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Working Paper
(WP 12/2022)

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INDIA
February 2022

Citation Guideline:
Sanati, Gargi and Anup Kumar Bhandari (2022), "Recovery Induced Operational Efficiency of Indian Commercial Banks: An Alternative Approach to Accommodate Stressed Assets as Undesirable Byproducts", NIBM Working Paper Series, WP 12/February.
https://www.nibmindia.org/static/working_paper/NIBM_WP12_GSAKB.pdf

Recovery Induced Operational Efficiency of Indian Commercial Banks: An Alternative Approach to Accommodate Stressed Assets as Undesirable Byproducts

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ABSTRACT

In a comparative framework, we estimate technical efficiency of Indian banks during 2009-10 to 2017-18. We consider *advances* and *recovery* of stressed assets as desirable outputs, while *NPA* and *slippage* as undesirable byproducts. Our conjecture (from the prior observations) that public sector banks lag way behind the private sector banks has also been validated. To be specific, an average public (private) sector banks has an opportunity to further expand its *recovery* by 69.7% (50.4%) while keeping its *GNPA* and three inputs (viz., *total fixed assets*, *deposits* and *operating expenses*) at their current levels. Our second stage econometric analyses help us drawing inference that *positive externalities* are predominant for *priority sector lending* in determining the efficiency of a banks. Moreover, overall *competitive scenario* within the baking sector, *secured loan* and *economic growth* play noteworthy role in improving bank's operational efficiency and reducing credit risk. Our results also suggest that *collateral type* might be of more exchangeable to liquid assets to improve the *recovery of stressed assets*.

Key Words: Financing Policy; Financial Risk and Risk Management; Banks' Ownership Structure; Stressed Assets; Slippage.

JEL Classifications: D24, G21, G32, G38, L25

Acknowledgement: The project was undertaken as a part of the 'RBI Scholarship Scheme for Faculty Members of Academic Institutions 2020'. We are immensely grateful to all who have enriched the concepts with their critical views and comments. The views expressed in the study are solely of the authors and not of Reserve Bank of India. The other usual disclaimer applies.

We thankfully acknowledge the Reserve Bank of India for granting us the opportunity to work under the Scholarship Scheme for Faculty Members from Academic Institutions, 2020.

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Recovery Induced Operational Efficiency of Indian Commercial Banks: An Alternative Approach to Accommodate Stressed Assets as Undesirable Byproducts

1. Introduction

Indian banking industry has been going through a major structural change in the recent times in terms of mergers and acquisitions. Quality of assets and inefficiency in recovery of stressed assets, in the current economic condition, are matters of high apprehension for the regulators and policy makers. In this backdrop, our study focuses on the recovery induced operational efficiency, while managing stressed assets of Indian commercial banks. We also examine the determinants of such performance considering both public and private sector banks in a comparative framework. The low recovery rate of defaulted loan account demands an imperative policy deliberation to safeguard the interest of Indian banking system and thereby the growth of the Indian economy. Decline in loan recovery not only mandates higher provisions and low profitability, it also condenses banks' lending capacity, thus affecting the economy adversely.

There has been a great deal of academic research to measure operational efficiency and productivity growth in the banking sector across various countries, including India. Besides, another extant of literature is highly focused on the determinants of Non- performing Assets (NPAs). It may also be noted that, efficiency measurement of banking institutions helps to benchmark the relative efficiency of an individual bank against the 'best practice' bank(s). Consequently, measuring the technical efficiency score (TES) of recovery of stressed assets (both *NPA* and *slippage*[1]) for individual banks is particularly critical in the aftermath of a cyclical downturn when banks are simultaneously saddled with both huge NPAs and considerably low recovery. There are many policy measures to improve the recovery channels of the stressed assets of the banks. These include Securitization and Reconstruction of Financial Assets and Enforcement of Security Interest (SARFESI) Act, 2002; Debt Recovery Tribunals; Lok Adalats and the latest is the enactment of the Insolvency and Bankruptcy Code, 2016. These all are welcome development towards improving the credit environment and enhancing the credit-debtor relationship, however, the impact is not long lasting (Misra et al., 2016). In this backdrop, our study attempts to understand the enabling factors which results in greater efficiency in recovery of defaulted loans. Especially, in the background of large extent of mergers and acquisition of public sector banks, this study throws light in terms of policy deliberation as well.

Over time, with nationalization in 1969 and 1980 and later financial reforms since 1991, the banking system continues to be the strongest financial pillar of Indian economy. Especially, an effective banking system has significant positive externalities and also has proved to be more instrumental in laying the inclusive growth path for the Indian economy. In fact, the operational inefficiency in managing the credit portfolio or credit risk of the bank might be proven to be detrimental for India's long term economic growth. The low credit risk of a bank desires for more attention towards two important factors: overall *NPA* situation to improve and *slippage* to reduce. As for the treatment of the

[1] *Slippage* is fresh accretion to NPAs during a period.

stressed assets of the Indian banks in the literature is concerned, Jayaraman and Srinivasan (2016) consider *GNPA* as an undesirable output, along with two other desirable outputs and four inputs, to study *profit efficiency* of the Indian banks. On the other hand, Das et al. (2005) and Zaman and Bhandari (2020) consider *performing loans* (i.e., amount of *loans* after due adjustment for the volume of *non-performing loans*) to study *cost efficiency*[2] of the Indian banking sector. Although the study by Misra et al. (2016) and Bajaj et al. (2021) cater around recovery of bad loans of the Indian banks, focus of their study was to investigate into the determining factors of such reduction of stressed assets. Also, both these studies have considered *reduction in stressed assets*,[3] whereas the focus of our study is to examine bank's operational efficiency in *cash recovery of stressed assets*. To the best of our knowledge, literature on estimating operational efficiencies of Indian banking and their determinants with due consideration for *stressed assets*, in general and that concerning the *cash recovery* of such assets, in particular is indeed scanty.

Given this backdrop, we examine TES of 21 public sector and 17 private sector banks during 2009-10 through 2017-18.[4] We consider six alternative models to address six interlinked scenarios:

Scenario1: To increase in *advances*, while maintaining the current *GNPA* level;

Scenario2: To increase in *recovery*, while maintaining the current *GNPA* level;

Scenario3: To increase in *recovery*, while maintaining the current *slippage* level;

Scenario4: To increase in *advances*, while maintaining the *net slippage*, defined as (*slippage* – *recovery*) at the current level;

Scenario5: To simultaneously (proportional) increase in both *advances* and *recovery*, while maintaining the current *slippage* level; and

Scenario6: To simultaneously (proportional) increase in both *advances* and *recovery* with parallel reduction of *slippage* in the same proportion.

Needless to note that, each of these models has its own appeal, considering the overall burden of bad loans the Indian banks face these days, possible channels of its improvement, and their day-to-day regular business activities. In the second stage, we explain such TES in terms of bank-specific and other macroeconomic and banking-sectoral characteristics in order to throw some light on the determining factors of such performance indicator of the Indian domestic commercial banks. To the best of our knowledge, our study is the first attempt which contributes in measuring the TES for credit risk of the Indian banks considering individual bank efficiency in managing *NPA* and *recovery* simultaneously.

Our major preliminary findings suggest that the performance of private sector banks in managing *recovery* are much better compared to public sector banks, although NPA shows a rising trend for both the groups. Hence, the scope of improvement in managing credit risk for public sector banks are more as compared to private sector banks. This is corroborated in our first stage results using data envelopment analysis and

[2] To add further, Das et al. (2005) also study *profit* and *revenue efficiencies* for Indian banking sector.

[3] As per bank's annual report reduction of NPA can have three segments; reduction from upgradation, reduction from write off, reduction from cash recovery.

[4] Due to large scale merger drives of the public sector banks, we keep aside the later periods from our analyses.

that even in each of six alternative models explored. Most interestingly, we find that banks have vast scope to improve in terms of the efficiency in dealing with the *recovery* even while *GNPA* and *slippage* are kept at their existing levels.

The rest of the paper is organized as follows. In section 2, we present a comprehensive review of the studies that have examined the NPA management and recovery of the banking sector. Also, we refer a few studies which measure the performance of the Indian banking sector. In section 3, we preclude the study with descriptive statistics and Section 4 provides a brief background on the database and methodology of the study. In section 5, we summarize our findings of different models employed for measuring technical efficiency scores of Indian commercial banks. Also, our findings on second stage regression analyses have been discussed in this section, while Section 6 concludes with some policy implications. Appendix shows some further results.

2. Literature Review

Estimation of efficiency score for managing credit risk of individual bank in terms of reduction in *NPA* and increase in *recovery* is critical to improve the overall performance of the banks. It is also important to examine the significant determinants of operational efficiency of the banks. There are many studies which address the determinants of NPA or stressed assets, however, there exists merely any study which address the efficiency in dealing credit risk of the banks. Moreover, hardly there exists any study which refers to the determinants of efficiency in bank performance in controlling NPA and increasing the cash recovery of Indian commercial banks. It may be noted that, most of the studies examining recovery rate pertain to advanced economies. By focusing on account-wise data, researchers have analyzed the recovery rate and its distribution. There is hardly any study which focuses on the emerging market economies, including India.

Asarnow and Edwards (1995) examine the US market scenario by delineating the components of Loss Given Default (LGD) such as write-offs, interest drag, cash interest collected, recoveries and some other expense or income events. They tested 831 defaulted loans of Citibank during 1970-1993 and reported an average cumulative recovery rate of 65% by employing discounted cash flow method. Another study based on the US market, namely, Moody's bank loan, by Carty and Lieberman (1996) who measure the recovery rate on a sample of 58 defaulted bank loans based on secondary market prices for the period 1989 to 1996 and reported an average recovery of 71%. In Latin America, Hurt and Felsovalyi (1998) investigate into 1149 bank loan losses over the period 1970 to 1996. They report an average recovery rate of 68.2%. Interestingly, they also show that large loans exhibit lower recovery rate. More often so, when the large loans are not secured and are made to economic groups that are family owned. Likewise, Dermine and Carvalho (2006) investigate into LGD characteristics for 374 corporate bank loans to small and medium sized firms in Banco Commercial Portugues over the period 1995 to 2000 and report an average recovery rate of 71%. Also, Khieu et al. (2012) observe that in the US, secured loans have higher recovery in comparison to unsecured loans.

Cross-country study by the Standard & Poor's Risk Solution Department (Franks, Servigny, Davydenko, 2004) on loans to small and medium sized enterprises reveals that, besides collateral, recovery rates also differ across countries where banks respond to different bankruptcy regimes and codes. On the other hand, the study on loan losses related to SME loan during 2001 to 2005 in the Eastern European Markets by Kosak and

Poljsak (2010) concludes that the type of collateral and industrial sector, loan rating, size of the debt and loan maturity are important determinants of LGD. Similarly, Grunert and Weber (2009) observe positive relationship between collateral and recovery rate for commercial lending to German companies.

Frye (2005) concludes that high default period might make LGD more sensitive and losses of the creditors to increase. Grunert and Weber (2009) suggest a negative relation between obligor creditworthiness and recovery rates. Also, a distress situation of the industry itself might cause low recovery (Acharya et al., 2007). Caselli et al. (2008) assess sensitivity of LGD to systematic risk in Italian loan market and report that, households are more sensitive to unemployment rates, default to loan ratio and household consumption.

Probability of default (PD) is another important but sensitive variable in the context of credit risk of the banks. However, the major constraint in using such data is the non-availability of the account wise information in the public domain. In India, banks are extremely vigilant in maintaining the high confidentiality for their clients' data. However, there are some studies which use the PD-LGD correlation model framework and conclude that the recovery is correlated with the firm's underlying asset process via both systematic factors and idiosyncratic shocks. PD-LGD correlation introduces additional variability into instrument value and portfolio value distributions, as viewed by Moody's in 2010. Altman et al. (2004) study the defaulted bonds' data for the period 1982 to 2000, which includes the relatively high default years of 1999 and 2000, and observe a negative correlation between the rates of default and recovery. Witzany (2011) studies default and recovery data on a retail portfolio of a large Czech bank over the period 2002 to 2008 and observes that the PD and LGD correlation is positive (viz., 0.0775), although, level of significance was low. However, too short sample period may be a reason for such low level significance.

On the other hand, there exists plethora of studies in the context of measuring efficiency score of Indian banks. To selectively elaborate on some of them, Das et al. (2005) use mathematical programming-based data envelopment analysis (DEA) method and observe that the Indian banks differ much in terms of revenue and profit efficiencies during 1997 to 2003. They also conclude that the *size* of a bank and its *ownership category* are important determining factors for average profit efficiency and (to some extent) revenue efficiency. Moreover, the median efficiency scores of Indian banks, in general, and of bigger banks, in particular, have improved during the post-reform period. Das and Ghosh (2006) examine a set of variables, for example, *bank size*, *ownership*, *capital adequacy ratio*, *non-performing loans*, and *management quality* by employing three different models, viz., intermediation approach, value-added approach and operating approach. They observe that the medium-sized public sector banks perform reasonably well and are more likely to operate at higher levels of technical efficiency. Their empirical results also show that the more efficient banks, on an average, have less nonperforming loans.

Bhandari (2012) studies overall total factor productivity (TFP) improvement for 68 Indian commercial banks during 1998-99 to 2006-07. Using DEA method, this study examines all three constituent components of TFP growth, viz., technical change, technical efficiency changes, and scale (efficiency) change factor and suggests that the public sector banks, on an average, are better performers in a changing environment relative to private and foreign banks operating in India. Using a two stage method, i.e., DEA at the first stage, followed by panel data econometric regression at the second stage, Bhandari (2014) also examines 68 Indian commercial banks for the period 1998-99 through 2006-07. The results show that, technical efficiency is positively linked to size of a bank. Moreover, public sector banks are observed to perform much better than the private and foreign banks.

Profit efficiency of banks, factoring desirable and undesirable outputs, is first estimated by Jayaraman and Srinivasan (2016). They use Nerlovian profit indicator approach and decompose the profit inefficiency into technical and allocation inefficiencies. Their results using directional distance function reveal that, profit inefficiency of banks is primarily due to allocative inefficiency. In a recent study, Zaman and Bhandari (2020) examine cost efficiency of Indian banking using NPA-adjusted loans as an output. Since NPAs can be thought of as a by-products of a bank's conventional lending activities, it would have a direct impact on its performance.

Misra et al. (2016) have discussed several measures which have been initiated to create enabling legal and regulatory environment to facilitate the recovery of NPAs of banks over the years. This study describes the measures like 'know your customer' (KYC) norms, 'early warning signals', etc. and proposes curative measures (such as recovery channels) which assume important to arrest the rise in NPAs. Moreover, using panel data regression on 71 public, private and foreign banks' data during 2000-01 to 2014-15, they conclude that, other than conducive macroeconomic environment, the collateral type and credit appraisal system of banks might be playing more instrumental role in determining *reduction* of the stressed assets of Indian commercial banks. This study suggests that the alternative channels of financial system also need to be strengthen. On the other hand, Bajaj et al. (2021) conclude that between bank specific and macroeconomic factors, the latter is more persuasive in the *reduction* of the stressed assets of public and private sector banks in India during 2003-04 to 2017-18. They have concluded that unemployment plays a significant role in determining banks' reduction of stressed assets.

So, a focused critical review of the literature states that there hardly exists any study which estimates the banks' operational efficiency considering *NPA* and *slippage* (which we treat as undesirable outputs) and *recovery* of stressed assets (which we treat as a desirable output) simultaneously. Although there is spectrum of literatures which examine the determinants of NPA, but there hardly exists any study that investigates into the causes behind the existing state of the art of operational efficiency of recovery rate of Indian banks. We explore towards that direction to bridge this existing gap, especially at a time when the mergers and acquisition of public sector banks have become a major concern subsequent to large NPAs and low recovery of Indian commercial banks. Next section throws light on our preliminary analyses where we hypothesize if there exists any visible difference in the trend of the performance of public and private sector banks in managing their credit risk.

3. Analytical Background

This section preludes our analysis, highlighting major differences in the trend of concerned important factors for public and private sector banks. Figure 1 shows that, although both the *GNPA* and *slippage* (or additional *NPA* of the respective year) follow increasing trend for both public and private sector banks, there is a sharp increase in the NPA accumulation for public sector banks since 2015, whereas the scenario for the private sector banks is not so gloomy. On the contrary, *recovery* rate of the public sector banks sees a sharp declining trend over this period, however, although the private sector banks also experience (to some extent) a similar trend, its *recovery* declining tendency is not so sharp and even slightly improves in the last year. Hence, we conjecture that the performance of the private sector banks to manage both the *NPA* and *recovery* is better than the public sector banks. This differential trend is also visible from the Table 1, which describes the trend in *GNPA* and *recovery* rates for the three largest banks under each of these two ownership categories. More GNPA trend is clearly visible in these three largest public sector banks *(SBI, PNB and BOB)* with low recovery rate compared to three largest private sector banks (*HDFC, ICICI and Axis*). Although GNPA is more in ICICI bank, it experiences a much higher parallel recovery.

Table 2 shows descriptive statistics of important business and financial health indicators of the Indian public and private sector banks during our study period. It may be noted that, during 2009-10 to 2017-18, the average *cash recovery* as a percentage of GNPA is only around 9 percent for the public sector banks, while that is around 17 percent for private sector banks. This might be an early warning signal for Indian banking sector to evaluate their credit risk portfolio. Moreover, we find public sector banks are larger contributors of average gross *advances* and average *GNPA* compared to their private sector counterparts. The average *slippage* for public sector banks is almost seven times higher compared to its own *recovery*, whereas the *former* is a little larger than four times of the *latter* for the private sector banks. This might be indicative of the fact that, given the same macroeconomic environment, public sector banks are stumbling to manage their own credit risk. Moreover, the kurtosis values of *slippage* show that there exists a much fatter tail for the public sector banks, although it is almost the same for both the groups for *GNPA*. This might be alarming for both public and private sector banks in terms of their exposure to high value unexpected loss or credit risk. Interestingly, the kurtosis value of *recovery* for private sector banks are much higher than that of the public sector banks, which might protect the interests of private sector banks in recovering large amount of stressed assets.

Tables 3 to 5 show the pairwise correlation structure for (a) major bank specific variables; and (b) macroeconomic variables to have an impression of their likely implications on the performance of the Indian domestic commercial banks.

Table 3 shows that, each of the *slippage*, *GNPA*, *recovery* and *gross advances* has significant positive pairwise correlation with others within the same ownership group. However, negative and significant relationship is observed between public sector banks' *gross advances* with the private sector banks' *slippage* and *GNPA*.

Table 4 shows that the pairwise correlations among bank specific variables are mostly significant, which is negative for *secured loan* (SecLoan) and *maturity*, indicating short term loans are more secured than the long-term loan. Moreover, the positive and significant correlation between *priority sector lending* (PriSecL) norm and SecLoan is indicative of the fact that a bank's portfolio of priority sector lending is mostly secured. However, negative and significant correlation indicates that PriSecL may not grow even if the *credit to deposit* (CD) ratio grows. On the other hand, a negative and significant correlation coefficient value indicates that increase in banks *provisioning* (provision) might reduce the bank's profitability. Moreover, positive and significant coefficient implies that, with the increase in the *total liability* (TL) provision also increases. Also, with the increase in *loan portfolio* (SecLoan and PriSecL), *provisioning* increases is evidential from the positive and significant correlation coefficient.

In the Table 5, Herfindahl-Hirschman index (HHI) is calculated on the basis of *gross advances* of the banks to have a picture of the extent of competitive scenario prevails within the Indian banking sector. Positive and significant correlation indicates that the increase in GDP growth (due to increase in overall economic activities that perhaps also increases the demand for loan) induces market capturing competition amongst the banks to lend, however, smaller banks fail to effectively compete with the larger ones in that direction. As a result, banking industry becomes more concentrated, at least in terms of extending advances. On the other hand, the negative and significant coefficient indicates that the lending rate (LR) within the economy reduces due to this increased market capturing competitive pressure.

4. Methodology and Database

We use mathematical programming-based data envelopment analysis (DEA) methodology for our analyses in the first stage to obtain TES of banks under study. More specifically, we conceptualize the underlying production correspondence for a year by considering all the banks of that year alone and TES of a bank in a year is obtained by comparing it vis-à-vis that year's estimated production correspondence. Hence, we would have one TES for each bank in each year. This score is used as a yardstick of performance of a bank. We then regress these TESs in the second stage in terms of certain bank-specific and other macroeconomic factors, which are assumed to influence the performance of a bank. As for the second stage regression methodology is concerned, we acknowledge that the separate cross-sectional regression for each year is preferred. It is advisable to follow so by virtue of the fact that the estimated technical efficiency scores (obtained at the first stage through DEA model) are not absolutely comparable over time, since these scores are relative measures, relative to the year-specific benchmark technology, where the benchmark itself is likely to change from one year to another. However, panel data regression is also used in the empirical literature in this regard (e.g., see Bhandari, 2014; Cheng et al., 2015; Samut and Cafri, 2016; and others). Moreover, although Tobit regression is often proposed at this stage for the fact that the value of the dependent variable (i.e., the efficiency scores obtained at the first stage) is bounded between zero and unity by definition, it is however not obvious that Tobit is the only, or optimal, approach to modelling DEA scores. In fact, it is shown in the literature that the OLS may actually in many cases replace Tobit as a sufficient second stage DEA model (e.g., see Hoff, 2007; Banker and Natarajan, 2008; and others). Hence, we follow (a) OLS for our second stage regression analyses; and (b) both year-specific cross-sectional as well as longitudinal regression using the entire panel of nine years' data.[5]

DEA method, introduced by Charnes, Cooper and Rhodes (1978) (for the case when underlying production technology follow constant returns to scale (CRS) property) and further generalized by Banker, Charnes and Cooper (1984) (to accommodate the case when underlying production technology follow more general variable returns to scale (VRS) property) requires no parametric specification of the production frontier. On the

[5] Another strand of literature is to use bootstrap-based analyses to (a) obtain biased-corrected TES at the first stage; and (b) truncated regression for drawing consistence inference at the second stage, *a la* Simar and Wilson (2007). However, the question of bias at the conventional DEA estimation arises in the absence of true data generating process while using sample data. Nonetheless, we restrain ourselves from doing so, since we use almost the entire set of the banks under the two chosen groups (for which consistent data is available) and only a handful of them is left out. Hence, extent of bias, if any, is expected to be negligible.

basis of a sample of observed input-output data on a given set of producing units, it makes a few assumptions about production technology in order to obtain a production possibility set relevant for the observed units.[6] Irrespective of the ownership, since each bank has some amount of non-performing assets (NPAs), we presume that such bad loan is a byproduct of Indian banking business, which can't be avoided. Hence, bad loan is treated as an undesirable output.

Let us consider a production process that uses a vector of N inputs $x = (x_1, x_2, ..., x_n, ..., x_N) \in \Re_+^N$ to produce a vector of M desirable outputs $y = (y_1, y_2, ..., y_m, ..., y_M) \in \Re_+^M$ and a vector of J undesirable outputs $b = (b_1, b_2, ..., b_j, ..., b_J) \in \Re_+^J$. The relationship between input and output is represented by the following output set:

$$P(x) = \{(y, b) : x \text{ can produce } (y, b)\}, x \in \Re_+^N . \quad \text{(a)}$$

The output set is assumed to satisfy the following properties:

Null-Jointness: It implies that production of strictly positive amount of desirable output must be accompanied by strictly positive amount of undesirable one. Formally, if

$$(y, b) \in P(x); b = 0 \Rightarrow y = 0 \quad \text{(b)}$$

Weak Disposability: It implies that desirable and undesirable outputs are jointly weakly disposable. Formally, if

$$(y, b) \in P(x) \text{ and } 0 \le \theta \le 1 \Rightarrow \theta(y, b) \in P(x) \quad \text{(c)}$$

In other words, reduction in undesirable output is not possible without reducing the desirable one. So, free disposability of undesirable output may not be possible.

Strong Disposability: Desirable output is strongly disposable, i.e., if

$$(y, b) \in P(x) \text{ and } y^0 \le y, \text{then } (y^0, b) \in P(x) \quad \text{(d)}$$

Literally, although undesirable output cannot be reduced without reducing desirable output, the reverse is possible, i.e., the desirable output can be reduced without reducing the undesirable one. So, disposal of desirable and undesirable outputs are asymmetrically treated in our analyses. We measure TE of a bank in output-oriented way[7] (i.e., expansion of desirable output, while keeping the undesirable output and usage of the inputs at their current levels). We assume VRS property for our underlying production technology. For that, we need to solve the following DEA linear programming problem (LPP), once for each bank. For instance, while evaluating k^{th} bank, the problem is:

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[6] The basic *assumptions* about the production technology that are made in this method are as follows: (a) All observed input-output bundles are feasible; (b) the production possibility set is *convex* implying that given a set of N feasible input-output bundles, *any* weighted average of these N input bundles can produce the same weighted average of the corresponding N output bundles and (c) any input or output is *freely disposable.* However, *free disposability* assumption needs to be adjusted if bad output(s) or some input(s) use of which beyond a threshold level may have detrimental effects on production process. Nonetheless, these assumptions enable one to construct a production possibility frontier on the basis of the observed inputs-output bundles of a given set of banks, following the DEA method.

[7] One may also define an *input-oriented* technical efficiency. This is not done in the present study. See Coelli et al (1998) and Ray (2004) for further details.

Maximize β

Subject to

$$\sum_{i=1}^{P}\lambda_i y_i^m \geq \beta\, y_k^m \qquad \forall\ m=1,2,\ldots,M\ ; \qquad \text{(i)}$$

$$\sum_{i=1}^{P}\lambda_i b_i^j = b_k^j \qquad \forall\ j=1,2,\ldots,J\ ; \qquad \text{(ii)} \qquad (1)$$

$$\sum_{i=1}^{P}\lambda_i x_i^n \leq x_k^n \qquad \forall\ n=1,2,\ldots,N\ ; \qquad \text{(iii)}$$

$$\sum_{i=1}^{P}\lambda_i = 1 \qquad \forall\, i=1,2,\ldots,P \qquad \text{(iv)}$$

$$\lambda_i \geq 0 \qquad \forall\, i=1,2,\ldots,P \qquad \text{(v)}$$

where P is the number of banks in a year and TE of the k^{th} bank is given by $\left(1/\beta_k^*\right)$ where β_k^* is the optimal solution of the problem (1) above. Alternatively, we have also used directional (technology) distance function to represent the technology. On the basis of Luenberger's (1992) benefit function (see Chambers at al., 1996; Färe and Grosskopf, 2000; Färe et al., 2005), directional distance function, an extension of Shephard's input and output distance function, provides a platform for representing the joint production of *desirable* and *undesirables*. In the presence of undesirable output, if firm's objective is to simultaneously expand the desirable output and reduce the undesirable one by same proportion without increasing its input use, the directional technology distance function becomes

$$\overrightarrow{D_T}\left(x,y,b;0,y,-b\right)=\sup\left[\beta:\left[(1+\beta)y,(1-\beta)b\right]\in P(x)\right] \qquad \text{(e)}$$

The directional distance function is obtained by solving the maximization problem as follows:

Maximize β

Subject to

$$\left\{\sum_{i=1}^{P}\lambda_i y_i^m - \beta\, y_k^m\right\} \geq y_k^m \qquad \forall\ m=1,2,\ldots,M\ ; \qquad \text{(i)}$$

$$\left\{\sum_{i=1}^{P}\lambda_i b_i^j + \beta\, b_k^j\right\} = b_k^j \qquad \forall\ j=1,2,\ldots,J\ ; \qquad \text{(ii)} \qquad (2)$$

$$\sum_{i=1}^{P}\lambda_i x_i^n \leq x_k^n \qquad \forall\ n=1,2,\ldots,N\ ; \qquad \text{(iii)}$$

$$\sum_{i=1}^{P}\lambda_i = 1 \qquad \forall\, i=1,2,\ldots,P \qquad \text{(iv)}$$

$$\lambda_i \geq 0 \qquad \forall\, i=1,2,\ldots,P \qquad \text{(v)}$$

and TE of the k^{th} bank is given by $\{1/(1+\beta_k^{**})\}$ where β_k^{**} is the optimal solution of the problem (2) above. Strong disposability of desirable output and weak disposability of undesirable output are imposed through the constraints (i) and (ii) respectively in each of the problems (1) and (2). We have followed six alternative models as summarized in the Table 6 below.

In the second stage of our analyses, we employ both cross section and static panel regression. We use estimated TES of all the six models as the dependent variables and estimated cross section regression with bank specific variables and ownership dummy. Similarly, we estimate panel regression under four different scenarios: (i) considering the bank specific variables alone; (ii) considering the bank specific variables, along with banking industry concentration index HHI and macroeconomic variable; (iii) considering the bank specific variables and interest rate channel; and (iv) considering the bank specific variables and ownership dummy. Table 7 represents the description of the variables used in our second stage regression analyses.

Except the recovery data and that of the macroeconomic variables like GDP growth and LR, we use Reserve Bank of India (RBI) database of *Statistical Tables Relating to Banks in India (STRBI).* We have extracted recovery data from the *Annual Report* of respective banks, which provides the data on cash recovery. In RBI database, we have data for opening GNPA of a particular year, addition during the year, reduction during the year, write off during the year, and closing GNPA of that year *(Refer, STRBI, Table 6: Movement of Non-Performing Assets (NPAs) of Scheduled Commercial Banks).* In annual report of bank, we get the data of reduction as the sum of upgradation, cash recovery and write off. We have considered cash recovery during the year. This data is available consistently in the banks' annual reports from 2009-10 onward. Information on GDP growth and LR are extracted from the world development indicator of the World Bank.

We first start with cross section analysis to capture the impact of the significant determinants of the TES of the banks for each of the sample years. The equation for cross sectional regression is represented by the equation (1) below.

$$TES_{ji} = \beta_1(Maturity_i) + \beta_2(SecLoan_i) + \beta_3(PriSecL_i) + \beta_4(CD_i) + \beta_5(Provision_i) + \beta_6(TL_i) + \beta_7 D + \alpha + u_i \quad \ldots\ldots (1)$$

In equation (1) we have used an ownership dummy defined as D = 0 for all public sector banks, and D = 1 for all private sector banks to examine the distinctive implication of ownership on TES, if any and u_i is the idiosyncratic error term.

For panel analysis, we have considered two important channels, for example, *macroeconomic factors* and *concentration index* for lending, in addition to *bank specific channels* and *ownership patterns of banks* which we have also used in the cross-section analysis. Under static panel regression analyses we use both fixed effects and random effects model. The fixed effects model controls for all time-invariant differences between the individuals. It enables one to study the causes of changes within an entity and a time-invariant characteristic cannot cause such a change, because it is *fixed* for each individual. Our analysis on *bank specific factors* is represented in *Panel Estimation-1*. Here, the specification of the equation with α_i, the *fixed* unknown intercept for each entity, is

$$TES_{jit} = \beta_1(Maturity_{it}) + \beta_2(SecLoan_{it}) + \beta_3(PriSecL_{it}) + \beta_4(CD_{it}) + \beta_5(Provision_{it}) + \beta_6(TL_{it}) + \alpha_i + \varepsilon_{it} \quad \ldots\ldots (2)$$

The rationale behind random effects model is that, unlike the fixed effects model, the variation across entities is assumed to be random and uncorrelated with the predictor or the independent variables included in the model. In our analysis of *Panel Estimation-I,* with *between entity error* u_{it} and *within entity error* ε_{it}, the specification of random effects equation is

$$TES_{jit} = \beta_1(Maturity_{it}) + \beta_2(SecLoan_{it}) + \beta_3(PriSecL_{it}) + \beta_4(CD_{it}) + \beta_5(Provision_{it}) + \beta_6(TL_{it}) + \alpha + u_{it} + \varepsilon_{it} \quad \text{……………………………………………} \quad (3)$$

Similarly, the *Panel Estimation -II* examines equation (4) and equation (5) with *bank specific factors, macroeconomic factor* and *concentration index for lending*; while *Panel Estimation -III* examines equation (6) and equation (7) capturing *bank specific factors* and *interest rate channel*. Lastly, *Panel Estimation – IV* examines equation (8) which deals with the *bank specific factors* and the *ownership pattern of the banks*. All these equations are represented below

$$TES_{jit} = \beta_1(Maturity_{it}) + \beta_2(SecLoan_{it}) + \beta_3(PriSecL_{it}) + \beta_4(CD_{it}) + \beta_5(Provision_{it}) + \beta_6(HHI_i) + \beta_7(GDP_i) + \alpha_i + \varepsilon_{it} \quad \text{……………………………}(4)$$

$$TES_{jit} = \beta_1(Maturity_{it}) + \beta_2(SecLoan_{it}) + \beta_3(PriSecL_{it}) + \beta_4(CD_{it}) + \beta_5(Provision_{it}) + \beta_6(HHI_i) + \beta_7(GDP_i) + \alpha + u_{it} + \varepsilon_{it} \quad \text{…………………………} (5)$$

$$TES_{jit} = \beta_1(Maturity_{it}) + \beta_2(SecLoan_{it}) + \beta_3(PriSecL_{it}) + \beta_4(CD_{it}) + \beta_5(Provision_{it}) + +\beta_6(LR_i) + \alpha_i + \varepsilon_{it} \quad \text{……………………………} (6)$$

$$TES_{jit} = \beta_1(Maturity_{it}) + \beta_2(SecLoan_{it}) + \beta_3(PriSecL_{it}) + \beta_4(CD_{it}) + \beta_5(Provision_{it}) + +\beta_6(LR_i) + \alpha + u_{it} + \varepsilon_{it} \quad \text{……………………………} (7)$$

$$TES_{jit} = \beta_1(Maturity_{it}) + \beta_2(SecLoan_{it}) + \beta_3(PriSecL_{it}) + \beta_4(Provision_{it}) + \beta_5(D) + \alpha + u_{it} + \varepsilon_{it} \quad \text{…………………} (8)$$

In all the above equations, *j* stands for efficiency scores derived from six different DEA models summarized in the Tables 6 and 8 and hence *j* = 1, 2, …, 6. As usual, *i* stands for cross sectional unit and varies from 1 to 38 (incorporating 21 public sector banks and 17 private sector banks) and *t* stands for time series unit and varies from 2009-10 to 2017-18,[8] indexed respectively by 1 to 9 for all the equations.

5. Empirical Findings

5.1 First Stage DEA Analyses

We summarize the findings of our (first stage) DEA analyses in this section. Table 8 reports the pairwise correlation coefficients of estimated TES for each of the alternative models we have considered: TE 1 through TE 6. It shows that our results are robust throughout, since TES across all the pairs are positive and significant. Moreover, very high

[8] For extensive mergers and acquisitions of public sector banks in India in the year 2018, 2019 and 2020, we exclude these years from our analyses. This helps us to keep the standard of the data without losing much of information.

value of the correlation coefficient for the pairs of TE 1[9] and TE 4 (i.e., 80%), Model 2 and TE 3 (i.e., 85%), and TE 5 and TE 6 (i.e., 96%) are quite understandable from the similarity of the output vector for each of these pairs. We also plot average performance scenario of the group of publicly and privately owned domestic banks in the Figure 2 and the counterpart statistics are reported in the Table A3. It shows that, private sector banks as a group outperform those under public ownership. Moreover, although the two groups face similar tendencies of performances over time, that of the public sector group experiences a nosedive in the last two years in TE 1, TE 4, TE 5 and TE 6. However, performance of these two group of banks show almost similar trend for the TE 2 and TE 3. In the banking performance literature in India, banks' efforts towards *recovery* of loans or reducing *slippage* or a combination of both is largely ignored. We explore into that direction, both considering *recovery* alone as a desirable output as well as simultaneously considering *recovery* and *advances* as two desirable outputs (in TE 5 and TE 6), in order not to lose bank's traditional business activity into the backdrop, i.e., lending to earn interest income. And in all of these alternative cases, privately owned banks' overall performance is quite visibly better as compared to the publicly owned banks. To be specific, average TES of the public (private) sector banks as a group for our entire sample period are 92.2% (96.2%), 58.9% (66.5%), 59.9% (68.9%), 92.1% (96.3%), 95.2% (97.8%), and 95.6% (98.1%) respectively for the models TE 1 through 6. In other words, according to the TE 1, an average public (private) sector bank has an opportunity to expand its *advances* by 8.5% (4.0%) further while keeping its *GNPA* and three inputs (viz. *total fixed assets*; *deposits*; and *operating expenses*) at their current levels. Similarly for TE 2, an average public (private) sector bank has an opportunity to expand its *recovery* by 69.7% (50.4%) further while keeping its *GNPA* and three inputs at their current levels. For TE 3, an average public (private) sector bank has an opportunity to expand its *recovery* by 67.0% (45.1%) further while keeping its *slippage* and three inputs at their current levels. As per TE 4, an average public (private) sector bank has an opportunity to expand its *advances* by 8.6% (3.9%) further while keeping its *net slippage* and three inputs at their current levels. Likewise, according to TE 5, an average public (private) sector bank has a scope to simultaneously expand its *advances* and *recovery* by 5.0% (2.3%) further while keeping its *slippage* and three inputs at their current levels. Finally for TE 6, an average public (private) sector bank has an opportunity to simultaneously expand its *advances* and *recovery* and reduce *slippage* by 4.7% (2.0%) further without increasing its usage of three inputs. Further details on individual bank-wise average TES over our entire sample period is reported in the Table A1 of the Appendix. Table A2 is simply Table A1's counterpart, interpreting TES in terms of further possibility of (proportional) expansion of desirable output(s) (in models TE 1 to 5) and that along with contraction of undesirable output (in TE 6).

Figure 2 presents a comparative framework of technical efficiency of banks on the basis of ownership pattern. Overall, we can conclude that private sector banks have been outperforming the public sector banks in managing credit risk with a widening gap over time. Especially, the sharp drifts in TE 5 and TE 6 reveal that public sector banks have substantial scope to improve the technical efficiency of banks in increasing *advances* and *recovery* of stressed assets while simultaneously reducing the accumulation of *bad loans*. Moreover, TE 4 reveals that given the current level of *net slippage* the technical efficiency

[9] Six alternative models used in our first stage DEA analyses are also referred as TE 1 through TE 6.

of private sector banks in providing *advances* is notably higher compared to public sector banks.

5.2 Second Stage Econometric Analysis

Our estimated cross sectional regression results (reported in the Table 9) throw thorough light on the important factors determining technical efficiencies of Indian commercial banks across 2009-10 to 2017-18. Overall, we observe banks' technical efficiency increases with the increase in credit-deposit ratio. Moreover, banks are more efficient in handling short-term loan better that the long-term loan. As expected, with an increase in secured loan to total loan banks' operational efficiency in dealing with the credit risk increases. It is also observed that the priority sector lending norm clearly has negative implication on banks' operational efficiency, however, which can be justified with its overall contribution in social development. Hence, we conclude that banks are able to handle the credit risk more efficiently for short term loan and there is further scope of improvement for the long-term loan management.

Very interestingly, we find that except the models TE 2 and TE 3, in 2018 public sector bank is more efficient in handling the advances and recovery compared to private sector banks. This corroborates the kink in 2017 which is observed for all the six alternative models (in Figure 2). Also, a pooled regression result with time dummy reveals that banks' performance in managing bad loans are exceptionally bad for both 2011 and 2017 (Table 10).

Our estimated panel regression analyses of *panel estimation I, panel estimation II and II.A, panel estimation III*, and *panel estimation IV* as reported in the Tables 11, 12, 13, 14, and 15 respectively, show similar kind of results. Importantly, for all our estimated models, we find negative and significant relationship with banks TES and their priority sector lending exposure. It might be an important finding as priority sector loan gets special emphasis due to its social benefit and overall contribution to the economic growth. Interestingly, the negative and significant coefficient values for maturity in models relating to TE 4, TE 5 and TE 6 reveal that the banks manage credit risk more efficiently for short term loan portfolios. As the tenure of loan increases, banks' TES reduces. Another important and interesting finding is the positive and significant coefficient values for secured loan, especially for TE 1, where the desired output is only *advances*. So, we can conclude that a bank's technical efficiency increases with the increase as the ratio of its *secured loan* to *total loan* increases. On the contrary, for TE 2 and TE 3, where the desirable output is only the *recovery*, we find bank's technical efficiency decreases with the increase in secured loan. So, it is obvious that the collateral pledged for providing loan might not be liquid enough so that it can be used for the repayment of loan in case of default. This suggests that the banks must look into their policy related to the type of collateral pledged against the advances. Moreover, it is revealed that the lending practices have further chances to improve the *credit* to *deposit* (CD) ratio, which in turn would improve the banks' efficiency in managing their credit risk.

In addition, we also observe that the coefficient of the HHI is negative and significant for the models presented in Table 12 and Table 13. (Table 13 exhibits the results without GDP, presence of which is the cause of insignificant estimated coefficients of HHI due to high positive correlation between the two shown in the Table 5). Given that HHI is a representation of market concentration, we can conclude that banks' operational efficiency to extend *advances* (good loan) and recovery fall with the increase in market concentration (i.e., reduction of market competition). Moreover, Table 12 also reveals that banks' technical efficiency in recovery of stressed assets increases with GDP (TE 2 and TE 3). At the same time economic boom can also lead to more advances, better recovery with a simultaneous fall in accumulation of bad loans. This conclusion is significant to understand the cyclicality in credit risk of Indian commercial banks happens with the macroeconomic boom and bust. It implies that besides banks' own performance parameters, macroeconomic fundamentals also play noteworthy role in determining banks' operational efficiency.

Table 14 presents the impact of interest rate channel in determining TES of banks in managing their credit risk. To avoid the problem of multicollinearity (as LR has high and significant negative correlation with HHI as shown in the Table 5), the effect of LR has been tested separately (i.e., in absence of the HHI and GDP). We observe it to have negative and significant coefficients for each of the models. It implies that the overall operational efficiency of the banks to manage their credit risk portfolio improves with reduction in the lending rate. This is due to the fact that a decrease in the cost of fund would have some favorable effect on the demand for loan. At the same time, it is likely that the recovery of stressed assets improves with a decrease in the cost of funds. Table 15 reveals that, private sector banks are overall better in handling both advances and recovery compared to the public sector banks. This corroborates with our preliminary results and the findings from cross section regressions.

6. Conclusion

In the backdrop of high GNPA and notably low recovery of the stressed assets, our study contributes in the literature by estimating Indian banks' operational efficiency during 2009-10 to 2017-18 considering *advances* and *recovery* of stressed assets (as desirable outputs) and *NPA* and *slippage* (as undesirable byproducts) simultaneously. To the best of our knowledge, there exists no such study that estimates technical efficiency score (TES) of banks in *cash recovery of stressed assets*. We employ DEA method to estimate six alternatives but interlinked models in managing credit risk of Indian commercial banks. In the next step, using the estimated TES as yardstick of performance of a bank, we examine the determinants of such performance of banks by considering bank-specific factors, banking industry competition scenario, economic growth and interest rate channel.

We observe that GNPA of both the Indian public and private sector banks increase over time, however, the rate of increment is much faster for the public sector banks. It may be noted that, on an average, public sector banks register only 9 percent recovery of GNPA, on the contrary it is around 17 percent for private sector banks during our study period. Also, the recovery of stressed assets is sharply declining for public sector banks since 2015, while such declining trend for the private sector banks is not so gloomy. In fact, it has slightly improved in the last year. TES performances reveal a widening gap between public and private sector banks where *advances* and/or *recovery* of stressed assets are considered as the desirable output(s). Alternatively, the trend is the same for both the ownership groups, with a better operational efficiency for the other cases where *recovery* is considered as the only desirable output. It is interesting to note that, an average public (private) sector bank has an opportunity to further expand its *recovery* by 69.7% (50.4%) while keeping its *GNPA* and three inputs (viz., *total fixed assets*, *deposit* and *operating expenses*) at their current levels. Moreover, an average public (private) sector bank has an opportunity to simultaneously further expand its *advances* and *recovery* and reduce *slippage* by 4.7% (2.0%) without increasing its usage of three inputs.

Our second stage econometric estimations conclude in the similar line for all the explored *bank specific variables*. The negative and significant relationship between *technical efficiency* of banks and *priority sector lending* has to be perceived from the social benefit or *positive economic externalities* attached to *priority sector lending* norms. Particularly, *priority sector lending* gets more emphasis from the regulator to achieve more inclusive growth path for the economy. Second, banks are found more efficient in credit risk management for *shorter-term loan portfolios*. Third, almost all analytical models conclude that, efficiency of a bank providing *advances* increases with an increase in the share of *secured loan* to *total loan*. On the contrary, there exists significant negative relationship between the *recovery of stressed assets* and *secured loan to total loan*. This suggests a need for policy attention on the types of collateral pledged against loans. One possible solution to this regard may be to move towards more of financial assets *(preferably with fixed return)* pledged as collateral against loan which can be easily convertible to liquidity in case of probable default. Financial assets, which earn fixed return, might enhance the feasibility of cash recovery. Especially, for large value loans that might lead to extreme value losses, if defaulted, banks have to be more cautious about the collateral as the liquidity of such pledged assets can improve the recovery of the stressed assets to a great extent. Same might be a better alternative and viable solution for the loans with longer maturity. Our findings also suggest that the banks' operational efficiency to extend *advances* and *recovery of stressed assets* fall with the increase in market concentration of lending. So, banks have to be more vigilant in handling high value accounts for managing their credit risk better. Moreover, the efficiency in recovery of bad loans is observed to be low during economic downturn. This is an obvious outcome due to the existence of procyclicality in the financial markets which is highly linked to the economic fundamental of a country.

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Table 1: Comparison in GNPA rate and Recovery rate among Three Largest Public and Private Sector Banks during 2009-10 to 2017-18

	Bank of Baroda (BOB)		***Punjab National Bank (PNB)***		***State Bank of India (SBI)***	
Year	*GNPA Rate*	*Recovery Rate*	*GNPA Rate*	*Recovery Rate*	*GNPA Rate*	*Recovery Rate*
2010	2%	16%	2%	30%	3%	11%
2011	2%	14%	2%	27%	3%	15%
2012	2%	13%	3%	19%	4%	10%
2013	2%	8%	4%	14%	4%	9%
2014	3%	11%	5%	14%	4%	13%
2015	4%	9%	7%	11%	3%	16%
2016	10%	4%	13%	8%	5%	4%
2017	10%	10%	13%	19%	6%	1%
2018	12%	8%	18%	5%	11%	2%
	HDFC Bank		***ICICI Bank***		***Axis Bank***	
Year	*GNPA Rate*	*Recovery Rate*	*GNPA Rate*	*Recovery Rate*	*GNPA Rate*	*Recovery Rate*
2010	1%	24%	7%	26%	1%	11%
2011	1%	9%	6%	14%	1%	16%
2012	1%	7%	5%	17%	1%	12%
2013	1%	31%	3%	12%	1%	11%
2014	1%	35%	3%	10%	1%	17%
2015	1%	41%	4%	8%	1%	9%
2016	1%	33%	6%	6%	2%	28%
2017	1%	29%	9%	11%	6%	9%
2018	1%	33%	10%	10%	8%	11%

Source: Authors' Own Calculation using RBI Database and Bank's Annual Report.

Table 2: Descriptive Statistics for Public and Private Sector Banks during the Sample Period 2009-10 to 2017-18

Public Sector Banks				
	Slippage	*GNPA*	*Gross Advances*	*Cash Recovery*
Average (Rupees Crore)	9062.5	15431.4	225348.3	1332.4
Standard Deviation (Rupees Crore)	14778.0	23846.7	317674.8	1530.6
Coefficient of Variation	163%	155%	141%	115%
Skewness	6.47	4.6	4.16	3.02
Kurtosis	59.77	32.5	18.48	12.35
Private Sector Banks				
Average (Rupees Crore)	1972.8	2477.5	79131.6	421.9
Standard Deviation (Rupees Crore)	4929.3	6626.0	124087.6	793.3
Coefficient of Variation	250%	267%	157%	188%
Skewness	4.90	5.33	2.55	3.70
Kurtosis	26.05	32.05	6.32	15.68

Source: Authors' Own Calculation using RBI Database and Banks' Annual Report.

Table 3: Correlation of Credit Variables of Public and Private Sector Banks Comparison (2009-10 to 2017-18)

	Private Slippage (Pr SL)	*Private GNPA (Pr G)*	*Private Gross Advances (Pr GA)*	*Private Recovery (Pr R)*	*Public Slippage (Pu SL)*	*Public GNPA (Pu G)*	*Public Gross Advances (Pu GA)*	*Public Recovery (Pu R)*
Pr SL	1							
Pr G	0.94***	1						
Pr GA	0.77***	0.72***	1					
Pr R	0.89***	0.85***	0.79***	1				
Pu SL	-0.002	-0.04	0.03	0.04	1			
Pu G	0.04	-0.001	0.06	0.08	0.96***	1		
Pu GA	-0.13*	-0.15**	-0.1053	-0.1219	0.76***	0.79***	1	1
Pu R	-0.0428	-0.076	0.0083	-0.0239	0.59***	0.63***	0.62***	1
*, **, and *** indicate significant at 10%, 5% and 1% level respectively.								

Source: Authors' Own Calculation using RBI Database and Bank's Annual Report

Table 4: Correlation of Bank Specific Variables[10] during 2009-10 to 2017-18

	Maturity	*SecLoan*	*PriSecL*	*CD*	*Provision*	*TL*
Maturity	1					
SecLoan	-0.43***	1				
PriSecL	-0.34***	0.50***	1			
CD	0.35***	-0.22***	-0.41***	1		
Provision	-0.06	0.16***	0.31***	-0.35***	1	
TL	0.07	-0.31***	-0.33***	-0.26***	0.22***	1
*** indicates significant at respectively 5% and 1% level.						

Source: Authors' Calculation using RBI database

Table 5: Correlation of Macroeconomic Variables and HHI during 2009-10 to 2017-18

	LR	*GDP Growth*	*HHI*
LR	1		
GDP Growth	-0.57	1	
HHI	-0.74**	0.59*	1
* and ** indicate significant at respectively 10% and 5% level.			

Source: Authors' Own Compilation using RBI Database.

Table 6: Description of the Alternative Models used in the First Stage DEA Analyses

	Model					
	TE 1	*TE 2*	*TE 3*	*TE 4*	*TE 5*	*TE 6*
Desirable Output	Advances	Recovery	Recovery	Advances	Advances; Recovery	Advances; Recovery
Undesirable Output	GNPA	GNPA	Slippage	Net Slippage	Slippage	Slippage
Input	Total Fixed Assets; Deposits; and Operating Expenses					
Note: Models TE 1 to TE 5 are based on LPP (1), while Model TE 6 is based on LPP (2); M = 1 in Models TE 1 to TE 4 and M = 2 in Models TE 5 and TE 6; J = 1 and N = 3 for all the six Models; We follow RBI definition for each of the variables; Net Slippage = Slippage – Recovery.						

Source: Authors' Compilation

[10] For description of the variables, see Section 4.

Table 7: Variable Descriptions

Variable	*Description*
Net Interest Income ratio (NII)	Ratio of interest income minus interest expenses to total assets. It is an indicator of financial stability. A decrease in spread prompt the bank to compromise on quality of borrowers.
Maturity	Ratio of share of term loans to total loans. This ratio is an indicator of longer term loan contract to fund medium to long-term projects, which reflect better relationship between banks and borrowers
Secured loan (SecLoan)	Proportion of secured loans to total loans. This ratio indicates how much collateral cushion the bank have against the loan amount and reflects the bank's approach towards risk management.
Priority Sector Loan (PriSecL)	Priority sector loan to total loan. This ratio is taken in order to account for the argument that the priority sector loans are responsible for most number of defaults in banks in India.
Credit-Deposits Ratio (CD)	It reflects credit orientation of the bank to earn more money through deposits. This variable is considered in order to capture aggressiveness of the banks' lending activity, which can lead to NPAs. The higher the ratio, the higher the loan-assets created from deposits.
Provisioning (Provision)	Provision for NPAs/Total Loans: higher provision appears to reduce the level of net NPAs (doubtful and loss assets) and reduces bank's profitability. Higher provisioning percentage hints to improve recovery efforts, to free the blocked funds in alternative uses.
Total Liabilities (TL)	Total liabilities to income ratio. Deposit having the largest share in the total liability of the bank, also a key contributor to the business of the bank. (Annex 2, Banking Stability Map and Indicator).
Slippage	Fresh Addition to NPAs during the year as a percentage of total standard advances at the beginning of the period. Strong credit appraisal and timely monitoring of loans is a foundation to avoid slippages in the account. Recent crisis suggest negative relationship between rising slippages and recovery of the banks
Recovery	The cash recovery of the bank. This does not include the amount of write off and/or upgradation
GNPA	Gross non-performing assets of the bank.
Operating Expenses	It is an indicator of banks' usual day-to-day operations and other business-related activities in carrying out due diligence in application, credit deployment, monitoring and recovery of loans.
Herfindahl-Hirschman index (HHI)	This is calculated by squaring the market share of each bank gross advances and then summing the resulting numbers. This is an indicator of market competition.
GDP Growth (GDP)	GDP growth rate is considers as a very importance macro-economic variable to judge default and recovery risk of the bank. When fundamental are good, default risk is less and recovery is more.
Lending Rate (LR)	Lending rate in India at which banks lend to its most creditworthy customer.
Abbreviation, if any, is shown in the parenthesis.	

Source: Authors' Own Compilation.

Table 8: Correlation of Technical Efficiency Scores of the Banks during 2009-10 to 2017-18

	TE 1	*TE 2*	*TE 3*	*TE 4*	*TE 5*	*TE 6*
TE1	1					
TE2	0.25***	1				
TE3	0.12**	0.85***	1			
TE4	0.80***	0.21***	0.21***	1		
TE5	0.64***	0.42***	0.43***	0.78***	1	
TE6	0.62***	0.40***	0.42***	0.74***	0.96***	1
** and *** represent significant at respectively 5% and 1% level.						

Source: Authors' Own Estimation using RBI Database and Annual Report of Individual Banks

Table 9: Year wise Cross Section Regression Analysis to Explain DEA Technical Efficiency Scores

	2018					
	TE 1	**TE 2**	**TE 3**	**TE 4**	**TE 5**	**TE 6**
Maturity	-0.003**	-0.002	-0.0007	-0.002**	-0.002**	-0.002**
SecLoan	0.005**	0.01	0.0001	0.006***	0.004*	0.004*
PriSecL	-0.006**	-0.022**	-0.016*	-0.007***	-0.006**	-0.005**
CD	0.007***	0.002	-0.001	0.008***	0.007***	0.006***
Provision	-0.004	0.015	0.04*	-0.008	-0.004	-0.003
TL	-0.022	-0.11	-0.034	-0.023	-0.04**	-0.04**
D	-0.12**	0.038	0.21	-0.11**	-0.12**	-0.11**
_cons	0.68	1.8	1.53	0.54	0.98**	0.996**
Adj R-square	51%	15%	17%	58%	49%	47%
	2017					
	TE 1	**TE 2**	**TE 3**	**TE 4**	**TE 5**	**TE 6**
Maturity	-0.003**	-0.0004	-0.0003	-0.002*	-0.002*	-0.001
SecLoan	0.002	0.008	0.011	0.003	0.002	0.002
PriSecL	-0.003	-0.015	-0.013	-0.003	-0.003	-0.003
CD	0.005**	-0.008	-0.0017	0.006	0.005**	0.004**
Provision	-0.003	0.075	0.068	-0.009	-0.011	-0.012
TL	0.0006	0.0003	0.052	0.013	0.012	0.013
D	-0.013	0.31*	0.37**	0.004	-0.001	0.005
_cons	0.71	0.68	-0.67	0.36	0.51	0.542
Adj Rsquare	34%	4%	11%	42%	42%	43%

	2016		2015		2014			
	TE 5	**TE 6**	**TE 3**	**TE 4**	**TE 1**	**TE 4**	**TE 5**	**TE 6**
Maturity	-0.0006	-0.0005	.0001**	-0.001	-0.00003	-0.0003	-0.0002	-0.0002
SecLoan	0.003**	0.003**	0.01	-0.001	-0.0009	-0.0002	-0.0009	-0.001
PriSecL	-0.004**	-0.004**	.0003**	0.001	-0.0006	-0.0009	0.0010	0.001
CD	-0.0001	-0.00016	-0.009	0.003**	0.0008	0.0011	0.0012	0.001
Provision	0.002	0.000907	0.12	0.027	0.038*	0.044*	0.044**	0.037*
TL	-0.021*	-0.02*	0.026	0.018	0.022*	0.025**	0.022**	0.02**
D	-0.005	-0.005	0.245	0.05**	0.091***	0.12***	0.09***	0.08***
_cons	1.12***	1.13***	.071*	0.67**	0.6990***	0.56**	0.62***	0.68***
Adj Rsquare	8%	8%	12%	18%	14%	29%	19%	17%

	2013		2012		2011					2010
Best Fit Model	**TE 1**	**TE 4**	**TE 1**	**TE 6**	**TE 1**	**TE 2**	**TE 4**	**TE 5**	**TE 6**	**TE 1**
Maturity	-0.0010	-0.0007	-0.0003	-0.001*	-0.0007	0.001	-0.002**	-0.001*	-0.0006	-0.0008
SecLoan	0.0002	-0.001	-0.002	-0.001	-0.0009	0.007	-0.002	-0.002	-0.0012	-0.0010
PriSecL	-0.0003	0.002	0.002	-0.0004	-0.0032	0.006	-0.008*	-0.005	-0.0034	-0.0012
CD	0.004***	0.005***	0.004**	0.001	0.0056**	0.008	0.004**	0.003**	0.002*	0.007**
Provision	-0.035	0.04	-0.076	-0.024	0.032	0.45***	-0.008	0.017	0.011	0.016
TL	0.017	0.03**	-0.003	0.009	-0.017	0.15	-0.018	-0.005	0.002	-0.011
D	0.033	0.06**	0.001	0.021	0.029	0.15	0.021	0.010	0.017	-0.001
_cons	0.51*	0.31	0.80**	0.98***	0.88**	-2.96**	1.31***	1.12***	0.98***	0.723
Adj Rsquare	25%	19%	15%	10%	20%	17%	28%	18%	13%	23%
*, **, and *** represent significant at respectively 10%, 5% and 1% level.										

Source: Authors' Own Estimation

Note: 2016 onwards we have presented only the best fitted model for the respective years

Table 10: Pooled Regression Results with Time Dummy

	TE 1	***TE 2***	***TE 3***	***TE 4***	***TE 5***	***TE 6***
Maturity	-0.0007**	0.0008	-0.0003	-0.0009***	-0.0008***	-0.0006***
SecLoan	0.0009	0.004*	0.004	0.0002	-0.00004	0.00005
PriSecL	-0.0013*	-0.0096***	-0.009***	-0.001*	-0.002***	-0.0014***
CD	0.0041***	-0.0015	-0.002	0.004***	0.0025***	0.0021***
TL	-0.0018	-0.032**	-0.021	0.002	-0.0032	-0.0033
D11	-0.035***	-0.075	-0.044	-0.029**	-0.024**	-0.019**
D17	0.0190	-0.14***	-0.14***	0.016	-0.003	-0.0011
_cons	0.67***	1.09***	1.09***	0.70***	0.92***	0.92***
Adj R -square	24%	7%	5%	22%	20%	18%
*, **, and *** represent significant at respectively 10%, 5% and 1% level.						

Source: Authors' Own Estimation

Note: We have estimated models with all the time dummies; However, time dummies are found statically significant only for the years 2011 and 2017. Here we present only the best fitted models.

Table 11: Panel Estimation – I: Impact of Bank Specific Factors on TES

	TE 1			*TE 2*		*TE 3*		*TE 4*		*TE 5*		*TE 6*
	FE	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***
Maturity	-0.0004	-0.0006	-0.0006	-0.0008	-0.001	-0.0017	-0.0004	-0.0008**	-0.00005	-0.0008**	0.0002	-0.0005*
SecLoan	0.0013*	0.0012**	-0.0058**	-0.004	-0.004	-0.0015	0.0007	0.0006	-0.0002	0.0001	-0.0000109	0.0002
PriSecL	-0.0017*	-0.0017**	-0.0062**	-0.007**	-0.007**	-0.008**	-0.0002	-0.0007	-0.0011	-0.0014**	-0.0008	-0.001*
CD	0.004***	0.0039***	0.0012	0.0005	0.001	0.0004	0.005***	0.0043***	0.0036***	0.003***	0.003***	0.0025***
Provision	0.0098***	0.0094***	0.0008	0.0006	0.008	0.008	0.0035	0.003	0.0010	0.0001	-0.0005	-0.0011
TL	-0.011**	-0.0097**	-0.07***	-0.062***	-0.046***	-0.04***	-0.0011	-0.001	-0.0085**	-0.0065***	-0.007**	-0.0053*
_cons	0.73***	0.73***	2.16***	1.96***	1.78***	1.63***	0.59***	0.65***	0.84***	0.89***	0.84***	0.89***
*, **, and *** represent significant at respectively 10%, 5% and 1% level.												

Source: Authors' Own Estimation.

Note: We couldn't reject the null hypothesis of Hausman test for any of the models. It means there exists no systematic difference between fixed effects and random effects model

Table 12: Panel Estimation – II: Impact of Bank Specific Factors, Macroeconomic Factor and HHI on TES

	TE 1		*TE 2*		*TE 3*		*TE 4*		*TE 5*		*TE 6*	
	FE	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***
Maturity	-0.0004	-0.0006	-0.0003	-0.0007	-0.00097	-0.0018	-0.0004	-0.0009**	-0.00007	-0.00078**	0.00014	-0.00051*
SecLoan	0.0019***	0.0017***	-0.0055**	-0.0033	-0.004	-0.0017	0.0009	0.0008	0.0002	0.0003	0.00023	0.00033
PriSecL	-0.0015	-0.0014*	-0.0026	-0.0027	-0.0044	-0.0046	-0.0006	-0.0009	-0.00098	-0.001	-0.0006	-0.0007
CD	0.004***	0.0045***	0.003	0.0027	0.0023	0.0022	0.0049***	0.0046***	0.0041***	0.0034***	0.0033***	0.0028***
Provision	0.010***	0.0092***	0.015	0.013	0.021*	0.019*	0.0051*	0.004	0.0026	0.0011	0.0008	-0.00023
HHI	-0.98	-0.76	-26.22***	-25.37***	-21.18***	-20.24***	-0.12	0.1	-1.817	-1.85*	-1.69	-1.67
GDP	0.0041	0.0040	0.048***	0.047***	0.043***	0.045***	0.006*	0.006*	0.0069**	0.0064**	0.005**	0.0052**
_cons	0.58***	0.57***	2.94***	2.72***	2.55***	2.35***	0.5***	0.55***	0.78***	0.87***	0.82***	0.88***
*, **, and *** represent significant at respectively 10%, 5% and 1% level.												

Source: Authors' Own Estimation.

Note: We couldn't reject the null hypothesis of Hausman test for any of the models. It means there exists no systematic difference between fixed effect and random effect model

Table 13: Panel Estimation – II.A: Impact of Bank Specific Factor and HHI on TES

	TE 1		***TE 2***		***TE 3***		***TE 4***		***TE 5***		***TE 6***	
	FE	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***
Maturity	0.00003	0.0002	-0.00005	-0.00013	-0.0008	-0.0011	0.0001	0.00005	0.0004	-0.00005	0.0005	0.00009
SecLoan	0.0013*	0.001	-0.005**	-0.0034	-0.0042*	-0.0024	0.0005	0.0003	-0.0002	-0.0002	-0.00005	-0.00003
Provision	0.0029	0.0016	-0.0066	-0.0075	-0.0006	-0.0014	-0.0027	-0.0037	-0.005**	-0.0059***	-0.005**	-0.0059***
HHI	-1.97*	-1.93*	-14.81***	-14.21***	-11.47***	-10.97***	-0.52	-0.4673	-1.8**	-1.72**	-1.62**	-1.54**
_cons	0.99***	1.005***	2.44***	2.22***	2.10***	1.93***	0.93***	0.96***	1.12***	1.14***	1.091***	1.11***
*, **, and *** represent significant at respectively 10%, 5% and 1% level.												

Source: Authors' Own Estimation.

Note: We couldn't reject the null hypothesis of Hausman test for any of the models. It means there exists no systematic difference between fixed effect and random effect model.

Table 14: Panel Estimation III: Impact of Bank Specific Factors and Interest Rate Channel on TES

	TE 1		***TE 2***		***TE 3***		***TE 4***		***TE 5***		***TE 6***	
	FE	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***	***FE***	***RE***
Maturity	-0.0005	-0.0007	-0.0005	-0.0007	-0.0011	-0.002	-0.0005	-0.0009**	-0.0001	-0.0008**	0.00008	-0.0005*
SecLoan	0.002***	0.0018***	-0.0023	-0.0004	-0.0015	0.0004	0.0009	0.0008	0.0004	0.0005	0.00044	0.00052
PriSecL	-0.0019*	-0.0017**	-0.0047	-0.0047	-0.0059	-0.0061*	-0.00098	-0.0013*	-0.0014*	-0.0014**	-0.00098	-0.001*
CD	0.0041***	0.0043***	0.0035	0.0029	0.0026	0.0021	0.0045***	0.004***	0.004***	0.0032***	0.0032***	0.0027***
Provision	0.0075**	0.0065**	-0.0021	-0.0033	0.0055	0.0044	0.0007	-0.00006	-0.0012	-0.0024	-0.0022	-0.0032
LR	-0.013	-0.015*	0.0290	0.0292	0.017	0.0176	-0.026***	-0.028***	-0.014*	-0.014**	-0.011*	-0.011*
_cons	0.67***	0.69***	0.5350	0.4176	0.7314	0.6403	0.84***	0.92***	0.83***	0.92***	0.83***	0.90***
*, **, and *** represent significant at respectively 10%, 5% and 1% level.												

Source: Authors' Own Estimation.

Note: We couldn't reject the null hypothesis of Hausman test for any of the models. It means there exists no systematic difference between fixed effect and random effect model

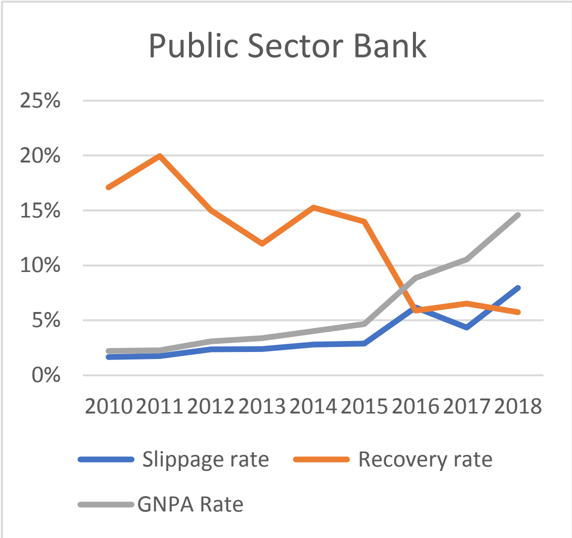
Table 15: Panel Estimation IV: Impact of Bank Specific Factors and Ownership Pattern on TES

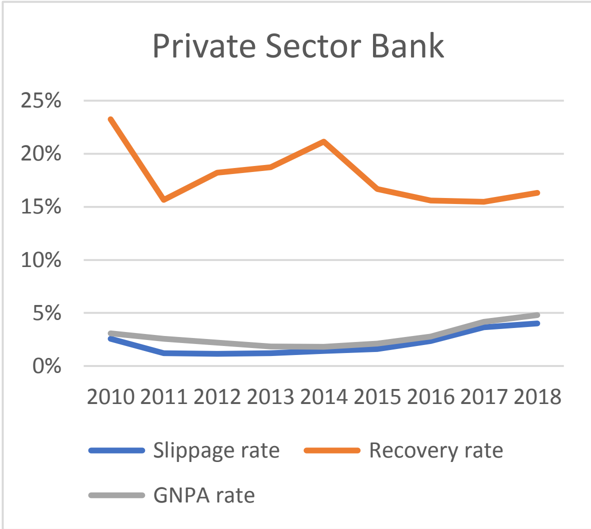
	Panel Estimation 5: Impact of Bank Ownership on TE					
	TE 1	***TE 2***	***TE 3***	***TE 4***	***TE 5***	***TE 6***
	RE	***RE***	***RE***	***RE***	***RE***	***RE***
Maturity	0.0001	-0.0004	-0.0014	-0.0001	-0.0002	-0.0001
SecLoan	0.0018***	-0.0001	0.0007	0.0007	0.0005	0.0005
PriSecL	-0.003***	-0.007**	-0.008***	-0.0025***	-0.0024***	-0.0019***
Provision	0.005**	-0.0077	0.0034	0.0004	-0.0031	-0.0037*
D	0.042**	0.0605	0.0825	0.041***	0.022**	0.021**
_cons	0.86***	0.94***	0.9514***	0.95***	1.011***	0.99***
*, **, and *** represent significant at respectively 10%, 5% and 1% level.						

Source: Authors' Own Estimation.

Note: We have estimated only the random effect models here.

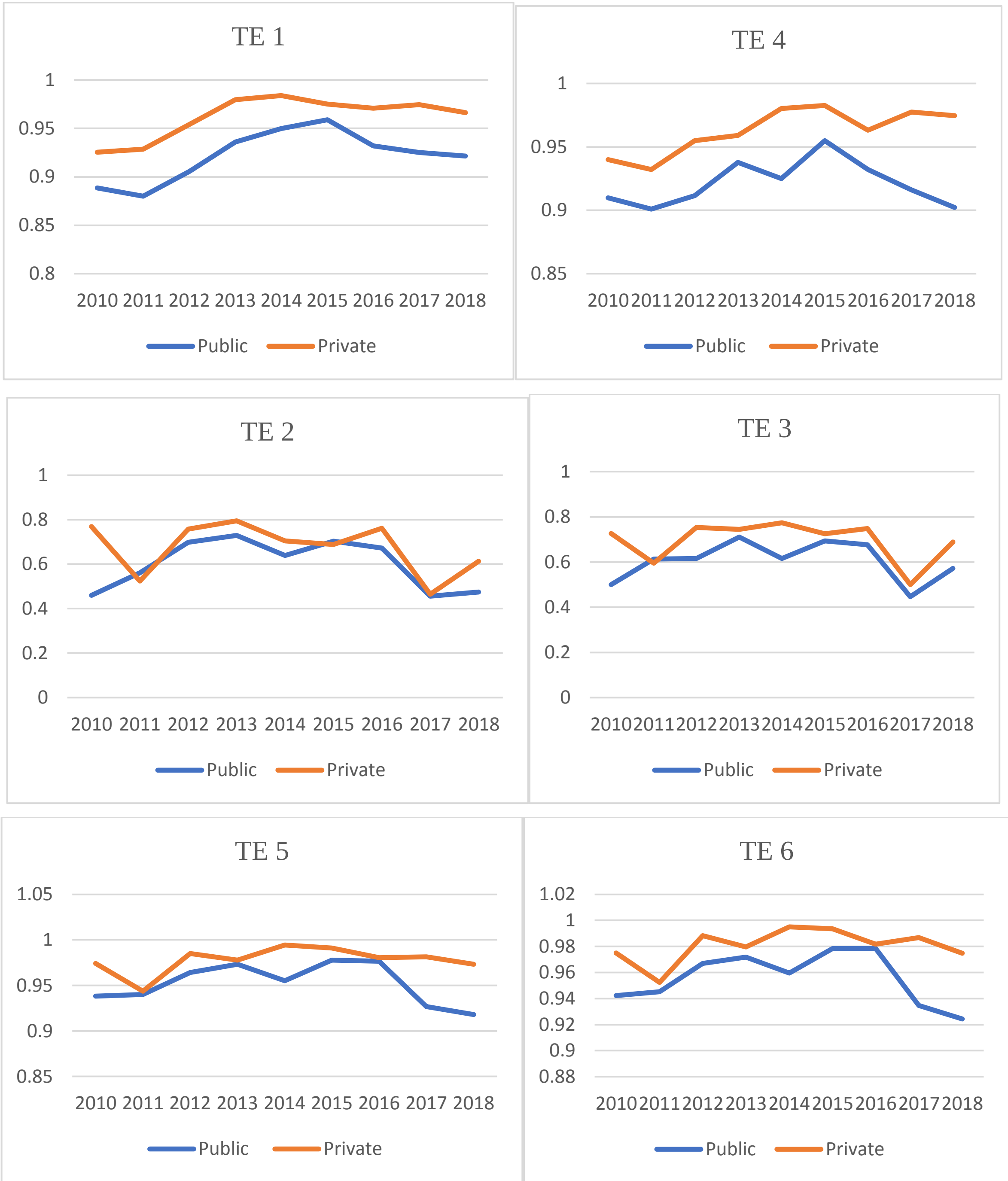
Figure 1: Trend in Slippage, GNPA and Recovery Rate of Public and Private Sector Banks (2009-10 to 2017-18)





Source: Authors' Own Compilation using RBI Database.

Figure 2: Ownership-Wise Performance of Indian Commercial Banks



Note: Comparative performance as per the ownership pattern.

Source: Authors' Own estimation.

Appendix

Table A1: Individual Bank-Wise Average TE Score during 2009-10 to 2017-18

	Average TES of the Public Sector Banks (in %)					
	TE 1	***TE 2***	***TE 3***	***TE 4***	***TE 5***	***TE 6***
Allahabad Bank	87.07	49.77	54.56	88.18	90.00	90.45
Andhra Bank	96.72	41.08	43.81	96.28	96.94	97.33
Bank of Baroda	95.75	42.80	52.29	97.79	98.65	99.19
Bank of India	91.05	70.93	76.67	93.05	96.56	94.96
Bank of Maharashtra	86.04	48.10	48.61	88.07	90.46	91.44
Canara Bank	98.34	68.26	67.31	95.98	98.92	99.02
Central Bank of India	80.02	74.29	84.24	82.91	90.95	92.64
Corporation Bank	99.88	18.01	17.12	99.56	99.70	99.55
Dena Bank	83.22	55.05	52.82	84.40	87.90	88.62
IDBI Bank	100.00	100.00	70.66	100.00	100.00	100.00
Indian Bank	94.03	51.78	53.91	92.37	93.84	94.46
Indian Overseas Bank	89.74	87.79	93.42	90.56	97.65	97.67
Oriental Bank of Commerce	90.54	83.17	86.84	92.23	97.17	98.06
Punjab and Sind Bank	93.91	34.56	36.35	93.33	94.46	94.86
Punjab National Bank	98.70	93.52	89.98	96.06	98.42	98.25
Syndicate Bank	92.14	61.24	61.13	92.35	95.95	96.45
UCO Bank	96.97	87.72	87.80	94.09	98.48	98.26
Union Bank of India	94.17	41.70	45.59	94.51	96.53	96.88
United Bank of India	76.16	64.94	66.18	77.17	85.31	87.31
Vijaya Bank	89.27	56.20	53.54	89.12	93.19	92.78
State Bank of India & its associates	100.00	100.00	100.00	100.00	100.00	100.00
	Average TES of the Private Sector Banks (in %)					
	TE 1	**TE 2**	**TE 3**	**TE 4**	**TE 5**	**TE 6**
Catholic Syrian Bank Ltd.	93.78	92.87	93.30	95.32	97.83	97.33
City Union Bank Ltd	97.50	75.78	66.45	95.83	98.36	98.47
Federal Bank Ltd.	91.93	67.66	73.81	92.73	98.86	99.18
Jammu & Kashmir Bank Ltd	83.37	51.92	73.93	90.37	92.75	94.27
Karnataka Bank Ltd	100.00	100.00	83.90	100.00	100.00	100.00
Karur Vysya Bank Ltd	92.70	28.68	43.67	92.69	94.09	95.57
Lakshmi Vilas Bank Ltd	96.33	87.15	93.33	98.53	100.00	100.00
Nainital Bank Ltd	100.00	100.00	100.00	97.91	100.00	100.00
Ratnakar Bank Ltd	100.00	100.00	94.44	100.00	100.00	100.00
South Indian bank Ltd	95.34	60.63	57.95	93.53	95.50	96.09
Tamilnad Mercantile Bank Ltd	93.73	43.91	46.42	92.05	95.06	95.31
Development Credit Bank Ltd.	99.96	92.90	84.72	97.92	98.84	98.73
HDFC Bank Ltd	100.00	82.32	78.26	100.00	100.00	100.00
ICICI Bank Ltd	100.00	70.75	82.57	100.00	100.00	100.00
IndusInd Bank Ltd	97.56	55.66	53.40	94.86	96.24	96.78
Kotak Mahindra Bank Ltd	95.73	42.29	52.85	97.39	97.99	98.21
Axis Bank Ltd	97.31	41.78	41.92	94.28	95.02	95.76
Yes Bank Ltd	100.00	73.94	65.02	100.00	100.00	100.00

Source: Authors' Own Estimation.

Table A2: Individual Bank-Wise Scope of Further Improvement

	Scope of Improvement (in %) for the Public Sector Banks					
	TE 1	***TE 2***	***TE 3***	***TE 4***	***TE 5***	***TE 6***
Allahabad Bank	14.85	100.90	83.29	13.41	11.11	10.56
Andhra Bank	3.40	143.45	128.24	3.87	3.15	2.74
Bank of Baroda	4.44	133.66	91.23	2.26	1.37	0.82
Bank of India	9.83	40.98	30.42	7.47	3.56	5.31
Bank of Maharashtra	16.22	107.90	105.74	13.55	10.55	9.36
Canara Bank	1.69	46.50	48.56	4.19	1.09	0.99
Central Bank of India	24.97	34.61	18.70	20.61	9.95	7.94
Corporation Bank	0.12	455.27	484.28	0.44	0.30	0.45
Dena Bank	20.17	81.66	89.30	18.48	13.77	12.85
IDBI Bank	0.00	0.00	41.52	0.00	0.00	0.00
Indian Bank	6.35	93.11	85.49	8.26	6.56	5.86
Indian Overseas Bank	11.43	13.90	7.04	10.42	2.40	2.38
Oriental Bank of Commerce	10.45	20.24	15.15	8.42	2.91	1.97
Punjab and Sind Bank	6.48	189.34	175.08	7.15	5.86	5.42
Punjab National Bank	1.31	6.93	11.13	4.11	1.61	1.78
Syndicate Bank	8.53	63.30	63.60	8.28	4.22	3.68
UCO Bank	3.13	13.99	13.89	6.28	1.55	1.77
Union Bank of India	6.19	139.80	119.34	5.81	3.59	3.22
United Bank of India	31.31	53.99	51.09	29.59	17.21	14.53
Vijaya Bank	12.02	77.93	86.79	12.21	7.31	7.79
State Bank of India & its associates	0.00	0.00	0.00	0.00	0.00	0.00
	Scope of Improvement (in %) for the Private Sector Banks					
	TE 1	**TE 2**	**TE 3**	**TE 4**	**TE 5**	**TE 6**
Catholic Syrian Bank Ltd.	6.63	7.68	7.18	4.91	2.22	2.74
City Union Bank Ltd	2.56	31.96	50.49	4.35	1.67	1.56
Federal Bank Ltd.	8.78	47.81	35.48	7.84	1.15	0.83
Jammu & Kashmir Bank Ltd	19.95	92.62	35.27	10.66	7.81	6.07
Karnataka Bank Ltd	0.00	0.00	19.20	0.00	0.00	0.00
Karur Vysya Bank Ltd	7.88	248.71	128.98	7.89	6.28	4.63
Lakshmi Vilas Bank Ltd	3.81	14.75	7.15	1.50	0.00	0.00
Nainital Bank Ltd	0.00	0.00	0.00	2.13	0.00	0.00
Ratnakar Bank Ltd	0.00	0.00	5.88	0.00	0.00	0.00
South Indian bank Ltd	4.88	64.95	72.55	6.92	4.72	4.07
Tamilnad Mercantile Bank Ltd	6.69	127.75	115.44	8.63	5.20	4.92
Development Credit Bank Ltd.	0.04	7.65	18.03	2.13	1.18	1.28
HDFC Bank Ltd	0.00	21.48	27.78	0.00	0.00	0.00
ICICI Bank Ltd	0.00	41.34	21.11	0.00	0.00	0.00
IndusInd Bank Ltd	2.50	79.66	87.26	5.41	3.91	3.33
Kotak Mahindra Bank Ltd	4.46	136.47	89.21	2.68	2.06	1.82
Axis Bank Ltd	2.77	139.33	138.54	6.07	5.24	4.43
Yes Bank Ltd	0.00	35.24	53.81	0.00	0.00	0.00

Source: Authors' Own Estimation.

Table A3: Ownership-Wise Performance of Indian Commercial Banks

	TES (in %)					
	TE 1		***TE 2***		***TE 3***	
Year	***Public***	***Private***	***Public***	***Private***	***Public***	***Private***
2010	88.87	92.54	45.92	76.88	49.97	72.65
2011	88.02	92.87	56.08	52.41	61.31	59.56
2012	90.55	95.41	69.83	75.69	61.62	75.30
2013	93.58	97.96	72.89	79.40	71.06	74.53
2014	94.99	98.39	63.85	70.43	61.54	77.43
2015	95.90	97.50	70.31	68.82	69.30	72.51
2016	93.19	97.07	67.25	76.14	67.71	74.87
2017	92.51	97.46	45.58	46.46	44.62	50.05
2018	92.16	96.64	47.47	61.26	57.15	68.86
	TES (in %)					
	TE 4		***TE 5***		***TE 6***	
Year	***Public***	***Private***	***Public***	***Private***	***Public***	***Private***
2010	90.99	94.00	93.82	97.42	94.23	97.51
2011	90.09	93.22	94.01	94.36	94.52	95.25
2012	91.16	95.48	96.41	98.49	96.69	98.82
2013	93.79	95.91	97.32	97.77	97.18	97.96
2014	92.50	98.02	95.51	99.44	95.96	99.51
2015	95.49	98.27	97.78	99.12	97.84	99.35
2016	93.21	96.31	97.66	98.03	97.84	98.18
2017	91.61	97.74	92.67	98.14	93.46	98.69
2018	90.22	97.45	91.81	97.33	92.43	97.47

Source: Authors' Own Estimation.