performed better than private sector banks (Bhattacharyya et al. 1997; Sathye 2003; Sengupta and De 2020; Ray and Das 2010; etc.) recently various studies have found the private sector banks outperforming the nationalized banks (Tzeremes 2015; Mukta 2016). In the recent times post the asset quality review (AQR) 2016, the Indian commercial banks have been facing the problem of huge non-performing assets (Hafsal et al. 2020). According to the financial survey report 2017, the bad loans problem has been a serious issue facing the public sector banks than the private banks. The gross NPA of public sector banks was 14.6% of the total loans while it was 11.2% for the other banks. The higher bad loans of the public sector banks have greatly impacted them adversely. Rajaraman and Vasishtha (2002) show that the public sector banks which have relatively higher NPAs also have less efficiency. While existing literature show that reducing the non-performing assets as well as optimizing on staff and bank branches will have efficiency gains (Sathye 2003) we would like explore ways in which we can take the undesirable non-performing assets into account while calculating the efficiency scores of the Indian banks.

Majorly, there are four methods in which bad outputs can be accounted for in the DEA methodology; ignoring the undesirable outputs, treating undesirable outputs as inputs, treating the undesirable outputs in the non-linear models and applying the necessary transformations:

a) *Ignoring the undesirable outputs* The easiest way in which bad outputs can be treated in the DEA is to simply ignore it altogether from the production process. However, this might not be the best way to deal with the undesirables since it simply assumes that bad outputs have no role in the evaluation process of the decision making units hence this will give the misleading outcomes (Yang and Pollitt 2009). In many cases, undesirable outputs are usually the by-products such that they cannot be separated from the desirable outputs. Therefore, ignoring these bad outputs might not be a feasible strategy. Hailu and Veeman (2001), Pathomsiri et al. (2008), Yang and Pollitt (2009) adopt this strategy to deal with bad outputs.
b) *Treating undesirable outputs as inputs* Another simple yet more convenient way to deal with bad outputs is treat them as inputs. The basic rationale behind this approach of accounting for undesirable output is that both the normal inputs as well as the undesirable outputs should be decreased. Researchers who used this simple and innovative method include Reinhard et al. (2000), Hailu and Veeman (2001), De Koeijer et al. (2002), Lansink and Bezlepkin (2003). In particular Fukuyama and Weber (2008) used this approach to model the undesirable non-performing assets in the loan production process of the Japanese banks.
c) *Treating the undesirable outputs in the non-linear models* This procedure includes the use directional distance function to evaluate the efficiency of the decision making units when there are both the desirable as well as the undesirable outputs involved in the production process. However, in this approach as well the desirable outputs are maximized while the undesirable outputs as well as the inputs are minimized directionally.
d) *Applying the necessary transformations* Under this approach researcher apply some monotonic transformations such that the desirable outputs are maximized

while undesirable outputs are minimized at the same time. One such transformation is to simply treat the undesirable outputs as negative of it such that it now becomes desirable.

In this paper we adopt the second approach to account for undesirable non-performing assets in the DEA methodology. Guo and Wu (2013) while differentiating between the desirable and undesirable outputs extended the traditional data envelopment analysis model to rank the decision making units, accounting for the undesirables in arriving at the efficiency scores. They treat the undesirable outputs in their model as inputs based on the fact that these bad outputs incur costs to the decision making units and they want to reduce them while trying to hold the current level of output constant. In our study we adopt Guo and Wu (2013) extended model where we include Net NPAs as input in our models to calculate the efficiency scores of Indian public and private sector banks. Table 2 below presents the review of few select studies that have incorporated the undesirable outputs in their models.

Objectives and Contribution of the Current Study

The present study delves into developing a different framework to compare the banks in India which are here viewed as production units in the realm of rising NPAs. The objectives of the present study discern itself from the proliferating stream of literature construing the technical efficiency of banks in India and abroad. In the current study we intend to work in the following directions. Firstly, we would work out the technical efficiency of commercial banks in India through DEA and SFA. Secondly, we would strive to ascertain the change in productivity in the Indian banking sector over 2014–2020 and disentangle the change in productivity due to catching up phenomenon and shifting of the production frontier. Thirdly, in order to explain the variability in the efficiency score we would perform Tobit analysis in a panel framework.

On the basis of the results obtained from TOBIT we would further comment on the appropriateness of the models. Fourthly, to give a framework/model for analyzing bad outputs in the DEA and the SFA framework. Fifthly, we would carry out a comparative analysis of the technical efficiency scores obtained from DEA and SFA across private and public sector banks over time. Sixthly, given the panel data set of 2014–2020 we would endeavour to advocate policy framework for ameliorating the efficiency and productivity of the Indian banking system during and post COVID.

Data and Methodology

Data

Input–Output Selection

There are two major approaches to the input and output selection in the data envelopment analysis. Benston (1965) developed the Production Approach, which

Table 2 Selected review of research articles incorporating undesirable output

Paper	Area of study	Methods	Variables	Undesirable output
Park and weber (2006)	Korea	directional technology distance function and sequential reference sets	MODEL 1: inputs: full-time labor, physical capital which equals the asset value of premises and fixed assets, and total deposits. Desirable outputs: commercial loans, personal loans, securities Undesirable output: non-performing loans MODEL 2: include fee income as an additional output MODEL 3: include demand deposits along with the outputs from Model 2	Non-performing loans
Barros et al. (2012)	Japan	Weighted Russell directional distance model (WRDDM), Data envelopment analysis (DEA)	Inputs: number of employees, deposits, premises outputs: securities, loans, bad loans	Non-performing loans (NPLs)
Chang et al. (2012)	china	Input slack—based productivity index (Färe–Lovell efficiency measure into the Luenberger productivity index)	Inputs: labor, total fixed assets, and funds (total deposits and short-term funding) Outputs: total loans, other earning assets	Non-performing loans (loan loss reserves are subtracted from total loans)
Assaf et al. (2013)	Turkey	Bayesian limited-information likelihood (LIL)	Inputs: number of employees, bank capital, fixed assets and deposits. Outputs: loans, securities, off-balance sheet assets and securities	NPLs
Fujii et al. (2014)	India	weighted Russell directional distance model (WRDDM), Malmquist Index and Luenberger Productivity Indicator	intermediation approach Inputs: labour, deposits and premises Outputs: other earning assets, customer loans and bad loans	NPLs

Table 2 (continued)

Paper	Area of study	Methods	Variables	Undesirable output
Jayaraman and Srinivasan (2014)	India	Nerlovian profit indicator, Directional distance function, DEA	Input: borrowed funds, branches, staff, cost of borrowed funds, per branch cost, Staff cost Output: non-interest income, gross NPA, return on deployed funds, return on non-interest income, NPA	Gross NPA
Wang et al. (2014)	China	Data envelopment analysis (DEA), Two-stage DEA	Input: fixed assets, labour Intermediate measure: deposits Output: interest income, non-interest income, bad loans	Bad loans
Chiu et al. (2016)	Taiwan	Two-stage DEA and meta-frontier DEA with undesirable output	Inputs: personnel expenses, fixed assets, operational expenses Desirable outputs: amount of loans, non-Interest incomes, investment revenues Intermediate: amount of deposits	Allowance for loan losses
Puri and Yadav (2014)	India	Fuzzy data envelopment analysis (FDEA-UFO)	Inputs: labour and total deposits Output: performing assets = total advance – NPA	NPA
Aghayi and Maleki (2016)	Iran	Data envelopment analysis, directional distance function, interval approach, robust optimization	Inputs: the term and amount of deposits, interest rate on each loan Output: gross balance of nongovernmental facilities, non-governmental deductions, desirable outputs: profit Undesirable output: non-performing loans	Non-performing loans

Table 2 (continued)

Paper	Area of study	Methods	Variables	Undesirable output
Zha et al. (2016)	china	Data envelopment analysis Slacks-based measure Dynamic two-stage model	*Profit-oriented approach* Inputs (cost components): personal expenses and interest expenses Outputs (revenue components): interest income and non-interest income	Non-performing loan generated in the previous year
Arora et al. (2018)	India	Meta frontier approach (DEA)	Inputs: physical capital, labour, loanable funds Bad output: NPA Outputs: net-interest margin, other income,	NPA
Zhou et al. (2019)	china	Multi-period three-stage DEA, Triangular type-2 fuzzy undesirable outputs (input-oriented models;slack-based measure (SBM); three-stage DEA)	Shared inputs: employees' salaries, Fixed assets Intermediates: deposits, dues from banks Input: interest payments Carryovers: unused assets Intermediates: total loans Final outputs: net interest incomes Non-performing loans	NPA
Hafsal et al. (2020)	India	two-stage network DEA,	Inputs: fixed assets, employees, and loanable funds (deposits + borrowings) Intermediaries: advances and investments Final outputs: net interest income, non-interest income Undesirable output: NPA	NPA

Table 2 (continued)

Paper	Area of study	Methods	Variables	Undesirable output
Safiullah and Shamsuddin (2020)	28 countries	Stochastic meta-frontier model with undesirable output	Inputs: total deposits, physical capital, labour Desirable outputs: total loans, other earning assets, total non-interest incomes Determinants of inefficiency: bank size, bank age, publicly traded banks, capitalization, bank concentration ratio, growth rate of per capita GDP	Non-performing loans, NPLs to gross-loan ratios
Zhao et al. (2021)	China	Two network models (productivity and profitability stage)	Inputs: interest costs, Operation costs Output: deposits, interest incomes, non interest incomes, nonperforming loans	Non-performing loans

views banks primarily as the service providers. The inputs are mainly the labour, capital and other physical assets, while the outputs generally are the loans and deposits. Sealey and Lindley (1977) developed the Intermediation Approach which considers a bank as an intermediary between the lenders and borrowers. The main function of the bank, according to this approach, is thus to make funds available using its inputs. The major inputs under this approach include labour, capital, assets etc. while outputs include loans, investments among other variables. According to Berger and Humphrey (1997), intermediation approach is the more appropriate for evaluating the bank efficiency at an aggregated level while production approach is more suited at the branch level. Arrif and Luc (2008) have used total deposits, number of employees and fixed assets as inputs and investments and total loans as outputs in their study. Luo (2003) also use number of employees, total assets and shareholders' equity as inputs and profits and revenue as outputs. In the Indian context, Kumar and Gulati (2010) have used advances and investment as output variables and physical capital (value of fixed assets), labour (number of employees) and loanable funds (deposits and borrowings) as inputs. In this study we follow Das et al. (2005), Kumar and Gulati (2010) and Mukta (2016) we use three output variables investment, loans, non-interest income and four input variables borrowings, labour, fixed assets and equity. In addition, the extended version of the DEA model incorporates NPA, a bad output, (Mukta 2016) as an input variable in the model to compute the technical and scale efficiency scores.

Variables and Data Sources

Table 3 describes all the variables that we use in this study. The data for the study has been extracted from the Statistical Tables relating to Banks in India, issued by the Reserve Bank of India. The time period of the study is 2014–2020. We choose this time period because there have been numerous studies that have worked with the previous data, however our purpose is in this paper is to analyse the efficiency score in the recent period so as to evaluate the recent policy shift toward privatization/ mergers of the nationalized banks. Appendix Table 13 gives the summary statistics of the various input and output variables over the time period 2014–20. On an average the public sector banks have higher amount of investments, advances, non-interest incomes, borrowings, fixed assets, labour expenses and equity. In line with this from the descriptive statistics presented in Appendix Table 13 we could observe a high degree of variation in the NPAs of the public sector banks over the private sector banks.

Table 3 Description of variables

Nature of variables	Variable name	Variable description	Hypothesis	Data source
Output variables	Investments	Investments by the bank	Positive impact on technical efficiency	Annual report of RBI on banks
	Advances	Advances by the bank (loans)	Positive impact on technical efficiency	Annual report of RBI on banks
	Non-Interest Income	Income earned other than interest (commission, brokerage, etc.)	Positive impact on technical efficiency	Annual report of RBI on banks
Input variables	Borrowings	Borrowings by the bank	Negative impact on technical efficiency	Annual report of RBI on banks
	Labor expenses	Payments to and provisions for employees	Positive impact on technical efficiency	Annual report of RBI on banks
	Fixed Assets	Fixed assets	Positive impact on technical efficiency	Annual report of RBI on banks
	Equity	Shares of the bank	Positive impact on technical efficiency	Annual report of RBI on banks
	Net NPA	Net NPAs as on March 31 (current ear)	Negative impact on technical efficiency	Annual report of RBI on banks
	Size	Total assets of the bank	Positive impact on technical efficiency	Annual report of RBI on banks
Regression Variables	Relative size	Total assets of the bank/the total assets of all SCHEDULED public and pvt. sector banks	Positive impact on technical efficiency	Annual report of RBI on banks
	Profit	Net profit of the bank	Positive impact on technical efficiency	Annual report of RBI on banks
	Ownership	Dummy variable taking value 0 for public sector banks and 1 for Pvt. Banks	Private sector banks have positive impact on efficiency	Annual report of RBI on banks
	Net NPA/advances	Proportion of bad loans of the bank	Negative impact on technical efficiency	Annual report of RBI on banks

Methods

Data Envelopment Analysis (DEA)

In this study we use both the CCR (1978) and the BCC (1984) models to evaluate the efficiency scores of the Indian public and private sector banks. Following Guo and Wu (2013) we augment the models such that the undesirable outputs enter the constraints. That is, let there be N decision making units, each DMU_n (n = 1, 2, …, N) employs m inputs to produce s desirable outputs and k undesirable outputs. The inputs, desirable outputs and undesirable outputs of DMU_n are respectively given by x_in (i = 1, …,m), y_rn (r = 1, …, s), b_tn (t = 1, …, k). Assuming strong disposability and that the inputs and bad outputs can be reduced proportionately while holding desirable output constant, we can find the relative efficiency of DMU_nas follows.

Input Oriented CCR Model Incorporating Undesirable Outputs

$$\min \theta_p$$

Subject to

$$\sum_{n=1}^{N} \lambda_n x_{in} \leq \theta_p x_{ip}, i = 1,2, \dots, m;$$

$$\sum_{n=1}^{N} \lambda_n y_{rn} \geq y_{rp}, r = 1,2, \dots, s;$$

$$\sum_{n=1}^{N} \lambda_n b_{tn} \geq \theta_p b_{tp}, t = 1,2, \dots, k;$$

$\lambda_n \geq 0, n = 1,2, \dots, N$ for Constant Returns to Scale technology.

Imposing the restriction, $\sum \lambda_n = 1$ we get the input oriented BCC Variable Returns to Scale model. The dual of above input oriented CCR model is given by the following output oriented CCR Model.

Output Oriented CCR Model Incorporating Undesirable Outputs

$$Max \sum_{r=1}^{s} u_r y_{rp}$$

Subject to

$$\sum_{r=1}^{s} u_r y_{rn} - \sum_{i=1}^{m} v_{in} - \sum_{t=1}^{k} \omega_t b_{tn} \leq 0, \forall_n$$

$$\sum_{i=1}^{m} v_i x_{ip} + \omega_t b_{tp} = 1,$$

$$u_r, v_i, \omega_t \geq 0, \forall_r \forall_i, \forall_t$$

Scale Efficiency Scale efficiency is simply given by the ratio of TE with CRS technology and TE with VRS technology. Thus

$$SE = \frac{TE^{CRS}}{TE^{VRS}}$$

Productivity Change: Malmquist Productivity Index

The Malmquist productivity index measures the productivity change over the years and subsequently decomposes this TFP change into the technological change and the efficiency change. The Malmquist productivity index requires a panel dataset to measure the TFP growth.

The output oriented Malmquist productivity growth index as given by Fare et al. (1994) is given by

$$m_o\left(y_{t+1}, x_{t+1}, y_t, x_t\right) = \left[\frac{d_o^t\left(x_{t+1}, y_{t+1}\right)}{d_o^t\left(x_t, y_t\right)} \times \frac{d_o^{t+1}\left(x_{t+1}, y_{t+1}\right)}{d_o^{t+1}\left(x_t, y_t\right)}\right]^{1/2}$$

This index represents the productivity growth from point (y_t, x_t) to point (y_{t+1}, x_{t+1}). The index is a geometric mean of two output based Malmquist productivity indices where one index uses the period t technology and the other uses the period t+1 technology. The value greater than 1 for the index represents a positive TFP growth and a value less than 1 represents a negative TFP growth.

Second Stage Regression Analysis: Tobit Model

After getting the efficiency scores from the first part of the study we next run a Tobit regression in the pooled framework as well as a Tobit regression in the panel setting to look for the sources of this efficiency, regressing the various technical efficiency scores on the explanatory variables like relative size, profits, Net NPA as a proportion of total advances, and ownership of the bank. Formally,

$$TE_b = \beta_0 + \beta_1 relativesize_b + \beta_2 profit_b + \beta_3 (NetNPA/Advances)_b + \beta_4 ownership_b + \varepsilon_b$$

where relative size refers to the total assets of the bank as a proportion of assets of all scheduled commercial banks, profit is the net profit of the bank. Net NPA/Advances refers to the net NPAs of the bank as a proportion of total advances. Ownership is the dummy variable taking value 1 if the bank is a private sector bank and zero otherwise. We also run a random effects Tobit model

$$TE_{bt} = \beta_0 + \beta_1 relativesize_{bt} + \beta_2 profit_{bt} + \beta_3 (NetNPA/Advances)_{bt} + \beta_4 ownership_{bt} + v_{bt} - u_{bt}$$

Ahmad et al. (2015) finds that the size is not a significant factor explaining the efficiency scores of the banks. Taking the total assets as the proxy for size of the bank, Kumar and Gulati (2010) find that smaller banks perform better than the larger banks. Along the similar lines, Ariff and Luc (2008) also find that large sized banks perform less efficiently than the smaller banks. Goswami et al. (2019) also find that bank size is not a significant factor. Thus existing literature suggests that the sign of the coefficient of size is expected to be negative and insignificant. Sharma et al. (2012) finds a positive and significant relationship between profits of a bank and the efficiency. We therefore expect out estimate of coefficient on profit to be positive and significant. Similarly, Ahmad et al. (2015) and Sharma et al. (2012) find a positive and significant relationship between public ownership and technical efficiency of banks. Das and Ghosh (2006) show using a Tobit regression that the banks with fewer non-performing assets are more efficient than those with very high NPAs. They also find public ownership of banks as a positive and significant factor explaining the efficiency.

Stochastic Frontier Analysis (SFA)

Among the two main approaches of frontier models, other than the most used parametric, linear programming technique named DEA with free disposal hull, there is a parametric model called stochastic frontier analysis (SFA). SFA assumes that most decision making units/firms are either very close to the frontier or are on the frontier. Furthermore, the inefficiency (DMUs away from the frontier) component in SFA can assume any form of distribution- half-normal, truncated normal or exponential. SFA is called parametric because the methodology requires the specification of functional form and establishing distributional assumptions on the inefficiency and noise term, but has the merit that it naturally handles noise in the data (Strange et al. 2021; Kumbhakar and Lovell 2003; Bogetoft and Otto 2011). Similar to the DEA model, the SFA model could be applied in a panel setting. The results obtained from DEA and SFA in most of the studies present contrasting inefficiency and moderately different rankings (Humphrey 2019). The stochastic frontier approach, independently proposed by Aigner et al. (1977) and Meeusen and van den Broeck (1977) specify a composed error with two components: a one-sided error (for non-negative inefficiency effects) and random component. Battese and Coelli (1995) have assumed that inefficiency effects are a function of some factors specific to DMU. We have chosen SFA to complement DEA because we aim at exploring the elasticities of the factors that explain the production and inefficiencies in banks.

In SFA, functional form plays an important role in the estimation of efficiency. There are four kinds of functional form; constant elasticity of substitution (especially, Cobb–Douglas), linear, quadratic, and the translog specification (Baumol et al. 1983). The linear functional form is the simplest but cannot evaluate interactions between factors. The quadratic functional form is well defined for zero values but is rarely employed in efficiency analysis. The Cobb–Douglas functional form is widely used and requires further assumptions on the elasticities of substitution in contrast with the translog function which provides a second-order differential approximation and the results provide heuristic explanation. Under the SFA, three different types of efficient frontiers are used to estimate managerial performance comprising cost, revenue, and profit frontiers (Kohers et al. 2000).

$$y_{it} = f\left(x_{it}, \beta\right)e^{U_{it}}, U_{it} = u_{it} - v_{it} \text{ where i} = 1, 2......., \text{n}$$

$\mathrm{y_{it}}$ = output of bank i in time t, $\mathrm{x_{it}}$ = vector($1 \times \mathrm{K}$) of input used by bank i in period t, β = vector ($\mathrm{K} \times 1$) of unknown parameters to be estimated, $\mathrm{u_{it}}$ = systematic random error, $\mathrm{v_{it}}$ = non − negative random error component and technical inefficiency effects.

$$u_{it} \sim i.i.d\left(0, \sigma_u^2\right), v_{it} \sim i.i.d., N\left(\mu, \sigma_v^2\right)cov\left[x, u_{it}\right] = 0, cov[x, v_{it}] = 0, cov[u_{it}, v_{it}\right] = 0$$

$\mathrm{u_{it}}$ subsumes measurement error and other exogenous factors beyond the control of banks).

A major advantage of panel data in SFA is that we can investigate the changes in technical efficiencies over time which is not possible in cross-section data. Based on the technical inefficiency effects there are two structures which are often considered namely time-invariant inefficiency model and the time-varying inefficiency effects model. In the time- invariant inefficiency model the inefficiency effects could be written as:

$$u_{it} = u_i, i = 1, \dots ..I; \quad t = 1, \dots .T$$

Here, the model would either be fixed effects or random effects. Fixed effect model could be determined from standard regression and the random effects model by either OLS or MLE.

On the other hand, in the time-varying inefficiency model we assume that the technical efficiency changes over time (Coelli et al. 2005).

$$u_{it} = f(t) \cdot u_i$$

Here, if we look at the f(.) this may take either of the two forms:

$$\text{Kumbhakar (1990)} : \mathrm{f(t)} = \left[1 = \exp\left(\alpha \mathrm{t} + \beta \mathrm{t}^2\right)\right]^{-1}$$

Or

$$\text{Battese and Coelli (1992)} : \mathrm{f(t)} = \exp\left[\eta(\mathrm{t} - \mathrm{T})\right]$$

Both these models propose the estimation of parameters using the method of MLE through which we can separate the inefficiency and technological change (Coelli et al. 2005). It is worth mentioning at this juncture that we have employed a production function approach with time-varying technical efficiency model. Additionally, we have assumed the inefficiency term (U_it) to be following truncated normal distribution, whereas, the random error component follows normal distribution which has been followed in Coelli and Battese (1996). The underlying reason given by Coelli and Battese (1996) is that it suffers from much fewer computational problems than other distributions (Odeck and Schoyen 2020). The variance parameter is:

$$\sigma_U^2 = \sigma_u^2 + \sigma_v^2$$

$$\lambda = \frac{\sigma_u^2}{\sigma_v^2}$$

$\gamma = \frac{\sigma_u^2}{\sigma_u^2 + \sigma_v^2}$ where $0 \le \gamma \le 1$

The technical efficiency of banks is given by;

$$TE_{it} = \frac{f\left(x_{it};\beta\right)e^{U_{it}}}{f\left(x_{it};\beta\right)e^{u_{it}}} = e^{-v_{it}} \quad where \quad 0 \le TE \le 1$$

Now, if we consider some other exogenous factors influencing technical inefficiency component (Z_it), then this effect would be subsumed in the v_it. This model was formulated by Battese and Coelli (1995);

$$v_{it} = Z_{it}\delta + W_{it}$$

Taking a cue from the literature we have adopted a trans-log form, because of its flexible functional form (Silva et al. 2017). In the current context we have considered three outputs namely, investments, advances and non-interest income in three different set-ups. Additionally, three explanatory variables—capital strength, labor expenses and borrowings have also been considered. As stated earlier in the research objective we intend to gauge the impact of undesirable output especially, NPAs. So, to contextualize the influence of environmental factors beyond the control of banks, variables like size, ownership and NPAs have been incorporated in the model. Table 4 presents the hypotheses that we test in the SFA analysis.

Empirical Results

Data Envelopment Analysis (DEA)

The appendix Table 14 reports various DEA efficiency scores that were calculated using the MaxDEA software. Table 5 below summarizes the DEA efficiency

Table 4 Hypotheses tested in SFA

Hypothesis	Meaning
$H_0 : \gamma = 0$	Technical inefficiency effects are not random. It is tested by using LR-test $LR = -2\{ln[L(H_0)] - ln[L(H_1)]\}$
$H_0 : \delta = 0$	Technical inefficiency effects are not influenced by the level of the explanatory variable
Kruskal Wallis test	Difference among the k populations(equality of the population rank)

Table 5 Summary statistics of DEA efficiency scores

Variables	N	Mean	SD	Min	Max	P25	P50	P75	P90	P99
Ownership: Public Sector Banks										
CRSTE	167	0.836	0.138	0.520	1	0.713	0.857	0.979	1	1
OVRSTE	167	0.950	0.080	0.676	1	0.913	1	1	1	1
OSE	167	0.879	0.113	0.576	1	0.801	0.900	0.999	1	1
IVRSTE	167	0.939	0.100	0.578	1	0.894	1	1	1	1
ISE	167	0.891	0.110	0.580	1	0.816	0.916	1.000	1	1
Ownership: Private Sector Banks										
CRSTE	147	0.912	0.125	0.537	1	0.834	1	1	1	1
OVRSTE	147	0.949	0.089	0.606	1	0.914	1	1	1	1
OSE	147	0.960	0.080	0.554	1	0.954	1	1	1	1
IVRSTE	147	0.946	0.093	0.604	1	0.915	1	1	1	1
ISE	147	0.963	0.075	0.559	1	0.955	1	1	1	1

scores of India public and private sector banks. The mean constant returns to scale technical efficiency (CRSTE) score of Indian public sector banks over the period 2014–2020 is 0.836 while that of the private sector banks it is 0.912. We report the CRSTE without mentioning the orientation of the technology assumed. This is due to the fact the both the input and output oriented CRS technical efficiency scores are the same by definition of the constant return to scale. A CRS technology means that increasing (decreasing) inputs by $x\%$ will increase (decrease) output by same $x\%$. So whether we reduce input and keep output constant (input orientation) or we increase output and keep input constant (output orientation) we will attain the same change in the efficiency scores due to the underlying CRS assumption. Hence the mean and median efficiency scores under CRS will be the same. We graphically depict various efficiency measures based on Table 5 in the time series graphs in Fig. 2 below. From these graphs we clearly see that the private sector banks have outperformed the nationalized banks in terms of CRS technological assumption. However, we do not see any unambiguous private ownership advantage when allowing for the variable returns technology to operate. We also find that the private sector banks have higher mean and median scale efficiency as compared to the public sector counterparts.

Our results indicate that the mean and median technical efficiency scores of the public sector bank have consistently been falling from 2014 to 2017 only to rise in the later years. There existed a huge difference in the efficiency scores of the public sector banks pre 2016 when the AQR was first initiated and consequently almost all of the public sector banks faced surmounting non-performing assets. However, post 2017 the divergence in the efficiency scores was minimized again. This result may be a direct consequence of the mega merger of the SBI Bank and its associates and few other small mergers along with the asset quality review.

Table 6 presents the summary statistics of the regression variables for the second stage DEA where we examine the factors that determine the DEA efficiency scores of Indian banks. In our regression analyses the dependent variables are the CRS technical efficiency scores and the output and input oriented VRS technical efficiency scores. The independent variables are the relative size of the bank, the

Fig. 2 Time series plots of mean and median DEA efficiency scores

Table 6 Descriptive statistics of regression variables

Variable	N	Mean	Std. dev	Min	Max
Dependent variables					
CRSTE	314	0.872	0.137	0.52	1
OVRSTE	314	0.95	0.085	0.606	1
IVRSTE	314	0.942	0.097	0.578	1
Independent variables					
Relative size	314	0.022	0.034	0	0.241
Profit	314	355.751	4297.014	− 16,418.031	26,257.315
Private ownership	314	0.468	0.5	0	1
Net-NPA/advances	314	0.0400716	0.03	0	0.1689

Source: RBI and author's exploration

profits, ownership which is a dummy variable taking a value 1 for the private sector banks and finally we have the proportion of the net NPA as a percentage of total advances of the bank. In our sample data around 47% of the banks are the private sector banks. The average size of the bank is 2.2% of the assets of all the scheduled commercial banks. The mean net NPA as a percentage of total advances is around 4%. Table 7 panel A reports the regression results from Tobit model in the pooled settings where we pool the data on dependent and independent variables for all the years. In the column 1 of Table 7 where regress the CRS technical efficiency scores on the independent variables, we find that the size of the bank as well as the non-performing assets are detrimental for the efficiency of the banks. They negatively and significantly affect the CRS efficiency scores of Indian banks. We find a significant and negative impact of relative size on the efficiency scores which is in line with the existing literature (Kumar and Gulati 2010; Ariff and Luc 2008). The bad loans also tend to negatively affect the efficiency of Indian banks which is again in line with the existing literature (Das and Ghosh 2006). In addition; our regression results show that the private sector banks tend to have higher CRS efficiency scores as compared to the public sector banks. For the VRS efficiency scores in columns 2 and 3, we do not find any significant differential effect of ownership and NPA on the efficiency scores. Table and panel B presents the results from the random effects Tobit model. Our results show that private ownership of banks increases the mean CRS efficiency score by 8% than the public ownership. We also find a significant and negative impact of NPAs on the CRS efficiency scores. However, size is no more a significant factor determining the CRS efficiency. None of our regressors do significantly determine the VRS efficiency scores.

Productivity Change: Results from Malmquist Productivity Index

Table 8 presents the summary of the annual means from the Malmquist productivity index. The average productivity growth for the year 2015 was 4.2% ($1.042-1\times 100$). This change in the total factor productivity has exclusively come from the upward shift in the frontier and a consequent deceleration of the efficiency. From the table,

Table 7 Results from the Tobit model using DEA efficiency scores as dependent variable

	Panel A: pooled settings			Panel B: random effects Tobit		
	CRSTE	OVRSTE	IVRSTE	CRSTE	OVRSTE	IVRSTE
Relative size	−0.614** (0.280)	1.474*** (0.555)	1.734*** (0.648)	−0.328 (0.674)	1.562 (1.007)	1.782 (1.137)
Profit	0.000003 (0.000003)	0.000001 (0.000004)	0.000002 (0.000004)	−0.000001 (0.000003)	−0.0000011 (0.0000045)	−0.0000017 (0.0000052)
Private ownership	0.0671** (0.0304)	0.00268 (0.0304)	0.0130 (0.0348)	0.0818* (0.0489)	0.0210(0.0470)	0.0331(0.0535)
Net NPA/advances	−1.270*** (0.461)	−0.679 (0.474)	−0.870 (0.568)	−1.355*** (0.377)	−0.520 (0.409)	−0.717 (0.475)
Constant	0.957*** (0.0305)	1.047*** (0.0327)	1.054*** (0.0382)	0.952*** (0.0420)	1.035*** (0.0439)	1.044*** (0.0502)
Sigma constant	0.187*** (0.00907)	0.175*** (0.0106)	0.201*** (0.0117)			
Sigma u constant				0.145*** (0.0202)	0.129*** (0.0215)	0.145*** (0.0245)
Sigma e constant				0.137*** (0.00783)	0.132*** (0.0102)	0.155*** (0.0120)
N	314	314	314	314	314	314
Pseudo R^2	0.349	0.0969	0.0895			
F/Chi^2	12.24	3.981	4.207	23.17[a]	4.839[b]	5.868[c]
p value	2.96e−09	0.00364	0.00248	0.000117	0.304	0.209
Log likelihood	−43.56	−71.25	−87.66	1.862	−44.69	−62.94
Standard error	Robust	Robust	Robust	OIM	OIM	OIM

Standard errors in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

[a, b, c]Indicate chi-square value

we see a positive TFP change in years 2015, 2017 and 2019 while a negative TFP change occurred in years 2016, 2018 and 2020. The positive TFP changes in years 2015 and 2019 are exclusively a product of the upward shift in the frontier (that is a due to technological change). Except for 2017 and 2018 we see a decline in the technical efficiency. Overall the mean productivity change over the study period of 7 years has been a negative 3.1% with a corresponding 3% downward shift in the frontier. The technical efficiency change (due to CRS as well as VRS) has not changed over the sample period. From Table 9 only 7 banks out of 18 public sector banks had a positive TFP growth during the study period. The Bank of Maharashtra, Central Bank of India, Indian Bank, Punjab National Bank, UCO Bank, Union Bank of India and United Bank of India were the public sector banks that experienced positive TFP growth rates among all public sector banks. Apart from the UCO bank and United Bank of India, the TFP growth was brought about by the technical efficiency change alone. Overall only 4 nationalized banks witnessed an upward shift in the production frontier while 7 such banks experienced an improvement in the technical efficiency. In contrast, 6 private banks had a positive TFP growth over the 7-year study period which was largely due to technological change. Out of 18 private sector banks only 7 banks experienced a fall in the technical efficiency while as many private banks experienced a positive technical change. On average, the Indian public and private sector banks experienced a negative TFP growth bought about exclusively by the downward shift of the frontier.

From Table 10 using 2014 as the base year we find that the 36 public and private sector banks jointly witnessed a fall of 11% in the TFP growth in the year 2020. This decline in the TFP growth can be attributed to an equivalent fall in the technological progress. The technical efficiency due to CRS did not change while technical efficiency change due to VRS fell by 1% during the 7-year period.

Stochastic Frontier Analysis (SFA)

We have used STATA to estimate the frontier production function for measuring different outputs like investments, advances and non-interest income. We are interested in determining the estimated coefficients in the inefficiency model in this study, as they would indicate how banks in India perform. Furthermore, we are also intending to understand the impact of environmental factors on the technical efficiency of the banks. Following Greene (2005) we have adopted true fixed effects model which disentangles time-invariant heterogeneity from time-varying inefficiency. The reason stems from the argument that while observing the output over time and across banks there might be a deviation from the production possibility frontier due to either unobserved time invariant heterogeneity or the technical inefficiency which could be clearly understood if we consider True fixed effects model. In STATA the true fixed effect results in the SFA framework provides maximum likelihood estimates. Thus, in Table 11, MLE results are shown. Estimation results of models with different output variables are presented in Table 11 to understand whether the SFA model established in this study performs well.

Table 8 Malmquist Index summary of annual means

Year	effch	techch	pech	sech	tfpch
2015	0.986	1.056	0.971	1.015	1.042
2016	0.966	0.832	1.031	0.937	0.804
2017	1.026	0.996	0.981	1.046	1.022
2018	1.062	0.917	1.043	1.018	0.973
2019	0.983	1.039	0.974	1.009	1.021
2020	0.974	1.001	0.984	0.991	0.976
Mean	0.999	0.970	0.997	1.002	0.969

Source: Authors' calculations using DEAP Software

In Table 11 we report the results that we have obtained by considering three different outputs-investments, advances and non-interest incomes as stated earlier. Additionally, to explain the frontier we have considered three inputs- capital strength, labour expenses and borrowing. These variables were recognized as inputs in the DEA as well. It is worth mentioning here that we have considered the logarithmic value of the explanatory and dependent variables for the analysis. Apart from this, the literature is divided on the impact of environmental factors influencing the technical inefficiency of the banks. To take into account the variables which are beyond the control of banks nonetheless explaining the technical inefficiency, we have assumed log of NPA, relative size and the ownership. Here, the variable ownership is a dummy which takes up 1 if the bank is public and 0 if it is private.

STATA 14 enables us to incorporate the output oriented SFA in a panel setting with true fixed effects (Greene 2005) under the assumption of truncated normal distribution of the technical inefficiency component. From Table 11 we see that with stable coefficients of parameters, variables like labour expenses and borrowings have passed the significance test at 1% level denoting a significant positive impact on investments, non-interest incomes and advances. But, as far as the capital strength, which is derived from adding up equity and fixed assets, is concerned it was not found statistically significant when advances and non-interest incomes were considered as output. Now, *mu* in the table is the dependent variable and is termed as *technical inefficiency*. Aforementioned, we have considered three variables explaining the variation in the technical inefficiency of the banks. A negative sign of the coefficient explaining *mu* implies negative impact on the technical inefficiency of the banks therefore; this would have a positive impact on the technical efficiency. In other words, the banks would have become much more efficient owing to the variables having negative sign. Based on the above findings we may conclude that there is a presence of technical inefficiency in the Indian banking sector. As shown in the table, the three main input indicators have significant positive effects on the output of investment. Variables in the technical inefficiency function have significant influence on the output variables. The coefficient of Net NPA (lnnetnpa) is significantly positive when investment was considered as output, which indicates that NPA exerts a positive effect on the technical inefficiency. In contrast, it has a negative impact on

Table 9 Malmquist Index summary of bank means

Bank	effch	techch	pech	sech	tfpch
Allahabad Bank	1.02	0.976	1	1.02	0.996
Andhra Bank	0.943	0.967	0.98	0.963	0.912
Bank of Baroda	0.978	0.972	0.994	0.984	0.95
Bank of India	0.969	0.985	0.998	0.971	0.954
Bank of Maharashtra	1.055	1.001	1.02	1.034	1.056
Canara Bank	0.994	0.946	1	0.994	0.941
Central Bank of India	1.106	0.976	1.017	1.087	1.079
Corporation Bank	1	0.926	1	1	0.926
Indian Bank	1.055	0.951	1	1.055	1.003
Indian Overseas Bank	1.05	0.935	1.037	1.012	0.982
Oriental Bank of Commerce	0.948	0.953	0.965	0.982	0.903
Punjab and Sind Bank	0.967	0.949	0.976	0.991	0.918
Punjab National Bank	1.083	0.953	1	1.083	1.032
State Bank of India	0.977	0.991	1	0.977	0.968
Syndicate Bank	0.922	1.016	0.96	0.96	0.937
UCO Bank	1	1.014	1	1	1.014
Union Bank of India	1.06	0.97	1.019	1.04	1.028
United Bank of India	0.986	1.025	1	0.986	1.01
Axis Bank	1	0.99	1	1	0.99
City Union Bank Limited	1	1.077	1	1	1.077
Catholic Syrian Bank Ltd.	1	0.908	1	1	0.908
DCB Bank Limited	0.986	0.969	0.952	1.036	0.955
Federal Bank	1.023	1.032	1.021	1.002	1.055
HDFC Bank	1	0.955	1	1	0.955
ICICI Bank	0.97	1.011	0.959	1.012	0.98
IndusInd Bank	1	1.003	1	1	1.003
Jammu & Kashmir Bank Ltd.	0.902	0.915	0.996	0.906	0.825
Karnataka Bank Ltd.	0.996	0.99	0.996	1	0.986
Karur Vysya Bank	1.015	0.97	1.006	1.009	0.985
Kotak Mahindra Bank Ltd.	1.023	1	1.024	0.999	1.023
Lakshmi Vilas Bank	0.98	0.932	0.985	0.995	0.913
RBL	0.971	0.765	0.988	0.984	0.743
South Indian Bank	0.98	0.954	0.989	0.99	0.934
Tamilnad Mercantile Bank Ltd.	1	1.017	1	1	1.017
Dhanlaxmi Bank	1.039	1.054	1.013	1.025	1.094
Yes Bank Ltd.	1	0.936	1	1	0.936
Mean	**0.999**	**0.97**	**0.997**	**1.002**	**0.969**

Source: Authors' calculations using DEAP Software

technical efficiency. Another key finding is that the Relative size has a positive influence on the efficiency of the output.

Table 10 Malmquist Index summary of annual means 2014 and 20

Year	effch	techch	pech	sech	tfpch
2020	0.994	0.900	0.981	1.013	0.894

Source: Authors' calculations using DEAP Software

We have performed some diagnostic checks which are presented in Table 11. Under 1% confidence level, the Gamma (γ) values are 0.11, 0.92 and 0.84 respectively, which indicate that most of the compound errors are due to technical inefficiency. In other words, technical inefficiency accounts for 11% variation in investments, 92% variation in the non-interest incomes and 84% variation in the advances. Following Kumbhakar et al. (2015) we further calculate the LR statistics to test the technical inefficiency. The restricted model in the table is the typical Cob-Douglas model and the unrestricted model is the stochastic frontier model. The LR statistics in models are 394 and 294 from investments and non-interest incomes respectively. These values are greater than the critical value at a 5% significance level (Kodde and Palm 1986) implying that the stochastic frontier model is appropriate in the current context for investments and non-interest incomes. In other words, we are strongly rejecting the null-hypothesis of no technical inefficiency. However, in the model with log of advances as dependent variable the value of LR test is less than the critical value thus, SFA is not appropriate in this case. Lambda indicates the ratio of σ_{u}^2 and σ_{v}^2 i.e. the relative proportion of one-sided inefficiency to random two-sided noise term (exogenous production shocks). The mean score derived from considering investments, non-interest incomes and advances come out to be 0.91, 0.89 and 0.99.

Furthermore, before pursuing any stance, it is critical to investigate whether there is a significant difference in the public and private sector banks in India. The rationale to compare the performance of both these categories of banks stem from the fact that where public sector banks have a whooping share of over 60% of banking assets, the gross NPA is 10.3% in contrast with private sector banks which have 5.5%. We have performed some parametric and non-parametric tests, the results of which are presented in the Table 11. The application of Kruskal–Wallis equality of population test in our findings underscores a statistically significant variation in the technical efficiency scores of the populations when log of non-interest incomes and advances was considered as output in two distinct cases. Similar results were obtained when t test, Two-sample Wilcoxon rank-sum (Mann–Whitney) test and Kolmogrov–Smirnov test were applied. In other words, we may say that in two out of three cases considered, there is an evidence of heterogeneity in the technical efficiency of private and public sector banks. The evidence of heterogeneity in public and private sector banks was not found when log of investment was considered.

Based on the translog production function and the assumption of truncated normal distribution we have presented the technical efficiency scores in Appendix Table 15. These values range between zero and one. The value of technical efficiency close to zero is a sign of inefficiency subsumed in the statistical noise term and the values close to 1 indicate the degree of efficiency. In addition, we have illustrated

Table 11 Results from maximum likelihood estimation (SFA)

	lninvestments	lnnoninterestincome	lnadvances
Frontier			
lncapitalstrength	0.2719*** (0.0467)	−0.065 (0.118)	−0.013 (0.052)
lnlaborexpenses	0.4513*** (0.04681)	0.648*** (0.0772)	0.6823*** (0.060
lnborrowings	0.1253*** (0.0179)	0.2904*** (0.072)	0.220*** (0.0242)
mu			
Relativesize	−4.815* (2.630)	−60.427 (76.789)	−2.1786 (8.276)
Ownership	−0.1969* (0.1139)	−1.467 (8.791)	−14.80*** (1.772)
lnnetnpa	0.1113*** (0.0138)	−0.02269 (0.2891)	−0.118 (0.1485)
_cons	−0.578	−2.664	−0.8267
Usigma_cons	−6.0773	−0.55	−1.493
Vsigma_cons	−4.03	−3.0564	−3.153
Sigma_u	0.0478	0.759	0.47406
Sigma_v	0.1332	0.21	0.20659
Gamma	0.11408	0.9288	0.84
Lambda	0.3594	0.3499	2.294
Log-likelihood (restricted)	166.42	−9.3944	−55,360
Log-likelihood (unrestricted)	−30.7546	−156.716	−27.09517
Computed LR from restricted and unrestricted LR test	394.366	294.6433	−110,665.8
Summarized technical efficiency score	0.91	0.89	0.99
Summary of technical efficiency scores			
Mean	0.914	0.8913	0.99
Std. dev	0.0579	0.068	0.002
Min	0.7006	0.3285	0.9875
Max	0.9984	0.98	0.994
Chi-squared	0.07	39.707***	221.680***

Table 11 (continued)

	lninvestments	lnnoninterestincome	lnadvances
Two-sample t test with equal variances (t value)	−1.0318	−6.352***	−68.3***
Two-sample t test with unequal variances (tvalue)	−0.998	−5.97***	−63.08***
Two-sample Wilcoxon rank-sum (Mann–Whitney) test	0.265	−6.301***	−14.889***
Two-sample Kolmogorov–Smirnov test for equality of distribution functions (combined K–S value)	0.1189	0.3524***	1***

#Dependent variables have been taken log of. Standard errors are in parentheses. *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$

the trajectory of technical efficiency scores of the banks over the analysis period in Fig. 3. It is clear from Fig. 3 that the total number of banks which were highly efficient ($0.91 \leq T.E \leq 1$) has fallen since 2016. Considering three cases with different set of outputs like Advances, non-interest income and investments have shown the degree of efficiency of banks in India. The comparison of technical efficiency sores based on three different outputs have unveiled the degree of technical inefficiency in the banking sector indicating that outputs of bank whether it is investment, non-interest incomes or advances could be increased by fixing the factors causing inefficiency.

Table 11 presents the technical efficiency scores based on the first three models with log of investments, non-interest incomes and advances as dependent variable. SFA scores obtained from considering log of investments shows that the technical efficiency scores of the banks in India fell from 0.96 to 0.89 over the period 2014–2017 and then after 2018 it started rising. The change in technical efficiency scores over 2014–2017 is due to a rise in non-performing loans ratio of scheduled commercial and decline in it over 2018–2020 (see Fig. 4). On the other hand, if we look at the technical efficiency scores obtained after considering non-interest incomes as an output variable we find that the scores have kept fluctuation over the period (Table 12).

Conclusion and Policy Implications

In the Indian context, the burgeoning stream of literature construing the technical efficiency of banks in the context of non-performing assets has gained traction among the scholars. In line with this we endeavour to not only buttress the research conducted in this area but we also bridge the research gap of linking the technical inefficiency caused due to NPA with the ownership of banks in India. We have empirically investigated the effects of undesirable output like NPA on the technical efficiency of banks through parametric and non-parametric methods of production frontier. On an average the public sector banks in our sample not just have higher amount of investments, advances, non-interest incomes, borrowings, fixed assets, labour expenses, equity and NPAs but, these banks also have a high degree of variation in the NPAs in contrast with private sector banks resulting in lower technical efficiency than the private sector banks. DEA unveiled the dichotomy in the technical efficiency of banks. Where the average technical efficiency of public sector banks over the analysis period stood at 0.836, private sector banks have fared better with the score of 0.912. This implies that there is a huge potential for the public sector banks to improve their performance. The contrasting results are evident with the fact that private sector banks have higher mean and median scale efficiency as compared to the public sector counterparts. Furthermore, the technical efficiency of banks has plummeted in the period 2014–2017 only to rise in the latter years. The underlying reason is the promulgation of a chain of reforms following the AQR and the merger of State Bank of India with the subsidiary banks to make it a global-sized bank among other mergers. Additionally, from the Tobit analysis we find that the relative size of the bank as well as the non-performing assets as detrimental for the

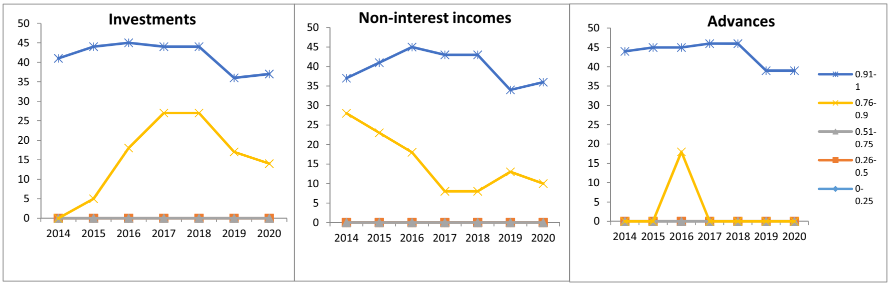
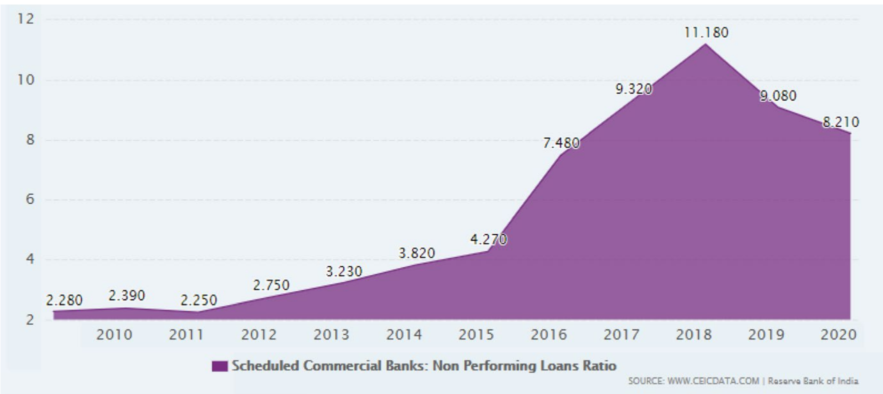


Fig. 3 Time series trend of technical efficiency (SFA)

efficiency of the banks (DEA). They negatively and significantly affect the CRS efficiency scores of Indian banks. The CRS efficiency score of private sector banks is higher as compared to the public sector banks, while we do not find any significant differential effect of ownership and NPA on the VRS efficiency scores. Since CRS efficiency score is an amalgamation of both the pure technical efficiency as well as the scale efficiency, a significant effect of ownership and NPA on CRS efficiency may rightly be explained by the fact that the source of inefficiency in the Indian public sector banks is due to the scale as opposed to the pure technical efficiency. We have demonstrated already this fact that the nationalized banks are less scale efficient than the private sector banks. It is worth mentioning here that private ownership of banks increases the mean CRS efficiency score by 8% than the public ownership. An important finding is; the size is no more a significant factor determining the CRS efficiency. The results for the Malmquist productivity index reveal that the overall total factor productivity growth has decline over the 7 years starting 2014. This decline in the TFP growth can largely be attributed to the adverse technological change. Therefore, in order to make the banking system more efficient and vibrant,



Source: CEIC database RBI

Fig. 4 India's NPA ratio from 1998 to 2020

Table 12 Change in technical efficiency scores from SFA over 2014–2020

Years	te_lninvestments	te_lnnoninter-estincome	te_lnadvances	Non-performing loans ratio of scheduled commercial[1]
2014	0.96	0.85	0.99	3.820
2015	0.94	0.88	0.99	4.270
2016	0.91	0.87	0.99	7.480
2017	0.89	0.92	0.99	9.320
2018	0.89	0.91	0.99	11.18
2019	0.90	0.90	0.99	9.18
2020	0.90	0.91	0.99	8.21

the banks need to keep up with the new technology viz., the internet banking, the ATMs, the online payment systems and the UPI payments among other technological advancements.

Considering the limitations of DEA to be a non-parametric method, we have corroborated DEA with a parametric method named SFA in our analysis of banks. We have adopted a production function approach with three different output variables-investments, advances and non-interest income; three explanatory variables- capital strength, labour expenses and borrowings; three environmental factors affecting the efficiency of banks- NPA, relative size and private ownership. Like DEA, SFA results also show the presence of technical inefficiency in the Indian banking sector. NPA exerts a positive effect on the technical inefficiency when the log of investment was considered as dependent variable. Another key finding is that the Relative size of the bank has a positive influence on the technical efficiency in case of SFA. Additionally, the technical efficiency sores obtained from SFA points towards the heterogeneity in the technical efficiency of private and public sector banks. SFA scores obtained from considering log of investments shows that the technical efficiency scores of the banks in India fell between 2014 and 2017. Post 2008 financial crisis when almost all the countries across the world faced the storm of plummeting growth rates, the banks in India came out unscathed. But, the surge in NPA latter on potentially held the technical efficiency of the banks to ransom as the growth of the banks tapered off with the rise in NPA. However, after 2018 it started rising due to probably the introduction of regulations like AQR and mergers of the banks beyond 2018. The COVID situation may alter the trend seen after 2018. Our future research would delve to incorporate the impact of COVID-19 on the efficiency and productivity of Indian banks. Our SFA results show that the public sector ownership has a positive impact on the efficiency of the banks. This suggests that concerted efforts needs to be taken by the government to improve the efficiency of the public sector banks which has to fulfil broader social and equity objectives in a developing country like India. One direction is through the digitalization and mechanization of the operations of the banks along with performing stress tests to ascertain its vulnerabilities to policy shocks.

The policy directions should be in line with Basel Norms which emphasizes on three pillars of banking regulations concerning with having minimum capital requirements (Pillar 1), supervisory review (Pillar 2), and market discipline (Pillar 3).Our findings are in conformity with the previous research. Thus, there is a further scope for future research in the sense that the study could be extended to provide insights from a novel methodology called Network DEA, and explore the impact of inclusion of bad outputs like NPA on the technical inefficiency and to what extent the dichotomy prevails in Indian banking sector. The underlying deficiencies in the banking sector could be overcome through a combination of policies targeting the rising NPAs.

Appendix

See Tables 13, 14 and 15.

Table 13 Descriptive statistics of input and output variables

	N	Mean	SD	Min	Max
Ownership: public sector banks					
Investments	167	103,403.91	154,036.08	413.335	1,060,986.7
Advances	167	236,385.17	342,469.11	88.531	2,325,289.6
Non-interest income	167	3970.326	6713.667	2.777	45,221.48
Borrowings	167	30,592.904	61,440.717	0	403,017.12
Fixed assets	167	3831.629	6193.447	8.961	42,918.918
Labor expenses	167	3844.048	6213.202	5.502	45,714.968
Equity	167	1099.252	1566.985	0	10,516.69
Net NPA	167	11,763.846	13,507.342	0	110,854.7
Ownership: private sector banks					
Investments	147	44,200.001	65,761.116	1139.74	391,826.66
Advances	147	113,614.26	174,483.61	2437.043	993,702.88
Non-interest income	147	2912.706	4769.668	25.945	23,260.819
Borrowings	147	27,352.997	46,688.318	0	182,858.62
Fixed assets	147	1240.895	1868.275	17.959	8410.285
Labor expenses	147	1470.528	1870.98	63.315	9525.668
Equity	147	296.728	548.928	0	2741.921
Net NPA	147	1937.978	4083.29	0	27,823.56

Table 14 DEA efficiency scores

Bank name	Year	CRSTE	OVRSTE	IVRSTE	OSE	ISE
State Bank of Hyderabad	2014	0.910	1.000	1.000	0.910	0.910
Bank of India	2014	0.970	1.000	1.000	0.970	0.970
State Bank of Patiala	2014	0.983	1.000	1.000	0.983	0.983
Andhra Bank	2014	1.000	1.000	1.000	1.000	1.000
Corporation Bank	2014	1.000	1.000	1.000	1.000	1.000
Dena Bank	2014	0.906	0.983	0.982	0.921	0.922
Vijaya Bank	2014	1.000	1.000	1.000	1.000	1.000
Syndicate Bank	2014	0.933	0.972	0.969	0.960	0.962
Union Bank of India	2014	0.706	0.888	0.820	0.795	0.861
Punjab National Bank	2014	0.590	1.000	1.000	0.590	0.590
United Bank of India	2014	0.924	1.000	1.000	0.924	0.924
UCO Bank	2014	1.000	1.000	1.000	1.000	1.000
State Bank of Bikaner & Jaipur	2014	1.000	1.000	1.000	1.000	1.000
State Bank of Mysore	2014	0.876	0.885	0.876	0.990	1.000
Indian Overseas Bank	2014	0.671	0.765	0.696	0.877	0.964
IDBI Bank Limited	2014	1.000	1.000	1.000	1.000	1.000
Canara Bank	2014	0.835	1.000	1.000	0.835	0.835
Indian Bank	2014	0.708	1.000	1.000	0.708	0.708
Punjab and Sind Bank	2014	0.816	1.000	1.000	0.816	0.816
Allahabad Bank	2014	0.765	0.970	0.950	0.789	0.806
State Bank of Travancore	2014	0.954	0.991	0.990	0.963	0.964
Bharatiya Mahila Bank Ltd.	2014	1.000	1.000	1.000	1.000	1.000
State Bank of India	2014	0.772	1.000	1.000	0.772	0.772
Central Bank of India	2014	0.520	0.902	0.828	0.576	0.628
Bank of Baroda	2014	1.000	1.000	1.000	1.000	1.000
Oriental Bank of Commerce	2014	0.900	1.000	1.000	0.900	0.900
Bank of Maharashtra	2014	0.701	0.857	0.835	0.818	0.839
Catholic Syrian Bank Ltd.	2014	0.712	1.000	1.000	0.712	0.712
HDFC Bank	2014	1.000	1.000	1.000	1.000	1.000
DCB Bank Limited	2014	1.000	1.000	1.000	1.000	1.000
Karnataka Bank Ltd.	2014	1.000	1.000	1.000	1.000	1.000
IndusInd Bank	2014	1.000	1.000	1.000	1.000	1.000
RBL	2014	1.000	1.000	1.000	1.000	1.000
Karur Vysya Bank	2014	0.916	0.920	0.921	0.995	0.995
Lakshmi Vilas Bank	2014	0.811	0.848	0.844	0.956	0.960
City Union Bank Limited	2014	1.000	1.000	1.000	1.000	1.000
ICICI Bank	2014	0.899	1.000	1.000	0.899	0.899
Dhanlaxmi Bank	2014	0.645	0.781	0.768	0.827	0.840
Nainital Bank	2014	1.000	1.000	1.000	1.000	1.000
Tamilnad Mercantile Bank Ltd.	2014	1.000	1.000	1.000	1.000	1.000
YES Bank Ltd.	2014	1.000	1.000	1.000	1.000	1.000
Jammu & Kashmir Bank Ltd.	2014	1.000	1.000	1.000	1.000	1.000
ING Vysya Bank	2014	0.622	0.702	0.687	0.886	0.905
Kotak Mahindra Bank Ltd.	2014	0.651	0.701	0.697	0.929	0.934

Table 14 (continued)

Bank name	Year	CRSTE	OVRSTE	IVRSTE	OSE	ISE
Axis Bank	2014	1.000	1.000	1.000	1.000	1.000
Federal Bank	2014	0.863	0.883	0.878	0.978	0.984
South Indian Bank	2014	0.907	0.909	0.907	0.998	1.000
Central Bank of India	2015	0.641	0.805	0.700	0.797	0.916
Syndicate Bank	2015	0.979	0.979	0.979	1.000	1.000
Andhra Bank	2015	0.760	0.760	0.761	1.000	0.999
Indian BaNK	2015	0.860	1.000	1.000	0.860	0.860
Allahabad Bank	2015	0.723	0.824	0.803	0.877	0.900
Punjab and Sind Bank	2015	0.809	0.950	0.942	0.851	0.859
State Bank of Patiala	2015	0.853	0.918	0.915	0.928	0.932
State Bank of Travancore	2015	0.875	1.000	1.000	0.875	0.875
Dena Bank	2015	0.835	0.965	0.958	0.865	0.872
United Bank of India	2015	1.000	1.000	1.000	1.000	1.000
State Bank of Bikaner & Jaipur	2015	0.902	0.956	0.954	0.944	0.946
Bharatiya Mahila Bank Ltd.	2015	1.000	1.000	1.000	1.000	1.000
IDBI Bank Limited	2015	1.000	1.000	1.000	1.000	1.000
Corporation Bank	2015	1.000	1.000	1.000	1.000	1.000
Oriental Bank of Commerce	2015	1.000	1.000	1.000	1.000	1.000
Vijaya Bank	2015	1.000	1.000	1.000	1.000	1.000
Indian Overseas Bank	2015	0.692	0.856	0.808	0.808	0.855
Bank of Maharashtra	2015	0.696	0.758	0.739	0.917	0.941
Canara Bank	2015	0.908	1.000	1.000	0.908	0.908
Punjab National Bank	2015	0.605	0.976	0.967	0.620	0.626
UCO Bank	2015	1.000	1.000	1.000	1.000	1.000
State Bank of Hyderabad	2015	0.856	0.977	0.974	0.877	0.879
State Bank of India	2015	0.733	1.000	1.000	0.733	0.733
Bank of India	2015	0.768	0.920	0.878	0.834	0.875
Bank of Baroda	2015	1.000	1.000	1.000	1.000	1.000
State Bank of Mysore	2015	0.769	0.815	0.784	0.943	0.982
Union Bank of India	2015	0.680	0.727	0.682	0.935	0.998
ING Vysya Bank	2015	0.603	0.606	0.604	0.996	0.999
Dhanlaxmi Bank	2015	0.687	0.704	0.699	0.976	0.984
RBL	2015	1.000	1.000	1.000	1.000	1.000
South Indian Bank	2015	0.794	0.880	0.856	0.903	0.928
YES Bank Ltd.	2015	1.000	1.000	1.000	1.000	1.000
Lakshmi Vilas Bank	2015	0.854	0.854	0.856	0.999	0.998
Axis Bank	2015	1.000	1.000	1.000	1.000	1.000
Nainital Bank	2015	1.000	1.000	1.000	1.000	1.000
Catholic Syrian Bank Ltd.	2015	0.922	1.000	1.000	0.922	0.922
Kotak Mahindra Bank Ltd.	2015	0.707	0.745	0.725	0.950	0.975
Karur Vysya Bank	2015	0.856	0.876	0.856	0.978	1.000
ICICI Bank	2015	0.955	1.000	1.000	0.955	0.955
Jammu & Kashmir Bank Ltd.	2015	0.825	0.917	0.901	0.900	0.915
DCB Bank Limited	2015	1.000	1.000	1.000	1.000	1.000

Table 14 (continued)

Bank name	Year	CRSTE	OVRSTE	IVRSTE	OSE	ISE
HDFC Bank	2015	1.000	1.000	1.000	1.000	1.000
Federal Bank	2015	0.868	1.000	1.000	0.868	0.868
Tamilnad Mercantile Bank Ltd.	2015	1.000	1.000	1.000	1.000	1.000
City Union Bank Limited	2015	1.000	1.000	1.000	1.000	1.000
IndusInd Bank	2015	1.000	1.000	1.000	1.000	1.000
Karnataka Bank Ltd.	2015	0.913	0.944	0.931	0.967	0.981
Allahabad Bank	2016	0.701	0.800	0.785	0.877	0.893
Dena Bank	2016	0.658	0.814	0.780	0.809	0.844
Indian Overseas Bank	2016	0.542	0.753	0.655	0.719	0.827
Andhra Bank	2016	0.848	1.000	1.000	0.848	0.848
Canara Bank	2016	0.793	1.000	1.000	0.793	0.793
State Bank of Bikaner And Jaipur	2016	1.000	1.000	1.000	1.000	1.000
State Bank of Travancore	2016	1.000	1.000	1.000	1.000	1.000
State Bank of Mysore	2016	0.670	1.000	1.000	0.670	0.670
Bank of Baroda	2016	0.761	1.000	1.000	0.761	0.761
State Bank of Patiala	2016	0.742	0.898	0.887	0.827	0.837
Bharatiya Mahila Bank Ltd.	2016	1.000	1.000	1.000	1.000	1.000
IDBI Bank Limited	2016	1.000	1.000	1.000	1.000	1.000
Punjab and SIND Bank	2016	0.884	1.000	1.000	0.884	0.884
UCO Bank	2016	1.000	1.000	1.000	1.000	1.000
State Bank of India	2016	0.801	1.000	1.000	0.801	0.801
Bank of Maharashtra	2016	0.696	0.945	0.938	0.736	0.742
Central Bank of India	2016	0.580	1.000	1.000	0.580	0.580
Vijaya Bank	2016	0.863	0.899	0.895	0.960	0.965
Punjab National Bank	2016	0.680	0.961	0.948	0.708	0.718
Syndicate Bank	2016	0.765	0.964	0.957	0.793	0.799
Corporation Bank	2016	1.000	1.000	1.000	1.000	1.000
United Bank of India	2016	0.766	1.000	1.000	0.766	0.766
Bank of India	2016	0.661	0.869	0.850	0.760	0.777
State Bank of Hyderabad	2016	0.995	1.000	1.000	0.995	0.995
Indian Bank	2016	0.875	1.000	1.000	0.875	0.875
Union Bank of India	2016	0.713	0.904	0.885	0.788	0.805
Oriental Bank of Commerce	2016	0.828	1.000	1.000	0.828	0.828
Axis Bank Limited	2016	1.000	1.000	1.000	1.000	1.000
South Indian Bank Ltd.	2016	0.723	0.834	0.785	0.867	0.921
Karnataka Bank Ltd.	2016	1.000	1.000	1.000	1.000	1.000
Lakshmi Vilas Bank Ltd.	2016	0.924	0.929	0.933	0.994	0.990
Bandhan Bank Limited	2016	1.000	1.000	1.000	1.000	1.000
City Union Bank Limited	2016	1.000	1.000	1.000	1.000	1.000
ICICI Bank Limited	2016	1.000	1.000	1.000	1.000	1.000
Karur Vysya Bank Ltd.	2016	1.000	1.000	1.000	1.000	1.000
Federal Bank Ltd.	2016	0.796	0.935	0.911	0.852	0.874
IndusInd Bank Ltd.	2016	1.000	1.000	1.000	1.000	1.000
The Dhanalakshmi Bank Ltd.	2016	0.752	0.765	0.753	0.984	0.999

Table 14 (continued)

Bank name	Year	CRSTE	OVRSTE	IVRSTE	OSE	ISE
Hdfc Bank Ltd.	2016	1.000	1.000	1.000	1.000	1.000
DCB Bank Limited	2016	0.929	0.991	0.989	0.938	0.939
Tamilnad Mercantile Bank Ltd.	2016	1.000	1.000	1.000	1.000	1.000
IDFC First Bank Limited	2016	1.000	1.000	1.000	1.000	1.000
RBL Bank Limited	2016	1.000	1.000	1.000	1.000	1.000
Nainital Bank Ltd.	2016	1.000	1.000	1.000	1.000	1.000
Jammu & Kashmir Bank Ltd.	2016	0.604	0.822	0.765	0.735	0.790
Kotak Mahindra Bank Ltd.	2016	0.656	0.832	0.814	0.789	0.806
Yes Bank Ltd.	2016	1.000	1.000	1.000	1.000	1.000
CSB Bank Limited	2016	1.000	1.000	1.000	1.000	1.000
Indian Overseas Bank	2017	0.555	0.751	0.578	0.740	0.961
Punjab And Sind Bank	2017	0.749	0.816	0.758	0.918	0.988
Andhra Bank	2017	0.761	0.906	0.889	0.840	0.856
Syndicate Bank	2017	0.655	1.000	1.000	0.655	0.655
UCO Bank	2017	0.940	1.000	1.000	0.940	0.940
Bharatiya Mahila Bank Ltd.	2017	0.664	1.000	1.000	0.664	0.664
Dena Bank	2017	0.698	0.796	0.746	0.877	0.936
Bank of Maharashtra	2017	0.604	0.743	0.705	0.813	0.857
Oriental Bank of Commerce	2017	0.785	0.815	0.785	0.963	1.000
State Bank of India	2017	0.747	1.000	1.000	0.747	0.747
State Bank of Travancore	2017	0.732	1.000	1.000	0.732	0.732
State Bank of Patiala	2017	0.576	0.676	0.616	0.851	0.935
Indian Bank	2017	0.893	0.978	0.976	0.913	0.915
Punjab National Bank	2017	0.821	1.000	1.000	0.821	0.821
Allahabad Bank	2017	0.703	0.731	0.703	0.962	0.999
Bank of India	2017	0.739	0.875	0.819	0.844	0.902
Corporation Bank	2017	1.000	1.000	1.000	1.000	1.000
Bank of Baroda	2017	0.922	1.000	1.000	0.922	0.922
Canara Bank	2017	0.774	0.969	0.957	0.798	0.808
IDBI Bank Limited	2017	0.897	0.989	0.987	0.907	0.909
Union Bank of India	2017	0.873	0.931	0.924	0.938	0.945
State Bank of Mysore	2017	0.549	0.836	0.744	0.657	0.739
United Bank of India	2017	0.924	1.000	1.000	0.924	0.924
Central Bank of India	2017	0.601	1.000	1.000	0.601	0.601
State Bank of Bikaner And Jaipur	2017	0.732	1.000	1.000	0.732	0.732
Vijaya Bank	2017	0.712	0.780	0.735	0.913	0.968
State Bank of Hyderabad	2017	0.663	0.745	0.682	0.890	0.973
The Dhanalakshmi Bank Ltd.	2017	0.776	0.900	0.844	0.862	0.920
Karnataka Bank Ltd.	2017	1.000	1.000	1.000	1.000	1.000
Bandhan Bank Limited	2017	1.000	1.000	1.000	1.000	1.000
Nainital Bank Ltd.	2017	1.000	1.000	1.000	1.000	1.000
Jammu & Kashmir Bank Ltd.	2017	0.633	1.000	1.000	0.633	0.633
Federal Bank Ltd.	2017	0.989	1.000	1.000	0.989	0.989
South Indian Bank Ltd.	2017	0.981	1.000	1.000	0.981	0.981

Table 14 (continued)

Bank name	Year	CRSTE	OVRSTE	IVRSTE	OSE	ISE
Karur Vysya Bank Ltd.	2017	0.873	1.000	1.000	0.873	0.873
DCB Bank Limited	2017	0.923	0.942	0.941	0.979	0.980
City Union Bank Limited	2017	1.000	1.000	1.000	1.000	1.000
Axis Bank Limited	2017	1.000	1.000	1.000	1.000	1.000
HDFC Bank Ltd.	2017	1.000	1.000	1.000	1.000	1.000
RBL Bank Limited	2017	0.856	0.907	0.915	0.943	0.935
Yes Bank Ltd.	2017	1.000	1.000	1.000	1.000	1.000
Lakshmi Vilas Bank Ltd.	2017	0.887	0.909	0.915	0.975	0.969
IndusInd Bank Ltd.	2017	1.000	1.000	1.000	1.000	1.000
Kotak Mahindra Bank Ltd.	2017	0.709	0.843	0.828	0.840	0.856
IDFC First Bank Limited	2017	1.000	1.000	1.000	1.000	1.000
CSB Bank Limited	2017	1.000	1.000	1.000	1.000	1.000
ICICI Bank Limited	2017	1.000	1.000	1.000	1.000	1.000
Tamilnad Mercantile Bank Ltd.	2017	1.000	1.000	1.000	1.000	1.000
Punjab and Sind Bank	2018	0.890	1.000	1.000	0.890	0.890
State Bank of India	2018	0.846	1.000	1.000	0.846	0.846
Union Bank of India	2018	1.000	1.000	1.000	1.000	1.000
Oriental Bank of Commerce	2018	1.000	1.000	1.000	1.000	1.000
UCO Bank	2018	1.000	1.000	1.000	1.000	1.000
Allahabad Bank	2018	0.829	0.841	0.831	0.986	0.997
Corporation Bank	2018	1.000	1.000	1.000	1.000	1.000
IDBI Bank Limited	2018	1.000	1.000	1.000	1.000	1.000
Indian Overseas Bank	2018	0.752	1.000	1.000	0.752	0.752
Central Bank of India	2018	0.897	1.000	1.000	0.897	0.897
Vijaya Bank	2018	0.868	1.000	1.000	0.868	0.868
Canara Bank	2018	0.778	1.000	1.000	0.778	0.778
Bank of Maharashtra	2018	0.857	1.000	1.000	0.857	0.857
Dena Bank	2018	0.776	1.000	1.000	0.776	0.776
Andhra Bank	2018	0.975	1.000	1.000	0.975	0.975
Syndicate Bank	2018	0.713	1.000	1.000	0.713	0.713
Indian Bank	2018	0.946	1.000	1.000	0.946	0.946
Bank of Baroda	2018	0.992	1.000	1.000	0.992	0.992
Punjab National Bank	2018	0.635	1.000	1.000	0.635	0.635
United Bank of India	2018	0.977	1.000	1.000	0.977	0.977
Bank of India	2018	0.790	0.971	0.968	0.813	0.816
CSB Bank Limited	2018	0.797	1.000	1.000	0.797	0.797
Tamilnad Mercantile Bank Ltd.	2018	1.000	1.000	1.000	1.000	1.000
Yes Bank Ltd.	2018	1.000	1.000	1.000	1.000	1.000
IndusInd bank Ltd.	2018	1.000	1.000	1.000	1.000	1.000
South Indian Bank Ltd.	2018	0.873	0.909	0.899	0.960	0.971
The Dhanalakshmi Bank Ltd.	2018	1.000	1.000	1.000	1.000	1.000
Axis Bank Limited	2018	1.000	1.000	1.000	1.000	1.000
Lakshmi Vilas Bank Ltd.	2018	0.759	0.798	0.817	0.951	0.929
RBL Bank Limited	2018	0.860	0.908	0.916	0.947	0.938

Table 14 (continued)

Bank name	Year	CRSTE	OVRSTE	IVRSTE	OSE	ISE
HDFC Bank Ltd.	2018	1.000	1.000	1.000	1.000	1.000
Karur Vysya Bank Ltd.	2018	0.862	0.942	0.920	0.915	0.937
City Union Bank Limited	2018	1.000	1.000	1.000	1.000	1.000
Kotak Mahindra Bank Ltd.	2018	0.834	1.000	1.000	0.834	0.834
Karnataka Bank Ltd.	2018	1.000	1.000	1.000	1.000	1.000
ICICI Bank Limited	2018	1.000	1.000	1.000	1.000	1.000
DCB Bank Limited	2018	0.894	0.914	0.917	0.979	0.975
Nainital Bank Ltd.	2018	1.000	1.000	1.000	1.000	1.000
Jammu & Kashmir Bank Ltd.	2018	0.557	0.949	0.881	0.587	0.632
IDFC First Bank Limited	2018	1.000	1.000	1.000	1.000	1.000
Federal Bank Ltd.	2018	1.000	1.000	1.000	1.000	1.000
Bandhan Bank Limited	2018	1.000	1.000	1.000	1.000	1.000
Central Bank of India	2019	1.000	1.000	1.000	1.000	1.000
Canara Bank	2019	0.809	1.000	1.000	0.809	0.809
Bank of Maharashtra	2019	0.925	0.926	0.925	0.999	1.000
State Bank of India	2019	0.642	1.000	1.000	0.642	0.642
Oriental Bank of Commerce	2019	0.859	0.906	0.894	0.948	0.961
Punjab National Bank	2019	0.862	1.000	1.000	0.862	0.862
Andhra Bank	2019	0.914	1.000	1.000	0.914	0.914
Indian Overseas Bank	2019	1.000	1.000	1.000	1.000	1.000
Corporation Bank	2019	1.000	1.000	1.000	1.000	1.000
Vijaya Bank	2019	0.708	1.000	1.000	0.708	0.708
Union Bank of India	2019	1.000	1.000	1.000	1.000	1.000
Bank of India	2019	0.700	0.854	0.811	0.820	0.864
Indian Bank	2019	0.965	1.000	1.000	0.965	0.965
Allahabad Bank	2019	0.876	0.896	0.894	0.978	0.981
Punjab and Sind Bank	2019	0.778	0.913	0.894	0.852	0.870
Bank of Baroda	2019	0.951	0.952	0.952	0.999	0.999
Syndicate Bank	2019	0.589	0.780	0.747	0.755	0.788
United Bank of India	2019	1.000	1.000	1.000	1.000	1.000
Dena Bank	2019	0.602	0.871	0.846	0.691	0.712
UCO Bank	2019	1.000	1.000	1.000	1.000	1.000
DCB Bank Limited	2019	0.827	1.000	1.000	0.827	0.827
HDFC Bank Ltd.	2019	1.000	1.000	1.000	1.000	1.000
IDBI Bank Limited	2019	1.000	1.000	1.000	1.000	1.000
Jammu & Kashmir Bank Ltd.	2019	0.537	0.732	0.663	0.734	0.810
South Indian Bank Ltd.	2019	0.829	0.862	0.839	0.962	0.988
Nainital Bank Ltd.	2019	1.000	1.000	1.000	1.000	1.000
RBL Bank Limited	2019	0.930	1.000	1.000	0.930	0.930
Kotak Mahindra Bank Ltd.	2019	0.776	0.821	0.786	0.945	0.988
Federal Bank Ltd.	2019	1.000	1.000	1.000	1.000	1.000
City Union Bank Limited	2019	1.000	1.000	1.000	1.000	1.000
IndusInd Bank Ltd.	2019	1.000	1.000	1.000	1.000	1.000
The Dhanalakshmi Bank Ltd.	2019	1.000	1.000	1.000	1.000	1.000

Table 14 (continued)

Bank name	Year	CRSTE	OVRSTE	IVRSTE	OSE	ISE
Lakshmi Vilas Bank Ltd.	2019	0.700	0.718	0.744	0.975	0.941
Bandhan Bank Limited	2019	1.000	1.000	1.000	1.000	1.000
CSB Bank Limited	2019	1.000	1.000	1.000	1.000	1.000
Karnataka Bank Ltd.	2019	0.996	1.000	1.000	0.996	0.996
ICICI Bank Limited	2019	0.828	0.896	0.839	0.924	0.986
Karur Vysya Bank Ltd.	2019	0.863	1.000	1.000	0.863	0.863
Axis Bank Limited	2019	1.000	1.000	1.000	1.000	1.000
IDFC First Bank Limited	2019	1.000	1.000	1.000	1.000	1.000
Yes Bank Ltd.	2019	1.000	1.000	1.000	1.000	1.000
Tamilnad Mercantile Bank Ltd.	2019	1.000	1.000	1.000	1.000	1.000
Oriental Bank of Commerce	2020	0.663	0.809	0.786	0.820	0.843
Syndicate Bank	2020	0.571	0.775	0.719	0.737	0.794
Bank of Baroda	2020	0.875	0.963	0.955	0.908	0.916
Canara Bank	2020	0.807	1.000	1.000	0.807	0.807
Punjab and Sind Bank	2020	0.752	0.863	0.832	0.872	0.904
Allahabad Bank	2020	0.874	0.982	0.978	0.891	0.894
UCO Bank	2020	1.000	1.000	1.000	1.000	1.000
Indian Bank	2020	0.974	1.000	1.000	0.974	0.974
United Bank of India	2020	0.916	1.000	1.000	0.916	0.916
Corporation Bank	2020	0.975	1.000	1.000	0.975	0.975
Andhra Bank	2020	0.703	0.884	0.869	0.795	0.809
Bank of Maharashtra	2020	1.000	1.000	1.000	1.000	1.000
Indian Overseas Bank	2020	0.898	0.958	0.956	0.937	0.939
Union Bank of India	2020	1.000	1.000	1.000	1.000	1.000
Bank of India	2020	0.803	0.984	0.978	0.816	0.821
State Bank of India	2020	0.703	1.000	1.000	0.703	0.703
Punjab National Bank	2020	0.953	1.000	1.000	0.953	0.953
Central Bank of India	2020	1.000	1.000	1.000	1.000	1.000
Federal Bank Ltd.	2020	1.000	1.000	1.000	1.000	1.000
The Dhanalakshmi Bank Ltd.	2020	1.000	1.000	1.000	1.000	1.000
Kotak Mahindra Bank Ltd.	2020	0.800	0.809	0.805	0.988	0.993
Tamilnad Mercantile Bank Ltd.	2020	1.000	1.000	1.000	1.000	1.000
City Union Bank Limited	2020	1.000	1.000	1.000	1.000	1.000
HDFC Bank Ltd.	2020	1.000	1.000	1.000	1.000	1.000
CSB Bank Limited	2020	0.986	1.000	1.000	0.986	0.986
South Indian Bank Ltd.	2020	0.802	0.850	0.833	0.943	0.962
IDBI Bank Limited	2020	0.667	0.670	0.668	0.996	1.000
Yes Bank Ltd.	2020	1.000	1.000	1.000	1.000	1.000
Nainital Bank Ltd.	2020	1.000	1.000	1.000	1.000	1.000
Karnataka Bank Ltd.	2020	0.974	0.975	0.975	1.000	1.000
Karur Vysya Bank Ltd.	2020	1.000	1.000	1.000	1.000	1.000
Jammu & Kashmir Bank Ltd.	2020	0.539	0.974	0.964	0.554	0.559
Lakshmi Vilas Bank Ltd.	2020	0.753	0.809	0.845	0.931	0.891
IndusInd Bank Ltd.	2020	1.000	1.000	1.000	1.000	1.000

Table 14 (continued)

Bank name	Year	CRSTE	OVRSTE	IVRSTE	OSE	ISE
DCB Bank Limited	2020	0.735	0.740	0.775	0.992	0.948
Bandhan Bank Limited	2020	0.801	0.971	0.980	0.825	0.817
RBL Bank Limited	2020	0.841	0.881	0.890	0.954	0.944
Axis Bank Limited	2020	1.000	1.000	1.000	1.000	1.000
ICICI Bank Limited	2020	0.767	0.776	0.769	0.988	0.998
IDFC First Bank Limited	2020	0.716	0.745	0.757	0.961	0.945

Note: Data Source is Statistical Tables Relating to Banks in India, RBI. CRSTE is the CRS technical efficiency, OVRSTE and IVRSTE are the output and input oriented VRS technical efficiency scores respectively. OSE and ISE are respectively the output and input oriented scale efficiencies. The scores are calculated using the MaxDEA software

Table 15 Average technical efficiency scores of banks in India based on SFA (2014–2020)

Banks	Investments	Non-interest income	Advances
Allahabad Bank	0.886	0.914	0.994
Andhra Bank	0.897	0.911	0.994
Axis Bank Limited	0.923	0.927	0.991
Bandhan Bank Limited	0.973	0.752	0.989
Bank of Baroda	0.975	0.940	0.994
Bank of India	0.949	0.931	0.994
Bank of Maharashtra	0.896	0.893	0.994
Canara Bank	0.951	0.935	0.994
Csb Bank Limited	0.935	0.791	0.989
Central Bank of India	0.895	0.899	0.994
City Union Bank Limited	0.922	0.873	0.990
Corporation Bank	0.895	0.907	0.994
Dcb Bank Limited	0.971	0.866	0.989
Dena Bank	0.897	0.898	0.994
The Dhanalakshmi Bank Ltd.	0.961	0.798	0.989
Federal Bank Ltd.	0.883	0.874	0.990
Hdfc Bank Ltd.	0.986	0.936	0.991
Icici Bank Limited	0.909	0.933	0.991
Idbi Bank Limited	0.849	0.913	0.993
Idfc First Bank Limited	0.889	0.851	0.989
Indian Bank	0.933	0.916	0.994
Indian Overseas Bank	0.862	0.898	0.994
Indusind Bank Ltd.	0.942	0.895	0.990
Ing Vysya Bank	0.957	0.871	0.989
Jammu & Kashmir Bank Ltd.	0.812	0.868	0.990
Karnataka Bank Ltd.	0.852	0.857	0.990
Karur Vysya Bank Ltd.	0.876	0.861	0.990
Kotak Mahindra Bank Ltd.	0.899	0.887	0.990
Lakshmi Vilas Bank Ltd.	0.878	0.844	0.990
Oriental Bank of Commerce	0.889	0.916	0.994
Punjab and Sind Bank	0.912	0.898	0.994
Punjab National Bank	0.950	0.931	0.994
Rbl Bank Limited	0.950	0.833	0.989
South Indian Bank Ltd.	0.863	0.862	0.990
State Bank of Bikaner And Jaipur	0.935	0.887	0.994
State Bank of Hyderabad	0.918	0.900	0.994
State Bank of India	0.997	0.971	0.994
State Bank of Mysore	0.935	0.900	0.994
State Bank of Patiala	0.907	0.887	0.994
State Bank of Travancore	0.945	0.894	0.994
Syndicate Bank	0.915	0.912	0.994
Tamilnad Mercantile Bank Ltd.	0.943	0.855	0.990

Table 15 (continued)

Banks	Investments	Non-interest income	Advances
Uco Bank	0.889	0.902	0.994
Union Bank of India	0.922	0.923	0.994
United Bank of India	0.888	0.904	0.994
Vijaya Bank	0.931	0.903	0.994
Yes Bank Ltd.	0.903	0.884	0.990

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