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An Examination of Technical, Pure Technical, and Scale Efficiencies in Indian Public Sector Banks using Data Envelopment Analysis

Sunil KUMAR *

Rachita GULATI **

Abstract

Using data envelopment analysis (DEA), the present study aims to measure the extent of technical, pure technical, and scale efficiencies in 27 public sector banks (PSBs) operating in India in the year 2004/05. The empirical findings reveal that PSBs operate at 88.5 percent level of overall technical efficiency i.e., inputs could be reduced by 11.5 percent without sacrificing output if all banks were efficient as 7 benchmark banks identified by DEA. Further, the contribution of scale inefficiency in overall technical inefficiency has been observed to be smaller than what been observed due to managerial inefficiency (i.e., pure technical inefficiency). The findings pertaining to returns-to-scale in Indian public sector banking industry highlight that the predominant form of scale inefficiency is decreasing returns-to-scale. The results of logistic regression analysis provide that the exposure of the banks to off-balance sheet activities (i.e., non-traditional activities) has a strong and positive impact on the overall technical efficiency of banks.

Keywords: *Public Sector banks; Technical efficiency; Pure technical efficiency; Scale efficiency; Data envelopment analysis; Logistic regression analysis.*

JEL Classification: *C21, C61, G21.*

* Reader in Economics, Punjab School of Economics, Guru Nanak Dev University, India, e-mail: sunil12eco@yahoo.com

** Junior Research Fellow (JRF), Punjab School of Economics, Guru Nanak Dev University, India, e-mail: rachita1302@yahoo.co.in

1. Introduction

While dealing with banking efficiency analyses, the very first question which strikes in the mind of the research analysts is that why regulators, customers, managers, and stakeholders bother about the relative efficiency of banks? The answers of this question will be different depending upon the perspectives of interested parties. From the regulators' perspective, inefficient banks are riskier and have a higher likelihood of failure. Further, the efficiency of banks is directly linked to the productivity of the economy. Without a sound and efficiently functioning banking system, the economy cannot function smoothly and efficiently. When banking system fails, the whole of a nations' payments system is in jeopardy. From the point of view of customers, only efficient banks can offer better services at reasonable prices. The standpoint of stakeholders is that only efficient banks ensure reasonable returns. The perspective of bank managers is that in a dynamic and competitive market environment, only efficient banks will survive and maintain their market share, and inefficient ones will eventually be eliminated through Darwinian selection. The efficient banks are better able to compete because of their lower operational costs and can steal business away from less efficient banks. In sum, the relative efficiency of banks is always a matter of serious interest to the regulators, customers, stakeholders, and managers.

In the prevailing market environment, the public sector banks (PSBs) operating in India are facing fierce price and non-price competition from private and foreign banks, especially from *de nova* private domestic banks. The dismantling of administered interest rates regime during the post-reform years since 1992 in a phased manner has also intensified the competition even among PSBs. As a result of intense competition, the share of PSBs in deposits, advances, and total assets of Indian banking industry is declining steadily. For arresting this decline, the PSBs are now reorienting and redesigning their operational strategies and offering several innovative financial products like internet banking, ATM services, insurance services, etc., to their customers. However, their success in retaining customers and meeting the aspirations of the regulators hinges upon how efficiently they utilize their financial resources in delivering financial services and products.

Against this background, it has become pertinent to measure the extent of relative (in)efficiency of individual PSBs and to explore the areas for bringing an improvement in their efficiency. Further, it is significant to unearth whether the observed inefficiency in Indian public sector banking industry is due to managerial underperformance or choice of inappropriate scale size. The present study is an attempt in these directions. In particular, we aim to measure the extent of technical, pure technical, and scale efficiencies of individual PSBs using a two-stage data envelopment analysis (DEA) methodology. In the first-stage of methodological framework, technical, pure technical, and scale efficiency scores for individual PSBs have been obtained by employing two popular DEA models, namely, CCR[1] and BCC[2] models, involving only the conventional inputs and outputs. In the second-stage, the *overall technical efficiency* (OTE) scores obtained in the first-stage are regressed on the environmental variables[3]. The sign of the coefficients of the environmental variables indicates the direction of the influence, and standard hypotheses tests can be used to assess the strength of the relationship. The advantages of the two-stage methodological framework include the following: it accommodates more than one variable; it accommodates both categorical and continuous variables; it does not make prior assumptions regarding the direction of the influence of the categorical variables; and it is easy to calculate, simple and therefore transparent (Boame, 2004).

Before proceeding further, the authors feel that the concepts of technical, pure technical, and scale efficiencies need some elaboration. Technical efficiency (TE) relates to the productivity of inputs (Sathye, 2001). The technical efficiency of a firm is a comparative measure of how well it actually processes inputs to achieve its outputs, as compared to its maximum potential for doing so, as represented by its production possibility frontier (Barros and Mascarenhas, 2005). Thus, technical efficiency of the bank is its ability to transform multiple resources into multiple financial services (Bhattacharyya *et al*., 1997). A bank is said to be technically inefficient if it operates below the frontier. A measure of technical efficiency under the assumption of constant returns-to-scale (CRS) is known as a measure *overall technical efficiency* (OTE). The OTE measure helps to determine inefficiency due to the input/output configuration as well as the size of operations. In DEA, OTE measure has been decomposed into two mutually exclusive and non-additive components: *pure technical efficiency* (PTE) and *scale efficiency* (SE). This decomposition allows an insight into the source of inefficiencies. The PTE measure is obtained by estimating the *efficient frontier* under the assumption of variable returns-to-scale. It is a measure of technical efficiency without scale efficiency and purely reflects the managerial performance to organize the inputs in the production process. Thus, PTE measure has been used as an index to capture managerial performance. The ratio of OTE to PTE provides SE measure. The measure of SE provides the ability of the management to choose the optimum size

[1] CCR model is named after its developers Charnes, Cooper and Rhodes (1978), and is based on the assumption of constant returns-to-scale.
[2] BCC model is named after its developers Banker, Charnes and Cooper (1984), and is based on the assumption of variable returns-to-scale.
[3] In the whole study, the terms 'technical efficiency' and 'overall technical efficiency' have been used interchangeably.

of resources, i.e., to decide on the bank's size or in other words, to choose the scale of production that will attain the expected production level. Inappropriate size of a bank (too large or too small) may sometimes be a cause of technical inefficiency. This is referred as scale inefficiency and takes two forms: decreasing returns-to-scale (DRS) and increasing returns-to-scale (IRS). Decreasing returns-to-scale (also known as diseconomies of scale) implies that a bank is too large to take full advantage of scale and has supra-optimum scale size. In contrast, a bank experiencing increasing returns-to-scale (also known as economies of scale) is too small for its scale of operations and, thus, operates at sub-optimum scale size. A bank is scale efficient if it operates at constant returns-to-scale (CRS).

Data envelopment analysis (DEA), introduced by Charnes *et al.* (1978) based on Farrell's work (Farrell, 1957), is a nonparametric technique for measuring the relative efficiency of a set of similar units, usually referred to as decision making units (DMUs)[4]. It was initially used to assess the relative efficiency of not-for-profit organizations such as schools and hospitals; however, gradually its application has been extended to cover for-profit organizations as well. Its first application in banking industry appeared with the work of Sherman and Gold (1985). Over the years, DEA has emerged as a very potent technique to measure the relative efficiency of banks (see survey article of Berger and Humphrey, 1997). DEA is capable of handling multiple inputs and outputs without requiring any judgment on their importance. DEA identifies the efficiency in a particular bank by comparing it to similar bank(s) regarded as efficient, rather than trying to associate a bank's performance with statistical averages that may not be applicable to that bank (Avkiran, 2006). Using linear programming technique, the various DEA models intend to provide efficiency scores under different orientations and assumptions of returns-to-scale.

In the present study, the use of DEA to compute various efficiency scores has been preferred over other competing techniques, especially stochastic frontier analysis (SFA) for measuring relative efficiency of banks for several reasons. First, it allows the estimation of overall technical efficiency (OTE) and decomposes it into two mutually exclusive and non-additive components, namely, pure technical efficiency (PTE) and scale efficiency (SE). Further, it identifies the banks that are operating under decreasing or increasing returns-to-scale. Second, in DEA, there is no need to select *a priori* functional form relating to inputs and outputs like Cobb-Douglas and Translog production/cost functions (Banker, 1984). Third, DEA easily accommodates multiple-inputs and multiple-outputs of the banks. Fourth, it

[4] DMUs are usually defined as entities responsible for turning input(s) into output(s), such as firms and production units. In the present study, DMUs refer to the public sector banks. A DMU must, as the name indicates, have at least some degree of freedom in setting behavioural goals and choosing how to achieve them.

provides a scalar measure of relative efficiency, and the areas for potential addition in outputs and reduction in inputs. Fifth, in DEA, it is not necessary to provide values for weights associated with input and output factors, although the user may exert influence in the selection of weight values. Sixth, DEA works particularly well with small samples (Evanroff and Israilevich, 1991). On the other hand, DEA's major shortcoming is that it assumes data to be free of measurement error, and could therefore, give unreliable results if the integrity of data is not assured (Avkiran, 1999a).

The remainder of the paper is organized in following ways. Section 2 describes the structure of Indian banking sector with a special reference to public sector banks. Section 3 briefly reviews the literature on the efficiency of Indian banks. Section 4 presents CCR and BCC DEA models that are used in the present study. The issues relating to selection of inputs and outputs are discussed in the Section 5. Section 6 presents and discusses the empirical results pertaining to technical, pure technical, and scale efficiencies in Indian public sector banking industry. The final section concludes the findings of the study and suggests the areas for future research.

2. The Structure of Indian Banking Sector

The Reserve Bank of India (RBI) is the central bank of the country that regulates the operations of other banks, manages money supply, and discharges other myriad responsibilities that are usually associated with a central bank. The banking system in India comprises commercial and co-operative banks, of which the former accounts for more than 90 percent of the assets of the banking system. Within the category of commercial banks, there are two types of the banks: i) schedule commercial banks (i.e., which are listed in Schedule II of the Reserve Bank of India Act, 1934); and ii) non-scheduled commercial banks. Depending upon the pattern of ownership, scheduled commercial banks can be classified into three broad categories: i) *Public Sector Banks* which include a) State Bank of India (SBI) and its associate banks, b) Nationalized banks, and c) other public sector banks; ii) *Private Sector Banks* consisting *private domestic banks* (which can further be classified as *old private banks* that are in business prior to 1992, and *de nova private banks* that had established after 1992) and *foreign banks*; and iii) Others comprising *Regional Rural Banks* (RRBs) and *Local Area Banks*.

Of these, PSBs have a countrywide network of branches and account for over 70 percent of total banking business. The contribution of PSBs in India's economic and social development is enormous and well documented. They have strong presence at rural and semi-urban areas, and employ a large number of staff. On the other hand, *de nova* private domestic banks are less labour-intensive, have limited number of branches, have adopted modern banking technology, and are more profitable. Though foreign banks are more techno-savvy and have carved a niche in the market but they confine their operations in major urban centres. Public sector banks sponsor the RRBs and their activities are localized. Further, RRBs serve the needs for rural credit and have a diminutive share (about 3 percent) in the commercial banking industry of India. Table 1 provides summary details of different types of commercial banks operating in India (excluding RRBs) as on the end March, 2005. It has been observed that the market share of PSBs in terms of investments, advances, deposits, and total assets is over 70 percent. About 88 percent of branches of the commercial banks in India belong to PSBs. Further, their share in the total employment provided by commercial banking industry is about 87 percent. In brief, PSBs command a lion's share of Indian banking industry.

Table 1. Structure of commercial banking in India* (As on March 2005)

Bank Group	No. of Banks	Branches	Staff	Investments	Advances	Deposits	Total Assets
		Number			Rupees in Crores		
I. Public Sector Banks (a+b)	28	48971	748710	685729	854671	1435852	1773939
Market Share (%)		88.2	87.3	79.1	74.3	78.2	75.4
a. State Bank of India Group	8	13896	278269	260704	284727	505649	627075
Market Share (%)		25.0	32.4	30.1	24.8	27.6	26.6
b. Nationalized Banks and IDBI Ltd.	20	35075	470441	425025	569944	930203	1146864
Market Share (%)		63.2	54.8	49.0	49.5	50.7	48.7
II. Indian Private Sector Banks	29	6321	92618	138968	220337	312645	425802
Market Share (%)		11.4	10.8	16.0	19.2	17.0	18.1
III. Foreign Banks in India	31	245	16386	42518	75318	86505	154128
Market Share (%)		0.4	1.9	4.9	6.5	4.7	6.5
IV. Total Indian Private and Foreign Banks (II+III)	60	6566	109004	181486	295655	399150	579930
Market Share (%)		11.8	12.7	20.9	25.7	21.8	24.6
V. Total Commercial Banks (I+IV)	88	55537	857714	867215	1150326	1835002	2353869
Market Share (%)		100.0	100.0	100.0	100.0	100.0	100.0

Notes: i) * indicates the exclusion of Regional Rural Banks; and ii) 1 Crore=10 Millions

Source: Authors' calculations from Statistical Tables Relating to Banks in India (2004/05)

In the post-reforms years since 1992, the PSBs got fierce competition from private banks, especially from *de nova* private domestic banks that were better equipped with banking technology and practices. Consequently, the market share of PSBs in terms of deposits, investments, advances, and total assets has declined constantly (see Table 2). It is evident from the table that the PSBs are still dominating players in the Indian banking sector, albeit their market share has declined in the deregulatory regime. The growth of PSBs is still high on the agenda of the policy makers because of their gargantuan role as an effective catalytic agent of socio-economic change in the country. During the last 16 years, the policy makers adopted a cautious approach for introducing reform measures in the Indian banking sector on the basis of the recommendations of Narasimham Committee I (1991), Narasimham Committee II (1998) and Verma Committee (1999). The principle objective of the banking reforms process was to improve the efficiency of PSBs in their operations and to inculcate competitive spirit in them. Against this backdrop, we confine our analysis to PSBs which constitute most significant segment of Indian banking sector.

Table 2. Market share of public sector banks: 1992/93 to 2004/05

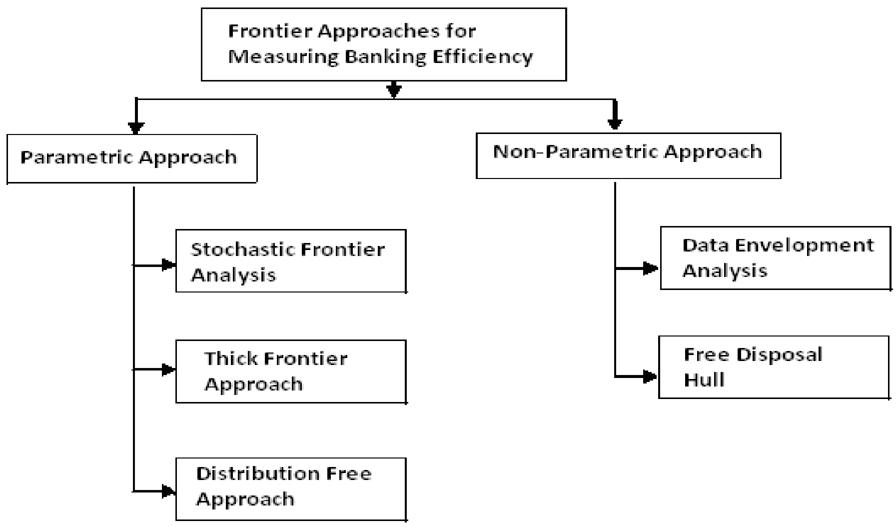
Year	Market Share (%)			
	Deposits	Investments	Advances	Total Assets
1992/93	87.9	85.9	89.3	87.2
1993/94	86.8	86.3	87.3	87.1
1994/95	85.9	87.0	85.1	85.2
1995/96	85.4	87.6	82.2	84.4
1996/97	83.6	85.3	79.9	82.7
1997/98	82.6	83.5	80.1	81.6
1998/99	82.6	81.5	80.5	81.0
1999/00	81.9	80.6	79.4	80.2
2000/01	81.4	80.1	78.9	79.5
2001/02	80.5	77.2	74.4	75.3
2002/03	79.6	78.7	74.3	75.7
2003/04	77.9	78.0	73.2	74.5
2004/05	78.2	79.1	74.3	75.4

Source: Authors' calculations from Statistical Tables Relating to Banks in India (various issues)

3. Efficiency of Banking Sector: A Brief Review of Literature

The literature on the efficiency of financial institutions in the US and other well-developed countries contains a large number of articles (see Berger *et al*., 1993; Berger and Humphrey, 1997; Berger and Mester, 1997 for an extensive review of literature on the efficiency of banking sector). Besides using conventional financial ratios such as return to equity, return on assets, expense to income ratios, etc., a number of alternative frontier techniques have been used for analyzing differences in efficiency across banks (see Figure 1 for categorization of various frontier techniques). It is significant to note here that each frontier technique involves various models for deriving a measure of *best practice* for the sample of banks and then determine how closely individual banks lie relative to this standard. The *best practice* is usually in the form of an *efficient frontier* that is estimated using econometric or mathematical programming techniques. The frontier techniques summarize bank performance in a single statistic that controls for difference among banks in a sophisticated multi-dimensional framework that has its roots in economic theory. Further, frontier efficiency measures dominate traditional ratio analysis in terms of developing meaningful and reliable measures of bank performance. Owing to these features of frontier methodology, the conventional ratio analysis is becoming obsolete.

Figure 1: Frontier approaches for measuring banking efficiency



Source: Authors' elaboration

Nevertheless, each frontier technique has its specific advantages and disadvantages and yields different efficiency estimates (see Bauer *et al*., 1998 for advantages and disadvantages of each frontier technique). Among all the frontier techniques (as illustrated in Figure 1), DEA has emerged over the years as a most potent approach for measuring relative efficiency across banks due to its intrinsic advantages over others. In the 122 studies reviewed by Berger and Humphrey (1997), DEA has been applied in 62 studies (i.e., just over 50 percent). This fact indicates DEA's significance, popularity and relevance in banking efficiency analyses.

Table 3. Efficiency of Indian banking sector: a brief survey of empirical literature

S. No	Author (Year)	Period	Data	Methodology	Conclusions
1.	Bhattacharya *et al.* (1997)	1986-1991	70 Banks	DEA	The publicly owned banks have been most efficient followed by foreign banks and domestic private banks in utilizing the resources at their disposal to deliver financial services to their customers.
2.	Das (1997)	Cross-sectional data at different points of time (1970, 1978, 1984, 1990 and 1996)	27 PSBs	DEA	The banks belonging to 'State Bank of India (SBI)' group are more efficient than 'nationalized' banks. Main source of inefficiency was technical in nature, rather than allocative. However, PSBs have improved their allocative efficiency in post-liberalization period.
3.	Das (2000)	Cross-sectional data for the year 1998	27 PSBs	DEA	SBI group is more efficient than 'nationalized' group. Inefficiency in PSBs is both technical as well as allocative in nature.
4.	Saha and Ravisankar (2000)	1991/92 to 1994/95	25 PSBs	DEA	PSBs have improved their efficiency scores over the study period.
5.	Mukherjee *et al.*(2002)	1996-99	68 Banks	DEA	PSBs outperform both private and foreign banks in the rapidly evolving and liberalizing sector.
6.	Sathye (2003)	Cross-sectional data for the year 1998	94 Banks	DEA	The mean efficiency score of Indian banks compares well with the world mean efficiency score. The efficiency of private banks as a group is, paradoxically lower than that of PSBs and foreign banks in India.
7.	Mohan and Ray (2004)	1992-2000	58 Banks	DEA	PSBs performed significantly better than private sector banks but not differently from foreign banks. Superior performance of PSBs is to be ascribed to higher technical efficiency.
8.	Das *et al.* (2004)	1997-2003	1997:71Banks 1998:72 Banks 1999:71 Banks 2000:73 Banks 2001:71 Banks 2002:71 Banks 2003:68 Banks	DEA	Indian banks are not much differentiated in terms of input- or output-oriented technical efficiency and cost efficiency, but differ sharply in respect of revenue and profit efficiencies. Median efficiency scores of Indian banks, in general, and bigger banks, in particular, have improved during the post-reforms period.
9.	Chakrabarti and Chawla (2005)	1990-2002	70 banks	DEA	PSBs have, in comparison, lagged behind their private counterparts in terms of performance. On a 'value' basis, the foreign banks, as a group, have been considerably more efficient than all other bank groups, followed by the Indian private banks.
10.	Ray (2007)	1997–2003	1997:71Banks 1998:72 Banks 1999:71 Banks 2000:73 Banks 2001:71 Banks 2002:71 Banks 2003:68 Banks	DEA	There exists widespread size inefficiency across banks.

Source: Authors' compilation

Although an extensive and sprawling literature on the banking efficiency exits for developed economies, there have been few studies aiming to analyze the efficiency of Indian banking sector using both parametric and non-parametric frontier approaches. Table 3 provides a brief review of literature on the efficiency of Indian banking sector. A thorough inspection of literature on Indian banks reveal that the findings of empirical studies differ substantially on the basis of selection of input and output variables, time period of the analysis, sample size, etc., and, thus, offer different conclusions.

The contribution of present study to the existing literature on the banking efficiency in India stems from three areas in which very scant attention has been paid by the researchers. These areas are i) decomposition of overall technical efficiency (OTE) into its components, namely, pure technical efficiency (PTE) and scale efficiency (SE), ii) targets setting for potential outputs' addition and inputs' saving in inefficient banks, and iii) the impact of environment factors on OTE. Using two-stage DEA methodological framework, this paper intends to enrich the existing literature by focusing on all the aforementioned areas.

4. Methodological Frameworks

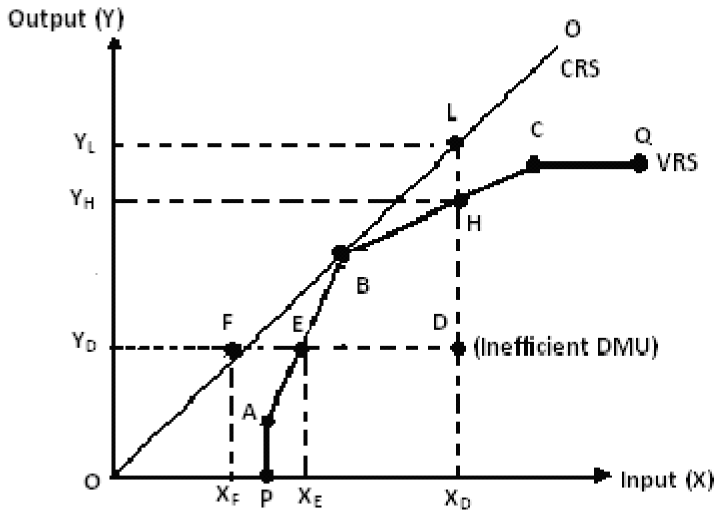
4.1. Measurement of Technical, Pure Technical, and Scale Efficiencies: CCR and BCC DEA models

As noted above, we intend to apply the technique of DEA for computing the measures of technical, pure technical, and scale efficiencies for individual PSBs. In general, DEA is referred to as a linear programming technique that converts multiple incommensurable inputs and outputs of each decision making unit (DMU) into a scalar measure of operational efficiency, relative to its competing DMUs. DEA identifies 'peer' DMUs for an individual DMU and then estimates the efficiency of the DMU by comparing its performance with that of the *best practice* DMUs chosen from its peers. Note that the idea here of *best practice* is not some theoretical and possibly unattainable concept, but the DMU(s) performing best amongst its (their) peers, which is assigned an efficiency score of 1. These units constitute the referrals 'standards' and 'envelop' the other units and, thus, form the *efficient frontier*. DEA involves solving a linear programming problem for each DMU. The solution to the linear programming problem consists of information about the peers of the DMU and the efficiency of the DMU relative to its peer group.

In DEA, technical efficiency (TE) can be viewed from two perspectives. First, input-oriented TE focuses on the possibility of reducing inputs to produce given output levels. Second, output-oriented TE considers the possible expansion in outputs for a given set of input quantities. A measure of TE for a DMU *o* can be defined as

$\theta_o^{output} = Actual\ output_o / Maximum\ possible\ output_o$ in output-oriented context, or $\theta_o^{input} = Minimum\ possible\ input_o / Actual\ input_o$ in input-oriented context. To quantify a measure of TE, we need to find out the divergence between actual production and production on the boundary of the feasible production set. This set summarizes all technological possibilities of transforming inputs into outputs that are available to the organization. A DMU is technically inefficient if production occurs within the interior of this production set. A measure of scale efficiency (SE) can be obtained by comparing TE measures derived under the assumptions of constant returns-to-scale (CRS) and variable returns-to-scale (VRS). As noted above, the TE measure corresponding to CRS assumption represents overall technical efficiency (OTE) which measures inefficiencies due to the input/output configuration and as well as the size of operations. The efficiency measure corresponding to VRS assumption represents pure technical efficiency (PTE) which measures inefficiencies due to only managerial underperformance. The relationship $SE = OTE / PTE$ provides a measure of scale efficiency. For the one-output and one-input case, the derivation of the concepts of technical, pure technical, and scale efficiency under DEA approach is illustrated in Figure 2.

Figure 2: OTE, PTE, and SE measures



Source: Authors' Self-construction

Figure 2 provides two *efficient frontiers*: one assumes CRS (shown by line *OO*) and one assumes VRS (shown by line segment *PABCQ*). Projecting the inefficient DMU *D* onto VRS *efficient frontier* (point E) by minimizing input *X* while holding output *Y* constant (i.e., input-orientation), PTE for DMU *D* is defined as X_E/X_D . Similarly, if we change the optimization mode to that of output maximization, PTE for firm *D* is now defined as Y_D/Y_H .Focusing on the CRS *efficient frontier*, DMU *D* is projecting onto point *F*, where the input-oriented OTE measure is defined by X_F/X_D . Output-oriented OTE measure is similarly defined as Y_D/Y_L . However, given that the slope of CRS *efficient frontier* equals to 1, then $X_F/X_D = Y_D/Y_L$ i.e., orientation does not change OTE scores. Extending the above illustration to scale efficiency, input- and output-oriented scale efficiency measures are defined as X_F/X_E and Y_H/Y_L , respectively. Increasing returns-to-scale (IRS) imply that the DMU can gain efficiency by increasing production of *Y* (which generally occurs when producing on the PAB of VRS *efficient frontier*), while decreasing returns-to-scale (DRS) imply that a reduction in scale increases efficiency (which occurs on the portion BCQ of VRS *efficient frontier*). If one is producing optimally, then, there is no efficiency gain by changing the scale of production. This occurs when firm operate at the point B where the two frontiers are tangent i.e., OTE=PTE.

The preceding graphical depiction of technical, pure technical, and scale efficiency measures can now be reframed in terms of linear programming models that can be used to work out efficiency of individual DMUs using actual data on input and output variables. Several different mathematical programming models have been proposed in the literature (see Charnes *et al.*, 1994; Cooper *et al*., 2007, for details). Essentially, each of these models seeks to establish which of *n* DMUs determine the *best practice* or *efficient frontier*. The geometry of this frontier is prescribed by the specific DEA model employed. In the present study, we utilized CCR model, named after Charnes, Cooper, and Rhodes (1978) and BCC model, named after Banker, Charnes and Cooper (1984) to obtain efficiency measures under CRS and VRS assumptions, respectively.

Formal notations of used input-oriented[5] DEA models for measuring TE scores for DMU *o*, under different scale assumptions are as follows.

[5] Concerning the model's orientation, Coelli and Perelman (1999) show that the choice of orientation does not significantly alter efficiency estimation results. The choice of the appropriate orientation is not as crucial as it is in the econometric estimation case and, in many instances, the choice of orientation will have only minor influences upon the scores obtained.

[1] *i*)

$$\min_{\theta_o,\lambda_1,\lambda_2,\ldots,\lambda_n,S_i^-,S_r^+} \quad TE_o=\theta_o-\varepsilon\left(\sum_{i=1}^{m}s_i^-+\sum_{r=1}^{s}s_r^+\right)$$

subject to

$$ii)\ \sum_{j=1}^{n}\lambda_j x_{ij}+s_i^-=\theta_o x_{io}$$

$$iii)\ \sum_{j=1}^{n}\lambda_j y_{rj}-s_r^+=y_{ro}$$

$$iv)\ s_i^-,s_r^+\geq 0 \qquad (i=1,\ldots,m;\ r=1,\ldots,s)$$

$$v)\ \lambda_j\geq 0,\ \text{if constant returns-to-scale}$$

$$vi)\ \sum_{j=1}^{n}\lambda_j=1, \text{if variable returns-to-scale}$$

where x_{io} = amount of input *i* used by DMU *o*,
y_{ro} = amount of output *r* produced by DMU *o*,
m = the number of outputs,
s = the number of inputs,
n = the number of DMUs, and
ε = a small positive number.

The solution to problem [1] is interpreted as the largest contraction of DMU *o*'s input that can be carried out, given that DMU *o* will stay within the reference technology. The restrictions *ii*) and *iii*) form the convex reference technology. The restriction *iv*) restricts the input slack (s_i^-) and output slack (s_r^+) variables to be non-negative. The restriction *v*) limits the intensity variables to be non-negative. The model involving *i*) – *v*) is known as envelopment form of CCR model and provides Farrell's input-oriented TE measure under the assumption of constant returns-to-scale. The measure of efficiency provided by CCR model is known as overall technical efficiency (OTE) and denoted as θ_o^{CCR} .The last restriction imposes variable returns-to-scale assumption on the reference technology. The model involving *i*) – iv) and *vi*) is known as BCC model and provides Farrell's input-oriented TE measure under the assumption of variable returns- to-scale. The measure of efficiency provided by BCC model is known as pure technical efficiency (PTE) and denoted as θ_o^{BCC}. The ratio ($\theta_o^{CCR} / \theta_o^{BCC}$) provides a measure of scale efficiency (SE). Note that all aforementioned efficiency measures are bounded between one and zero. The measure of scale efficiency (SE) does not indicate whether the DMU in question is operating in the area of increasing or decreasing returns-to-scale. The nature of returns-to-scale can be determined from the magnitude of optimal $\sum_{j=1}^{n} \lambda_j^*$ in the CCR model (Banker, 1984). Seiford and Zhu (1999) listed following three cases:

i) If $\sum_{j=1}^{n} \lambda_j^* = 1$ in any alternate optima, then CRS prevail on DMU *o*;

ii) If $\sum_{j=1}^{n} \lambda_j^* < 1$ in any alternate optima, then IRS prevail on DMU *o*; and

iii) If $\sum_{j=1}^{n} \lambda_j^* > 1$ in any alternate optima, then DRS prevail on DMU *o*.

The CCR and BCC models need to be solved *n* times, once for each DMU to obtain the optimal values for

$\theta_o, \lambda_1, \lambda_2, ..., \lambda_n, s_i^-, s_r^+$ (i.e., $\theta_o^*, \lambda_1^*, \lambda_2^*, ..., \lambda_n^*, s_i^{-*}, s_r^{+*}$). The interpretation of the results of above models can be summarized as:

a) If $\theta_o^* = 1$, then DMU under evaluation is a frontier point, i.e., there is no other DMUs that are operating more efficiently than this DMU. Otherwise, if $\theta_o^* < 1$, then the DMU under evaluation is inefficient, i.e., this DMU can either increase its output levels or decrease its input levels.

b) The left-hand side of the constraints *ii*) and *iii*) is called the 'Reference Set', and the right-hand side represents a specific DMU under evaluation. The non-zero optimal λ_j^* represents the benchmarks for a specific DMU under evaluation. The Reference Set provides coefficients (λ_j^*) to define hypothetical efficient DMU.

c) The efficient targets for inputs and outputs can be obtained as $\hat{x}_{io} = \theta_o^* x_{io} - s_i^{-*}$ and $\hat{y}_{ro} = y_{ro} + s_r^{+*}$, respectively. These efficiency targets show how inputs can be decreased and outputs increased to make the DMU under evaluation efficient.

4.2. Second-Step Analysis of OTE Scores: Logistic Regression Analysis

As a part of two-stage DEA approach, we carried out a regression analysis to estimate the effect of a set of environmental variables on the overall technical efficiency of PSBs. In DEA literature, the influence of these variables is usually analyzed by applying either tobit or logistic regression models because the distribution of efficiency scores is confined to the interval (0, 1]. In the presence of censored range of efficiency scores obtained through DEA, the OLS regression method yields inconsistent estimates of regression parameters. Following Ray (1988), Brännlund *et al.*(1996), Worthington (1998), Pina and Torres (2001) and Garcia-Sanchez (2007), we applied logistic regression analysis in the present context to explore the factors causing inter-bank differences in overall technical efficiency. Logistic regression is a part of a category of statistical models called generalized linear models. It allows one to predict a dichotomous dependent variable from a set of predictors that may be continuous, discrete, dichotomous, or a mix of any of these.

The ordinary least squares regression involves finding a function that relates a continuous outcome variable (dependent variable *y*) to one or more predictors (independent variables x_1, x_2, etc.). A multiple linear regression assumes a function of the form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots$$

and finds the values of β_0, β_1, β_2,etc. (β_0 is called the 'intercept' or 'constant term').

Logistic regression is a variation of OLS regression, which is useful when observed outcome is restricted to be binary and takes the values 0 or 1. It fits a special *S*-shaped curve by taking the linear regression (as mentioned above), which could have any *y* value between $-\infty$ and $+\infty$, and transforming it with the function:

$$\theta = \frac{\exp(y)}{\left(1 + \exp(y)\right)}$$

which produces θ-values between 0 (as *y* approaches $-\infty$) and 1 (as *y* approaches $+\infty$).

In the present study, we defined the dependent variable on the basis of relative OTE scores obtained from CCR model. The dependent variable takes value equal to 0 for inefficient banks and value equal to 1 when bank is efficient. Thus, the dependent variable turns out to be a binary variable having values either 0 or 1.

The independent variables are the environmental factors (like market share, asset quality, exposure to off-balance sheet activities, profitability, and size) that can cause the inter-bank variations in OTE. The next section explains the definition of these variables and the direction of the relationship between OTE and these environmental variables on the basis of economic theory. All the calculations for logistic regression analysis have been performed by the statistical software SPSS 13.0 for Windows. To check the overall goodness of fit of the logistic regression equation and statistical significance of individual regression coefficients, we employed standard Likelihood-Ratio and Wald tests, respectively.

5. Data and Specification of Variables

To realize the objectives of the study, we utilize two sets of variables which have been collected from two distinct sources: (i) Statistical Tables Relating to Banks in India: 2004/05, a publication of Reserve Bank of India, and (ii) Performance Highlights of Public Sector Banks: 2004/05, a publication of Indian Banks' Association. The first set of variables pertains to input and output variables selected for computing various efficiency scores for individual PSBs. However, the second set of variables includes the environmental factors that explain the inter-bank differences in overall technical efficiency.

5.1. Input and Output Variables for Computing Efficiency Scores

In computing the efficiency scores, the most challenging task that an analyst always encounters is to select the relevant inputs and outputs for modeling bank behaviour. It is worth noting here that there is no consensus on what constitute the inputs and outputs of a bank (Casu and Girardone, 2002; Sathye, 2003). In the literature on banking efficiency, there are mainly two approaches for selecting the inputs and outputs for a bank: i) the *production approach*, also called the *service provision* or *value added approach*; and ii) the *intermediation approach*, also called the *asset approach* (Humphrey, 1985; Hjalmarsson *et al.*, 2000). Both these approaches apply the traditional microeconomic theory of the firm to banking and differ only in the specification of banking activities. The production approach as pioneered by Benston (1965) treats banks as the providers of services to customers. The output under this approach represents the services provided to the customers and is best measured by the number and type of transactions, documents processed or specialized services provided over a given time period. However, in case of non-availability of detailed transaction flow data, they are substituted by the data on the number of deposits and loan accounts, as a surrogate for the level of services provided. In this approach, input includes physical variables (like labour, material, space or information systems) or their associated cost. This approach focuses only on operating cost and completely ignores interest expenses.

The intermediation approach as proposed by Sealey and Lindley (1977) treats banks as financial intermediaries channeling funds between depositors and creditors. In this approach, banks produce intermediation services through the collection of deposits and other liabilities and their application in interest-earning assets, such as loans, securities, and other investments. This approach is distinguished from production approach by adding deposits to inputs, with consideration of both operating cost and interest cost. Berger and Humphrey (1997) pointed out that neither of these two approaches is perfect because they cannot fully capture the dual role of banks as providers of transactions/document processing services and being financial intermediaries. Nevertheless, they 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. This is because, at the bank level, management will aim to reduce total costs and not just non-interest expenses, while at the branch level a large number of customer service processing take place and bank funding and investment decisions are mostly not under the control of branches. Also, in practice, the availability of flow data required by the production approach is usually exceptional rather than in common. Therefore, as in majority of the empirical literature, we adopted the intermediation approach as opposed to the production approach for selecting input and output variables for computing the various efficiency scores for individual PSBs. The selected output variables are i) *net-interest income* (measured as the difference between interest earned and interest expanded), and ii) *non-interest income* (proxied by 'other income'). The inputs used for computing the efficiency scores are i) *physical capital* (measured as the value of fixed assets), ii) *labour* (measured as the number of employees), and iii) *loanable funds* (measured as the sum of deposits and borrowings). Thus, the efficiency scores capture the ability of the banks to generate interest and non-interest incomes using the inputs of physical capital, labour and loanable funds. Further, all the input and output variables except labour are measured in Rupee lacs (note that 10 lacs=1 million).

The output variable 'net-interest income' connotes net income received by the banks from their traditional activities like advancing of loans and investments in government and other approved securities. The output variable 'non-interest income' accounts for income from off-balance sheet items such as commission, exchange and brokerage, etc. The inclusion of 'non-interest income' enables us to capture the recent changes in the production of services as Indian banks are increasingly engaging in non-traditional banking activities. As pointed out by Siems and Clark (1997), the failure to incorporate these types of activities may seriously understate bank output and this is likely to have statistical and economic effects on estimated efficiency. Some notable banking efficiency analyses that include 'non-interest income' as an output variable are Isik and Hassan (2002), Drake and Hall (2003), Sufian (2006), Sufian and Majid (2007), Hahn (2007) among others. Further, most of the studies on the efficiency of Indian banks also included 'non-interest income' in the chosen output vector (see Appendix Table A1 for perusal). It is worth noting here that our choice of output variables is consistent with the managerial objectives that are being pursued by the Indian banks. In the post-reform years, intense competition in the Indian banking sector has forced the banks to reduce all the input costs to the minimum and to earn maximum revenue with less of less inputs. Mohan and Ray (2004) rightly remarked that in the post-reforms period, Indian banks are putting all their efforts in the business of maximizing incomes from all possible sources.

Since DEA results are influenced by the size of the sample, some discussion on the adequacy of sample size is warranted here. The size of the sample utilized in the present study is consistent with the various rules of thumb available in DEA literature. Cooper *et al*. (2007) provides two such rules that can be jointly expressed as: $n \geq \max\{m \times s\ ;\ 3(m+s)\}$ where n=number of DMUs, m=number of inputs and s=number of outputs. The first rule of thumb states that sample size should be greater than equal to product of inputs and outputs. While the second rule states that number of observation in the data set should be at least three times the sum of number of input and output variables. Given m=3 and s=2, the sample size (n=27) used in the present study exceeds the desirable size as suggested by the abovementioned rules of thumb to obtain sufficient discriminatory power. The sample size in this study is feasible and larger than that used in some of the studies in the DEA literature (see, for example, Avkiran, 1999b).

5.2. Environmental Factors Explaining Inter-Bank Differences in OTE

The financial analysts are often interested to know about the factors attributing the efficiency differences among banks. In the present study, we have considered five important factors which may exert an influence on the OTE of a bank. Table 4 provides the description of these factors and their expected effect on the efficiency of the banks.

We hypothesize that larger profitability, market share, and exposure to off-balance sheet activities have positive effect on the OTE of the bank. Also, the poor asset quality (i.e., larger volume of NPAs in relation to total assets) has a negative effect on the OTE of the bank. However, we are not ascertained about the effect of size (measured in terms of total assets) on the level of OTE.

Table 4. Description and expected sign of the predictors

Predictor	Symbol	Description	Expected Sign
1) Market Share in Deposits	MS	$\frac{\text{Deposit of } i\text{-th Bank}}{\text{Total Deposits of 27 PSBs}} \times 100$	+
2) Exposure to Off-balance Sheet Activities	OFFBALANCE	$\frac{\text{Non-interest Income}}{\text{Total Assets}} \times 100$	+
3) Profitability	ROA	$\frac{\text{Net Profit}}{\text{Total Assets}}$	+
4) Asset Quality	AQ	$\frac{\text{Net NPAs}}{\text{Net Advances}}$	–
5) Size	SIZE	log (Total Assets)	±
Source: Authors' elaboration			

6. Empirical Results

In this section, the input-oriented efficiency scores obtained from the CCR and BCC models have been discussed. It is significant to note that input-oriented efficiency measures address the question: 'By how much can input quantities be proportionally reduced without altering the output quantities produced?' Table 5 presents OTE scores of 27 PSBs, along with the magnitude of overall technical inefficiency (OTIE)[6]. The results indicate that Indian public sector banking industry has been characterized with large asymmetry between banks as regards their OTE (in percentage terms) that ranges between 63.2 percent and 100 percent. The average of efficiency scores turned out to be 0.885 for 27 PSBs (see Table 6 for descriptive statistics of OTE scores). This suggests that an average PSB, if producing its outputs on the *efficient frontier* instead of its current (virtual) location, would need only 88.5 percent of the inputs currently being used. The connotation of this finding is that the magnitude of OTIE in Indian public sector banking industry is to the tune of 11.5 percent. This suggests that, by adopting best practice technology, PSBs can, on an average, reduce their inputs of physical capital, loanable funds and labour by at least 11.5 percent and still produce the same level of outputs. However, the potential reduction in inputs from adopting best practices varies from bank to bank. Alternatively, PSBs have the scope of producing 1.13 times (i.e., 1/0.885) as much as outputs from the same level of inputs.

[6] OTIE(%)=(1-OTE)×100

Table 5. Overall Technical Efficiency, Pure Technical Efficiency, and Scale Efficiency Scores for Public Sector Banks

Code	Banks	OTE Score	OTIE (%)	PTE Score	PTIE (%)	SE Score	SIE (%)	RTS
B1	State Bank of India	0.865	13.5	1.000	0	0.865	13.5	CRS
B2	State Bank of Bikaner and Jaipur	1.000	0.0	1.000	0	1.000	0	CRS
B3	State Bank of Hyderabad	0.859	14.1	0.860	14	0.999	0.1	IRS
B4	State Bank of Indore	0.923	7.7	1.000	0	0.923	7.7	IRS
B5	State Bank of Mysore	1.000	0.0	1.000	0	1.000	0	CRS
B6	State Bank of Patiala	1.000	0.0	1.000	0	1.000	0	CRS
B7	State Bank of Saurashtra	0.960	4.0	1.000	0	0.960	4	IRS
B8	State Bank of Travancore	1.000	0.0	1.000	0	1.000	0	CRS
B9	Allahabad Bank	0.806	19.4	0.829	17.1	0.972	2.8	DRS
B10	Andhra Bank	1.000	0.0	1.000	0	1.000	0	CRS
B11	Bank of Baroda	0.869	13.1	0.982	1.8	0.885	11.5	DRS
B12	Bank of India	0.632	36.8	0.696	30.4	0.908	9.2	DRS
B13	Bank of Maharashtra	0.759	24.1	0.764	23.6	0.994	0.6	IRS
B14	Canara Bank	0.801	19.9	0.896	10.4	0.895	10.5	DRS
B15	Central Bank of India	0.890	11.0	0.977	2.3	0.911	8.9	DRS
B16	Corporation Bank	1.000	0.0	1.000	0	1.000	0	CRS
B17	Dena Bank	0.804	19.6	0.864	13.6	0.931	6.9	IRS
B18	Indian Bank	0.844	15.6	0.869	13.1	0.972	2.8	DRS
B19	Indian Overseas Bank	0.974	2.6	1.000	0	0.974	2.6	DRS
B20	Oriental Bank of Commerce	0.945	5.5	1.000	0	0.945	5.5	DRS
B21	Punjab & Sind Bank	1.000	0.0	1.000	0	1.000	0	CRS
B22	Punjab National Bank	0.889	11.1	0.997	0.3	0.891	10.9	DRS
B23	Syndicate Bank	0.859	14.1	0.909	9.1	0.945	5.5	DRS
B24	UCO Bank	0.676	32.4	0.705	29.5	0.959	4.1	DRS
B25	Union Bank of India	0.796	20.4	0.887	11.3	0.897	10.3	DRS
B26	United Bank of India	0.816	18.4	0.821	17.9	0.994	0.6	DRS
B27	Vijaya Bank	0.918	8.2	0.926	7.4	0.992	0.8	IRS

Notes: OTE= Overall technical efficiency, OTIE%=Overall technical inefficiency=(1-OTE)×100, PTE= Pure technical efficiency, PTIE%=Pure technical inefficiency=(1-PTE)×100, SE= Scale efficiency, SIE(%)=Scale inefficiency=(1-SE)×100, RTS=returns-to-scale, IRS= increasing returns-to-scale, CRS=constant returns-to-scale; and DRS=decreasing returns-to-scale

Source: Authors' calculations

Recall that the bank with OTE score equal to 1 is considered to be most efficient amongst the banks included in the analysis. The bank with OTE score less than 1 is deemed to be relatively inefficient. Of the 27 PSBs, 7 banks were found to be technically efficient since they had OTE score of 1. These banks together define the *best practice* or *efficient frontier* and, thus, form the *reference set* for inefficient banks. The resource utilization process in these banks is functioning well. It means that the production process of these banks is not characterizing any waste of inputs. In DEA terminology, these banks are called *peers* and set an example of good operating practices for inefficient banks to emulate. The efficient banks in Indian public sector banking industry are State Bank of Bikaner and Jaipur, State Bank of Mysore, State Bank of Patiala, State Bank of Travancore, Andhra Bank, Corporation Bank, and Punjab and Sind Bank (see Table 5). The remaining 20 banks have OTE score less than 1 which means that they are technically inefficient. The results, thus, indicate a presence of marked deviations of the banks from the *best practice frontier*.

These inefficient banks can improve their efficiency by reducing inputs. OTE scores among the inefficient banks range from 0.632 for Bank of India to 0.974 for Indian Overseas Bank. This finding implies that Bank of India and Indian Overseas Bank can potentially reduce their current input levels by 36.8 percent and 2.6 percent, respectively while leaving their output levels unchanged. This interpretation of OTE scores can be extended for other inefficient banks in the sample. On the whole, we observed that OTIE levels ranged from 2.6 percent to 36.8 percent among inefficient PSBs.

Table 6. Descriptive statistics of overall technical efficiency scores for Indian public sector banking industry

Statistics	All Banks	Efficient Banks	Inefficient Banks
N	27	7	20
AOTE	0.885	1.000	0.844
SD	0.102	0	0.088
Minimum	0.632	1.000	0.632
Q_1	0.806	1.000	0.802
Median	0.889	1.000	0.859
Q_3	1.000	1.000	0.911
Maximum	1.000	1.000	0.974
AOTIE (%)	11.53	0	15.57
Interval	(0.782;0.983)	(1.000;1.000)	(0.756;0.932)

Notes: AOTE= Average overall technical efficiency; SD= Standard Deviation; Q_1= First Quartile; Q_3= Third Quartile; AOTIE (%)=Average overall technical inefficiency=(1-AOTE)×100; and Interval=(AOTE-SD; AOTE+SD)

Source: Authors' calculations

6.1. Discrimination of Efficient Banks

To discriminate 7 efficient PSBs, we followed the method proposed by Chen (1997) and Chen and Yeh (1998) used the frequency in the 'reference set' to discriminate them. The frequency, which an efficient bank shows up in the reference sets of inefficient banks, represents the extent of robustness of that bank relative to other efficient banks. The higher the frequency, the more robust it is. In other words, a bank which appears frequently in the reference set of inefficient banks is likely to be a bank which is efficient with respect to a large number of factors, and is probably a good example of a 'well-rounded performer' or 'global leader' or 'bank with high robustness'. Further, these banks are likely to remain efficient unless there are major shift in their fortunes. Efficient banks that appear seldom in the reference set of inefficient banks are likely to possess a very uncommon input/output mix and are, thus, not suitable examples to emulate for other inefficient banks. In sum, the frequency with which an efficient bank shows up in the reference set of inefficient banks is actually an indication of what may be called exemplary operating practices. When this frequency is low, one can safely conclude that the bank is somewhat of an odd or peculiar institution and cannot treat as a good example to be followed. In fact, the banks with low frequency in the reference set are the 'marginally efficient banks' and would likely to drop from *efficient frontier* if there is even a small drop in the value of an output variable (or a small increase in the value of an input variable). Further, the efficient banks with zero frequency in the reference set may also be observed in the analysis. In DEA terminology, the bank with zero frequency count is termed as 'efficient by default' because it does not possess the characteristics which must be followed by other inefficient banks. Table 7 provides the reference sets of inefficient banks along with the frequency (or peer count) of each efficient bank in that reference sets.

On the basis of frequency in the reference sets (as provided in Table 7), we categorized the efficient banks into two broad categories: (i) Highly Robust Banks; (ii) Marginally Robust Banks (see Table 8). The former category includes State Bank of Bikaner and Jaipur, and Corporation Bank which appear in the reference sets of inefficient banks relatively more frequently than other efficient banks. Their frequency counts have been observed to be 19 and 18, respectively. On the basis of such a high frequency count, they have been appropriately considered as global leaders of Indian public sector banking industry. However, in the latter category, State Bank of Patiala, State Bank of Travancore, State Bank of Mysore, Andhra Bank, and Punjab and Sind Bank got a berth on account of their low frequency count. It is interesting to note that although State Bank of Mysore, and Andhra Bank are efficient banks yet they do not exemplify any best practices (as indicated by zero frequency count) to be followed by the inefficient banks in their pursuit to enhance their efficiency levels. In fact, these banks may be rightly designated as 'efficient by default'.

Table 7. Reference Sets for Inefficient Banks

Inefficient banks	OTE score	Reference set						
		B2	**B5**	**B6**	**B8**	**B10**	**B16**	**B21**
B1	0.865	9.485	0	1.434	0	0	3.810	0
B3	0.859	0.077	0	0.391	0.292	0	0.224	0
B4	0.923	0.054	0	0.414	0	0	0.045	0
B7	0.960	0.165	0	0	0.377	0	0	0.046
B9	0.806	0.646	0	0	0	0	0.711	0
B11	0.869	1.364	0	0	0	0	1.589	0
B12	0.632	1.285	0	0	0	0	0.992	0
B13	0.759	0.332	0	0.392	0	0	0.186	0
B14	0.801	1.513	0	0.687	0	0	1.032	0
B15	0.890	2.514	0	0	0	0	0.169	0
B17	0.804	0.398	0	0	0	0	0.302	0
B18	0.844	1.278	0	0	0	0	0.171	0
B19	0.974	1.388	0	0	0	0	0.575	0
B20	0.945	0	0	0	0	0	1.349	0
B22	0.889	3.107	0	0	0	0	1.158	0
B23	0.859	1.198	0	0	0	0	0.578	0
B24	0.676	0.816	0	0	0	0	0.618	0
B25	0.796	0.587	0	0	0	0	1.376	0
B26	0.816	1.053	0	0	0	0	0	0
B27	0.918	0.330		0	0	0	0.618	0
Frequency count		19	0	5	2	0	18	1

Note: Bold figures are λ_j^* values obtained from solution of CCR model for individual inefficient PSBs.

Source: Authors' calculation

Table 8. Discrimination of Efficient Banks

Highly Robust Banks	**Marginally Robust Banks**
State Bank of Bikaner and Jaipur (19)	State Bank of Patiala (5)
Corporation Bank (18)	State Bank of Travancore (2)
	Punjab and Sind Bank (1)
	State Bank of Mysore (0)
	Andhra Bank (0)

Note: The figures in the parenthesis are frequency count.

Source: Authors' elaboration

6.2. Discrimination of Inefficient Banks

Besides discriminating the efficient banks, we also made an attempt to separate out 20 inefficient banks. For this, we utilized the quartile values of OTE scores obtained from CCR model as cut-off points to segregate the inefficient banks into four categories (see Table 6 for the quartile values). Among these categories, the banks belonging to 'most inefficient' and 'marginally inefficient' category requires special attention.

In the 'most inefficient' category, those banks have been included which attained the OTE score below the value of first quartile. The candidates of this group are worst performers in the sample and may be considered as 'target banks' in any probable recapitalization and consolidation exercise that may take place in Indian banking industry. It is significant to note that these banks lack vitality in terms of the efficiency of resource utilization. The banks that have attained OTE score above the third quartile value but less than 1 are included in 'marginally inefficient' category. It is worth mentioning here that these banks are operating at a high level of operating efficiency even though they are not fully efficient. In fact, these banks are marginally inefficient and operate close to the *efficient frontier*. Further, these banks can attain the status of efficient banks by bringing little improvements in the resource utilization process. Infact, these banks are would-be champions. Therefore, the regulators must pay special attention to enhance their efficiency.

Table 9. Classification of inefficient public sector banks

Category I (Most Inefficient)	**Category II (Below Average)**	**Category III (Above Average)**	**Category IV (Marginally Inefficient)**
Canara Bank (23)	Syndicate Bank (17)	Central Bank of India (13)	Indian Overseas Bank (8)
Union Bank of India (24)	State Bank of Hyderabad (18)	Punjab National Bank (14)	State Bank of Saurashtra (9)
Bank of Maharashtra (25)	Indian Bank (19)	Bank of Baroda(15)	Oriental Bank of Commerce (10)
UCO Bank (26)	United Bank of India (20)	State Bank of India (16)	State Bank of Indore (11)
Bank of India (27)	Allahabad Bank (21)		Vijaya Bank (12)
	Dena Bank (22)		

Notes: 1) The 'Most Inefficient' category includes those banks which have OTE score below the first quartile; 2) Those banks are included in the 'Below Average' category whose OTE score lies between first and second quartile; 3) The 'Above Average' category consists of the banks wherein OTE score lies between median and third quartile; 4) The banks with OTE scores above the third quartile are included in the 'Marginally Inefficient' category; 5) Figures in brackets are ranks; and 6) Q_1=0.802, Median=0.859, and Q_3=0.911.

Source: Authors' calculations

6.3. Decomposition of OTE: PTE and SE

It should be noted that OTE measure helps to measure combined inefficiency that is due to both pure technical inefficiency (PTIE) and inefficiency that is due to inappropriate bank size i.e., scale inefficiency (SIE). However, in contrast to OTE measure, the PTE measure derived from BCC model under assumption of VRS devoid the scale effects. Thus, the PTE scores provide that all the inefficiencies directly result from managerial underperformance (i.e., managerial inefficiency) in organizing the bank's inputs. It is significant to note here that the efficiency scores of the banks rise on allowing VRS because BCC model (i.e., a DEA model under VRS assumption) forms a convex hull of intersecting planes which envelops the data points more tightly than CRS conical hull and provides efficiency scores which are greater than or equal to those obtained using the CCR model (i.e., a DEA model under CRS assumption). In DEA literature, the banks attaining OTE and PTE scores equal to 1 are known as 'globally efficient' and 'locally efficient' banks, respectively.

Table 5 also provides the PTE and SE scores. It has been observed that 12 banks acquired the status of 'locally efficient' banks because they attained the PTE score equal to 1. In addition to those 7 banks that have acquired the status of 'globally efficient' banks and lie on *efficient frontier* under CRS assumption, 5 banks, namely, State Bank of India, State Bank of Indore, State Bank of Saurashtra, Indian Overseas Bank, and Oriental Bank of Commerce, attained the PTE score equal to 1 and lie on the *efficient frontier* under VRS assumption. For these five banks that became efficient under VRS assumption but have been found to be inefficient under CRS case, we can infer that the OTIE in these banks is not caused by poor input utilization (i.e., managerial inefficiency) rather caused by the operations of the banks with inappropriate scale size. It has been further noticed that in the remaining 15 banks (having PTE<1) managerial inefficiency exits, albeit of different magnitude. In these banks, OTIE stems from both PTIE and SIE as indicated by the fact that these banks have both PTE and SE scores less than 1. Out of these 15 banks, 9 banks have PTE score less than SE score. This indicates that the inefficiency in resource utilization (i.e., OTIE) in these 9 banks is primarily attributed to the managerial inefficiency rather than to the scale inefficiency.

Turning to the analysis of PTE and SE measures for the industry as a whole, we observed that OTIE in Indian public sector banking industry is due to both poor input utilization (i.e., pure technical inefficiency) and failure to operate at most productive scale size (i.e., scale inefficiency). The average PTE score for 27 PSBs has been observed to be 0.925 (see Table 10 for descriptive statistics of OTE, PTE, and SE scores). This implies that 7.5 percentage points of the about 11.5 percent of

OTIE is due to the bank managers who are not following appropriate management practices and selecting incorrect input combinations. The rest of OTIE appears due to inappropriate scale of banking operations. Further, lower mean and high standard deviation of the PTE scores compared to SE scores indicate that a greater portion of OTIE is due to PTIE.

Table 10. Descriptive statistics of OTE, PTE, and SE scores

Statistics	OTE	PTE	SE
N	27	27	27
Average efficiency	0.885	0.925	0.956
SD	0.102	0.096	0.045
Minimum	0.632	0.696	0.865
Q_1	0.806	0.864	0.911
Median	0.889	0.982	0.972
Q_3	1.000	1.000	1.000
Maximum	1.000	1.000	1.000
Average inefficiency (%)	11.5	7.5	4.4
Interval	(0.783; 0.987)	(0.829;1.021)	(0.911;1.001)

Notes: SD=Standard Deviation; Average inefficiency(%)=(1-Average efficiency)*100; Interval=(Average efficiency -SD; Average efficiency+ SD)

Source: Authors' calculations

6.4. Returns-to-Scale

Microeconomic theory of the firms guide that one of the basic objective of the firms is to operate at most productive scale size i.e., with constant returns-to-scale (CRS) in order to minimize costs and maximize revenue. In the short run, firms may operate in the zone of increasing returns-to-scale (IRS) or decreasing returns-to-scale (DRS). However, in the long run, they will move towards CRS by becoming larger or smaller to survive in the competitive market. The process might involve changes of a firms' operating strategy in terms of scaling up or scaling down of size. The regulators may use this information to determine whether the size of representative firm in the particular industry is appropriate or not.

Recall that the existence of IRS or DRS can be identified by the sum of intensity variables (i.e., $\sum_{j=1}^{n} \lambda_j^*$) in the CCR model. If $\sum_{j=1}^{n} \lambda_j^* < 1$ then scale inefficiency appears due to increasing returns-to-scale. The implication of this is that the particular bank has sub-optimal scale size. On the other hand, if $\sum_{j=1}^{n} \lambda_j^* > 1$ then scale inefficiency occurs due to decreasing returns-to-scale. The connotation of this is that the bank has supra-optimal scale size. Table 5 also provides the nature of returns-to-scale for individual public sector banks. The results indicate that 7 efficient banks (i.e., 26 percent) are operating at most productive scale size and experiencing CRS. Further, 6 banks (i.e., 22 percent) are operating below their optimal scale size and thus, experiencing IRS. The policy implication of this finding is that these banks can enhance OTE by increasing their size. The remaining 14 (i.e., 52 percent) banks have been observed to be operating in the zone of DRS and, thus, downsizing seems to be an appropriate strategic option for these banks in their pursuit to reduce unit costs. On the whole, decreasing returns-to-scale is observed to be the predominant form of scale inefficiency in Indian public sector banking industry.

6.5. Areas for Efficiency Improvement: Slacks and Targets Setting Analysis

The optimum solution of linear programme [1] provides non-zero input and output slacks corresponding to input and output constraints. It is important to note that, slacks exist only for those DMUs that are identified as inefficient in a particular DEA run. These slacks provide the vital information pertaining to the areas which an inefficient bank needs to improve upon in its drive towards attaining the status of efficient one. Coelli *et al.* (2005) clearly pointed out that both the Farrell measure of technical efficiency and any non-zero input and output slacks should be reported to provide an accurate indication of technical efficiency of a firm in a DEA analysis. Thus, the slacks should be interpreted along with the efficiency values. However, slacks represent only the leftover portions of inefficiencies; after proportional reductions in inputs or outputs, if a DMU cannot reach the *efficient frontier* (to its efficient target), slacks are needed to push the DMU to the frontier (target) (Ozcan, 2008). The presence of non-zero slacks for a DMU implies that the DMU under scrutiny can improve beyond the level implied by the estimate of technical efficiency (Jacobs *et al.*, 2006). In the input-oriented DEA model, the input-slack represents the input excess and output slack indicates the output which is under-produced (Avkiran, 1999a; Ozcan, 2008).

Table 11 provides the input and output slacks derived from CCR model for 20 inefficient PSBs in India. For interpreting the contents of the table, consider the case of a single bank, say, Oriental Bank of Commerce. The OTE score of Oriented Bank of Commerce is 0.945, implying that the bank could become technically efficient (under the Farrell's definition) provided if all of its inputs are proportionally reduced by 5.5 percent (i.e., (1-OTE score) $\times$100). However, even with this required proportional reduction in all inputs, this bank would not be *Pareto-efficient*, as it would be operating on the vertical section of the *efficient frontier*. In order to project this bank to a *Pareto-efficient* point, some further slack adjustments are necessary because non-zero input and output slacks appear for this bank. Ultimately, Oriental Bank of Commerce has to make three adjustments in order to operate at the *efficient frontier*. First, it has to reduce all inputs by 5.5 percent. Second, it has to reduce loanable funds and physical capital by another 15.2 percent and 3.7 percent, respectively. Third, it has to augment non-interest income by 50.8 percent. The first type of adjustment is known as radial adjustment while second and third types of adjustments are known as slack adjustments. The similar explanation can be extended for other inefficient banks.

The analysis of slacks for all inefficient banks delineates that among the input variables, 14 banks have non-zero slacks for physical capital, 1 bank has non-zero slacks for loanable funds and 1 bank has non-zero slack for labour. With regard to non-zero slacks for output variables, it has been observed that 19 banks have non-zero slacks for non-interest income. Further, no non-zero slack has been observed for net-interest income. This suggests that besides the proportional reduction of all inputs by the levels of observed technical inefficiency, most of the inefficient banks in Indian public sector banking industry need to reduce the use of physical capital and to augment the level of non-interest income, for projecting themselves onto the *efficient frontier*.

For getting the more focused diagnostic information about the sources of inefficiency for each bank with respect to the input and output variables, we computed the target values of these variables at bank level using OTE scores, optimum values of slacks and actual values. The target point $(\hat{x},\hat{y})$ is defined by the following formulae:

$$\hat{x}_{io} = \theta_o^* x_{io} - s_i^{-*} \qquad i = 1,2,\ldots,m$$
$$\hat{y}_{ro} = y_{ro} + s_r^{+*} \qquad r = 12,,\ldots,s.$$

where $\hat{x}_{io}$ =the target input *i* for *o*-th bank, $\hat{y}_{ro}$ = target output *r* for *o*-th bank; x_{io} = actual input *i* for *o*-th bank; y_{ro} =actual output *r* for *o*-th bank; θ_o^* =OTE score of *o*-th bank; s_i^{-*} =optimal input slacks; and s_r^{+*} =optimal output slacks. The difference between the observed value and target value of inputs (i.e., $\Delta x_{io} = x_{io} - \hat{x}_{io}$) represents the quantity of input *i* to be reduced, while the difference between the target values and observed values of outputs $(\Delta y_{ro} = \hat{y}_{ro} - y_{ro})$ represents the amount of output *r* to be increased, to move the inefficient bank onto the *efficient frontier*. Finally, the potential input reduction for input *i* and potential output addition for output *r* can be obtained by $(\Delta x_{io} / x_{io}) \times 100$ and $(\Delta y_{ro} / y_{ro}) \times 100$, respectively.

Table 11. Slacks and targets for inefficient public sector banks

		Slacks					Targets					Potential Improvement				
												Input Reduction (%)			Output Addition (%)	
Bank	TE	x_1	x_2	x_3	y_1	y_2	x_1	x_2	x_3	y_1	y_2	x_1	x_2	x_3	y_1	y_2
State Bank of India	0.865	0 (0)	0 (0)	0 (0)	12360.6 (1.7)	0 (0)	177681	33392184	233231	724352	1394464	13.5	13.5	13.5	1.7	0
State Bankof Hyderabad	0.859	0 (0)	0 (0)	0 (0)	0.0	0 (0)	11255	2554177	14791	42165	96237	14.1	14.1	14.1	0.0	0
State Bank of Indore	0.923	0 (0)	0 (0)	0 (0)	2064.9 (11.6)	0 (0)	5958	1355314	7115	19892	50221	7.7	7.7	7.7	11.6	0
State Bank of Saurashtra	0.96	0 (0)	0 (0)	0 (0)	13171.5 (115.5)	0 (0)	7034	1305182	6372	24573	50800	4.0	4.0	4.0	115.5	0
Allahabad Bank	0.806	0 (0)	0 (0)	32829 (44.8)	7346.4 (11.5)	0 (0)	15571	3297486	26199	71334	136402	19.4	19.4	64.2	11.5	0
Bank of Baroda	0.869	0 (0)	0 (0)	17265 (20.1)	25096.1 (19.2)	0 (0)	33774	7213061	57567	155579	297927	13.1	13.1	33.1	19.2	0
Bank of India	0.632	0 (0)	0 (0)	10123 (12.4)	2503.5 (2.2)	0 (0)	26671	5355815	41308	118082	223688	36.8	36.8	49.3	2.2	0
Bank of Maharashtra	0.759	0 (0)	0 (0)	0 (0)	1988.0 (5.2)	0 (0)	10725	2244644	13886	40510	88165	24.1	24.1	24.1	5.2	0
Canara Bank	0.801	0 (0)	0 (0)	0 (0)	1397.5 (0.9)	0 (0)	37978	7775639	53921	155782	315048	19.9	19.9	19.9	0.9	0
Central Bank of India	0.89	0 (0)	0 (0)	31569 (42.0)	38966.2 (42.3)	0 (0)	34108	5422308	35412	130979	237494	11.0	11.0	52.9	42.3	0
Dena Bank	0.804	0 (0)	0 (0)	10934 (37.3)	5142.9 (16.5)	0 (0)	8204	1643140	12654	36262	68660	19.6	19.6	56.9	16.5	0
Indian Bank	0.844	0 (0)	0 (0)	17750 (39.5)	14516.9 (25.5)	0 (0)	18208	2999856	20189	71398	130364	15.6	15.6	55.1	25.5	0
Indian Overseas Bank	0.974	0 (0)	0 (0)	12179 (26.9)	35539.5 (55.5)	0 (0)	23744	4368817	31902	99520	185552	2.6	2.6	29.5	55.5	0
Oriental Bank of Commerce	0.945	0 (0)	740690 (15.2)	1389 (3.7)	25646.6 (50.8)	0 (0)	13760	3849166	34564	76166	152369	5.5	20.8	9.2	50.8	0
Punjab National Bank	0.889	0 (0)	0 (0)	17690 (18.3)	47870.6 (28.6)	0 (0)	51829	9408487	68077	215439	400673	11.1	11.1	29.5	28.6	0
Syndicate Bank	0.859	0 (0)	0 (0)	3121 (8.2)	34059.7 (60.3)	0 (0)	21330	4003872	29626	90514	169383	14.1	14.1	22.3	60.3	0
UCO Bank	0.676	0 (0)	0 (0)	1193 (3.0)	22723.1 (44.1)	0 (0)	16808	3365548	25914	74279	140638	32.4	32.4	35.4	44.1	0
Union Bank of India	0.796	0 (0)	0 (0)	23028 (28.0)	29456.7 (38.5)	0 (0)	21602	5080663	42521	106067	206456	20.4	20.4	48.4	38.5	0
United Bank of India	0.816	702 (4.0)	0 (0)	3395 (16.9)	3046.1 (6.4)	0 (0)	13572	2070468	13028	50894	91535	22.4	18.4	35.3	6.4	0
Vijaya Bank	0.918	0 (0)	0 (0)	75 (0.3)	15456.9 (43.7)	0 (0)	10552	2411400	19911	50824	98454	8.2	8.2	8.5	43.7	0
Average												15.8	16.3	30.6	29	0

Notes: y_1 =non-interest income; y_2 =net-interest income; x_1 =labour; x_2 =loanable funds; x_3 =physical capital

Source: Authors' calculations

Table 11 also presents the target values of inputs and outputs for inefficient banks along with potential addition in outputs and potential reduction in inputs. The potential improvement shows those areas of improvement in input-output activity needed to put an inefficient bank onto the *efficient frontier*. For getting what these figures of potential input reduction and output addition show, consider the case of UCO bank, most inefficient bank in the sample. To move onto the *efficient frontier*, UCO needs to reduce its capital input by 35.4 percent, cut labour by 32.4 percent and use 32.4 percent less loanable funds and augment non-interest income by 44.1 percent.

We can also draw the similar conclusions for other inefficient banks,. Considering Indian public sector banking industry as a whole, we need to reduce, on an average, physical capital, labour, and loanable funds by 30.6, 15.8, and 16.3 percent, respectively and increase the non-interest income by 29 percent if we wish to project all the inefficient banks onto the *efficient frontier*.

6.6. Factors Explaining Inter-Bank Differences in OTE: Logistic Regression Analysis

Table 12 describes the results of logistic regression analysis. It figures out that by taking all the five predictors together (see Model 1.1), the overall goodness of fit of the model has been found to be significant on the basis of Log-Likelihood Ratio test $(\chi^2_{cal} = 19.884, \chi^2_{tab} = 11.1, d.f. = 5, n = 27)$. The Nagelkerke R^2 has been observed to be 0.765 which indicates that approximately 76.5 percent of the variation in whether or not bank is efficient can be predicted from the linear combination of five independent predictors. Although, as noted above, the Model 1.1 turned to be significant by considering all the predictors together yet individually each predictor has been found to be statistically insignificant. This conclusion has been drawn on the basis of Wald test. The values of Wald statistics for each individual predictor has been noted to be lesser than 3.84 (i.e., a tabulated value of χ^2 corresponding to 1 *d.f.*) which is not sufficient to reject the null hypothesis $H_o : \beta_j = 0$. Furthermore, the predictors MS and ROA bear the signs which are inconsistent with *a priori* considerations. Therefore, we re-estimated logistic regression model by dropping these two predictors and represented the results so obtained under Model 1.2. The Model 1.2 depicts that only the predictor OFFBALANCE is statistically significant. Also, the insignificant predictor AQ has very high standard error relative to that of predictor SIZE. We, therefore, dropped the variable AQ and re-estimated the logistic regression involving two predictors viz., OFFBALANCE and SIZE and presented the results in Model 1.3. The Model 1.3 indicates that the predictor OFFBALANCE has a statistically significant regression coefficient while the predictor SIZE again found to be statistically insignificant.

Table 12. Results of logistic regression analysis

Independent Variables	*Model 1.1*					*Model 1.2*					*Model 1.3*				
	β	*S.E.*	*Wald*	*Odds*	*p-values*	β	*S.E.*	*Wald*	*Odds*	*p-values*	β	*S.E.*	*Wald*	*Odds*	*p-values*
MS	-9.62	12.59	0.54	0.00	0.45	-	-	-	-	-	-	-	-	-	-
OFFBALANCE	0.84	0.58	0.58	2.31	0.15	0.71	0.36	3.87	2.02	0.05	0.69	0.34	4.06	2.00	0.04
ROA	-3.35	4.87	2.07	0.03	0.49	-	-	-	-	-	-	-	-	-	-
AQ	-0.48	0.97	0.47	0.62	0.62	-0.06	0.38	0.025	0.94	0.87	-	-	-	-	-
SIZE	12.69	18.61	0.25	323755.67	0.49	-3.27	2.26	2.09	0.04	0.14	-3.10	1.95	2.53	0.04	0.11
Constant	-124.08	169.57	0.46	0.00	0.46	21.45	22.42	0.92	2.1E+09	0.34	19.78	19.48	1.03	3.9E+08	0.31
	χ^2 =19.884 -2LL=11.019 Nagelkerke R^2 =0.765					χ^2 =18.321 -2LL=12.582 Nagelkerke R^2 =0.723					χ^2 =18.296 -2LL=12.607 Nagelkerke R^2 =0.722				
Source: Authors' calculations															

On the basis of these findings, we conclude that efficiency of PSBs is positively influenced by their exposure to off-balance sheet activities. Thus, the phenomenon that 'larger the exposure of bank to off-balance sheet activities, larger is the level of efficiency' holds in the Indian public sector banking industry. In addition, the proposition that 'larger the bank in terms of total assets, the higher is its efficiency' does not seem to hold for Indian public sector banks.

7. Summary and Conclusions

This paper endeavors to evaluate the extent of technical, pure technical, and scale efficiencies in Indian public sector banking industry using cross-sectional data for 27 banks in the year 2004/05. Besides this, an attempt has been made to explain the impact of environmental factors (like market share, asset quality, exposure to off-balance sheet activities, size, and profitability) on the overall technical efficiency of the PSBs. To realize the research objectives, a two-stage DEA framework has been applied in which the estimates of technical, pure technical, and scale efficiencies for individual PSBs have been obtained by CCR and BCC models in the first stage; and logistic regression analysis has been used to work out the relationship between overall technical efficiency and environmental factors in the second stage.

The present study followed an intermediation approach to select input and output variables. The output vector contains two outputs: i) net-interest income, and ii) non-interest income, while input vector contains three inputs: i) physical capital, ii) labour, and iii) loanable funds. The results indicate that the level of overall technical efficiency in Indian public sector banking industry is around 88.5 percent. Thus, the magnitude of technical inefficiency is to the tune of 11.5 percent. The 7 PSBs scored OTE score of unity and, thus, defined the *efficient frontier*. On the basis of frequency count in the reference set of inefficient banks, State Bank of Bikaner and Jaipur, and Corporation Bank have been figured out as the 'global leaders' of Indian public sector banking industry. The worst performer banks in the sample have been noticed to be Bank of India, followed by UCO Bank, Bank of Maharashtra, Union Bank of India, and Canara Bank.

Turning to the sources of overall technical inefficiency, it has been noticed that the observed technical inefficiency in the Indian public sector banking industry is due to both poor input utilization (i.e., managerial inefficiency) and failure to operate at most productive scale size (i.e., scale inefficiency). However, in most of the inefficient banks, overall technical inefficiency is mainly attributed by pure technical inefficiency rather than scale inefficiency. Thus, Indian PSBs are more successful in choosing optimal levels of output than adopting best practice technology. From the analysis of returns-to-scale, it has been noticed that 52 percent banks operate in the zone of decreasing returns-to-scale and, thus, need a down sizing in their operations to observe an efficiency gains.

In the present study, we also carried out a slacks and targets setting exercise to assess the directions for improvement in the operations of inefficient banks. The results provide that the inefficient PSBs should concentrate more on off-balance sheet activities to garner more revenue. It has been further observed that on an average, 30.6 percent of physical capital, 15.8 percent of labour, and 16.3 percent of loanable funds could be theoretically reduced if all the inefficient banks operate at the same level as the efficient banks. The results of logistic regression analysis provides that the factors like market share, profitability, and asset quality do not have any significant impact on the overall technical efficiency of Indian public sector banking industry. Also, the efficiency of PSBs is positively influenced by their exposure to off-balance sheet activities. The proposition that 'larger the bank in terms of assets, the higher is its efficiency' does not seem to hold in the Indian public sector banking industry. On the whole, the study suggests that there is an ample scope for improvement in the performance of inefficient PSBs by choosing a correct input-output mix and selecting appropriate scale size. The future work could extend our research in various directions not considered in this study. First, we could examine the inter-temporal variations in technical, pure technical, and scale efficiencies using longitudinal data for PSBs. Second, using the data across different ownership groups, there is a possibility to analyze the technical, pure technical, and scale efficiencies of PSBs vis-à-vis their private counterparts.

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Appendix

Table A1: Input and Output Variables in Selected Indian Studies on Banking Efficiency

Author (Year)	Approach	Inputs	Outputs
Bhattacharyya *et al.* (1997)	VA	1. Interest expense 2. Operating expense	1. Advances 2. Investments 3. Deposits
Das (1997)	Both IA and PA	1. Labour 2. Loanable funds	**Intermediation Approach** 1. Net-interest margin 2. Commission, exchange, brokerage, etc. **Production Approach** 1. Number of account services.
Das (2000)	IA	1. Deposits 2. Borrowings 3. Number of employees	1. Net-interest margin 2. Commission, exchange, brokerage, etc.

Saha and Ravisankar (2000)	NS	Model A 1. Branches 2. Staff 3. Establishment expenditure, 4. Non-establishment expenditure Model B 1. Interest expenditure 2. Establishment expenditure 3. Non-establishment expenditure 4. Fixed assets	Model A 1. Deposits 2. Advances 3. Investments 4. Spread 5. Total income 6. Interest income 7. Non-interest income Working funds. Model B 1. Deposits 2. Advances 3. Investments 4. Non-interest income 5. Spread 6. Total income
Mukherjee *et al*. (2002)	IA	1. Net worth 2. Borrowings 3. Operating expenses 4. Number of employees 5. Number of bank branches	1. Deposits 2. Net profit 3. Advances 4. Non-interest income 5. Interest spread
Sathye (2003)	IA	Model A 1. Interest expenses 2. Non-interest expenses Model B 1. Deposits 2. Staff	Model A 1. Net-interest income 2. Non-interest income Model B 1. Net Loans 2. Non-interest income.
Mohan and Ray (2004)	IA	1. Labour 2. Loanable funds	1. Net-interest margin 2. Commission, exchange, brokerage, etc.
Das *et al.* (2004)	IA	1. Borrowed funds 2. Staff 3. Fixed assets 4. Equity	1. Investments 2. Performing loan assets 3. Other non-interest fee based income.
Chakrabarti and Chawla (2005)	Both PA and VA	Model A 1. Interest expenses 2. Operating expense Model B 1. Interest 2. Non-interest expenses	Model A 1. Advances 2. Investments 3. Deposits Model B 1. Interest income 2. Non-interest income
Ray (2007)	IA	1. Borrowed funds 2. Labour 3. Physical capital 4. Equity	1. Credit 2. Investments 3. Other income

Notes: i) IA, PA, and VA stand for intermediation approach, production approach, and value-added approach, respectively, and ii) NS means 'not specified' by the authors.

Source: Authors' compilation.