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Efficiency and technology gaps in Indian banking sector: Application of meta-frontier directional distance function DEA approach

Jatin Goyal [a,*], Manjit Singh [a], Rajdeep Singh [a], Arun Aggarwal [b]

[a] University School of Applied Management, Punjabi University, Patiala, India
[b] Chitkara Business School, Chitkara University, Punjab, India

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Abstract

Government of India aims at making the Indian Banks internationally competitive. In the wake of intense competition and changing global and national business environment, the efficiency issues have emerged as an important pillar of success in the Indian banking sector. Therefore, it is an essential task to comprehend the efficiency levels of the overall Indian banking sector and also across different ownership structures (viz. Public, Private and Foreign). The present study endeavors to carry out an assessment of intra-sector efficiency in the Indian banking sector based on a cross-sectional data of 66 banks for the year 2015-16. The authors employ directional distance function based meta-frontier DEA approach and the results reveal that the Indian banking sector is 73.44% efficient. It also confirms the existence of different production functions across different ownership structures of the industry. Among the different ownership structures, the group frontier of foreign banks coincides with the meta-frontier. The group frontier of private sector banks is the second closest to the meta-frontier and public sector banks are found to be the laggards in the overall industry. The study gains special significance in the backdrop of the recommendations floated by the Reserve Bank of India and Ministry of Finance (Government of India) to consolidate the public sector banks in order to retain fewer but healthier banks. The finding of the study fully support these recommendations and affirms that consolidation in the industry will bring positive synergies and will lead to the enhancement of efficiency levels in the industry.

Keywords: Efficiency; DEA; Directional distance function; Meta-frontier; Banking; India; Ownership structure

1. Introduction

The present competitive era marked by developments in the information technology and the ever increasing globalization has exerted tremendous pressure on the banks across all countries to ensure their sustainability. The prior

* Corresponding author.
E-mail addresses: jatin2goyal@gmail.com (J. Goyal), smanjitt@gmail.com (M. Singh), rajdeep.srcc@gmail.com (R. Singh), arun.aggarwal@chitkara.edu.in (A. Aggarwal).
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experience of the 1997-98 Asian financial crisis and the 2007-08 global financial crisis has highlighted the importance of a stable, sound and an efficient banking system in ensuring macroeconomic stability in the country. The existence of an inefficient and unstable banking system may push the economy into a slump.[1] Owing to increased liberalization and a globally integrated financial system only robust and efficient banks can ensure their sustainability. In fact, the existence of a large number of weak banks in the Indian banking sector has led to misallocation of the limited available resources and is hampering the growth of the banking sector in particular and the Indian economy in general. Therefore, the Ministry of finance, Government of India and the Reserve Bank of India are considering the consolidation of various banks in the Indian banking arena to retain fewer but healthier banks. Given the aforementioned considerations, it becomes imperative for the policymakers to have an insight into the intra-sector efficiency comparison in the Indian banking sector. The inferences from the study will help in evolving a focused strategy to restructure and revive the Indian banking sector and make it competitive at a global level.

Indian banking industry is one of the oldest in India and was well developed even before the country became politically independent in 1947. The Government of India decided to nationalize fourteen large commercial banks in 1969 and further in 1980, six more banks were nationalized. After the New Economic Policy, 1991 that brought in liberalization, privatization and globalization, the Indian banking sector saw the emergence of ever intense competition due to entry of new private and foreign players in the sector. The sector has grown at a healthy pace since then despite some global upheavals. According to IBEF[2] report, during the period 2006-17, the total deposits grew at a CAGR of 12.03% and by the year 2017 it reached to USD 1.54 trillion. The increase in total deposits can be attributed to the rising disposable incomes and increase in the savings rate. The total credit extended also surged and reached USD 1016 billion owing to increasing consumerism and an easier access to credit.[2] The consolidated balance sheets of the banking sector continued to grow at a modest pace during 2015-16 with assets/liabilities expanding at 7.7 per cent as compared to 9.7 per cent in 2014-15.[3] India's banking industry is growing exponentially and according to report by KPMG and CII[4]; India's banking industry has the potential to become the fifth largest in the world by 2020 and third largest by 2025. Therefore, in the light of such a significant contribution of the banking industry to the Indian economy, maintaining and improving the efficiency of the industry is a key focus area for Indian policymakers.

Although the Indian banking industry is one of the leaders in the world, however, the future journey does not seem to be easy. The banking sector has been under continued stress due to the increased burden of non-performing assets (NPAs). During 2015-16, the interest and non interest earning of the scheduled commercial banks declined due to slowdown in credit growth. The provisions and contingencies witnessed an uptrend owing to the deterioration in asset quality. The Asset Quality Review (AQR) of banks was done in the year 2015-16 to deal with the rising concerns of NPAs. Provisioning for NPAs was more than doubled which had an adverse impact on the profitability of the banks and the net profits declined by more than 60%.[3] Although private and foreign banks reported net profits, the profits of public sector banks declined by a whopping 148% and losses of Rs. 180 billion were reported.[3] The Government of India and RBI are taking measures such as capital infusion, increasing provisioning requirements, consolidation of banks, etc. However, such measures will not be effective unless and until they are focused in their approach. In order to render these measures effective, it is necessary that an efficiency analysis of the sub-sectors of the banking industry should also be done and various inefficiencies should be pointed out. The production technology used by different banks may not be same across different sub-sectors owing to the existing intra-industry heterogeneity. In the light of such a situation, measuring technical efficiencies of individual decision making units (banks) using a best practice technology (assumed for all the banks in the industry) may not provide a true picture.[5] Therefore, the major objective of this paper is to analyze the intra-sector efficiencies based on ownership structures in the Indian banking sector.

In order to achieve the above mentioned objective, a non-parametric linear programming based frontier technique named Data Envelopment Analysis (DEA) has been used. The advantage of using DEA over its close rival Stochastic Frontier Analysis (SFA) is that there is no need of defining the functional relationship between inputs and outputs or the specification of weights of inputs and outputs.[6] The resultant efficiency scores from SFA are partially dependent on how accurately the chosen functional form represents the true production function.[7] However, this is not the case with DEA. DEA has the capability to simultaneously take multiple inputs and multiple outputs for calculating the relative efficiency and come up with a scalar measure of overall performance. It also has the ability to investigate the changes in efficiency resulting from input saving and to assess whether the reasons for such changes are improvements in scale (scale efficiency) or in management practices (pure technical efficiency).[8] In order to have an in depth analysis into the efficiencies across different ownership groups, we have used directional distance based meta-frontier production function that has been successfully used by different authors (See Bogetoft and Otto[9]; Chambers et al.[10]; Färe and Grosskopf[11]; Huang et al.[12]; Ray[13]; Yao et al.[14]).

The current study is a unique addition to the sparse literature on managing efficiencies in the Indian banking sector and making it competitive at a global level. Firstly, owing to the significant contribution made by the Indian banking sector to the economy, it becomes imperative to evaluate the efficiency of the industry and make improvements wherever necessary. Secondly, to the best of our knowledge, till date no study has explored and analyzed the intra-sector efficiencies based on ownership types in the Indian banking sector. Thirdly, the current study has used directional distance function based meta-frontier analysis using DEA which allows us to incorporate different production functions for the sub-sectors in the same industry in a better manner. Lastly, looking at the methodological and geographical coverage of the previous work, it was found that there was no study that used directional distance function based meta-frontier analysis in the Indian banking sector. This study will be the first of its kind for banking industry in an emerging economy like India.

The rest of the paper is organized as follows. Section 2 comprises a brief theoretical background covering studies related to the banking industry and the application of DEA in various contexts. Data description and the research methodology part have been discussed in the Section 3 followed by empirical findings and discussion in the Section 4. Finally, Section 5 concludes the paper.

2. Theoretical background

Notwithstanding, a substantial body of literature exists that have analyzed and studied the technical efficiencies of banking industries all over the world using either the Data Envelopment Analysis or the Stochastic Frontier Analysis. For instance, Berg et al.[15]; Bhattacharya et al.[16]; Charles and Kumar[17]; Chatterjee[18]; Das et al.[19]; Favero and Papi[20]; Kumar et al.[21]; Kumar et al.[22]; Mester[23]; Miller and Noulas[24]; Mohan and Ray[25]; Rangrajan and Mampilly[26]; Resti[27]; Saha and Ravishankar[28]; Sahoo et al.[29]; Sathye[30]; Subrahmanyam[31]; Tyagarajan[32]; Wheelock and Wilson[33]; Yue[34] are some of the studies that have examined the technical efficiencies using DEA or SFA in banking industry all over the world.

As regards to the Indian banking industry, Rangarajan and Mampilly[26], Tyagarajan[32] and Subrahmanyam[31] were the earlier works that have examined various performance related issues in the Indian banking sector. However, none of these prior studies examined the efficiency of bank service in India. The prior literature on performance of Indian banking falls short of bringing us to any consensus. Bhattacharya et al.[16] used DEA to study the impact of liberalization on performance of the banks in India. The study reported that public sector banks performed better than the private sector banks as by that time private sector banks had not emerged fully in the Indian banking industry. On the same lines Das (1997) in his study on efficiency in Indian banking sector for the period 1990−1996 reported an improvement in the allocative efficiency of banks from the public sector. However, the study reported a decline in the technical efficiency of these banks. Contrary to this Saha and Ravisankar[28] reported an improvement in the efficiency of public sector banks during the period 1992−1995 barring few exceptions. While conducting an investigation into the efficiency in Indian banking industry based on ownership types, Sathye[30] highlighted that the public sector banks were the most efficient. The foreign banks ranked second while the private banks ranked third in terms of efficiency. However, Sahoo et al.[29] in their study investigated the efficiency levels in Indian banking sector from the period 1998−2005 and reported contrary results to Sathye.[30] The study highlighted that both foreign banks and private banks were better performers as compared to the public banks. Recently, Kumar et al.[22] highlighted that public sector banks can leverage the benefits of increasing returns to scale. The study highlighted that steps such as capital infusion or consolidation of the banks in the sector can lead to enormous gains in the efficiency.

Over time, it has been advocated by a vast section of the researchers that DEA is a superior technique than SFA in computing overall efficiency scores across diverse industries (Chandra et al.[6]; Kumar and Arora[7]; Kumar and Gulati[35]; Kumar[36]). Charnes et al.[37] developed DEA as a mathematical technique based on linear programming to measure the relative efficiencies of decision making units. Banker et al.[38] expanded the technique further to incorporate variable returns as well. DEA as a technique has been acknowledged worldwide. In the present study, we have used a directional distance based meta frontier approach to conduct an intra-sector comparison across the entire spectrum of ownership groups in Indian banking industry. The findings give valuable insights to policymakers to devise their strategy to enhance efficiency in the sector by taking into consideration diffrentials in efficiency across ownership types.

3. Methodological framework

3.1. Technical efficiency (TE) and its measurement

In economic terms, the TE of a firm is defined as producing maximum output(s) using given level of input(s) or utilizing minimum input(s) for producing given level of output(s). The concept of TE reflects the producer's ability to avoid the wastage of resources given the constraints faced by all companies within a group. The first theoretical discussion related to the measurement of TE exists in the ideas of Farrell[39]; who sketched upon the work of Debreu[40] and Koopmans[41] to define a simple measure of productive efficiency to account for multiple inputs. In this approach, the author decomposed the productive efficiency into technical and allocative efficiency. TE was defined as an ability of a firm to maximize output from a set of given inputs and allocative efficiency as an ability of a firm to use these inputs in optimal proportions, given their respective prices.

To illustrate Farrell's efficiency, let us assume output $y \in \Re^S_+$ is a non-negative vector of quantities of outputs produced from $x \in \Re^M_+$, a non-negative vector of quantities of inputs, to obtain feasible input-output bundle $(x,\ y)$ where feasible input-output bundles constitutes the production possibility set T given as:

$$T = \{(x, y) : x\, can\, produce\ y; x \geq 0; y \geq 0\} \quad [1]$$

Therefore, an input-output combination (x^o, y^o) is feasible if and only if $(x^o, y^o) \in T$. In the single input-output case, the frontier or the graph of the technology is defined by the production function $L(y)$ representing the minimum quantity of x that can be used to produce given level of y.

The corresponding production possibility set can be defined as:

$$T = \{(x, y) : x \geq L(y); x \geq 0; y \geq 0\} \quad [2]$$

However, the above efficiency measure given by Farrell has been challenged by many researchers who called for alternative measures of efficiency improvement. One such alternative is directional distance function based efficiency measurement. The directional distance function based efficiency method considers simultaneous improvements on input and output side by basically combining the Farrell input and output efficiency measures into one measure.[10] We define directional distance function as:

$$\overrightarrow{D}_T\left(x, y; g_x, g_y\right) = Sup\left\{\beta :\ \left(x - \beta g_x\ , y + \beta g_y\right) \in T\right\}$$

Where (g_x, g_y) is a non-zero vector in $\Re^M_+ \times \Re^S_+$. This vector determines the direction in which inputs and outputs have to move. Essentially, βg_x is subtracted from x and βg_y is added to y, we may choose $(-x, y)$ for (g_x, g_y) and in that case the directional distance function becomes (See Ray[13]; Chambers et al.[10]):

$$\overrightarrow{D}_T(x,\ y) = \max\beta : \left\{(1-\beta)x, (1+\beta)y\right\} \in T$$

Thus, this function is defined by simultaneously contracting inputs and expanding outputs.

3.2. The DEA approach − CCR and BCC models

We can transform the Farrell's idea of measuring efficiency to obtain the mathematical programs that many consider it as synonym with the DEA approach and usually refer to as mathematical programming approach to efficiency analysis. DEA is a linear programming technique that maps out non-parametric surface frontiers (isoquants) over the sample to measure the efficiency level of each decision making unit (DMU) relative to the frontier.[8] Since the inception of DEA methodology, numerous mathematical programming models have been proposed in DEA literature (See Charnes et al.[42]; Zhu[43]). Essentially, these DEA models seek to establish which of the n DMUs determine the envelopment surface, or efficiency frontier. The production frontier is empirically constructed using mathematical programming methods from observed input-output data of sample companies. Efficiency of DMUs is then measured in terms of how far they are from the production frontier.

The concept of TE got wide attention only after the seminal paper of Charnes et al.[37]; who developed a linear programming based mathematical technique viz. Data Envelopment Analysis (DEA) for measuring the relative TE of similar units referred to as decision making units (DMUs). The model proposed by Charnes et al.[37]; also known as the CCR model, was based on the assumptions of constant returns-to-scale (CRS). CCR model imposes three restrictions on the frontier technology viz. constant returns-to-scale, convexity of the set of feasible input-output combinations, and strong disposability of inputs and outputs.[44] CCR model was further expanded by Banker et al.[38] to embrace variable returns-to-scale (VRS). This model later on got recognition as BCC model. Various other DEA models have been developed to use either the input or output orientation, and these models emphasize proportional reduction of excessive inputs (input slacks) or proportional augmentation of lacking outputs (output slacks).[45] However, in the present study, we used directional distance function based DEA efficiency model which reduces the input consumption with simultaneous increase in outputs.

To illustrate the CCR model, consider n DMUs, $j = 1, 2, \ldots, n$. The units are homogeneous with the same types of inputs and outputs. Assume there are m inputs, $i = 1, 2, \ldots, m$ and s outputs, $r = 1, 2, \ldots, s$. Let x_{ij} and y_{rj} denote, respectively, the input and output vectors for the j^{th} DMU. Thus, x_{ij} is a $(m \times 1)$ column vector and y_{rj} is a $(s \times 1)$ column vector. Moreover, $X = (x_1, x_2, \ldots, x_n)$ is the $(m \times n)$ input matrix and $Y = (y_1, y_2, \ldots, y_n)$ is the $(s \times n)$ output matrix. The CCR model assigns weights to each input and output, and then assesses the efficiency of a given DMU by the ratio of the aggregate weighted output to the aggregate weighted input. The weights assigned must be non-negative. Also, they must restrict each DMU from receiving a ratio (of the weighted output to the weighted input) that is greater than 1. Mathematically, the corresponding optimization problem which we use to evaluate the efficiency of the DMU k using directional distance function based CCR model can be written as follows:

$$
\begin{aligned}
& \mathit{Maximize}\ \beta \\
& \mathit{Subject\ to}: \sum_{j=1}^{N} \lambda_j x_{ij} + \beta x_{ik} \le x_{ik} \\
& \sum_{j=1}^{N} \lambda_j y_{rj} - \beta y_{rk} \ge y_{rk} \\
& \lambda_j \ge 0; \beta = \mathit{free}
\end{aligned}
\tag{3}
$$

where, λ is a $(n \times 1)$ column vector; $i = 1, 2, \ldots, m$ (Counter for inputs); $r = 1, 2, \ldots, s$ (Counter for outputs);$j = 1, 2, \ldots, n$ (Counter for companies); x_{ij} = amount of input i used by DMU j; y_{rj} = amount of output r produced by DMU j; and k represents the DMU whose efficiency is to be evaluated.

We denote $TE_{CRS} = (1 - \beta) = \theta$, the overall technical efficiency (OTE) score measured by the directional distance function based CCR method. Let $\theta_k{}^*$ denotes the solution to equation [3] then obviously $\theta_k^* \le 1$. If $\theta_k^* = 1$, it indicates a CCR technically efficient DMU, if $\theta_k^* < 1$, it indicates CCR technically inefficient. Here it is worthwhile to note that the above linear programming problem must be solved n times, once for each DMU in the sample. A value of θ is then obtained for each DMU.

The CRS assumption is appropriate in cases where all DMUs operate at an optimal scale. However, there might exist some DMUs which do not operate at an optimal scale due to certain constraints. Imperfect competition, constraints on finance, etc. may cause a DMU to be not operating at optimal scale.[46] Note that some DMUs that are not efficient in the CCR model considered so far may become efficient if we assume the VRS relaxing the assumption of CRS.[47] Therefore, one needs to use the VRS model of DEA, where overall technical efficiency (OTE) can be decomposed into pure technical efficiency (PTE) and scale efficiency (SE). The PTE provides a measure of managerial efficiency which can be interpreted as management's capacity to convert the inputs into outputs. Likewise, SE measure provides us with the indication whether the DMU under consideration is operating at optimal scale size or not. The VRS assumption implies that an increase in inputs may result in either more or less than proportionate increase in output. The VRS model incorporates the dual of CRS model, with an extra convexity constraint $\sum_{j=1}^{N} \lambda_j = 1$ into problem, which essentially ensures that an inefficient DMU is only benchmarked against DMU of similar size.

The corresponding optimization problem to directional distance function based BCC model can be written as follows:

$$
\begin{aligned}
&\textit{Maximize } \beta\\
&\textit{Subject to}: \sum_{j=1}^{N} \lambda_j x_{ij} + \beta x_{ik} \le x_{ik}\\
&\sum_{j=1}^{N} \lambda_j y_{rj} - \beta y_{rk} \ge y_{rk}\\
&\sum_{j=1}^{N} \lambda_j = 1\\
&\lambda_j \ge 0; \beta = \textit{free}
\end{aligned}
\qquad [4]
$$

We denote $TE_{VRS} = (1-\beta) = \mu$, the pure technical efficiency (PTE) score measured by the directional distance function based BCC method. It is worthwhile to mention that BCC model measures the PTE, whereas CCR model measures both PTE and SE. Clearly, $TE_{CRS} \le TE_{VRS}$, hence by using TE^k_{CRS} and TE^k_{VRS} measures, we derive a measure of SE as a ratio of TE^k_{CRS} to TE^k_{VRS} given as:

$$SE^k = \delta_k = TE^k_{CRS} / TE^k_{VRS} = \theta_k / \mu_k = OTE/PTE \qquad [5]$$

3.3. Group frontier and Meta-frontier

It is necessary to recognize that even if the banks considered in this study are homogeneous in nature and come under the broader umbrella of banking industry. However, the production technology used by them may not be all unique and it may vary across different ownership structures because there exists intra-industry heterogeneity. Different geographical, political, structural and other economic factors may give rise to such a situation. So, measuring TE of individual DMUs (banks) using a best practice technology (assumed for all DMUs in the industry) as the benchmark may not provide a complete picture.[5] Rather, a group frontier (also called local frontier) may be formed taking the banks belonging to a particular ownership structure alone. Besides this, one meta-frontier or grand-frontier will also be created taking all the banks together. We can thus evaluate a particular bank against these two frontiers, viz., group frontier or local frontier vis-à-vis the meta-frontier or grand frontier.

It is possible to conceptualize the existence of sub-technologies that represent the production possibilities of different ownership structures of banks.[48] In order to construct different production frontiers we first categorize the banks into different groups based on ownership structure. Suppose N banks are observed, $J = 1, 2, \ldots.., N$ and these banks are classified into H number of distinct groups (the group-wise complete list of banks is provided in Appendix I), where g^{th} group contains N_g number of banks, such that:

$$N = \sum_{g=1}^{H} N_g \qquad [6]$$

We then partition banks into non-overlapping subsets given as:

$$J_g = \{j : \textit{Bank } j \textit{ belongs to group } g; (g = 1, 2, \ldots.H)\} \qquad [7]$$

In this case, the production possibility set for group g will be:

$$T^g = \left\{ (x, y) : x \ge \sum_{j\in J_g} \lambda_{gj} x^j_g; y \le \sum_{j\in J_g} \lambda_{gj} y^j_g; \sum_{j=J_g} \lambda_{gj} = 1; \lambda_{gj} \ge 0; g = 1, 2, \ldots.H; j = 1, 2, \ldots.N_g \right\} \qquad [8]$$

The set T^g is the free disposal convex hull of the observed input-output bundles of banks from group g and (x^j, y^j) are the observed input-output bundle of an individual bank j in a sample of N_g banks in the data. In directional distance function based CCR model, a measure of within-group technical efficiency (TE_g) of bank k (belonging to group g) can be given as:

$$TE_g^k = \left(1 - \beta_g^k\right) = \theta_g^k$$

Where θ_g^k solves the following linear program:

$$\begin{aligned}
&\textit{Maximize } \beta \\
&\textit{Subject to}: \sum_{j \in J_g} \lambda_{gj} x_g^j + \beta_g^k x_g^k \le x_g^k \\
&\sum_{j \in J_g} \lambda_{gj} y_g^j - \beta_g^k y_g^k \ge y_g^k \\
&\lambda_{gj} \ge 0\,;\ \beta_g^k = \textit{free}
\end{aligned} \qquad [9]$$

The above linear programming problem is solved for each bank in g^{th} group.

If we assume the VRS assumption, an extra convexity constraint $\sum_{j \in J_g} \lambda_{gj} = 1$ will be added to the above linear programming problem.

Now, we consider the TE of the same bank k of g^{th} group relative to a grand technological frontier, or what we call is the meta-frontier. The meta-frontier is the outer envelope of all of the group frontiers. It consists of the boundary points of the free disposal convex hull of the input-output vector of all banks in the sample. The grand TE (TE_G) of the bank k of g^{th} group is measured as:

$$TE_G^k = \left(1 - \beta_G^k\right) = \theta_G^k$$

Where θ_G^k solves the following linear program:

$$\begin{aligned}
&\textit{Maximize } \beta \\
&\textit{Subject to}: \sum_{g=1}^{H} \sum_{j \in J_g} \lambda_{gj} x_g^j + \beta_G^k x_g^k \le x_g^k \\
&\sum_{g=1}^{H} \sum_{j \in J_g} \lambda_{gj} y_g^j - \beta_G^k y_g^k \ge y_g^k \\
&\lambda_{gj} \ge 0; \beta_G^k = \textit{free}
\end{aligned} \qquad [10]$$

If we assume the VRS assumption, an extra convexity constraint $\sum_{g=1}^{H} \sum_{j \in J_g} \lambda_{gj} = 1$ will be added to the above linear programming problem.

One important observation here is that the meta-frontier encompasses each and every group's production possibility set, hence it is quite obvious that $\theta_G^k \le \theta_g^k$, for every k and g. In other words, banks, when evaluated against a group frontier, cannot be more technically efficient against the meta-frontier.

3.4. Technology closeness ratio (TCR)[1]

The technology closeness ratio (TCR), measures the closeness of group frontiers to the meta-frontier. When a bank's (say bank k in group g) group efficiency (i.e., TE of the bank evaluated against the group frontier as the benchmark) and the grand efficiency (i.e., TE of the bank evaluated against the meta-frontier as the benchmark) measures are close to each other, it is easily understood that the two frontiers themselves are very close, at least corresponding to the bank k. For an understanding of overall proximity of a group frontier to the meta-frontier, instead of evaluating the proximity of the group frontier to the meta-frontier at each such individual point within the group, one can have overall measure of proximity for the group as a whole. For that, we first define an average TE of the banks in the group by taking the geometric average of such individual TEs. For the group g, this will be given by:

[1] This ratio is also defined in literature as the technology gap ratio. (See Battese et al.[58]; Battese and Rao[62]).

$$TE_g(g) = \left(\prod_{k=1}^{N_g} TE_g^k\right)^{1/N_g} \quad [11]$$

Similarly, the average TE of group g, measured from the meta-frontier, will be:

$$TE_G(g) = \left(\prod_{k=1}^{N_g} TE_G^k\right)^{1/N_g} \quad [12]$$

For group g, an overall measure of proximity of the group frontier to the meta-frontier is called technology closeness ratio (TCR), given by:

$$TCR(g) = \frac{TE_G(g)}{TE_g(g)} \quad [13]$$

TCR increases if the group frontier shifts towards the meta-frontier, ceteris paribus, and is bounded above by unity which would be realised if and only if group frontier coincides with the meta-frontier. It implies that banks belonging to a specific group are quite efficient amongst themselves. However, the efficiency tends to decrease when the canvas of comparison is increased by including all the banks in the analysis. That is why the group frontiers always lie below the meta-frontier.

3.5. Description of data and sample

All the data relating to the input and output variables concerning this study is based on the cross-sectional bank level data for the year 2015–16 and has been obtained from the Prowess database of Centre for Monitoring Indian Economy (CMIE) and Reserve Bank of India's (RBI) official website. Initially, we considered the entire list of banks to have a momentary look for the purpose of checking the availability of data. The banks with incomplete financial information were then excluded. The filtered sample size provided us with the data of 66 banks. The next step was the identification of different ownership structures for the estimation of meta-frontier model. Based on the intra-industry classification of Indian banking industry, we have selected three major banking groups based on ownership structure viz. Public Banks, Private Banks and Foreign Banks. The ownership structure wise distribution of sample banks is listed in Table 1. Since our sample includes most of the leading banks on the top and also the banks which are struggling to make ends at the bottom, we truly believe that our sample is representative enough represent the Indian banking industry. We used software R[2] to perform the empirical analysis.

3.6. Selection of input and output variables

The foremost task for the computation of efficiency using DEA is to specify a set of input and output variables. Since an organisation's performance is a complex phenomenon requiring more than a single criterion, recent studies have argued that a multi-factor performance measurement model may be used.[49] Two diverse approaches appear in the

Table 1
Ownership structure wise distribution of Banks.

Ownership Structure	No. of Banks	Percentage
Public Banks	22	33.33
Private Banks	21	31.82
Foreign Banks	23	34.85
Total	66	100

[2] *Benchmarking*, *ucminf* and l*pSolveAPI* packages.

DEA literature regarding the choice of outputs and inputs for assessing the efficiency of banks. One is called the intermediation approach while the other is called the production approach. The intermediation approach views the banks as using deposits together with purchased inputs to produce various categories of bank assets. In this approach, the outputs are measured in monetary values and total costs include all operating and interest expenses.[50] On the contrary, in production approach the banks are viewed as service providers to customers and emphasis is given to operating costs. Production approach excludes the interest expenses paid on deposits since deposits are viewed as outputs. Although the intermediation approach is most commonly used in the empirical studies, neither approach is completely satisfactory, largely because the deposits have both input and output characteristics which are not easily disaggregated empirically[51]. Berger and Humphrey[52] suggested that the intermediation approach is best suited for analyzing bank level efficiency, whereas the production approach is well suited for measuring branch level efficiency. Also, in practice, the availability of data required by the production approach is usually very difficult to collect. Hence, considering this limitation, we also followed the intermediation approach.

So far our choice of input and output variables is concerned, we referred to various natural choices amongst various researchers (See Berg et al.[15]; Kumar et al.[22]; Saha and Ravisankar[28]; Sahoo et al.[29]; Sathye[30]; Kumar[51]; Debasish[53]; Sherman and Gold[54]; Yeh[55]). In the present study, our first choice of input is governed by the fact that the primary business of banks is to borrow funds from the savers (i.e. deposits) and lend those funds to others for profits. Besides this, banks also take loans from the central bank or other commercial banks (i.e. borrowings). Both these sources i.e. deposits and borrowings account for total loanable funds of a bank. As a second input the personnel and operating charges of the banks, which constitute a significant proportion of a bank's total cost have been considered. Besides this, physical capital employed (sum of all fixed assets less depreciation) in business has also been taken into account as a third input. The final input variables which have been considered are (i) total loanable funds (sum of all deposits and borrowings), (ii) personnel and operating charges, and (iii) physical capital.

While making the choice of output variables, we found spread i.e. net interest income and non-interest income as most accepted amongst various researchers. Net interest income represents the net income received by the banks from advancing of all types of loans less interest paid on all deposits. The output variable ‘non-interest income’ accounts for income from other important activities of banks such as commission, fee, discounting of bills, forex income and brokerage etc. Likewise, following the same pattern, we used (i) net interest income, and (ii) non-interest income as two output variables for this study. We have divided the input and output variables with the individual bank's number of branches to remove extreme heterogeneity in the data. Table 2 shows the descriptive statistics of all the inputs and outputs variables used in this study.

Since, the DEA efficiency scores depend heavily on the size of the sample, the number and choice of input and output variables chosen, some discussion on the adequacy of sample size is justified here. The size of the sample utilised in the present study is consistent with the various rules of thumb available in the DEA literature. Cooper et al.[56] provides two such rules that together can be expressed as: $n \geq \{m \times s\}$ or $n \geq \{3(m+s)\}$, $\forall\ n =$ number of DMUs, $m =$ number of inputs, $s =$ number of outputs. The first rule of thumb states that number of DMUs should be greater than equal to product of inputs and outputs. While the second rule states that number of DMUs should be at least three times the sum of number of input and output variables. Given $m = 3$ and $s = 2$ in our study, the sample size $n = 66$ used in the present study exceeds the above cited criterion. Further, the number of DMUs in each sub-sector also fulfil the desirable size as suggested by the above mentioned rules of thumb to obtain sufficient discriminatory power.

Table 2
Descriptive statistics of input and output variables (N = 66).

Rs. (Million)/Per Branch.

Variable	Mean	Standard Deviation	Minimum	First Quartile	Median	Third Quartile	Maximum	Skewness	Kurtosis
Net Interest Income	40.51	86.73	0.74	1.59	2.26	42.89	525.19	3.59	15.74
Non-Interest Income	20.43	42.55	0.18	0.60	0.91	17.57	196.72	2.66	6.88
Personnel & Operating Charges	17.28	33.92	0.55	0.96	1.27	18.28	162.11	2.76	7.78
Physical Capital	5.51	12.38	0.13	0.57	0.91	4.63	81.24	4.31	22.43
Total Loanable Funds	978.72	1953.76	17.96	62.59	94.01	815.32	9625.92	2.90	8.88

4. Empirical findings

Appendix II lists the β values from meta-frontier and group-frontiers. The summary statistics and frequency distribution of overall technical efficiency (OTE) scores, pure technical efficiency (PTE) scores and scale efficiency (SE) scores of all the 66 banks for the year 2015-16 have been presented in Table 3. The mean of OTE scores is 0.7344 indicating that the overall technical inefficiency (OTIE) in the Indian banking industry is 26.56 percent. Since we have used the directional distance function based DEA model, it represents that on an average the Indian banks have the potential to decrease inputs along with a simultaneous increase in outputs by 26.56 percent. The underlying reason behind such inefficiency may the selection of sub-optimal scale size or inefficiency due to poor management of the banks.

The OTE scores obtained through CCR model can be decomposed into two mutually exclusive non-additive components viz. pure technical efficiency (PTE) and scale efficiency (SE). It can be done by using the BCC model upon the same data. The results obtained through BCC model gives us the measure of PTE, which is devoid of scale effect. If there is a difference in scores for a particular bank, it indicates that there exists scale inefficiency (SIE). In DEA literature, the DMUs getting OTE scores equal to 1 are referred to as 'globally technical efficient' and banks getting PTE scores equal to 1 but OTE scores not equal to 1 are called 'locally technical efficient'. It is significant to note VRS assumption based BCC model forms a convex hull of intersecting planes which envelope the data points more tightly than the CRS conical hull and thus provides technical efficiency scores (i.e. PTE) which are greater than or equal to those obtained using the CCR model (i.e. OTE).[57]

Table 3 further reveals that out of 66 banks included in the sample, only 9 banks (i.e. 13.64 percent) have acquired the status of locally technical efficient since they attained PTE score equal to 1. The mean value of PTE scores is 0.8343 indicating that the extent of pure technical inefficiency (PTIE) in the Indian banking industry is 16.57 percent. The results outline that 16.57 percentage points of 26.56 percent of overall technical inefficiency (OTIE) as identified above in the Indian banking industry are primarily attributed to managerial inefficiency. Out of these 66 banks, 4 banks are also relatively efficient under CRS with OTE score equal to 1 i.e. they are globally as well as locally technical efficient. Further, for remaining 5 banks it may be stated that they are locally technical efficient but globally inefficient. The OTIE in these 5 banks is caused due to failure to operate at most productive scale size (MPSS). In other words, the technical inefficiency in these banks is not due to managerial incapability to effectively allocate the resources in the production process but rather inappropriate choice of the scale size. It has been further noted that in 28 banks (i.e. 42.42 percent) the extent of PTIE is more than 20 percent.

So far the SE scores are concerned, the value of SE score of 1 implies that the particular bank is operating at MPSS i.e. optimal scale size. On the contrary, a value of SE score $\neq$ 1 implies that bank is experiencing inefficiency because it is not operating at its optimal scale size. In our analysis, the mean value of SE scores is 0.8798 indicating that the

Table 3
Frequency distribution & descriptive statistics of OTE, PTE and SE scores of Indian banking industry.

Range of Efficiency Scores	OTE		PTE		SE	
	No. of Banks	Percentage	No. of Banks	Percentage	No. of Banks	Percentage
$0.5 \leq$ Score < 0.6	7	10.61	1	01.52	0	00.00
$0.6 \leq$ Score < 0.7	24	36.36	8	12.12	2	03.03
$0.7 \leq$ Score < 0.8	13	19.70	19	28.78	14	21.21
$0.8 \leq$ Score < 0.9	14	21.21	20	30.30	21	31.82
$0.9 \leq$ Score < 1	4	06.06	9	13.64	25	37.88
Score $= 1$	4	06.06	9	13.64	4	06.06
Total	**66**	**100**	**66**	**100**	**66**	**100**
Mean	**0.7344**		**0.8343**		**0.8798**	
	Minimum	First Quartile	Median	Third Quartile	Maximum	Standard Deviation
Descriptive Statistics						
OTE	0.5148	0.6336	0.7101	0.8386	1	0.1281
PTE	0.5925	0.7548	0.8415	0.9087	1	0.1068
SE	0.6292	0.8045	0.8709	0.9694	1	0.0941

average level of SIE in the Indian banking industry is about 12.02 percent. SE scores range from a minimum of 0.6292 to a maximum of 1. The lower mean and high standard deviation of PTE scores as compared to SE scores indicate that a greater portion of OTIE is due to PTIE.

In Table 3, it can also be observed that out of 66 banks included in the sample, only 4 banks (6.06 percent) have attained SE score equal to 1 and are operating at MPSS. Thus, it portrays that the remaining 62 (93.94 percent) banks are operating with some degree of SIE, albeit of different magnitude. It was also found that 50 out of 66 banks have got the SE score more than 0.8 and are operating either at MPSS or near to MPSS.

An ownership structure wise descriptive statistics of efficient banks of Indian banking industry (from meta frontier) have been given in Table 4. Under CRS assumption, out of 4 globally efficient banks, all the banks belong to the foreign banks group of industry, and if the technology is assumed to be the VRS, 6 foreign banks and 3 private banks have been found locally technical efficient. One important highlighting point of Table 4 is that none of the public sector banks has been turned out to be efficient. Therefore, it can be inferred that the public banks are the laggards and the foreign banks are the leaders of the Indian banking industry.

4.1. Group frontiers vis-à-vis the meta-frontier

As outlined earlier, due to different economic, geographical, political, structural and administrative factors even the banks belonging to the same industry may face different production functions. Therefore, the inference drawn on the basis of overall analysis of the industry will not provide the true picture. Hence, it becomes essential to account for the intra-industry variations in efficiency of different banks. To account for these variations, we have applied the technique of meta-frontier which has been used earlier by different researchers in different industries (See Battese et al.[58]; Hayami and Ruttan[59]; Rao et al.[60]). Fig. 1 shows the demonstrated layout of meta-frontier (i.e. industry as a whole) and group frontiers (representing one particular ownership structure) of Indian banking industry. It can be clearly observed that meta-frontier envelopes all the group frontiers representing different ownership structures of Indian banking industry. Fig. 2 shows the actual projected layout of group frontiers.

This two way comparison of the efficiency of banks will help us to identify the technological gaps and provide with the possible solutions to cover such gaps. TCR captures the distance between the local and global frontier that may arise due to different factors i.e. gaps due to different ownership structure. A high level of TCR does not imply that banks in a specific group are, on an average, more efficient. TCR of any group is an index of the proximity of the group frontier to the grand or meta-frontier. A high value of the TCR for any group implies that, on an average, the maximum output producible from minimum input bundle by a bank required to produce within a group would be almost as high as what could be produced if the bank could choose to locate in the corresponding alternative group.[61]

Table 5 summarizes the mean (geometric mean) OTE, PTE & SE scores of different banks of Indian banking industry measured against the meta-frontier (constructed by considering all the banks in the sample) and respective group frontiers (constructed by considering the banks belonging to one particular ownership structure only). It also presents the differences in efficiency captured through TCR i.e. the ratio between the geometric mean of efficiency scores measured through meta-frontier to the efficiency scores measured through group frontier.

In the case of public sector banks, the OTE score value of 0.6377 computed against the meta-frontier implies that banks belonging to this group have the potential to decrease inputs along with a simultaneous increase in outputs by

Table 4
Ownership structure wise descriptive statistics of efficient banks of Indian banking industry.

Ownership Structure	OTE		PTE		SE	
	No. of Banks	Percentage	No. of Banks	Percentage	No. of Banks	Percentage
Public Banks	0	00.00	0	00.00	0	00.00
Private Banks	0	00.00	3	33.33	0	00.00
Foreign Banks	4	100.00	6	66.67	4	100.00
Total	**4**	**100**	**9**	**100**	**4**	**100**

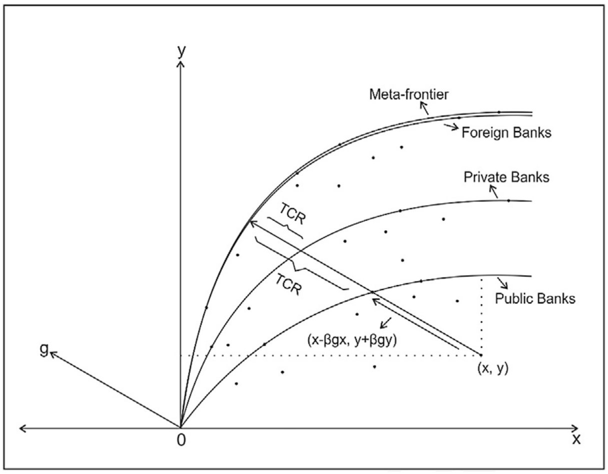

Fig. 1. Demonstrated layout of group frontiers vis-à-vis the meta-frontier.

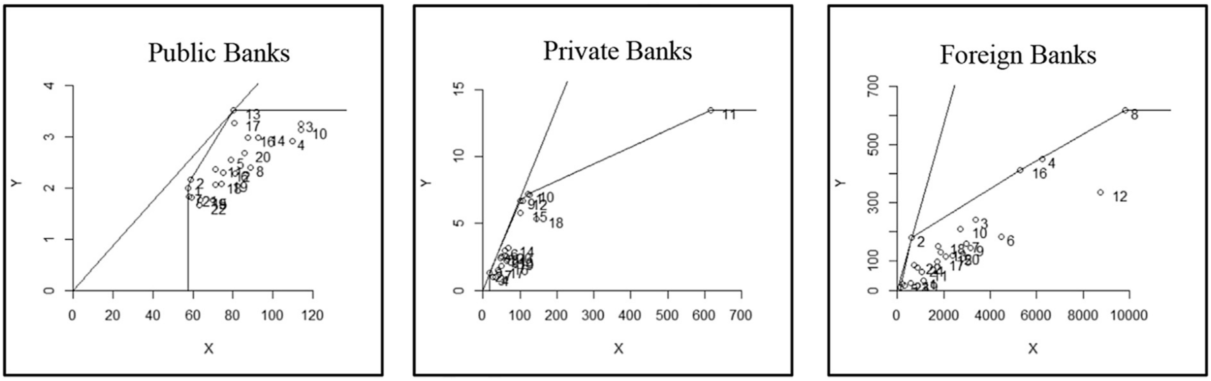

Fig. 2. Layout of group frontiers.

Table 5
Ownership structure wise OTE, PTE & SE scores of Indian banking industry measured against the meta-frontier and respective group frontiers and TCR.

OTE				
Ownership Structure	Mean OTE (From Meta Frontier)	Mean OTE (From Group Frontier)	TCR	Rank
Public Banks	0.6377	0.9381	0.6798	3
Private Banks	0.6890	0.8680	0.7934	2
Foreign Banks	0.8544	0.8544	1	1
PTE				
Ownership Structure	Mean PTE (From Meta Frontier)	Mean PTE (From Group Frontier)	TCR	Rank
Public Banks	0.7765	0.9724	0.7986	3
Private Banks	0.8286	0.9129	0.9076	2
Foreign Banks	0.9063	0.9067	0.9996	1
SE				
Ownership Structure	Mean SE (From Meta Frontier)	Mean SE (From Group Frontier)	TCR	Rank
Public Banks	0.8212	0.9648	0.8512	3
Private Banks	0.8316	0.9507	0.8747	2
Foreign Banks	0.9427	0.9427	1	1

36.23 percent. However, the magnitude of inefficiency computed against group frontier stands at 6.19 percent. Unsurprisingly, under meta-frontier technology the efficiency of public sector banks stands below the group frontier. Hence, we can see that there exists more scope of improvement in efficiency when we compare the public sector banks to meta-frontier as against the group frontier. A value of 0.6798 in OTE based TCR implies that the gap between the group frontier and meta-frontier for public sector banks remains at 32.02 percent. This gap can either be covered by eliminating managerial inefficiencies or by expanding its scale of operation as adopted by industry as a whole or both.

For this, we decomposed the OTE into PTE and SE which helps us to go into more depth and identify the individual effects of managerial inefficiency and scale inefficiency. The PTE score value of 0.7765 computed against the meta-frontier implies that the public sector banks face the managerial inefficiency to the tune of 22.35 percent. However, the magnitude of managerial inefficiency computed against the group frontier of public sector banks stands at around 2.76 percent. A value of 0.7986 in PTE based TCR implies that public sector banks suffered from a technological gap of a magnitude of around 20.14 percent and can gain more managerial efficiency by eliminating the gap between group frontier and meta-frontier. Similarly, the SE score value of 0.8212 computed against the meta-frontier implies that level of SIE in the public sector banks is to the tune of about 17.88 percent as against 3.52 percent when measured from the group frontier. The SE based TCR value of 0.8512 implies that for public sector banks the gap between the group frontier and meta-frontier in terms of scale size is to the enormity of around 14.88 percent.

Likewise, in the group of private sector banks, it can be inferred from the TCR scores that there exists a technological gap of a magnitude of around 20.66 percent, 9.24 percent and 12.53 percent according to OTE, PTE & SE measures respectively. The private sector banks can also additionally gain more managerial as well as scale efficiency by eliminating the gap between its group frontier and meta-frontier. One interesting observation is that so far the group frontier was concerned, both the public sector banks and private sector banks performed better than the foreign banks with higher OTE, PTE and SE scores. Thus, in terms of group frontier, the public sector banks and private sector banks are more efficient and hence only minor improvement in efficiency is possible.

In case of foreign banks, the OTE score value of 0.8544 computed against the meta-frontier implies that banks belonging to this group have the potential to decrease inputs along with a simultaneous increase in outputs by 14.56 percent. The magnitude of efficiency computed against the foreign bank's group frontier also stands at same level. Since TCR value of OTE scores is equal to one, it entails that group frontier & meta-frontier coincides with each other. Similarly, the PTE & SE based TCR also depicts the same picture. The TCR scores highlight the fact that foreign banks represent the overall Indian banking industry by taking the position of meta-frontier. Foreign banks can be considered as a benchmark for the remaining groups of ownership structure of Indian banking industry.

It can be clearly observed from the last column of Table 5 that the public sector banks ranked last amongst all the three groups of ownership structure of Indian banking industry. The proximity of public sector banks' group frontier to the meta-frontier is the farthest as compared to other groups. But in terms of overall proximity of this group's frontier with meta-frontier, both the public sector banks and private sector banks lagged behind in the race and only foreign banks have emerged as a leader of Indian banking industry.

5. Conclusion and policy implications

The Indian banking sector has been under continued stress due to the increased burden of non-performing assets (NPAs). Enticed by the rising level of inefficiencies in the Indian banking sector, the Reserve Bank of India and Ministry of Finance (Government of India) recommended to consolidate the banks in order to retain fewer but healthier banks. In that light, the present study attempted to evaluate the efficiency levels of the entire Indian banking sector and also to identify productivity differentials across different ownership groups. The study is the pioneer one to have used directional distance based meta-frontier DEA approach on a cross-sectional data of 66 banks for the year 2015-16. The results highlight that the Indian banking sector is only 73.44% efficient. This implies that there is a huge scope of enhancing the efficiency in the sector and to make it globally competitive. There is a scope of simultaneous reduction of inputs and enhancement of outputs in the sector to the tune of 26.56%. It also confirms the existence of different production functions across different ownership structures of the industry. Among the different ownership structures, the group frontier of foreign banks coincides with the meta-frontier. The group frontier of private sector banks was the second closest to the meta-frontier and public sector banks were found to be the laggards in the overall industry. The results of our study are consistent with the findings of Sahoo et al.[29] who also highlighted that foreign and private banks were better performers as compared to the public sector banks.

The results of this study are indicative in many ways. First, the Indian banking sector is not fully efficient and the directional distance function DEA results indicate the need for simultaneous reduction of inputs and improvement in outputs so as to induce efficiency in the sector. Second, the superior performance of the foreign banks over the other ownership types highlight that they are more competitive, probably because of their exposure to international markets and because of lower social obligations. Third, public sector banks are the laggards in terms of the efficiency due to rising NPA levels and the corresponding recommendations of the AQR's to enhance provisioning requirements that have adversely affected their profitability.

The findings affirm the recent recommendations of the Ministry of Finance (Government of India) and Reserve Bank of India to consolidate the public sector banks in order to retain fewer but healthier banks. The consolidation in the industry will bring positive synergies and will lead to the enhancement of efficiency levels in the industry by curtailing redundant activities and lowering NPA levels.

Appendix I. Group-wise classification of banks.

Name of the Bank	Ownership	Group **g** = 1	Name of the Bank	Ownership	Group **g** = 2	Name of the Bank	Ownership	Group **g** = 3
Allahabad Bank	Public	1	Axis Bank	Private	2	Abu Dhabi Commercial Bank	Foreign	3
Andhra Bank	Public	1	Bandhan Bank	Private	2	American Express Bank	Foreign	3
Bank of Baroda	Public	1	Capital Small Finance Bank	Private	2	Australia & New Zealand Banking Group	Foreign	3
Bank of India	Public	1	Catholic Syrian Bank	Private	2	Bank of America	Foreign	3
Bank of Maharashtra	Public	1	City Union Bank	Private	2	Bank of Bahrain & Kuwait	Foreign	3
Canara Bank	Public	1	DCB Bank	Private	2	Bank of Nova Scotia	Foreign	3
Central Bank of India	Public	1	Dhanlaxmi Bank	Private	2	Bank of Tokyo-Mitsubishi	Foreign	3
Corporation Bank	Public	1	Federal Bank	Private	2	Barclays Bank	Foreign	3
Dena Bank	Public	1	HDFC Bank	Private	2	BNP Paribas	Foreign	3
IDBI Bank	Public	1	ICICI Bank	Private	2	Citibank	Foreign	3
Indian Bank	Public	1	IDFC Bank	Private	2	Credit Agricole Corporate & Investment Bank	Foreign	3
Indian Overseas Bank	Public	1	IndusInd Bank	Private	2	Credit Suisse AG	Foreign	3
Jammu and Kashmir Bank	Public	1	Karnataka Bank	Private	2	Deutsche Bank	Foreign	3
Oriental Bank of Commerce	Public	1	Karur Vysya Bank	Private	2	Doha Bank QFA	Foreign	3
Punjab & Sind Bank	Public	1	Kotak Mahindra Bank	Private	2	Hongkong & Shanghai Banking Corporation	Foreign	3
Punjab National Bank	Public	1	Lakshmi Vilas Bank	Private	2	J P Morgan Chase Bank	Foreign	3
State Bank of India	Public	1	Nainital Bank	Private	2	Mizuho Corporate Bank	Foreign	3
Syndicate Bank	Public	1	RBL Bank	Private	2	Rabobank International	Foreign	3
UCO Bank	Public	1	South Indian Bank	Private	2	Shinhan Bank	Foreign	3
Union Bank of India	Public	1	Tamilnad Mercantile Bank	Private	2	Societe Generale	Foreign	3
United Bank of India	Public	1	Yes Bank	Private	2	Standard Chartered Bank	Foreign	3
Vijaya Bank	Public	1				United Overseas Bank	Foreign	3
						Woori Bank	Foreign	3
$N_{g=1} = 22$			$N_{g=2} = 21$			$N_{g=3} = 23$		
			$N = \sum_{g=1}^{H} N_g = 66$					

Appendix II. β Values from Meta-frontier and Group-frontiers.

Bank ↓/ β Values →	Meta-frontier		Group-frontier		Bank ↓/ β Values →	Meta-frontier		Group-frontier		Bank ↓/ β Values →	Meta-frontier		Group-frontier	
	OTE	PTE	OTE	PTE		OTE	PTE	OTE	PTE		OTE	PTE	OTE	PTE
Allahabad Bank	0.328	0.141	0.040	0.000	Axis Bank	0.172	0.086	0.000	0.000	Abu Dhabi Commercial Bank	0.413	0.407	0.413	0.404
Andhra Bank	0.282	0.091	0.000	0.000	Bandhan Bank	0.240	0.000	0.000	0.000	American Express Bank	0.000	0.000	0.000	0.000
Bank of Baroda	0.365	0.262	0.067	0.024	Capital Small Finance Bank	0.394	0.079	0.214	0.037	Australia & New Zealand Banking Group	0.161	0.140	0.161	0.140
Bank of India	0.367	0.260	0.111	0.072	Catholic Syrian Bank	0.485	0.319	0.349	0.293	Bank of America	0.120	0.000	0.120	0.000
Bank of Maharashtra	0.334	0.203	0.072	0.062	City Union Bank	0.264	0.078	0.102	0.042	Bank of Bahrain & Kuwait	0.267	0.255	0.267	0.000
Canara Bank	0.391	0.240	0.046	0.007	DCB Bank	0.291	0.214	0.117	0.110	Bank of Nova Scotia	0.068	0.066	0.068	0.064
Central Bank of India	0.438	0.308	0.134	0.000	Dhanlaxmi Bank	0.460	0.353	0.310	0.306	Bank of Tokyo-Mitsubishi	0.135	0.135	0.135	0.134
Corporation Bank	0.315	0.135	0.000	0.000	Federal Bank	0.365	0.237	0.193	0.170	Barclays Bank	0.124	0.000	0.124	0.000
Dena Bank	0.447	0.308	0.207	0.160	HDFC Bank	0.182	0.104	0.000	0.000	BNP Paribas	0.263	0.263	0.263	0.263
IDBI Bank	0.383	0.268	0.000	0.000	ICICI Bank	0.157	0.116	0.000	0.000	Citibank	0.094	0.035	0.094	0.035
Indian Bank	0.368	0.225	0.060	0.046	IDFC Bank	0.347	0.320	0.203	0.000	Credit Agricole Corporate & Investment Bank	0.126	0.120	0.126	0.116
Indian Overseas Bank	0.424	0.335	0.130	0.088	IndusInd Bank	0.157	0.113	0.000	0.000	Credit Suisse AG	0.000	0.000	0.000	0.000
Jammu and Kashmir Bank	0.285	0.185	0.000	0.000	Karnataka Bank	0.328	0.159	0.180	0.135	Deutsche Bank	0.153	0.118	0.153	0.118
Oriental Bank of Commerce	0.331	0.213	0.050	0.020	Karur Vysya Bank	0.289	0.158	0.132	0.099	Doha Bank QFA	0.276	0.256	0.276	0.000
Punjab & Sind Bank	0.341	0.151	0.079	0.026	Kotak Mahindra Bank	0.280	0.242	0.057	0.035	Hongkong & Shanghai Banking Corporation	0.195	0.194	0.195	0.194
Punjab National Bank	0.341	0.219	0.027	0.012	Lakshmi Vilas Bank	0.372	0.176	0.236	0.170	J P Morgan Chase Bank	0.000	0.000	0.000	0.000
State Bank of India	0.334	0.246	0.000	0.000	Nainital Bank	0.358	0.000	0.000	0.000	Mizuho Corporate Bank	0.071	0.070	0.071	0.069
Syndicate Bank	0.376	0.209	0.069	0.024	RBL Bank	0.352	0.319	0.176	0.040	Rabobank International	0.164	0.092	0.164	0.092
UCO Bank	0.311	0.116	0.022	0.000	South Indian Bank	0.380	0.238	0.243	0.199	Shinhan Bank	0.168	0.151	0.168	0.000
Union Bank of India	0.370	0.241	0.049	0.048	Tamilnad Mercantile Bank	0.294	0.143	0.112	0.081	Societe Generale	0.259	0.253	0.259	0.253
United Bank of India	0.432	0.326	0.047	0.000	Yes Bank	0.237	0.000	0.000	0.000	Standard Chartered Bank	0.108	0.107	0.108	0.105
Vijaya Bank	0.372	0.172	0.116	0.000						United Overseas Bank	0.000	0.000	0.000	0.000
										Woori Bank	0.032	0.013	0.032	0.000

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