COVID-19 crisis and the efficiency of Indian banks: Have they weathered the storm?

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Abstract

The purpose of this study is to determine whether Indian banks were able to weather the COVID-19 storm. We estimate banks' deposits-generating and operating efficiencies using a two-stage directional distance function-based network data envelopment analysis (DDF-NDEA) approach and seek to capture the immediate impact of COVID-19 on these efficiency measures by comparing their magnitudes in the pre-pandemic (2014/15-2019/20), just 1-year prior to the pandemic (2019/20), and during the pandemic year (2020/21) periods. The study looks at whether the impact of the COVID-19 pandemic was uniform across ownership types and size classes. The empirical findings suggest that the Indian banking system was resilient and withstood the immediate impact of the COVID-19 pandemic. During the study period, however, the large and medium-sized banks experienced some effi ciency losses. By and large, regardless of bank group, banks have shown resilience to the shock of the global health pandemic and improvements in efficiency.

JEL Codes: G01, G10, G21, G32

Keywords: Bank Efficiency; COVID-19 Pandemic; Two-Stage Network Model; Directional Distance Function; Data Envelopment Analysis; Indian Banks

1. Introduction

In times of an economic, financial, or political crisis, an efficient banking system unquestionably plays a vital role in mitigating the impact of the shock of the crisis on the entire economy by maintaining adequate liquidity and credit funding for businesses and households (Acharya *et al.*, 2020; Berger & Demirgüç-Kunt, 2021; Demirgüç-Kunt *et al.*, 2021). The recent COVID-19 pandemic is a one-of-a-kind of a health crisis that has caused not only the death and physical suffering of millions, but also the most unexpected economic destruction worldwide since the 2007-09 global financial crisis (GFC). According to official statistics, there were 3.4 million deaths worldwide and 303,720 in India by May 2021 (Reserve Bank of India, 2021a). Consequently, the real and financial sectors of both developed and developing countries have been under much greater strain than ever before. The observed economic strain appeared due to a variety of pandemic-control measures, such as nationwide lockdowns, supply chain disruptions and directing funds to the countries' health systems.

In India, the COVID-19 pandemic posed a severe threat to the country's macroeconomic environment, resulting in a 24.4 percent drop in the gross domestic product (GDP) during the second quarter of the financial year 2020/21 (Reserve Bank of India, 2022). The macroeconomic slowdown caused by the pandemic severely affected the capacity of individuals and businesses to service their loans, which negatively impacted the balance sheets of banks. During the financial year 2020/21, the banking industry in India witnessed subdued credit growth with a rate of 5.6 percent, which was the lowest in the preceding four financial years (Reserve Bank of India, 2021b). In addition, distressed and non-performing loans (NPLs) have surged, notably in the personal loan sector since the COVID-19 pandemic struck the Indian economy. All of these reasons exacerbated the stress on the Indian banking sector and posed a grave threat to banks' stability and efficiency levels. Overall, such a pandemic-induced economic slowdown that India has experienced raises concerns about the spillover effects of such economic fallout on the efficiency performance of the nation's banking sector because the slowdown in the macroeconomy increases the default risk (Beck, 2020). The increase in the likelihood of default by firms and individuals increases the inefficiency levels of the banking system. In light of this argument, it seems, therefore, critical to comprehend the immediate impact of the COVID-19 crisis on bank efficiency levels.

The recent literature on the impacts of COVID-19 on banking and finance focuses primarily on the following areas: i) the changes in banks' financial characteristics in response to policy announcements (Demir & Danisman, 2021; Demirgüç-Kunt *et al*., 2021); ii) the speed, strength, and direction of stock market reactions to information on COVID-19 crisis (Jin *et al*., 2022; Igan *et al.*, 2023; Naidu & Ranjeeni, 2021; Sun *et al*., 2021); iii) the bank stock performance during the pandemic (Ashraf *et al*., 2022; Mirzaei *et al*., 2022); and iv) the impact of COVID-19 on systematic risk (Baumöhl *et al*., 2020; Duan *et al*., 2021; Rizwan *et al*., 2020). Hassan *et al*. (2022) examined the immediate impact of COVID-19 on the FDIC chartered banks' performance in terms of profitability, asset quality, and capital position in the United States. Tran *et al.* (2022) found that international banks faced elevated accounting risk (proxied by z-score) and increased stock return volatility during the period of 2020:Q1 to 2021:Q1. One of the striking aspects of the extant research is that empirical evidence regarding the immediate effects of a pandemic on bank efficiency is under-researched and unclear, with barely any effort from the banking system in an emerging market economy like India. To the best of our knowledge, only Boubaker *et al.* (2022) attempted to analyse the impact of COVID-19 on the efficiency of 49 Islamic banks across 10 countries by comparing 2019 and 2020 efficiency levels.

In this study, we examine the immediate impact of the COVID-19 crisis on deposits-generating and operating efficiencies of Indian banks. In addition, we see whether the underlined impact was uniform across ownership types. The empirical analysis in this study enables us to answer our key research question: *Did Indian banks weather the COVID-19 storm?* In an extremely uncertain situation such as that of the COVID-19 pandemic, the propensity of individuals to hold more liquid assets than usual restrains the growth of deposits. This, in turn, has a negative impact on the deposits-generating efficiency of banks. The crisis also impairs the loan-servicing capacity of individuals and businesses, so reducing the flow of bank income from traditional credit activities. In this circumstance, the operating efficiency of banks would undoubtedly take a major hit, particularly for those banks that rely heavily on traditional interest-bearing activities as opposed to fee-generating and other non-interest-bearing activities. Based on the foregoing, we postulate that banks experienced lower deposits-generating and operating efficiency levels during the COVID-19 pandemic.

The literature on bank efficiency, especially for developed countries, is extensive (see the survey articles by Ahmad *et al.*, 2020, Aiello & Bonanno, 2018, and Fethi & Pasiouras, 2010, among others). The existing works have covered a wide range of research issues on this subject matter, notably on ownership effects (Doan *et al.*, 2018; Yildirim & Philippatos, 2007), financial crises (Beck *et al.*, 2013, Moradi-Motlagh & Babacan, 2015), efficiency convergence (Izzeldin *et al.*, 2022), and contextual factors (Wanke *et al.*, 2016; Wang *et al.*, 2022), among others. In most of these studies, including those on bank efficiency in India, researchers have predominantly relied on traditional "black-box" DEA models for bank efficiency measurement. Interested readers are directed to refer to Table A1 in Appendix A for more details on the studies on bank efficiency in India. Unlike most bank efficiency studies that employed a black-box DEA model, we model the bank's production process as a two-stage process and utilise a network data envelopment analysis (NDEA) model, which yields deposits-generating and operating efficiencies in Stage 1 and Stage 2, respectively. Interestingly, the two-stage NDEA model employed directly includes two risk management control variables: "non-performing loans (NPLs)" as an undesirable output and "bank equity" as a quasi-fixed input, resulting in a more accurate measurement of bank efficiency. It is worth mentioning here that the two-stage bank production process conceptualised in this paper considers deposits as an intermediate product to overcome the well-known "deposit dilemma", which surrounds the challenge of identifying deposits as inputs or outputs in the production process. More details on this dilemma can be found in Fukuyama and Weber (2010) and Holod and Lewis (2011).

The study undoubtedly makes several significant contributions to the literature on bank efficiency, particularly related to India. First, this is the first study to assess the impact of the COVID-19 pandemic on bank efficiency in India. We capture the immediate effect of the global health pandemic on deposits-generating and operating efficiencies of banks. For the investigation purpose, we categorise the whole period from 2014/15 to 2019/20 into sub-periods and examine how deposits-generating and operating efficiencies changed in the pre-pandemic and the pandemic periods. Second, we compare the deposits-generating and operating efficiency levels of banks across ownership groups and size classes for the years 2020/21 with 2019/20, as well as the average for the years 2014/15 to 2019/20. Note here that prior research on Indian bank efficiency mainly focused on the effects of deregulation, the global financial crisis, and efficiency variations across ownership types (see, for example, Gulati, 2022; Kumar *et al*., 2016; Ray & Das, 2010; Tzeremes, 2015; Wanke *et al*., 2021, among others). To the best of our knowledge, this is the first endeavour to examine the potential impact of the COVID-19 pandemic on bank efficiency in the Indian context. The significance of a study such as ours lies in the fact that the resilience of the banking sector to the crisis is essential for economic recovery. Policy analysts can use the results of this study to design policies with a clear focus on reducing future loan and impairment risks.

Third, in terms of methodology, most of the existing works have used the traditional "black-box" DEA model (see, for instance, Bhattacharyya *et al.*, 1997; Jayaraman & Bhuyan, 2020; Kumar & Gulati, 2014; Kumbhakar & Sarkar, 2003; Mallick *et al*., 2020; Ray & Sethia, 2022; Zhao *et al.*, 2010, among others). Interestingly, only limited efforts have been made to explicitly accommodate equity risk capital and bad loans in the bank's production process. The "equity capital" has been treated to account for the "insolvency risk" in the bank efficiency and productivity estimation (see, for instance, Bos *et al*., 2009; Färe *et al*., 2004; Ray & Das, 2010).

Unlike existing literature, this study applied a two-stage directional distance function-based NDEA model that directly accounts for equity capital as a quasi-fixed input, NPLs in the current period (*t*) as an undesirable output and that of the previous period (*t*-1) as an undesirable input in efficiency measurement, and offers more reliable efficiency estimates of deposits-generating and operating efficiencies. We specifically deal with how impaired loans from the past period constrain the bank's lending decisions in the current period. Such NPLs might occur due to risky lending and lax credit monitoring processes, exogenous shocks, economic downturn, or non-repayment of loans, which is precisely what happened in the form of the twin-balance sheet crisis in India (Government of India, 2017). As far as we know, no previous research has considered the baggage of NPLs in the previous year (*t*-1) when measuring bank efficiency for Indian banks (Fukuyama & Weber, 2010; Wang *et al.*, 2014; Zhao *et al.*, 2021). This method was adopted by Akther, Fukuyama, and Weber (2013) for Bangladeshi banks. However, we differ from their approach in two ways. First, we view equity as a quasi-fixed input rather than a desirable input. Second, we define the second stage of our network process as the operating stage since it is where we assess the banks' ability to generate earning assets and income. The empirical findings suggest that the Indian banking system was resilient and weathered the COVID-19 pandemic well. However, large banks suffered some efficiency losses during the study period.

The remainder of the article is structured as follows. Section 2 briefly describes the structure of the Indian banking sector and discusses the major policy responses to the COVID-19 pandemic. Section 3 describes the methodology and data used in the present study. Section 4 presents the empirical results. The final section concludes the article.

2. Indian banking sector and key policy responses to the COVID-19 pandemic

2.1 Structure of the Indian banking sector

The financial architecture of the Indian banking system has undergone a complete overhaul and reorientation over the past two decades. The Reserve Bank of India (RBI) (India's central bank) has used the banking system as a potent tool for meeting the rising demand for credit and evolved a regulatory framework that enabled the banks to opt for the universal banking model. RBI issued differentiated licenses and created an environment for banks to expand their capacity to better serve the needs of the economy in order to promote financial stability, competition, and inclusivity. As of the end of March 2021, scheduled commercial

(SCBs) and scheduled cooperative (SCoBs) banks form the major pillars of the multi-tiered banking system of India. SCBs account for approximately 90 percent of India's banking business and are governed by the Banking Regulation Act 1949 (latest amended in 2020). This group of banks includes 12 public sector banks (PSBs), 21 private banks (PBs), 45 foreign banks (FBs), 10 small finance, and 6 payments banks[1] (excluding 43 regional rural banks). The first three bank groups control the majority of the banking business in India. Table 1 compares the structure of commercial banking in India as of March 2010 and 2021. It has been observed that the relative share of private banks has increased over time. In the financial year 2020/21, their share of total deposits and advances reached 30.79 percent and 36.41 percent, respectively. Since 2010, a decline in the share of PSBs in these business parameters has been observed. Foreign banks and Small Finance & Payments banks hold a very small share of the commercial banking business, less than 5 percent.

2.2 RBI's policy response to the COVID-19 pandemic for banks

As noted in the introductory section, the COVID-19 pandemic has had a devastating impact on the economies of the world, and the Indian economy was no exception. Supply chain disruptions and prolonged lockdowns caused macroeconomic disruptions, resulting in a drop in exports, higher unemployment, and mass migration (Feyen *et al*., 2021; Demirgüç-Kunt *et al*., 2021). There is no doubt that commercial banks and other credit institutions play a countercyclical role in such an unprecedented situation by absorbing the pandemic-induced shock and meeting the credit requirements through relevant policy interventions. With this perception, the central banks across nations, including India, have played a vanguard role and served as a bulwark by taking proactive measures to improve the operational capacity of banks to respond to the COVID-19 shock[2]. According to the World Bank COVID-19 Financial Policy Response Database, policymakers in India implemented a total of 134 financial policy response measures in response to the pandemic outbreak, as of June 2022 (IMF, 2022)[3]. These measures are broadly classified into four categories: i) liquidity and funding measures, ii) financial

[1] It is important to note that India has a multi-tiered banking structure with distinct ownership groups, and that policy measures aimed to diversify the banking business by activity type. The RBI extended authorisation for the establishment of 11 payments banks in August 2015, 10 small finance banks in September 2015, and two new private commercial banks (IDFC Bank and Bandhan Bank) in 2014. Airtel Payments Bank Ltd. began operating as the first payments bank in India. There are currently just six payments banks that are active.

[2] For details on the policy measures announced by developed and developing nations, refer to the IMF Policy Tracker available at: https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19 and https://datacatalog.worldbank.org/search/dataset/0037999.

[3] The reported statistics are based on the World Bank COVID-19 Financial Response Database, the latest updated in June 2022.

markets and non-bank financial intermediaries related measures, iii) insolvency measures, and iv) payment systems measures. Of these, 84 policy steps were exclusively announced by the RBI and 45 measures were directly linked to the banking sector in India. The key relief measures that pertain to banks' resilience and ensure liquidity/credit flow to the economy are briefly discussed in Appendix Table B1.

As the apex institution, the RBI unveiled initiatives related to liquidity and lending support, borrower assistance, the functioning of financial markets, and conventional and unconventional monetary policy tools (Reserve Bank of India, 2021a). In March 2020, the RBI's first action was to establish a crisis management team and create bio-bubble arrangements to ensure the continuous operation of central banking services. Under the monetary and liquidity measures, a spectrum of conventional and unconventional measures were adopted (refer to Appendix Table B1 for major policy announcements), which are briefly discussed here. These include i) maintaining an accommodative monetary policy stance; ii) reducing the policy repo rate by 115 bps and reverse repo rate by 155 bps from March 2020 to May 2020, and reducing the CRR by 100 basis points; iii) implementing large-scale open market operations during the first three quarters of 2020-21, which increased banking system liquidity by INR 1,370,000 million; and iv) using long-term repo operations (LTRO) and targeted long-term repo operations (TLRO) for liquidity infusions. Overall, the RBI made efforts to alleviate strain on the macroeconomy by reducing policy rates and injecting liquidity.

In order to deal with insolvency concerns, the RBI introduced a series of prudential regulatory measures, such as asset re-classification, loan moratorium, ease in working capital financing, temporary ease on liquidity coverage ratio, restrictions on dividend payments, and restructuring of advances to small borrowers and medium and small enterprises. Another proactive step was the adoption of digital technology to create a "less cash" society. On August 6, 2020, the Monetary Policy Committee (MPC) decided to keep the policy rates unchanged and focused on restoring the pre-COVID rates. It is interesting to note that despite the fact that these policy actions were taken primarily to safeguard the Indian economy from the immediate adverse effects of the pandemic, these measures would also have significant ramifications for the future resilience of the Indian banking sector.

Table 1: Structure of scheduled commercial banking in India

(Amount in INR billion)

Bank group	**Number of Banks**		**Branches (in number)**		**Staff (in number)**		**Investments**		**Advances**		**Deposits**		**Total Assets**	
	2010	**2021**	**2010**	**2021**	**2010**	**2021**	**2010**	**2021**	**2010**	**2021**	**2010**	**2021**	**2010**	**2021**
I. Public Sector Banks	27	12	58651	92469	739646	783518	12155.98	34008.95	27010.19	63487.58	36920.19	99007.66	44408.27	117313.77
Market Share (%)			(84.90)	(67.99)	(92.96)	(52.56)	(70.31)	(62.75)	(77.24)	(58.68)	(77.78)	(63.50)	(73.68)	(59.87)
II. Private Banks	22	21	10133	36678	182520	570713	3541.17	15124.80	6324.41	39392.93	8228.01	48006.46	11507.36	64310.48
Market Share (%)			(14.67)	(26.97)	(22.94)	(38.28)	(20.48)	(27.91)	(18.09)	(36.41)	(17.33)	(30.79)	(19.09)	(32.82)
III. Small Finance & Payments Banks	0	12	-	5851	-	108719	-	330.73	-	1086.13	-	1120.15	-	1676.25
Market Share(%)			-	(4.30)	-	(7.29)	-	(0.61)	-	(1.00)	-	(0.72)	-	(0.86)
IV. Foreign Banks	32	45	299	924	28012	27752	1592.91	4734.19	1632.60	4235.46	2320.99	7771.73	4353.62	12645.67
Market Share (%)			(0.43)	(0.68)	(3.52)	(1.86)	(9.21)	(8.73)	(4.67)	(3.91)	(4.89)	(4.98)	(7.22)	(6.45)
V. Total Domestic Banks (I+II+III)*	49	33	68784	134998	922166	1354231	15697.15	49464.48	33334.60	103966.63	45148.20	148134.27	55915.63	183300.49
Market Share (%)			(99.57)	(99.26)	(115.90)	(98.13)	(90.79)	(91.27)	(95.33)	(96.09)	(95.11)	(95.02)	(92.78)	(93.55)
VI. Total Commercial Banks (IV+V)	81	78	69083	136003	795670	1490702	17290.06	54198.66	34967.20	108202.08	47469.20	155906	60269.25	195946.17
Market Share (%)	100	100	100	100	100	100	100	100	100	100	100	100	100	100

Notes: '*' indicates the exclusion of Regional Rural Banks.
Source: Authors' calculations based on the data extracted from "Statistical Tables Relating to Banks in India"(various issues).

3. Methodology and data

Data envelopment analysis (DEA) is a well-known data-enabled performance evaluation technique (Charles *et al*., 2018; Zhu, 2022; Zhu & Charles, 2021) that has been shown to be effective in a variety of disciplines and fields, hence easing decision-making around the world (Charles *et al*., 2021). Moreover, in view of Charles *et al*. (2022), DEA can be positioned as a prescriptive analytics-oriented technique because it helps provide recommendations for improving the efficiency of decision-making units (DMUs) by identifying the best practice frontier. The DEA approach evaluates the relative efficiency of DMUs based on multiple inputs and outputs, and it seeks to identify the most efficient DMUs that can be used as benchmarks for improving the efficiency of other DMUs. In other words, DEA provides a roadmap for improving the performance of DMUs by recommending changes to their input-output mix, while considering the constraints and objectives of the organisation. DEA is thus a powerful technique that can help organisations optimise their performance and make better decisions by providing prescriptive insights on the best course of action to take. An inquisitive reader of DEA applications is directed to the well-known survey on the 40 years of DEA by Emrouznejad and Yang (2018). In the banking industry, DEA has been used in a wide variety of contexts. Review articles such as those written by Aiello and Bonanno (2017), Ahmad *et al*. (2020), Fethi and Pasiouras (2010), and Kumar and Gulati (2014) provide a comprehensive overview of the various contexts that have been studied in the context of bank efficiency across nations. It is interesting to note that most of the prior literature on bank efficiency relies on traditional black-box DEA models (like CCR and BCC) and their extensions.

When evaluating efficiency, traditional DEA models treat the system as a whole unit and disregard the interconnections between the system's sub-processes (Kao, 2014; Kao & Hwang, 2008; Kao & Hwang, 2010). As a result, it is possible that the efficiency figures obtained using the traditional models may be inflated. Furthermore, the diagnostic information provided by traditional DEA models for determining the sources of inefficiency is more likely to be erroneous and insufficient. Using the network DEA modelling framework, one can easily overcome the fundamental limitations of traditional DEA models and get more precise efficiency estimates for the whole process and its various sub-processes. A typical network DEA model unlocks the "black-box" and analyses the internal operational relationship between distinct sub-processes of a multi-stage production process and, hence, provides valuable diagnostic information regarding each stage of the production process. Due to its inherent advantages over the classical DEA models, the network DEA modelling framework, and in particular its class of two-stage network DEA models, has been increasingly popular in recent research on bank efficiency (Henriques *et al.*, 2020). In keeping with the existing research on bank efficiency, we use a two-stage network DEA to calculate risk-adjusted estimates of bank efficiency for Indian banks. Specifically, we postulate a two-stage network structure of bank production and solve a directional distance function network DEA (DDF-NDEA) model with quasi-fixed inputs and undesirable inputs and outputs to obtain an overall bank efficiency measure and its components measures, *i.e.*, deposits-generating efficiency and operating efficiency. The two-stage DEA network procedure employed is described in detail below.

3.1 The two-stage production process of a bank

We assume that a typical bank has a two-stage production process with multiple inputs and outputs, as depicted in Figure 1. In stage 1, which we call the deposits-generating stage, it is hypothesised that the bank makes use of two controlled inputs (labour and physical capital) and one uncontrolled or quasi-fixed input (equity) in order to produce deposits. The deposits are the sole output of stage 1 and act as an input to stage 2. Thus, deposits serve as a linking factor between the two stages. There are two main takeaways here. First, to control managerial risk preferences and the risk-return trade-off, we include equity as an uncontrolled (quasi-fixed) input that cannot be adjusted in the short run. Notable bank efficiency studies that have treated equity as a quasi-fixed input include Bos *et al*. (2009), Färe *et al.* (2004), Girardone *et al*. (2004), Gulati (2022), Koutsomanoli-Filippaki *et al.* (2009), Maudos *et al*. (2002), and Yildirim and Philippatos (2007). Second, the treatment of deposits as an intermediate product in the production stage addresses the popular ‘deposit dilemma' that exists in the bank efficiency literature as a result of a disagreement between the intermediation and production approaches developed by Sealey and Lindley (1977) and Benston and Smith (1976), respectively, for selecting bank inputs and outputs. Here, we neither treat deposits as an input as proposed in the intermediation approach nor as an output as advocated in the production approach. Instead, we treat deposits as an intermediate output purely, as suggested by Holod and Lewis (2011).

In stage 2, which we refer to as an operating stage, it is postulated that the bank uses deposits (an intermediate product originating in stage 1) along with inter-bank borrowings (an additional controlled input to this stage) and non-performing loans from the previous period (an undesirable input to this stage) to produce a portfolio of earning assets and income from off-balance sheet activities. There is no denying the fact that previously incurred problem loans constrain the lending activities of the current period. For this reason, we view the NPLs from the previous period as an undesirable input in stage 2. The treatment of previously incurred bad loans altogether is in line with proposals by Akther *et al.* (2013) and Fukuyama and Weber (2013). Three desirable final outputs of this stage are performing loans, securities investments, and non-interest income. One of the inescapable by-products of the lending activities of a bank is non-performing loans, which is considered an undesirable final output here. The inclusion of non-performing loans as an undesirable final output is entirely in accordance with the contemporary bank efficiency literature that amply infers that not accounting for NPLs leads to substantially distorted estimates of bank efficiency and productivity. Some prominent bank efficiency studies that include non-performing loans as a jointly produced undesirable by-product of the loan production process include Akther *et al.* (2013), Bansal *et al.* (2022), Fujii *et al.* (2014), Fukuyama and Weber (2013), Fukuyama and Matousek (2017), Park and Weber (2006), and Partovi and Matousek (2018), amongst others.

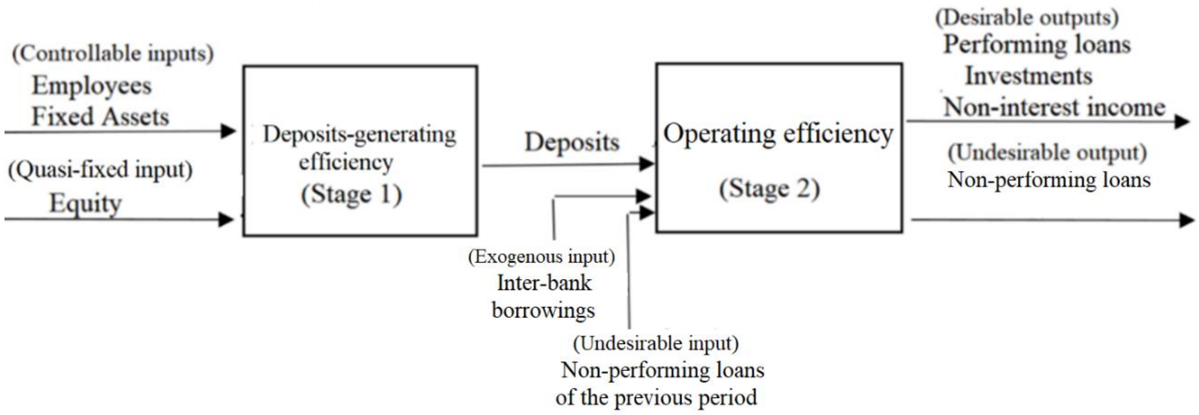


Figure 1: Two-stage production process of a typical bank.

One of the key characteristics of the two-stage network production model outlined above is that it is competent for delivering risk-adjusted efficiency estimates for banking firms. The most recent bank efficiency literature recognises that for a fairer and more accurate assessment of bank performance, an input-output model specification for a banking firm should include at least two risk management control variables depending on data availability along with the standard inputs and outputs (see Simper *et al.*, 2017 for more details). The extant literature suggests three prominent risk control variables: loan loss provisions and bank equity as good (but uncontrollable) inputs and non-performing loans as a bad (undesirable) output. Here, it is reasonable to conclude that the above-described two-stage network structure is optimally designed to derive bank efficiency estimates since it includes two risk control variables (equity and NPLs).

3.2 A DDF-based NDEA model with quasi-fixed inputs and undesirable inputs and outputs

Let us assume that the production process of a bank comprises two distinct sub-stages: stage 1 and stage 2. Further, assume that a typical bank j $(j=1,...,J)$ uses I controllable inputs $\mathbf{x}_j=(x_{1j},...,x_{Ij})\in\Re^I_+$ and K uncontrollable (quasi-fixed) inputs $\mathbf{f}_j=(f_{1j},...,f_{Kj})\in\Re^K_+$ to produce D intermediate products $\mathbf{z}_j=(z_{1j},...,z_{Dj})\in\Re^D_+$ in stage 1. The intermediate products are then used as inputs along with L additional controllable inputs $\mathbf{q}_j=(q_{1j},...,q_{Lj})\in\Re^L_+$ and P undesirable (bad) inputs $\mathbf{b}_j=(b_{1j},...,b_{Pj})\in\Re^P_+$ to produce R desirable (good) outputs $\mathbf{y}_j=(y_{1j},...,y_{Rj})\in\Re^R_+$ and S undesirable (bad) outputs $\mathbf{u}_j=(u_{1j},...,u_{Sj})\in\Re^S_+$ in stage 2. A typical bank faces two production possibility sets: T^1 and T^2, which indicate the production technology of the first and second stages, respectively. T^1 and T^2 can be represented by:

$$T^1=\left\{(\mathbf{x}\ ,\mathbf{f}\ \ ,\mathbf{z}\ )\middle|(\mathbf{x}\ \in\Re^I_+\ ,\mathbf{f}\ \ \in\Re^K_+)\text{ can produce }\mathbf{z}\ \ \in\Re^D_+\ \right\} \tag{1}$$

and

$$T^2=\left\{(\mathbf{z}\ ,\mathbf{q}\ ,\mathbf{b}\ ,\mathbf{y}\ ,\mathbf{u}\ )\middle|(\mathbf{z}\ \in\Re^D_+,\mathbf{q}\ \ \in\Re^L_+\ ,\mathbf{b}\ \ \in\Re^P_+)\text{ can produce }(\mathbf{y}\ \ \in\Re^R_+\text{ and }\mathbf{u}\ \ \in\Re^S_+)\ \right\} \tag{2}$$

By combing (1) and (2), we get the network production possibility set (T^N), which is represented as:

$$T_N=\left\{(\mathbf{x},\mathbf{f},\mathbf{z},\mathbf{q},\mathbf{b},\mathbf{y},\mathbf{u})\middle|\begin{array}{l}(\mathbf{x}\in\Re^I_+,\mathbf{f}\in\Re^K_+,\mathbf{q}\in\Re^L_+,\ \mathbf{b}\in\Re^P_+)\text{ can produce}\\(\mathbf{y}\in\Re^R_+\text{ and }\mathbf{u}\in\Re^S_+)\text{ through the production of }\mathbf{z}\in\Re^D_+\end{array}\right\} \tag{3}$$

The directional distance function seeking to augment the final desirable outputs and decrease the controllable and undesirable inputs and undesirable outputs directionally can be defined by the following formulation:

$$\vec{\mathrm{D}}(\mathbf{x},\mathbf{f},\mathbf{z},\mathbf{q},\mathbf{b},\mathbf{y},\mathbf{u};\mathbf{g})=\sup_{\beta^1,\beta^2}\left\{\beta^1+\beta^2:(\mathbf{x}-\beta^1g_x,\mathbf{f},\mathbf{z},\mathbf{q}-\beta^2g_q,\mathbf{b}-\beta^2g_b,\mathbf{y}+\beta^2g_y,\mathbf{u}-\beta^2g_u)\in T^N)\right\} \tag{4}$$

where the nonzero vector $\mathbf{g}=(g_x,g_q,g_b,g_y,g_u)$ determines the directions in which the controllable inputs of stage 1, controllable inputs of stage 2, undesirable inputs of stage 2, final desirable outputs, and final undesirable outputs of stage 2 are scaled, and the technology reference set T^N satisfies the assumptions of variable returns-to-scale, weak disposability of undesirable inputs, strong disposability of desirable outputs and (controllable and uncontrollable) inputs, and weak disposability of undesirable outputs. DEA piecewise reference technologies T^1, T^2 and T^N under variable returns-to-scale can be, respectively, constructed as follows:

$$T^1 = \left\{ \begin{array}{l} (\mathbf{x}, \mathbf{f}, \mathbf{z}): \sum_{j \in J} \lambda_j x_{ij} \le x_i, \sum_{j \in J} \lambda_j f_{kj} \le f_k, \sum_{j \in J} \lambda_j z_{dj} \ge z_d,\ \lambda_j \ge 0, \\ \qquad i = 1, \ldots, I, k = 1, \ldots, K, d = 1, \ldots, D, j = 1, \ldots, J \end{array} \right\} \tag{5}$$

$$T^2 = \left\{ \begin{array}{l} (\mathbf{z}, \mathbf{q}, \mathbf{b}, \mathbf{y}, \mathbf{u}): \sum_{j \in J} \mu_j z_{dj} \le z_d, \sum_{j \in J} \mu_j q_{lj} \le q_l, \sum_{j \in J} \mu_j b_{pj} = b_p, \sum_{j \in J} \mu_j y_{rj} \ge y_r, \sum_{j \in J} \mu_j u_{sj} = u_s, \\ \qquad \mu_j \ge 0, d = 1, \ldots, D, l = 1, \ldots, L, p = 1, \ldots, P, r = 1, \ldots, R, s = 1, \ldots, S, j = 1, \ldots, J \end{array} \right\} \tag{6}$$

and

$$T^N = \left\{ \begin{array}{l} (\mathbf{x}, \mathbf{f}, \mathbf{z}, \mathbf{q}, \mathbf{b}, \mathbf{y}, \mathbf{u}): \sum_{j \in J} \lambda_j x_{ij} \le x_i, \sum_{j \in J} \lambda_j f_{kj} \le f_k, \sum_{j \in J} \lambda_j z_{dj} \ge z_d, \sum_{j \in J} \mu_j z_{dj} \le z_d, \\ \sum_{j \in J} \mu_j q_{lj} \le q_l, \sum_{j \in J} \mu_j b_{pj} = b_p,\ \sum_{j \in J} \mu_j y_{rj} \ge y_r, \sum_{j \in J} \mu_j u_{sj} = u_s, \lambda_j, \mu_j \ge 0, i = 1, \ldots, I, \\ k = 1, \ldots, K, d = 1, \ldots, D, l = 1, \ldots, L, p = 1, \ldots, P, r = 1, \ldots, R, s = 1, \ldots, S, j = 1, \ldots, J \end{array} \right\} \tag{7}$$

where λ_j and μ_j $(j = 1, \ldots, J)$ are the intensity variables associated with the first and second stages under the network production technology, respectively.

Given the two-stage network technology set defined in (7), by choosing an observed input-output vector $\mathbf{g} = (g_x, g_f, g_z, g_q, g_b, g_y, g_u) = (-\mathbf{x}_o, 0, 0, -\mathbf{q}_o, -\mathbf{b}_o, \mathbf{y}_o, -\mathbf{u}_o)$ of bank *o*, the inefficiency of this bank for the whole system can be obtained by solving the following linear programming model under the VRS assumption:

$$\vec{D}\left(\mathbf{x}, \mathbf{f}, \mathbf{z}, \mathbf{q}, \mathbf{b}, \mathbf{y}, \mathbf{u}; g\right) = \max \beta = \left(w^1 \beta_o^1 + w^2 \beta_o^2 \right) \tag{8}$$

subject to

Stage 1 constraints

$$\sum_{j=1}^{J} \lambda_j x_{ij} \le (1 - \beta_o^1) x_{io}, \quad i = 1, \ldots, I \tag{8.1}$$

$$\sum_{j=1}^{J} \lambda_j f_{kj} \le f_{ko}, \qquad n = 1, \ldots, N \tag{8.2}$$

$$\sum_{j=1}^{J} \lambda_j z_{dj} \ge z_{do}, \qquad d = 1, \ldots, D \tag{8.3}$$

Stage 2 constraints

$$\sum_{j=1}^{J} \mu_j z_{dj} \le z_{do}, \qquad d = 1,...,D \qquad (8.4)$$

$$\sum_{j=1}^{J} \mu_j q_{lj} \le (1-\beta_o^2) q_{lo}, \quad l = 1,...,L \qquad (8.5)$$

$$\sum_{j=1}^{J} \mu_j b_{pj} = (1-\beta_o^2) b_{po}, \quad p = 1,...,P \qquad (8.6)$$

$$\sum_{j=1}^{J} \mu_j y_{rj} \ge (1+\beta_o^2) y_{ro}, \quad r = 1,...,R \qquad (8.7)$$

$$\sum_{j=1}^{J} \mu_j u_{sj} = (1-\beta_o^2) y_{so}, \quad s = 1,...,S \qquad (8.8)$$

Generic constraints

$$\sum_{j=1}^{J} \lambda_j = 1, \qquad (8.9)$$

$$\sum_{j=1}^{J} \mu_j = 1, \qquad (8.10)$$

$$\lambda_j, \mu_j \ge 0 \qquad j = 1,..., J \qquad (8.11)$$

where the subindex o is associated with the bank whose efficiency is being evaluated; λs and μs are the intensity variables of stage 1 and stage 2, respectively, which serve to construct the reference technology as convex combinations of the observed data; $\vec{D}(\mathbf{x},\mathbf{f},\mathbf{z},\mathbf{q},\mathbf{b},\mathbf{y},\mathbf{u};g)$ serves as a measure of technical inefficiency of the system; β_o^1 is an input-oriented measure of inefficiency in stage 1 and measures the maximum proportion reduction of inputs of this stage; β_o^2 is a non-oriented inefficiency measure of stage 2 and captures the simultaneous maximum proportional contraction of inputs and undesirable outputs and expansion of desirable final outputs of this stage; and w^1 and w^2 are positive numbers, which represent the relative importance given to stage 1 and stage 2, respectively, and their sum is standardised to be equal to 1 (*i.e.*, $w^1 + w^2 = 1$). In the present study, we adopt the same weighting scheme as Chao *et al.* (2015) and assign equal weight to both stages with the objective of not introducing any subjective element in the computational process that is hard to defend. Constraints (8.1) and (8.5) have been added for controllable inputs in stages 1 and 2, respectively. Following Färe *et al.* (2004), constraint (8.2) has been added for uncontrollable (quasi-fixed) inputs. Intermediate products are modelled using the inequality constraints (8.3) and (8.4) suggested by Fukuyama and Mirdehghan (2012) rather than the fixed link constraints of equality proposed by Tone and Tsutsui (2009). The equality constraint (8.6) for undesirable inputs models the notion of weak disposability of inputs. Weak disposability of inputs means that if more undesirable inputs are used, more desirable inputs must also be used to offset their negative effect if the final output is to remain constant (Fukuyama & Weber, 2013). Constraint (8.7) indicates that the desirable final outputs of stage 2 are freely disposable. The equality constraint (8.8) for undesirable outputs models the notion of weak disposability of outputs. The case of weak disposability refers to situations when a reduction in undesirable outputs forces a lower production of desirable outputs (Hua & Bian, 2007). Thus, weak disposability here indicates an opportunity cost of reducing undesirable outputs. Finally, constraints (8.9) and (8.10) allow the model to exhibit variable returns-to-scale.

As can be seen in Model (8), the objective function seeks to maximise the weighted inefficiency of stage 1 and stage 2 for bank *o*. Let β_o^*, β_o^{1*} and β_o^{2*} be the optimal values of β_o, β_o^1 and β_o^2. The bank *o* is overall technically efficient with the value $\beta_o^* = 0$, which is possible if the bank is technically efficient in stage 1 with $\beta_o^{1*} = 0$ and also technically efficient in stage 2 with $\beta_o^{2*} = 0$. If $\beta_o^{1*} (\text{or } \beta_o^{2*}) > 0$, then bank *o* operates inefficiently in stage 1 (or stage 2). Bank *o* is overall technically inefficient if it is inefficient in at least one sub-process or stage. The following definitions provide overall efficiency and stage-specific efficiency measures for bank *o*:

Definition 1: In stage 1, the bank focuses on input-contraction (input-oriented) only. Therefore, in stage 1, the efficiency of bank *o* is:

$$E_o^1 = (1 - \beta_o^{1*}).$$

Definition 2: In stage 2, the bank focuses simultaneously on the contraction of exogenous inputs and bad outputs and the expansion of good outputs. Therefore, in stage 2, the efficiency of bank *o* is:

$$E_o^2 = (1 - \beta_o^{2*}) / (1 + \beta_o^{2*}).$$

Definition 3: Bank *o* is efficient if it is efficient in both stages.

For a typical bank, Model (8) identifies three types of technical efficiencies: efficiency of stage 1, efficiency of stage 2, and overall bank inefficiency. Thus, compared to a conventional DEA model, Model (8) offers more useful information to policymakers by detailing the stage-specific performance.

Table 2: Description of variables in the network structure

Stages↓	Variables	Mean (σ) 1-Year prior to pandemic	During pandemic
Controllable inputs of stage 1	Labour	35.08 (48.01)	38.97 (81.04)
	Fixed assets	31.76 (48.87)	30.94 (43.96)
Quasi-fixed input of stage 1	Equity	3072.31 (5978.01)	3577.49 (6256.51)
Stage link	Deposits	7016.82 (12818.60)	7365.39 (13214.48)
Exogenous input of stage 2	Inter-bank borrowings	2085.81 (5396.33)	2157.05 (8212.25)
Undesirable input of stage 2	Non-performing loans of the previous period	152.16 (298.29)	100.45 (178.75)
Desirable outputs of stage 2	Investments	5517.50 (11557.17)	6429.92 (14135.95)
	Other income	219.88 (672.73)	241.44 (546.68)
	Performing loans	4749.40 (7955.99)	4076.22 (6457.62)
Undesirable output of stage 2	Non-performing loans of the current period	104.79 (176.87)	121.52 (320.21)

Notes: Amount in millions. Except for labour, which is expressed as a per branch value, all other reported values are expressed as price deflated per bank branch. The figures in parentheses are standard deviations (σ).
Source: Authors' calculations.

3.3 Data

We collect the required bank-level data to compute efficiency from various issues of the "Statistical Tables Relating to Banks in India" (an official annual publication of the Reserve Bank of India). The dataset includes banks from all ownership groups, including public, private, and foreign banks that were active in India from 2014/15 to 2020/21[4]. As noted in Section 2, as of March-end 2021, the Indian banking industry consisted of 12 state-owned banks, with the Government of India owning a majority stake. In addition, the banking industry has 21 private banks (PBs) and 45 foreign banks (FBs). In the present study, we confine to these three bank groups as they constitute 90 percent of the banking business in India. Before computation, we made a few data adjustments. First, we only consider banks that have been in operation for at least three years and have at least three branches. Second, all the controllable, uncontrollable, and undesirable inputs and outputs (which are monetary in nature) are deflated using the

[4] It is important to note that in India, a bank's annual financial statement is prepared from April 1 to March 31. For example, the fiscal year 2020/21, which runs from April 1, 2020, to March 31, 2021, could be referred to as the financial year 2021. As a result, only one year's worth of financial data for the pandemic period, 2020/21, is currently accessible.

implicit price deflator of GDP (with base 2011/12=100). Third, we normalise the variables by a number of branches to reduce the noise in the dataset.

To determine the immediate impact of the COVID-19 outbreak on the bank's efficiency, the entire study period is divided into sub-periods. We examine how deposits-generating and operating efficiencies changed over time in the pre-pandemic period (2014/15 to 2019/20), just 1-year prior to the pandemic (2019/20), and during the pandemic period (2020/21). In particular, we compare the mean efficiency levels in the pre-pandemic and just 1-year prior to the pandemic to those during the pandemic year. Note that for the pandemic period, bank-level financial data for only one year (*i.e.*, 2020/21) are currently available. Hence, we are constrained to capture only the immediate effect of the COVID-19 pandemic on bank efficiency.

4. Empirical results

4.1 Magnitude of deposits-generating, operating, and overall (in)efficiencies

This section documents the observed differences in deposits-generating, operating, and overall (in)efficiencies across bank ownership groups and provides a broad overview of bank efficiency in India. Table 3 shows the yearly estimates of mean efficiency scores. During the sample period, we observe that a typical bank operating in India has ample room for efficiency improvement in both stages of the production process. Specifically, we find that, on average, a typical bank has scope for efficiency improvement of roughly 30 percent in both deposits-generating efficiency (36.5 percent) and operating efficiency (30.4 percent). The observed average overall inefficiency rate of 33.3 percent for a typical bank is massive by any standard. Interestingly, the temporal analysis reveals that operating efficiency has increased more rapidly than deposits-generating efficiency and overall efficiency.

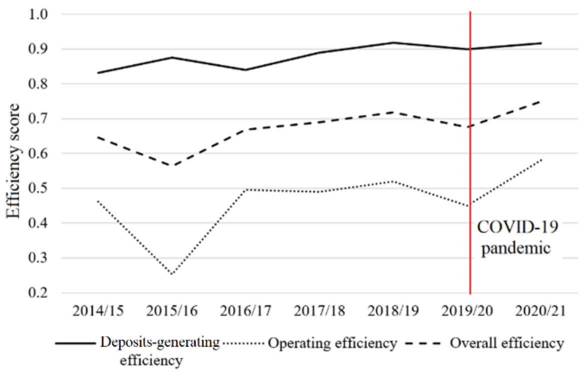
Table 3: Year-wise mean deposits, operating, and overall efficiencies (2014/15-2020/21)

Efficiency↓	Year	All banks	Public sector banks (PSBs)	Private banks (PBs)	Foreign banks (FBs)
Deposits-generating efficiency $\left(\bar{E}^1\right)$	2014/15	0.564 (0.299)	0.832 (0.139)	0.583 (0.225)	0.370 (0.268)
	2015/16	0.590 (0.312)	0.876 (0.119)	0.626 (0.241)	0.358 (0.259)
	2016/17	0.671 (0.267)	0.840 (0.889)	0.625 (0.248)	0.547 (0.301)
	2017/18	0.674 (0.284)	0.889 (0.088)	0.695 (0.224)	0.508 (0.308)
	2018/19	0.698 (0.286)	0.918 (0.088)	0.711 (0.255)	0.567 (0.302)
	2019/20	0.625 (0.314)	0.899 (0.111)	0.563 (0.304)	0.513 (0.311)
	2020/21	0.632(0.302)↑	0.917 (0.095)↑	0.601(0.282)↑	0.544 (0.307)↑
	Mean (σ)	***0.635*** *(0.297)*	***0.876*** *(0.116)*	***0.629*** *(0.256)*	***0.487*** *(0.301)*
Operating efficiency $\left(\bar{E}^2\right)$	2014/15	0.733 (0.268)	0.461 (0.152)	0.666 (0.216)	0.953 (0.131)
	2015/16	0.627 (0.349)	0.253 (0.094)	0.525 (0.274)	0.961 (0.102)
	2016/17	0.696 (0.306)	0.496 (0.178)	0.554 (0.333)	0.988 (0.058)
	2017/18	0.637 (0.316)	0.490 (0.132)	0.397 (0.328)	0.906 (0.162)
	2018/19	0.678 (0.270)	0.519 (0.121)	0.511 (0.254)	0.867 (0.212)
	2019/20	0.736 (0.251)	0.450 (0.144)	0.765 (0.212)	0.878 (0.185)
	2020/21	0.781(0.228)↑	0.581 (0.179)↑	0.721 (0.245)↓	0.899 (0.157)↑
	Mean (σ)	***0.696*** *(0.291)*	***0.467*** *(0.171)*	***0.592*** *(0.291)*	***0.922*** *(0.157)*
Overall efficiency $\left(\bar{E}\right)$	2014/15	0.648 (0.147)	0.646 (0.096)	0.626 (0.207)	0.661 (0.142)
	2015/16	0.609 (0.159)	0.564 (0.078)	0.576 (0.235)	0.659 (0.659)
	2016/17	0.683 (0.188)	0.668 (0.106)	0.593 (0.258)	0.767 (0.153)
	2017/18	0.655 (0.177)	0.689 (0.073)	0.556 (0.224)	0.707 (0.162)
	2018/19	0.688 (0.184)	0.718 (0.065)	0.611 (0.610)	0.717 (0.192)
	2019/20	0.681 (0.166)	0.675 (0.094)	0.664 (0.223)	0.696 (0.181)
	2020/21	0.707(0.176)↑	0.749 (0.010)↑	0.661 (0.193)↓	0.722(0.148)↑
	Mean (σ)	***0.667*** *(0.173)*	***0.673*** *(0.102)*	***0.612*** *(0.225)*	***0.704*** *(0.163)*

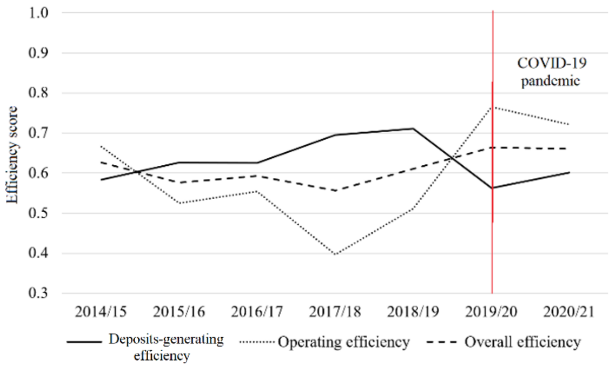
Notes: This table presents the mean efficiency estimates for the banking industry as a whole and by ownership groups. The figures in parentheses are standard deviations (σ). In the pandemic year 2020/21, the arrow ↑ (or ↓) indicates the increase (or decrease) in mean efficiency levels.
Source: Authors' calculations.

Next, we look at the efficiency asymmetries between banks under different ownership groups. We achieve this by comparing the magnitudes of deposits-generating, operating, and overall efficiency levels among public, private, and foreign banks. The yearly mean efficiency estimates are reported in Table 3 and depicted in Figure 2. We note that despite large efficiency gaps in deposits-generating and operating performance between bank groups, public and foreign bank groups have improved their performance on both fronts, especially in the year 2020/21. In terms of deposits-generating efficiency, PSBs do better than the banks in their peer groups, while foreign banks perform the worst in this dimension of bank efficiency. This is well reflected by the observed grand means of deposits-generating efficiency that turns out to be 0.876 and 0.487 for PSBs and FBs, respectively. Thus, there was a huge gap of 38.9 percent in the deposits-generating efficiency of PSBs and FBs. Private banks, on the other hand, had a (-)4.4 percent decline in operating performance in the latter year (0.721 in 2020/21 vis-à-vis 0.765 in 2019/20). This decline may be attributable to reduced off-balance sheet exposures of PBs and a decline in non-interest revenue from 32.6 percent in 2019/20 to (-)2.9 percent in

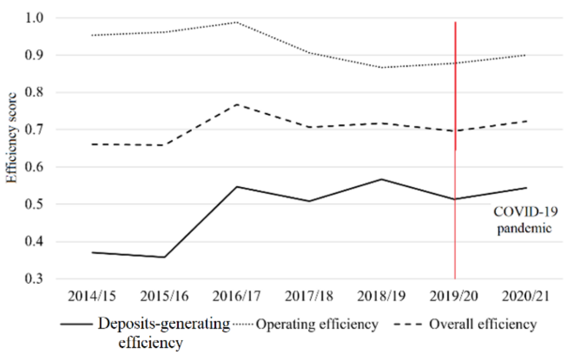
2020/21. Better performance of PSBs on deposits-generating efficiency could be attributed to increased depositors' confidence and strong government support for these banks during times of crisis. Foreign banks have demonstrated sound efficiency performance in the operating stage of the production process when compared to their peers.



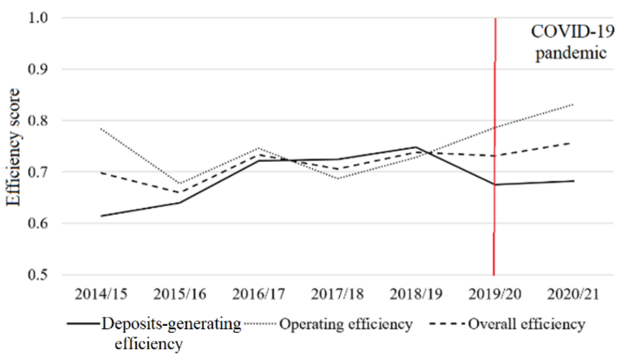
(a) Public Sector Banks



(b) Private Banks



(c) Foreign Banks



(d) All Banks

Figure 2: Trends in bank efficiency during 2014/15-2020/21.

4.2 COVID-19 pandemic and bank efficiency: Asymmetries across ownership groups

We now do a focused investigation into whether Indian banks were able to weather the COVID-19 storm. Based on the results reported in Table 4, we draw some interesting conclusions by comparing bank efficiency estimates from the pre-pandemic period (2014/15 to 2019/20) and just 1-year prior to the pandemic (2019/20) with those reported for the pandemic year (2020/21). Regardless of bank group, the COVID-19 crisis essentially had little impact on overall bank efficiency levels in India. Rather, it is fascinating that the overall efficiency of PSBs increased by 8.9 percent during the pandemic year compared to the pre-pandemic period (0.749 vis-à-vis 0.660). Using the Simar-Zelenyuk-adapted-Li (SZL) test developed by Simar and Zelenyuk (2006)[5], we observe a significant difference in the

[5] We test the null hypothesis of equality of probability distributions of DDF-NDEA efficiency levels utilising the Simar-Zelenyuk-adapted-Li (SZL) test, which is a bootstrapped-based statistical tool. Simar and Zelenyuk (2006) adapted the test developed by Li (1996) to the DEA context, where score lies in 0 and 1.

conditional distribution of overall efficiency between pre-pandemic and pandemic periods. Our findings support the RBI's observation that financial services, notably banking, have exhibited resilience in their early reaction to the global health pandemic and have weathered the COVID-19 storm (Reserve Bank of India, 2022).

Table 4: COVID-19 pandemic, ownership groups, and bank efficiency

Efficiency↓	**Bank groups**	**(1) Pre-Pandemic**	**(2) Just 1-year prior to Pandemic**	**(3) During Pandemic**	**(4) Δ_1** (in %)	**(5) Δ_2** (in %)
Deposits-	All Banks	0.637	0.625	0.632	-0.5[a]	0.7[a]
generating	PSBs	0.876	0.899	0.917	4.1[a]	1.8[a]
efficiency	PBs	0.634	0.563	0.601	-3.3[a]	3.8[a]
$\bar{E}^1$	FBs	0.477	0.513	0.544	6.7[a]	***3.1****
Operating	All Banks	0.685	0.736	0.781	9.7[a]	4.5[a]
efficiency	PSBs	0.445	0.450	0.581	***13.6****	13.1[a]
$\bar{E}^2$	PBs	0.570	0.765	0.721	15.1[a]	-4.4[a]
	FBs	0.926	0.878	0.900	***-2.6*****	2.2[a]
Overall	All Banks	0.661	0.681	0.707	4.6[a]	2.6[a]
efficiency	PSBs	0.660	0.675	0.749	***8.9****	7.4[a]
$\bar{E}$	PBs	0.604	0.664	0.661	5.7[a]	-0.3[a]
	FBs	0.701	0.696	0.722	2.1[a]	2.6[a]

Note: This table reports the mean efficiency across distinct ownership groups in the pre-pandemic, one-year prior to pandemic, and pandemic periods. Pre-pandemic period= 2014/15-2019/20, Just 1-year prior to pandemic= 2019/20, During Pandemic= 2020/21. In the last two columns, $\Delta_1= \bar{E}_{\text{During Pandemic}} - \bar{E}_{\text{Pre-Pandemic}}$, $\Delta_2= \bar{E}_{\text{During Pandemic}} - \bar{E}_{\text{Just 1-year before Pandemic}}$. [a] refers to not rejecting the null hypothesis for the Simar and Zelenyuk (SZL) test of no significant difference in the conditional efficiency distributions (*pdf*) as $H_0 : pdf\ (E_{\text{During Pandemic}})_t = pdf\ (E_{\text{Pre-Pandemic}})_t$ in Column (4) and $H_0 : pdf\ (E_{\text{During Pandemic}})_t = pdf\left(E_{\text{Just 1-year before Pandemic}}\right)_t$ in Column (5). The figures in bold and italic indicate that the change during the pandemic is statistically significant. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.
Source: Authors' calculations.

During the pandemic period, PSBs excelled over their counterparts in terms of deposits-generating efficiency, with an average efficiency of 0.917, which was significantly higher than 0.601 and 0.544 for PBs and FBs, respectively (see Table 4). Although PBs were less deposit-generating efficient during the pandemic year when compared to the pre-pandemic period, the decline in efficiency was not statistically significant. The SZL test found that the mean deposits-generating efficiency of FBs significantly improved by 3.3 percent during the pandemic year compared to the level observed just 1-year prior to the COVID-19 outbreak. Therefore, the analysis reveals that during the pre-pandemic and pandemic periods, the observed deposits-generating efficiency rating of bank groups was PSBs>PBs>FBs. As far as operating efficiency is concerned, we note that, on average, PSBs reported an increase of 13.6 percent in operating efficiency during the pandemic year compared to the pre-pandemic period (see Table 4). FBs, on the other hand, experienced a (-)2.6 percent decline in efficiency at this stage. The observed decline is attributable to the accrual of fresh NPLs and a slight decline in their off-balance sheet exposures during the pandemic year. Despite this, FBs continue to outperform PBs and PSBs in terms of operational performance (FBs=0.900>PBs=0.721>PSBs=0.581).

Furthermore, we deploy the non-parametric Kernel density method to intuitively analyse the trend and distribution characteristics of deposits-generating and operating efficiency levels in just 1-year prior to the pandemic and during the pandemic years. The density curves for PSB, PB, and FB groups corresponding to stage-wise efficiency levels are shown in Figures 3(i)-(ix). We find that the kernel densities narrate a similar tale. Based on the shape of the density curves, we can see that the overall efficiency of PSBs peaked at approximately 0.7 during the pandemic year, while deposits-generating and operating efficiency levels appeared to be bimodal, with a double peak and slightly skewed to the right, depicting a higher efficiency in the pandemic year (see Figures 3(i)-(ii)). At a peak density of 1, several PSBs have made significant progress in the efficiency with which they generate deposits. The operating efficiency has a flat double peak in 2020-21, suggesting that some PSBs have larger operating efficiency than others. The majority of PSBs peaked at around 0.5, thus indicating a sizable room to boost operating efficiency in the long run. The density curve for PBs in the pandemic year is somewhat to the left of the density curve, peaking at 0.9 in the pandemic year instead of 1 in the years prior to the pandemic. Overall, banks need to strengthen the efficiency at both stages of production and make production activities to generate lower impaired loans and higher operating incomes. As also shown in Table 5, only a handful of PSBs reported a decline in efficiency across distinct sub-processes and the entire production process, indicating that PSBs remained resilient during the pandemic year. When comparing various bank groups, we observe that the deposits-generating efficiency of 55 percent of foreign banks declined (see Table 5). Over 50 percent of the sampled banks reported an increase in operational efficiency.

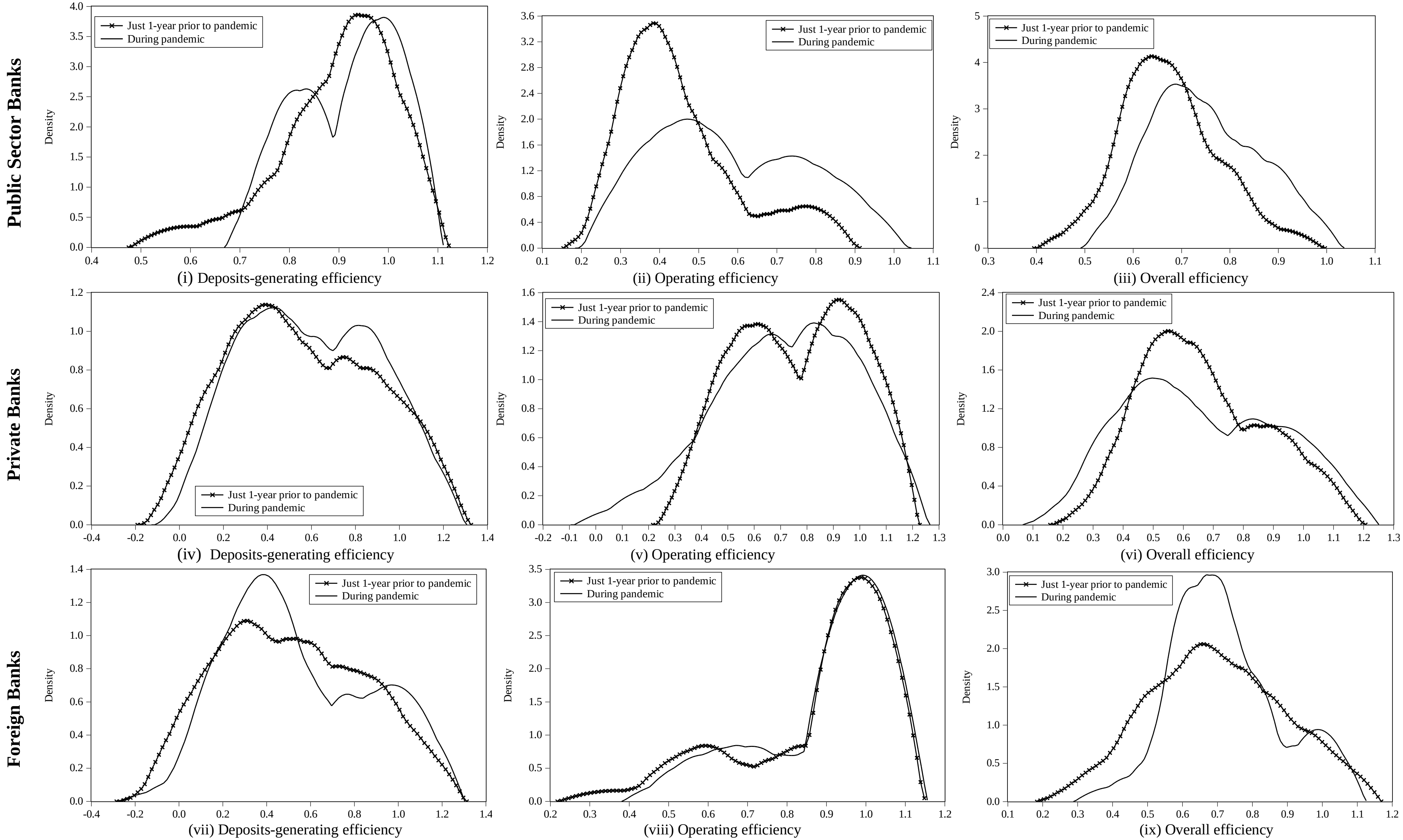


Figure 3: Kernel distributions of efficiency scores for bank groups in 1-year prior and during pandemic periods.

Table 5: Number (Percentage) of banks that experienced a decline in efficiency during the pandemic

Bank groups↓	Deposits-generating efficiency	Operating efficiency	Overall efficiency
Public sector banks (12)	5 (16)	3 (11)	3 (11)
Private banks (21)	9 (29)	10 (36)	10 (37)
Foreign banks (27)	17 (55)	15 (53)	14 (52)
All banks (60)	31 (100)	28 (100)	27 (100)

Notes: This table reflects the number and percentage of banks that experienced a decline in their efficiency levels during the pandemic compared to the efficiency observed in just 1-year prior to the pandemic. Figures in parentheses indicate the percentage with respect to the total number of banks that experienced a fall in efficiency levels.
Source: Authors' calculations.

To get support for the results of the two-stage network DEA efficiency analysis presented above, we supplemented the analysis by evaluating the behaviour of traditional financial ratios during the COVID-19 outbreak. For this purpose, we followed Hassan *et al*. (2022) to see how financial ratios changed during the pandemic period compared to just 1-year prior to the pandemic. Selected financial ratios during the pandemic and just 1-year prior to the pandemic are reported in Appendix Table C1. During the pandemic year, the asset quality of scheduled commercial banks, particularly of PSBs, improved. This is evidenced by the decline in gross NPLs and net NPLs ratios for PSBs and PBs, implying domestic banks have weathered the COVID-19 storm. Based on the *t*-test, we find that the gross NPLs and net NPLs ratios for PSBs are statistically significantly lower than those for PBs. On the other hand, FBs experienced fresh NPLs accruals and deteriorating asset quality as a result of the merger of troubled private banks with foreign banks (Reserve Bank of India, 2021c). It is interesting to note that the Indian banking industry went through a prolonged forbearance period from April 2008 to August 2015 that followed immediately after the GFC. This has led banks to take undue risk by lending to less productive and inefficient projects without proper credit screening and monitoring of loans. This double-digit credit growth failed to materialise and resulted in a phenomenon of the "zombification" and "evergreening" of balance sheets by banks and corporate companies with an increased volume of dead loans (Government of India, 2021). This has led to the twin-balance sheet crisis in India. However, sobered the fresh lending, adoption of resolution measures like the Asset Quality Review and Insolvency and Bankruptcy Code, etc., propelled the persistent exercise of banks' balance sheet clean-up and subsequently contributed to a decline in gross NPLs and net NPLs ratios. The improved asset quality of domestic banks thus aided in enhanced profitability in terms of ROA and ROE. We found that the industry's average ROA and ROE improved significantly in 2020/21 compared to 2019/20. In addition, the banks' interest earnings exceeded their interest expenses in 2020/21, indicating a slight improvement in the net interest margin (NIM). There was a moderate decline in the NIM level for bank groups, but this did not appear to be statistically significant. Overall, the inferences drawn from our research, which are based on network DEA-based estimates of efficiency, are consistent with those derived from financial ratio analysis.

4.3 COVID-19 pandemic and bank efficiency: Asymmetries across size classes

After documenting the efficiency analysis across bank groups, we now test for efficiency disparities across size classes during the crisis. For this, we classify banks into four size classes – very small (VS), small (S), medium (M), and large (L) – based on the quartile values of their total assets. The mean efficiency estimates for each size class are reported in Table 6. We note that large banks outperform small and very small banks in terms of deposits-generating efficiency (L=0.714>M=0.684>S=0.673>VS=0.400) and enjoy a strong position in the Indian banking system, with a significant market share in deposits. Regarding operating efficiency, however, very small, small, and medium-sized banks outperformed large banks, with a mean efficiency gap of 35.7, 34.3, and 22.6 percent, respectively. The results also indicate that large banks increased their operating efficiency by 11.28 percent during the pandemic year (0.452 in the pre-pandemic period vis-à-vis 0.565 during the pandemic period). In all, large banks were found to be less efficient than medium and small banks in terms of their operating and overall efficiencies during the study period.

Table 6: COVID-19 pandemic, size and bank efficiency

Efficiency↓	**Bank groups**	**(1) Pre-Pandemic**	**(2) Just 1-year prior to Pandemic**	**(3) During Pandemic**	**(4) Δ_1** (in %)	**(5) Δ_2** (in %)
Deposits-generating efficiency $\overline{E}^1$	Very small	0.401	0.345	0.400	-0.15[a]	5.508[a]
	Small	0.565	0.614	0.673	10.75[a]	5.917[a]
	Medium	0.726	0.712	0.684	-4.18[a]	-2.790[a]
	Large	0.748	0.723	0.714	-3.37[a]	-0.828[a]
Operating efficiency $\overline{E}^2$	Very small	0.929	0.856	0.922	-0.71[a]	6.628[a]
	Small	0.865	0.923	0.908	4.25[a]	-1.495[a]
	Medium	0.622	0.710	0.791	16.83[a]	8.063[a]
	Large	0.452	0.551	0.565	***11.28*****	1.381[a]
Overall efficiency $\overline{E}$	Very small	0.665	0.600	0.661	-0.43[a]	6.068[a]
	Small	0.715	0.768	0.790	7.50[a]	2.211[a]
	Medium	0.674	0.711	0.737	6.32[a]	2.636[a]
	Large	0.600	0.637	0.639	3.95[a]	0.277[a]

Note: This table reports the mean efficiency across size classes in the pre-pandemic, 1-year prior to pandemic, and pandemic periods. Pre-pandemic period= 2014/15-2019/20, Just 1-year prior to pandemic= 2019/20, During Pandemic= 2020/21. In the last two columns, $\Delta_1 = \overline{E}_{\text{During Pandemic}} - \overline{E}_{\text{Pre-Pandemic}}$, $\Delta_2 = \overline{E}_{\text{During Pandemic}} - \overline{E}_{\text{Just 1-year before Pandemic}}$. [a] refers to not rejecting the null hypothesis for the SZL test of no significant difference in the conditional efficiency distributions (*pdf*) as $H_0: pdf\ (E_{\text{During Pandemic}})_t = pdf\ (E_{\text{Pre-Pandemic}})_t$ in Column (4) and $H_0: pdf\ (E_{\text{During Pandemic}})_t = pdf\left(E_{\text{Just 1-year before Pandemic}}\right)_t$ Column (5). The figures in bold and italic indicate that the change during the pandemic is statistically significant. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

Source: Authors' calculations.

4.4 Econometric validation of the impact of the COVID-19 pandemic on bank efficiency

To econometrically investigate the impact of COVID-19 on efficiency levels, we follow Wanke and Barros (2014) and Gulati and Kumar (2017) and estimate the regression equations (2) and (3) using a bootstrapped truncated regression algorithm (Algorithm #1) by Simar and Wilson (2007).

$$\hat{E}_{j,t} = \alpha_0 + \beta_0 PANDEMIC_t + \sum_{k=1}^{K} \varphi_k D\_OWN_{j,t}^{k} + \sum_{k=1}^{K} \delta_k D\_OWN_{j,t}^{k} \times PANDEMIC_t + \lambda_1 SIZE_{j,t} + \lambda_2 SIZE_{j,t} \times PANDEMIC_t + \sum_{m=1}^{M} \gamma_m X_{j,t}^{m} + \varepsilon_{j,t} \quad (9)$$

$$\hat{E}_{j,t} = \alpha_0^{'} + \beta_0^{'} PANDEMIC_t + \sum_{k=1}^{K} \varphi_k^{'} D\_OWN_{j,t}^{k} + \sum_{k=1}^{k} \delta_k^{'} D\_OWN_{j,t}^{k} \times PANDEMIC_t + \sum_{l=1}^{L} \lambda_l^{'} D\_SIZE_{j,t}^{l} + \sum_{l=1}^{L} \phi_l^{'} D\_SIZE_{j,t}^{l} \times PANDEMIC_t + \sum_{m=1}^{M} \gamma_m^{'} X_{j,t}^{m} + \varepsilon_{j,t} \quad (10)$$

where $\hat{E}_{j,t}$ represents the efficiency estimate for bank *j* in period *t*. αs, βs, δs, λs, φs, ϕs, γs are model coefficients. By using a dummy variable - *PANDEMIC* – with a value of 1 for the period of the COVID-19 (2020/21) and 0 otherwise, we are able to capture the immediate impact of the pandemic on efficiency levels. The sign and magnitude of the estimated coefficient values of β_0 and $\beta_0^{'}$ reflect this impact. We also look at how efficiency varies across bank groups and size classifications. For this, we use two dummy variables for ownership groups (D_OWN), where D_OWN is proxied with *PUBLIC* and *PRIVATE* dummies. Here, *PUBLIC*, which takes a value of 1 for public sector banks, and *PRIVATE*, which takes a value of 1 for private banks. The base group is the foreign banks group. To differentiate between the effects of COVID-19 on different ownership groups, we use the interaction of ownership dummies with the *PANDEMIC* dummy. The estimated coefficients of δ and $\delta^{'}$ will assist in determining whether the COVID-19 outbreak had any distinct effects on efficiency performance across bank groups.

We utilised various model specifications to determine the effect of bank size (*SIZE*) on efficiency performance. In the model specifications (i), (iii), and (v) based on equation (2), we use the natural logarithm of a bank's total assets as a measure of the bank's size (*SIZE*) (Mansour & Moussawi, 2020; Matthews *et al*., 2009). In the specifications (ii), (iv), and (vi) derived from equation (3), three dummies are incorporated for four distinct size classes, *D_SIZE*, where is demoted with *LARGE*, *MEDIUM*, and *SMALL* dummy variables. The very small bank group is taken as a reference category. Additionally, the interaction term of *PANDEMIC* and bank size (*SIZE*) or size dummies (*D_SIZE*) is included to differentiate the impact of COVID-19 on efficiency performance of banks in different size classes. We do not anticipate any *a priori* relationship between *SIZE* and bank efficiency.

Finally, the estimated regression models control for the impact of the profitability (*ROA*), capital adequacy ratio (*CAR*), and diversification effect (*DIV*). The sign of the variable return on assets (a measure of bank profitability) is expected to be positive because a more profitable bank is more likely to be more efficient. There are two strands in the literature regarding the relationship between CAR and efficiency. The first strand is founded on the premise that a risk-averse manager may maintain a high capital buffer at the expense of high-yield products, thereby decreasing the efficiency of the bank. Another strand is that higher capital requirements reduce the risk of insolvency, thereby enhancing the efficiency of banks (Chortareas *et al*., 2011; Harris *et al*., 2013). The *DIV* is the bank income diversification index, which is calculated as a proportion of non-interest income to total assets.

Table 7: Econometric validation using the Simar and Wilson's (2007) approach

Independent Variable ↓	Deposits-generating efficiency (E^1)		Operating efficiency (E^2)		Overall efficiency (E)	
Model specifications→ *Model coefficients↓*	(i)	(ii)	(iii)	(iv)	(v)	(vi)
Constant	0.958***	0.530***	1.011***	0.546***	0.912***	0.684***
	(0.143)	(0.043)	(0.168)	(0.090)	(0.071)	(0.022)
PUBLIC	0.658***	0.647***	-0.244***	-0.271***	0.0258	0.031
	(0.064)	(0.063)	(0.053)	(0.049)	(0.026)	(0.025)
PRIVATE	0.231***	0.205***	-0.254***	-0.302***	-0.088***	-0.102***
	(0.043)	(0.039)	(0.043)	(0.044)	(0.022)	(0.021)
PANDEMIC	0.006	-0.037	0.409	0.099	0.005	-0.015
	(0.363)	(0.082)	(0.416)	(0.133)	(0.188)	(0.044)
PUBLIC×PANDEMIC	0.0144	-0.015	0.153	0.126	0.084	0.057
	(0.224)	(0.214)	(0.132)	(0.121)	(0.079)	(0.072)
PRIVATE×PANDEMIC	-0.092	-0.149	0.143	0.121	0.005	-0.027
	(0.121)	(0.106)	(0.112)	(0.111)	(0.004)	(0.057)
SIZE	-0.073***	-	-0.051*	-	-0.035***	-
	(0.022)		(0.026)		(0.011)	
SIZE×PANDEMIC	0.006	-	-0.049	-	0.0037	-
	(0.062)		(0.064)		(0.031)	
LARGE	-	-0.154***	-	0.043	-	-0.063**
		(0.058)		(0.077)		(0.029)
MEDIUM	-	-0.054	-	0.102	-	-0.0006
		(0.052)		(0.077)		(0.028)
SMALL	-	-0.016	-	0.176**	-	0.039*
		(0.043)		(0.075)		(0.075)
LARGE×PANDEMIC	-	0.122	-	-0.078	-	0.072
		(0.155)		(0.173)		(0.075)
MEDIUM×PANDEMIC	-	0.138	-	-0.007	-	0.076
		(0.132)		(0.175)		(0.073)
SMALL×PANDEMIC	-	0.154	-	0.001	-	0.088
		(0.118)		(0.0904)		(0.067)
ROA	0.012	0.010	-0.009	-0.018	-0.00005	0.0008
	(0.008)	(0.008)	(0.011)	(0.02)	(0.004)	(0.004)
CAR	-0.002***	-0.002***	-0.0004	0.0015	-0.0006***	-0.0003
	(0.0005)	(0.0004)	(0.001)	(0.0018)	(0.0002)	(0.0002)
DIV	-0.053***	-0.045***	0.042	0.064**	-0.0103***	-0.008***
	(0.009)	(0.008)	(0.027)	(0.027)	(0.0027)	(-0.002)
Model diagnostics						
Number of observations	413	413	321	321	474	474
Number of efficient banks	106	106	198	198	45	45
Wald chi^2	177.33***	184.77***	112.95***	122.46***	86.27***	104.13***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes: *, **, and *** indicate statistically significance at 10%, 5%, and 1% levels, respectively. Simar and Wilson's algorithm is run with 10,000 bootstrap replications. The figures in parentheses are bootstrapped standard errors.
Source: Authors' calculations.

The econometric estimates are reported in Table 7. The results validate our previous findings. In particular, we find that there are notable variations in the efficiency of bank groups. During the study period, PSBs are far more efficient in the deposits generation process than their private and foreign counterparts. This is supported by the statistically significant and higher coefficient value of $\hat{\varphi}_1$ (and $\hat{\varphi}_1^{'}$) compared to $\hat{\varphi}_2$ (and $\hat{\varphi}_2^{'}$) in model specifications (i) and (ii). In contrast, foreign banks perform better in the operating stage of the production process in terms of producing desirable outputs such as non-interest income, investments, and performing loans, as well as lowering credit risk emanating from NPLs. This is evidenced by the negative coefficient of φ's for *PUBLIC* and *PRIVATE* dummies in specifications (iii) and (iv). During the sample period, private banks experienced a substantial drop in overall bank efficiency levels. Regarding the effect of the COVID-19 pandemic on the efficiency of banks, we note some interesting findings (see the estimated coefficient of β's). The regression results fully support the aforementioned deduction, indicating that the global health pandemic had no immediate discernible effect on the bank's deposits-generation and operating performance. Furthermore, the insignificant coefficients of $\hat{\delta}$ and $\hat{\delta}$'s show that all bank groups were able to withstand the initial impact of the COVID-19 outbreak. Observed efficiency disparities among bank groups may be attributable to endogenous factors other than the underlined pandemic.

As with control variables, the coefficient of *SIZE* is negative and statistically significant for both stages (see model specifications (i) and (ii)), implying that large banks experienced a loss in efficiency throughout the sample period. This conclusion is further supported by the negative coefficient of the *LARGE* dummy for deposits-generating and overall efficiency in models (ii) and (vi), and the positive coefficient of the *SMALL* dummy for operating and overall performance in models (iv) and (vi). According to the results, CAR and efficiency levels have an inverse relationship. One possible explanation is that banks with higher capital buffers have lower profit margins, which lowers their income-generating efficiency. Finally, income diversification improves a bank's operational performance. Overall, the econometric results indicate that the COVID-19 crisis appears to have had no negative effect on bank efficiency levels in India. Endogenous factors other than the COVID-19 pandemic may be to blame for the observed efficiency disparities among bank groups.

5. Conclusions

The ongoing COVID-19 pandemic has put the banking systems to the test in terms of their resilience to exogenous shocks. This study examined the initial effect of the COVID-19 pandemic on the efficiency of Indian banks. An empirical investigation was carried out for the period from 2014/15 to 2020/21. In doing so, we sought to comprehend the temporal behaviour of bank efficiency during the pre-pandemic (2014/15 to 2019/20), just 1-year prior to the pandemic (2019/20), and the pandemic (2020/21) periods. Additionally, efficiency disparities in response to the coronavirus outbreak were also explored across banks of various ownership groups and size classes. As opposed to the traditional black-box DEA modelling framework used in the majority of previous studies on bank efficiency in India, this study employed a two-stage directional distance function-based network DEA model. The key feature of the two-stage network DEA model used is that it directly includes equity capital and accounts for NPLs in both the current and past periods in the input-output specification while obtaining the risk-adjusted deposits-generating, operating, and overall efficiency estimates.

We draw several intriguing conclusions from this study. The main finding is that the COVID-19 crisis had essentially no initial negative impact on overall bank efficiency levels in India regardless of bank group. This may be due to the result of a flurry of policy interventions and a monetary tightening cycle by the RBI in line with global trends that safeguard the Indian banking sector from the immediate effect of the pandemic outbreak. The results of our study completely align with RBI’s most recent Report on Trends and Progress of Banking in India for the year 2021, the Report on Currency and Finance for the year 2022, and the Economic Survey 2020-21 by the Government of India. Compared to pre-pandemic levels, the results clearly indicate an improvement in the operating efficiency of public sector banks and a drop in the deposits-generating efficiency of foreign banks during the COVID-19 period. This could be due to the time-bound resolution and balance sheet clean-up exercise that helped recover the banks’ lending ability. Although large banks performed better than medium and small banks in generating deposits, they were less efficient in terms of operational and overall efficiencies. The econometric analysis strengthens the previous findings and demonstrates the resilience of Indian banks in the face of potential adverse effects.

The contribution of this study is significant for several reasons. First, it provides empirical evidence on the resilience of Indian banks during the COVID-19 pandemic, which is critical for policymakers and stakeholders. Second, the study highlights the efficiency gains and losses among different ownership types and size classes of banks, which could inform regulatory policies and market strategies. Third, the use of DEA as a prescriptive analytics approach demonstrates the potential of this technique in evaluating the efficiency of complex systems, such as the banking sector. Overall, this study is a valuable contribution to the literature on the impact of COVID-19 on the banking sector and the use of prescriptive analytics in evaluating the efficiency of complex systems.

The results have wide-ranging policy implications. The research suggests that financial policies should be formulated with a strong emphasis on enhancing performing loans and mitigating the fresh accruals of NPLs and impairment risks in the post-pandemic years. In order to prevent bank fraud or loan defaults and increase operational efficiency to support economic growth, the study recommends that banks use early resolution methods and effectively use deployed technology for loan screening and monitoring. In addition, specific measures should be implemented for small banks to increase their deposits-generating efficiency in order to boost their competitiveness in achieving the regulator's goal of efficient financial intermediation. Importantly, since the consequences of the COVID-19 pandemic are still unfolding, and data for the pandemic have been available for just one year, it is crucial that the readers cautiously understand that our results only reflect the initial effects of the COVID-19 pandemic. The long-term impact and dynamic change in response to the evolving circumstances in the post-pandemic are unknown and will require further investigation in the coming years when data for a longer time horizon will be accessible. Moreover, future researchers can consider the impact of the banks' deployed technology and investments in IT infrastructure on their deposits-generating and operating efficiencies amid the crisis.

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Appendix A: Prominent studies on bank efficiency in India

Table A1: Studies on bank efficiency analysis in India

Author(s) (Year)	**Period**	**Efficiency measure**	**Efficiency estimation approach**	**Black-box/ Network production structure**	**Treatment of NPLs**	**Treatment of risk/ equity capital**
Ray and Das (2010)	1997-2003	Cost and Profit efficiency	Cost and Profit-DEA models	Black-box	Yes (Net loans)	Yes (Quasi-fixed input)
Tabak and Tecles (2010)	2000-2006	Technical efficiency	Bayesian SFA	Black-box	No	No
Das and Kumbhakar (2012)	1995-2005	Technical efficiency	Input distance function based hedonic indicator	Black-box	No	No
Fujii *et al*. (2014)	2004-2011	Input and output technical inefficiencies	Weighted Russell DDF and MLPI	Black-box	Yes (Undesirable output)	No
Tzeremes (2015)	2004-2012	Time-dependent technical efficiency	Conditional DDF	Black-box	No	No
Kumar *et al*. (2016)	1996-2010	Technical efficiency and TFP	BCC and MPI	Black-box	No	No
Gulati and Kumar (2017)	2011-2013	Intermediation and Operating efficiency	Two-stage NDEA	Network structure (cross-sectional setting)	No	No
Jayaraman and Bhuyan (2020)	2005-2017	Nerlovian profit efficiency	DDF	Black-box	Yes (Undesirable output)	No
Mallick *et al*. (2020)	1996-2014	Technical efficiency	Time-dependent non-parametric efficiency	Black-box	No	No
Wanke *et al*. (2021)	2005-2017		Dynamic SBM	Network structure	Yes (Undesirable carry over)	No
Gulati (2022)	2001-2019	Technical efficiency	DDF-meta frontier analysis	Black-box	Yes (Undesirable output)	Yes (Quasi-fixed input)
This study	***2015-2021***	***Deposits-generating and Operating efficiencies***	***Two-stage NDEA with quasi-fixed inputs and undesirable input and output***	***Network structure***	***Yes (Undesirable input in t-1 and undesirable output in t)***	***Yes (Quasi-fixed input)***

Source: Authors' elaboration

Appendix B: COVID-19 pandemic and policy responses by the RBI

Appendix Table B1: Major policy responses to COVID-19 by the RBI for the banking sector

Type of policy measures	Policy announcement (March 2020-June 2022)
Monetary Policy Actions and Other Prudential Measures	• Accommodative monetary policy stance with policy repo rate reduced by 115 basis points by the monetary policy committee (MPC) in phases from 5.15 percent to 4.40 percent on March 27, 2020, and a further 40 basis points to 4.00 percent on May 22, 2020. • Reverse repo rate was fixed at 3.35 percent on May 22, 2020, from 4.90 percent on October 4, 2019, with an effective reduction of 155 basis points from October 2019 to May 2020. • Reduction in Cash Reserve Ratio (CRR) by 100 basis points at a low of 3 percent on March 27, 2020, freed up INR 1,370,000 million worth of bank resources. • Restrictions on the distribution of profits in the form of dividend payouts by banks • Maintenance of SLR at 18 percent of their net demand and time liabilities and increased limit up to 22 percent of NDTL under the held-to-maturity (HTM) category for SLR securities up to March 31, 2021 • Ease in credit exposure limits as a one-time measure up to June 2021 • Reduction in the non-essential regulatory reporting requirements by banks • Revision in the priority sector lending guidelines and incremental priority sector credit flow to identified districts. • Advances in loan-to-value limit for loans against gold ornaments and jewellery for non-agricultural purposes till March 2021 • Harmonised bank's investment in debt mutual funds and debt exchange-traded funds • The borrowing facility for banks under MSF (announced on March 27, 2020) was extended further for the period of 6 months till March 31, 2021. MSF rate for banks increased by 100 basis points. • Revised limit for a risk weight of regulatory retail portfolio and individual housing loans
Borrower assistance	• Moratorium on payments for three months between March 1, 2020, and May 31, 2020, and then extended till August 2020. Banks must maintain higher provisions of 10 percent of all such accounts that standstill. • Continue the availability of 2 percent Interest Subvention and 3 percent Prompt Repayment Incentive to farmers for the extended repayment period. • One-time restructuring of loan accounts under Loan Restructuring Framework for COVID-19-related stress announced on August 6, 2020 • Resolution Frameworks 1.0 and 2.0 were announced on August 6, 2020, and May 2021, respectively, for COVID-19 stressed assets and restructuring of corporate, small businesses and MSMEs debts • Caps on interest rates or fees and refund "interest on interest" charged on loans during the moratorium period.
Liquidity and lending support & Insolvency	• Roll out of prudential norms pertaining to capital conservation buffer and the net stable funding ratio (NSFR), and temporary ease on the liquidity coverage ratio (LCR) requirements • OMOs of government securities amounting to INR 150,000 million were announced on March 20, 2020, and INR 200,000 million in two tranches on September 10, 2020, and September 17, 2020. • Auction of Targeted Long-Term Operations (TLTRO) for an aggregate amount of INR 1,000,000 million with tenors of up to three years. • Variable rate term repo auctions for a cumulative/aggregate amount of Rs 1,000,000 million on March 26, 2020 • Injection of 500 billion rupees in the corporate bond market through LTROs • Special refinance facility for a total amount of INR 500,000 million to NABARD, SIDBI and NHB • A line of credit of INR 150,000 million was extended to EXIM bank for a period of 90 days.

Source: Authors' elaboration from Annual Reports and World Bank COVID-19 Financial Response Database

Appendix C: *COVID-19 pandemic and financial ratios*

Appendix Table C1: Selected financial ratios during the pandemic and just 1-year prior to the pandemic

Ratios↓	**All Banks**		**Public Sector Banks**		**Private Banks**		**Foreign Banks**	
Period(s)→	**Just 1-year prior to Pandemic**	**During Pandemic**	**Just 1-year prior to Pandemic**	**During Pandemic**	**Just 1-year prior to Pandemic**	**During Pandemic**	**Just 1-year prior to Pandemic**	**During Pandemic**
ROA	0.15	***0.66*****	-0.23	0.28	0.51	***1.17****	1.55	***1.56****
ROE	0.78	***7.73******	-4.16	***4.67******	3.30	***10.33*****	8.75	9.20
Gross NPLs	8.2	7.3	10.3	***9.1****	5.5	4.9	2.3	3.6
Net NPLs	2.8	2.4	3.7	***3.1*****	1.5	1.4	0.5	0.7
NIITA	1.35	1.28	1.13	1.11	1.75	1.54	1.43	1.42
ICTA	2.01	1.94	1.84	1.80	2.28	2.13	1.86	1.75
NIM	2.81	2.91	2.37	2.45	3.43	3.58	3.26	3.30
CAR	14.8	16.3	12.9	***14.0******	16.5	***18.4*****	17.7	19.5

Notes: This appendix table presents the comparison of the selected financial ratios across bank groups during the pandemic over the reported estimates just 1-year prior to the pandemic year. ROA is the return on assets, ROE is the return on equity, Gross NPLs is the ratio of gross non-performing loans to total advances, Net NPLs is the ratio of net non-performing loans to net advances, NIITA is the ratio of non-interest income to total assets, ICTA is the ratio of intermediation cost to total assets, NIM is the net-interest margin to total assets, and CAR is the capital to risk-weighted assets. *,**, and *** indicate statistical significance at 10%, 5%, and 1% levels, respectively, corresponding to rejecting the null hypothesis for the *t*-test that the mean value of the ratio improved during the pandemic period relative to the mean level observed 1-year prior to the pandemic.

Source: Authors' computation from "Statistical Tables Related to Banks in India: 2020-21".