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Impact of Non-Performing Assets over Bootstrapped Efficiency of Banks: Analysis of Indian Domestic Banks

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Abstract

The present paper examines the possible impact of Non-Performing Assets (NPAs) on the efficiency estimates of banks. The bootstrapped efficiency scores of 44 domestic banks of India have been examined over a period of 12 years from 2010–11 to 2021–22. The results indicate that public-sector banks performed well in the efficiency aspect as compared to private-sector banks. The Wilcoxon signed-rank test discerned that there is a significant impact of NPAs over the efficiency estimates. The results divulge that non-consideration of NPAs leads to underestimation of the efficiency of banks. The results are expected to be fruitful for policymakers, regulators, banks, and researchers. The inference is very crucial for researchers as well as regulators while comparing the efficiency of public and private sector banks because public sector banks seriously suffer from the problem of mounting NPAs. The comparison of efficiency scores in different years unveils the strong relationship of efficiency estimates with money deposited into banks and the amount lent by banks. The outcomes of the study hold significant potential for policymakers, regulators, and banks alike, as they seek to get a comprehensive understanding of the intricate dynamics surrounding lending, deposits, and the overall efficiency of banking institutions. Further, since the impact of not including NPAs was found to be worse on managerial efficiency, the managers have to make rational use of banking inputs in order to maximise outputs. The study is likely to be a useful reference for researchers interested in researching various aspects of efficiency.

Keywords: Bootstrapped DEA, Domestic Banks, Efficiency and Non-Performing Assets
JEL Classification: C15, G20, G210

1. Introduction

Economic operations are accelerated and facilitated by banks. An economy's financial system is dominated by the banking industry, which also connects savers and borrowers. It is essential to regularly evaluate the performance of the banking system in a country because it forms the backbone of its financial system. Efficient banks have better loan and deposit rates, higher service quality, and lower service charges, but failing banks pose a serious threat to the entire financial system[1]. Low efficiency has been noticed as one of the causes of bank collapses[2]. Thus, evaluating efficiency is useful for policymakers in preserving the soundness of the banks[3]. Researchers continue to examine aspects that may have an impact on the efficiency levels of banks in addition to efficiency measurement; one such factor is undesirable output, or Non-Performing Assets (NPAs). The importance of NPAs in the Indian banking system has also been

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highlighted in literature[4], where it has been mentioned as an essential measure or factor to be taken into account while assessing the performance of the financial system. NPAs arise from the loan-advancing function of banks. Loans provided by banks make up a significant component of the asset side of the balance sheet of a bank. Additionally, loan portfolios serve as main revenue generators for the banking sector, from wherein the banks derive their interest income. However, the lending activities occasionally expose the banks to credit risk due to borrower's failure to repay their loans. The non-recoverability of loans influences the credit creation process and eventually affects the financial health and soundness of the economy.

In the Indian context initially, the concept of bad loans was not taken as a worrying factor because of the social banking philosophy[5]. However, the Committee on Financial System 1991 led by Shri M. Narasimham, took serious note of the issue. The committee recommended that any loan or asset in which interest and/or principal instalments have been overdue beyond ninety days in the case of a term loan will be termed as NPAs[6]. Accordingly, the Reserve Bank of India (RBI) introduced the concept of NPAs that aimed to reflect the real financial health of the banks in their balance-sheet. On December 17, 1991, the committee's report was first put forward in the Parliament. The Committee on "Financial System Reforms" made suggestions, on the basis of which RBI developed the prudential norms on income recognition, asset classification, and provisioning in April 1992. Frequent revisions have been made in these norms (classifying NPAs into substandard assets, doubtful assets, and loss assets) but the concept of NPAs remains the same[7]. An asset is considered to be a substandard asset if it is an NPAs for less than or equal to twelve months. On the other side, if an asset remains a NPAs for more than twelve months, then it will be known as a doubtful asset. When a loss has been discovered by the RBI, an external auditor, or the bank internally, but has not yet been fully written off, the asset is categorised as a loss asset. Further, NPAs can be taken as Gross NPAs or Net NPAs. Gross NPAs (GNPAs) refer to the sum of all the loans that have been defaulted by the borrowers within the provided period of 90 days while Net NPAs (NNPAs) are the amount that results after deducting provision for unpaid debts from gross NPAs. In India, the NPA ratios of banks are depicting an upward trend. NPAs ratios for domestic banks ranged from 3.4 percent of gross advances in March 2013 to 4.7 percent in March 2015 to 9.9 percent in March 2017. Further, the GNPAs increased from 3.8 percent during 2013-14 to 11.2 percent during 2017-18. There are a number of factors that contribute to the unabated rise in NPAs like a decline in commodity prices, prolonged regulatory forbearance, the failure of public-private partnership projects in some important infrastructure sectors, and governance concerns in commercial banks.

However, due to rising deleveraging and regulatory intervention, the GNPA ratio in India started to decline from 2019-20, a trend that has been observed over the pandemic period as well. These interventions include a six-month moratorium on loan repayments; a Covid-related restructuring plan for micro, small and medium enterprises and also for large corporate; personal loans; Emergency Credit Line Guarantee Scheme; special refinancing offerings for NABARD, SIDBI, and NHB catering to sector-specific credit needs and Extended Partial Guarantee Plan. These schemes helped borrowers conserve cash flows and brought down the level of the GNPA ratio from 7.3 percent in March 2021 to 6.9 percent in September 2021[8]. The ratio further declined to a six-year low of 5.9 percent in March 2022[9]. It is pertinent to note that despite a modest drop, the NPAs ratio for India is still one of the highest amongst comparable nations like China (1.8 percent), Indonesia (2.6 percent) and South Africa (5.2 percent). NPAs in the case of developed economies as a whole were reported to be below 3 percent, for the UK these were about 1.2 percent and for the American economy, this ratio stands at 1.1 percent[10]. The volume of NPAs has serious implications on operations costs, interest income, and future deposits of banks. The higher level of NPAs affect the efficiency estimates of banks but usually, this undesirable by-product of the lending process is ignored leading to incorrect and spurious results[11,12]. The negligence of NPAs in the efficiency estimation process leads to biased rankings of banks in terms of efficiency[12]. In this context, the current study intends to explore the potential influence of NPAs on the efficiency of India's public and private sector banks. The expected results would throw light on whether the inclusion of NPAs causes any significant change in the efficiency scores of Indian domestic banks or not. The forthcoming section reviews the literature to identify research gaps. The same is followed by research methodology, findings and conclusion of the study.

2. Literature Review

Efficiency analysis is a matter of great concern to researchers due to the importance of financial institutions in facilitating economic activity[13]. Since the importance of bank efficiency in a growing economy like India can hardly be overlooked[14], many researchers have made an attempt to explore various facets of banking efficiency in India. It generally happens that apart from consuming inputs and producing outputs, the decision-making units also generate undesirable outputs[15]. NPAs, which are recognised as undesirable outputs, tend to go unaccounted for in most analyses, but they should be taken into account as they may have contributed to bank inefficiency[12]. The importance of incorporating undesirable outputs in analysis can also be highlighted from the past economic crisis that witnessed many issues related to liquidity and non-performing loans, especially in the case of European countries[3].

Globally researchers have acknowledged the issue of NPAs while estimating of efficiency of financial institutions. A study[16] on the level of inefficiency of the Japanese banks considering Non-Performing Loans (NPL) as an undesirable output and employing dynamic network model in Data Envelopment Analysis (DEA), found that NPL led to increased inefficiency for Japanese banks. The efficiency analysis of 12 Chinese commercial banks over the period 2005-13 also reported that the inclusion of an undesirable output resulted in change in efficiency scores for Chinese commercial banks[17]. Another study examining the efficiency of 423 European banks over a span of two years, from 2013 to 2015, found that most European banks' average inefficiency was rising[18]. The investigation of the efficiency of ASEAN banks revealed that the incorporation of undesirable output resulted in a decline in the benchmarked bank's efficiency and an improvement in the efficiency of the other banks[19]. In the case of Turkish banks, the researchers[20] observed a significant impact of NPLs on operational efficiency over a period of 15 years from 2002 to 2017. The data was analysed through the integration of non- convex meta frontier and undesirable outputs in data envelopment analysis. The study found that the performance of state-owned banks was best and it was followed by joint-stock banks and foreign banks[21].

In the context of India, few studies have analysed the banks' efficiency by taking NPAs into consideration. A 2014 study[6], observed that rising NPAs ratios led to a decline in the number of efficient banks. The analysis of the profit efficiency of Indian domestic banks after consideration of NPAs as undesirable output revealed the inefficiency of banks over a span of seven years (2005 to 2012) due to high operating expenses, and low non-interest income[22]. The efficiency analysis of 46 Indian domestic banks over the period 2014 to 2016, proclaimed that NPAs generated a loss of 16.2 percent in Indian banking efficiency level[11]. Efficiency analysis of Indian banks investigated through parametric and non-parametric production frontier techniques have also discerned that public banks had higher levels of NPAs variation and NPAs overall, which reduced their technical efficiency[23]. Collateral damage generated by such a large number of toxic assets has an impact on banks' overall efficiency[24].

In traditional DEA models, the undesirable outputs are ignored, however, it is important to reduce undesirable outputs or bad outputs along with increasing desirable outputs[3]. If undesirable outputs are neglected, bank efficiency may be overstated or biased. Though NPAs are a crucial variable to be considered while estimating banking efficiency, these are usually ignored in most of the studies. In this context, the present paper aims to seek an answer to the question of whether there is any significant impact of NPAs on banking efficiency or not. Here it is essential to mention that few researchers[11,18,20] have attempted similar exercises. However, these studies have not portrayed bias-corrected scores to analyse banking efficiency. To fill the gap, the present study applies bootstrapping to get bias-free estimates of banking efficiency[25] for a period of 12 years from 2010–11 to 2021–22.

3. Research Methodology

The purpose of the current study is to determine whether or not NPAs have an impact on Indian banking efficiency. The estimation of efficiency can be done through two approaches - traditional and frontier-based approaches. The traditional method uses financial ratios to determine efficiency, but the frontier-based method compares a firm's performance with the best-performed firm situated at the frontier. Since ratio analysis is unsuitable for financial institutions having many inputs and outputs[26], a frontier-based approach has been considered to compute the efficiency level of banks. The frontier-based approach can be either a parametric frontier technique or a non-parametric frontier technique. The parametric techniques presuppose that every parameter exists in a parameter space with a finite number of dimensions. On the other hand, non-parametric methods presuppose that their parameters are spread across an infinitely large parameter space. Parametric approaches have some drawbacks, such as the requirement of specifications being too stringent for efficiency assessment[27]. Further, non- parametric approaches are preferable in the case of banks having multiple inputs and ouputs[3,28,29] because DEA, a non-parametric technique is more flexible in allowing the use of various input and output variables to compute the efficiency scores whereas through the parametric method, only a single or multiple input and single output can be used. Most importantly, DEA permits accounting for undesirable outputs (inputs) that are incompatible with Stochastic Frontier Analysis (SFA) methods[23]. According to Ahmad et al. (2020)[30], out of 74 papers that used the frontier approach to estimate efficiency, 34 employed parametric techniques and 40 nonparametric techniques. Given the constraints imposed by parametric techniques[3,27], the present study employs one of the most common non-parametric techniques.

DEA applies linear programming that uses inputs and output variables to calculate overall technical efficiency as well as pure technical efficiency[31]. The organisation being studied is called as the Decision Making Unit (DMU) in DEA. The efficiency of DMU is assessed through the transformation of inputs into outputs[32]. Through these estimates, a DMU can identify the best practice units and can imitate them by avoiding wastage of inputs (or loss of outputs). The efficiency scores obtained by incorporating input and output data into a mathematical model are relative for each DMU. Since the primary aim of DEA and relevant tools is the evaluation of efficiency rather than scaling activities, the analysis is applicable for constant returns or variable returns to scale. The DEA handles such activity shifts as stepmotherly[33].

The Overall Technical Efficiency (OTE) is calculated assuming constant returns to scale between inputs and outputs while Pure Technical Efficiency (PTE) is calculated assuming variable returns to scale[34]. Charnes et al. (1978) provided a formula to estimate efficiency for the constant return to scale measure[35].

$$\text{Max} \sum_{r=1}^{s} u_r y_{r0}$$

$$\text{Subject to} : \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0$$

$$\sum_{i=1}^{m} v_i x_{io} = 1; \quad \begin{cases} -u_r \leq -\varepsilon \\ -v_i \leq -\varepsilon \end{cases} \tag{1}$$

where, for the j^{th} DMU, x_{ij} and y_{rj} are positive known inputs and outputs. Equation (1) helps determine the variable weights (u_r and v_i). $\sum^{m}_{i=1}$ ensures possibility of shift to linear programming form, from ratio form and vice versa. u_r, $v_i \geq \varepsilon > 0$, for all r and i are from the non-Archimedean conditions. Additionally, Banker *et al.,*'s model developed in 1984 helped build the variable return to scale variant of DEA:

$$\max \sum_{r=1}^{s} u_r y_{r0} - u_0$$

$$\text{Subject to} : \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} - u_0 \leq 0$$

$$\sum_{i=1}^{m} v_i x_{io} = 1; \quad \begin{cases} -u_r \leq -\varepsilon \\ -v_i \leq -\varepsilon \end{cases} \tag{2}$$

Here, u^*depicts the return to scale possibilities. $u^* < 0$ and $u^* > 0$ show increasing and decreasing returns to scale respectively.

A DMU is deemed to be fully efficient if it is found on the frontier and if the unit is located farther away, the same is treated to be comparatively inefficient. Such units have scope for improvement in performance. The improvement may be by either increasing output (if DMU has control over outputs to be used, i.e., output-oriented DMUs) or by decreasing inputs (if DMU has control over inputs, i.e., input-oriented DMUs). In a service industry, setting targets for inputs is more practical than attempting to do the same for outputs[36]. Since banks typically have stronger control over their inputs[1,37], an input-oriented model has been used.

Efficiency scores are estimated based on certain input and output variables. Variable selection depends upon the approach to be used- production approach, asset approach, intermediation approach, operating approach, user cost approach or value-added approach. Amongst these, the intermediation approach is the most widely used approach and is better suited to the banking industry[1,2,30,37-39]. The current study, also employs the intermediation approach and accordingly, three input variables and three output variables (two desirable outputs and one undesirable output) have been finalised. The selected variables are as follows:

- Input variables:
    - Labour proxied as total employees,
    - Physical Capital proxied as fixed assets
    - Loanable funds (total of deposits and borrowings)

- Output variables:
  - Desirable outputs:
  - Net Interest Income (excess of interest earned over interest paid)
  - Non-interest Income or Other Income
- Undesirable Output: NPA

Among the above output variables, NPA is an undesirable output that in contrast to other outputs, needs to be minimised. Many academics have sidestepped this problem since DEA programming simply maximises outputs or minimises inputs. A novel methodology has been suggested[40] in which NPA is categorised as an input variable. The approach's reasoning is to maintain the level of desired outputs of the DMU by proportionally reducing inputs and undesirable outputs. The same methodology has been applied in the current study. The data for selected input and output variables has been collected for all 44 Indian domestic banks (21 public and 23 private sector banks) for the period of 12 years from 2010-11 to 2021-22. The published reports of RBI and CMIE Prowess database are considered as data sources. The same has been analysed to test null hypotheses through the "Benchmarking" package of R software.

Given that DEA is non-stochastic, random error and overall deviation from the technological frontier are not expressly taken into account hence, the DEA values may be impacted by sampling variations[25,41]. To encounter the problem, Simar and Wilson (1998)[42] applied bootstrapping in DEA and computed bootstrapped efficiency scores. The term bootstrap was first introduced by Efron (1979)[43]. Bootstrapping randomises the sample and introduces stochasticity by imitating the data-generating procedure to replicate the sample. Since within the bootstrap framework, resampling is done through drawing with replacement from a sample, multiple estimates are obtained that can be used for statistical inferences. Here, it is pertinent to mention that the computed values follow the original distribution of the estimators. Bootstrapping makes it possible to generate confidence intervals for DEA estimators and adjust them for bias. That is the reason why, the bootstrapped efficiency scores are comparatively more accurate.

If there are n DMUs with output vector given by y and input vector, x, and the constant vector, λ, the score computed through linear programming[42] is

$$\hat{\theta}_k = \min\left\{ \theta > 0 \,\middle|\, y_k \le \sum_{i=1}^{n} \lambda_i y_i ; \theta_{x_k} \ge \sum_{i=1}^{n} \lambda_i x_i ; \sum_{i=1}^{n} \lambda_i = 1 ; \lambda_i \ge 0 \forall i = 1, \ldots, n \right. \tag{3}$$

To bootstrap, resampling will be done by drawing with replacement and $\beta^*_1, \ldots, \beta^*_n$ will be generated from $\hat{\theta}_1, \ldots, \hat{\theta}_n$. The resampled values will be computed through following formula:

$$\hat{\theta}^*_i = \begin{cases} \beta^*_i + h \in^*_i & \text{if } \beta^*_i + h \in^*_i \le 1 \\ 2 - \beta^*_i - h \in^*_i & \text{Otherwise} \end{cases} \tag{4}$$

Here, $\in^*$ is random error and h is the bandwidth of a standard normal kernel density.

The variance of the generated bootstrap sequence is corrected by computing:

$$\theta^*_i = \bar{\beta}^* \frac{\tilde{\theta}^*_i - \bar{\beta}^*}{\sqrt{1 + h^2 / \hat{\sigma}^2_{\hat{\theta}}}} \tag{5}$$

Here $\bar{\beta}^* = \Sigma^n_{i=1} \beta^*_1 / n$ and $\hat{\sigma}^2_{\hat{\theta}}$ is the sample variance of $\hat{\theta}_1, \ldots \ldots \hat{\theta}_n$

Thereafter the pseudo-data $\eta^*_b = \{(x^*_{ib}, y_i), i = 1, \ldots \ldots, n\}$ is computed by $x^*_{ib} = \frac{\hat{\theta}_i}{\theta^*_{ib}}$ and bootstrap estimate of $\hat{\theta}^*_{k,b}$ are estimated $k = 1, \ldots \ldots, n$ through the following equation:

$$\hat{\theta}^*_{k,b} = \min\left\{ \theta > 0 \,\middle|\, y_k \le \sum_{i=1}^{n} \lambda_i y_i ; \theta_{x_k} \ge \sum_{i=1}^{n} \lambda_i x^*_{ib} ; \sum_{i=1}^{n} \lambda_i = 1 ; \lambda_i \ge 0 \forall i = 1, \ldots, n \right. \tag{6}$$

The above procedure will be repeated by B times to get $k = 1, \ldots, n$ a set of estimates $\hat{\theta}^*_{k,b} b = 1, \ldots \ldots, B$

The present paper also computes bootstrapped efficiency scores and examines the impact of NPAs on bootstrapped efficiency of Indian domestic banks. If the bootstrapped efficiency scores of Indian domestic banks computed without considering NPAs are represented by 'E' and the efficiency scores computed with due consideration of NPAs are represented by 'En,' the null hypotheses for overall and pure technical efficiency i.e., OTE and PTE will be as follows:

- H01: There is no significant difference between OTE and OTEn of Indian domestic banks including public sector and private sector banks.
- H02: There is no significant difference between PTE and PTEn of Indian domestic banks including public sector and private sector banks.

These null hypotheses have been tested through Wilcoxon signed-rank test which is a non- parametric technique. The following section presents the major findings of the study.

4. Findings and Analysis

The present study analyses the bootstrapped overall technical and pure technical efficiency scores for 44 Indian domestic banks considering the period of 12 years from 2010-11 to 2021-22. The efficiency scores have been calculated without considering NPAs as well as after considering NPAs and are presented in Table 1. The annual analysis of efficiency scores divulges that the efficiency score of domestic banks was discerned to be lowest during the year 2015-16. The reason is the wreaked havoc of asset quality review on bank profitability. During 2015-16, there was a decline in lending growth which resulted in reduced interest and non- interest income of banks as well[44]. A notable increase in efficiency was observed in 2016–17. This may be attributed to large amounts of deposits made in banks as a result of the declaration of the prohibition on the acceptance of the 500 and 1000 notes as legal currency. In the case of public sector banks, it was accompanied by a significant number of mergers[24]. In the case of private sector banks, improvement in efficiency in 2016-17 may be attributed to the demonetisation as well as the healthy pre-provision profits of private banks[45]. These pre-provision profits that include net interest revenue and net fee income exhibit the success (or failure) of banking operations. Even after taking into account a small increase in credit costs, the majority of private banks' return on equity ratios during 2016–17 was estimated to be between 12 and 20 per cent due to solid pre–provision earnings. Further, improvement in efficiency was observed during 2020-21. The outbreak of coronavirus fuelled electronic transactions through banks. Other than that, the strategic choice of merging ten public sector banks into four, taking effect from April 1, 2020, has paid off in terms of increased net interest income, return on equity, return on assets and earnings before provisions and taxes. In the fiscal year 2020–21, Punjab National Bank was able to turn a loss of Rs 83.1093 billion into a good amount of profit that was reported to be Rs 20.2162 billion thanks to the merger of Oriental Bank of Commerce and United Bank of India[46]. Sustained growth in net interest income and a decrease in provisions during the second quarter of the financial year 2021 helped the private sector banks achieve a 159 percent increase (year over year) in net profit at Rs 188.14 billion[47].

The significance of the possible difference between efficiency scores calculated without considering NPAs and efficiency scores calculated after considering NPAs has been tested through the Wilcoxon signed-rank test. The computed test statistics have been compared with the critical value and the probability of not rejecting (or rejecting) the null hypothesis has been indicated with the test statistics (Table 1). The null hypothesis of no significant impact over efficiency estimates is not rejected only when the probability is more than 5 percent level of significance. However, if the probability value is less than 5 percent, then the null hypothesis will be rejected, indicating a significant difference between the efficiency scores estimated without considering NPA and the efficiency scores estimated after considering NPA. In other words, the inclusion of NPA in the efficiency estimation process significantly affects the efficiency scores.

As depicted in the table, ignorance of NPAs leads to underestimation of overall as well as pure technical efficiency scores. In the context of public sector banks, the average efficiency scores have been underestimated by 1.4 percent, and 1.6 percent respectively for OTE and PTE. The same for private banks was found to be underestimated by 0.2 percent and 0.7 percent. Our findings are similar to those of a previous study concluding that non-consideration of NPAs could overestimate the inefficiency measurements and underestimate the efficiency of the decision-making unit[48]. Further, the impact is more on public sector banks which clearly endorses the view that the problem of NPAs is worse for public sector banks due to mounting NPAs in their case.

The first null hypothesis for overall technical efficiency has been rejected for five years for both public-sector as well as private-sector banks. However, the null hypothesis for pure technical efficiency has been rejected for eight years for public sector banks and for seven years for private sector banks. The rejection of the null hypothesis implies that the NPA of banks significantly influenced the estimated scores of efficiencies. The findings coincide with the previous studies[17,22]. Here, it is important to note that the difference was observed to be significant mostly prior to 2015–16. Post 2015-16, though NPAs continue to affect the efficiency estimates, however, the impact is not statistically significant. The reason for this may be attributed to the Asset Quality Review conducted by the RBI in 2015–16. The review resulted in the betterment of

Table 1. Bootstrapped Efficiency Estimates and Results of Wilcoxon Signed-Rank Test

Years	OTE	OTE_n	z statistics	Probability	Null Hypothesis	PTE	PTE_n	z statistics	Probability	Null Hypothesis
Public Sector Banks										
2010-11	0.830	0.833	-1.31	0.19	Not Rejected	0.887	0.897	-2.76	0.01	Rejected
2011-12	0.828	0.834	-1.54	0.12	Not Rejected	0.886	0.895	-2.08	0.04	Rejected
2012-13	0.814	0.857	-3.83	0.00	Rejected	0.892	0.921	-3.81	0.00	Rejected
2013-14	0.811	0.864	-4.02	0.00	Rejected	0.831	0.911	-4.02	0.00	Rejected
2014-15	0.814	0.835	-2.38	0.02	Rejected	0.822	0.864	-4.02	0.00	Rejected
2015-16	0.807	0.811	-0.24	0.81	Not Rejected	0.815	0.819	-1.91	0.06	Not Rejected
2016-17	0.841	0.857	-3.22	0.00	Rejected	0.884	0.889	-2.46	0.01	Rejected
2017-18	0.823	0.827	-0.83	0.41	Not Rejected	0.868	0.868	-0.76	0.45	Not Rejected
2018-19	0.859	0.859	-0.2	0.84	Not Rejected	0.894	0.896	-1.4	0.16	Not Rejected
2019-20	0.825	0.838	-2.31	0.02	Rejected	0.856	0.866	-3.42	0.00	Rejected
2020-21	0.895	0.895	-0.42	0.67	Not Rejected	0.934	0.937	-2.96	0.00	Rejected
2021-22	0.913	0.916	-1.13	0.26	Not Rejected	0.944	0.944	-0.28	0.78	Not Rejected
Average	0.838	0.852				0.876	0.892			
Private Sector Banks										
2010-11	0.775	0.785	-2.14	0.03	Rejected	0.798	0.806	-3.42	0.00	Rejected
2011-12	0.748	0.761	-2.72	0.01	Rejected	0.81	0.82	-2.34	0.02	Rejected
2012-13	0.716	0.734	-1.35	0.18	Not Rejected	0.755	0.78	-3.62	0.00	Rejected
2013-14	0.738	0.735	-1.52	0.13	Not Rejected	0.773	0.779	-1.13	0.26	Not Rejected
2014-15	0.73	0.731	-1.05	0.29	Not Rejected	0.76	0.762	-0.62	0.54	Not Rejected
2015-16	0.689	0.684	-2.32	0.02	Rejected	0.751	0.748	-0.39	0.69	Not Rejected
2016-17	0.73	0.73	-0.31	0.75	Not Rejected	0.81	0.819	-2.97	0.00	Rejected
2017-18	0.727	0.721	-2.72	0.01	Rejected	0.806	0.805	-0.33	0.74	Not Rejected
2018-19	0.678	0.67	-2.99	0.00	Rejected	0.755	0.767	-2.57	0.01	Rejected
2019-20	0.678	0.674	-1.81	0.07	Not Rejected	0.757	0.78	-3.3	0.00	Rejected
2020-21	0.765	0.768	-0.85	0.39	Not Rejected	0.84	0.84	-0.66	0.51	Not Rejected
2021-22	0.749	0.752	-0.96	0.34	Not Rejected	0.831	0.816	-3.63	0.00	Rejected
Average	0.727	0.729				0.787	0.794			

Source: Author's Calculation

asset quality and a fall in the level of NPAs. That is the reason why, after 2016, the influence of NPAs is relatively less observable.

Public sector banks are discerned to be more efficient than private sector banks, according to their relative analysis. The efficiency scores show that in terms of constant returns to scale and variable returns to scale assumption, public sector banks have performed better compared to private sector banks. The results are consistent with those of previous studies[34,49].

5. Conclusion and Policy Implications

The non-performing assets negatively affect the credit creation capability of banks. The aim of the current study was to look at any potential effects that NPAs might have on Indian banking efficiency. For a period of 12 years, from 2010–11 to 2021–22, the efficiency scores of Indian domestic banks have been estimated using a bootstrapped data envelopment approach. The scores have been estimated without considering NPAs as well as after considering NPAs and the Wilcoxon signed-rank test has been applied to examine the statistical significance of possible differences. The results indicate that ignorance of NPAs leads to underestimation of overall as well as pure technical efficiency. The difference was observed to be significant prior to 2015-16. Further, public sector banks performed well in the efficiency aspect as compared to the private sector banks. This calls for changing the general notion of the inefficiency of public sector banks in comparison to private banks. The results are expected to be beneficiary for researchers who may draw inaccurate inferences due to the underestimation of efficiency owing to the ignorance of NPAs. The estimated scores of efficiencies explicitly pronounced an acute decline in banking efficiency during 2015-16 and these results were similar for public as well as private sector banks. The fall in efficiency calls for the serious attention of policymakers, regulators and managers to be extremely cautious about the asset quality and volatility of lending rates. The wreaked havoc of asset quality review caused a massive fall in net interest income during 2015-16 which led to a bearish trend of efficiency. On the contrary, the massive flow of deposits during 2016-17 led to an appreciable rise in the efficiency scores of the banks. This indicates the need to ensure cash inflows into banks so as to make them capable of keeping healthy pre-provision profits. Further, while recommending any change in the bank rates, the regulators should consider its implications on the efficiency scores of banks. The results also stress the consideration of NPAs for the accurate measurement and analysis of banking performance. The results clearly indicates that impact of non-consideration of NPAs was observed to be worse on PTE than OTE. Since PTE is a reflector of the effectiveness of bank managers to optimally utilise various inputs in the lending process, the managers need to make rational use of banking inputs in order to maximise the outputs. The results are expected to be useful for non-banking financial institutions as they are also exposed to surmounting burden of bad debts. The study is expected to be a fruitful guide for researchers to indulge in exploring various facets of efficiency. The analysis can be extended further by enriching the sample size and including foreign banks that operate in India. In addition to NPAs, additional factors, such as bank- and market-specific characteristics, also can be considered at to analyse the impact on banking efficiency.

6. References

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