Banking Against the Odds: Performance and Lending Efficiency of Government Banks during Crisis. *

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Abstract

Government-owned banks are often inefficient but can stabilize economies during downturns. Using difference-in-differences analyses of Indian banks during the Covid-19 crisis, we show that government-owned banks significantly expanded lending, especially in severely impacted regions. However, contrary to prior literature, these banks outperformed private banks, achieving higher profitability, lower non-performing loans, and better stock market performance without compromising lending quality. We attribute this outperformance to pre-pandemic policy interventions, including the adoption of digital banking and regulator-driven balance sheet clean-ups, which enabled sustainable counter-cyclical lending. Deposit growth and non-banking activities do not explain the observed increases in lending and profitability.

1 Introduction

Despite the reduction in state ownership of banks in recent decades, governments in at least a hundred countries continue to own a significant stake in their banking systems. On average, government-owned banks hold 20.53% of the banking system's assets in these hundred countries.[1] La Porta et al. (2002) document that higher government ownership by banks slows down the financial development and economic growth of a country. However, these banks perform one critical function: providing counter-cyclical support during times of crisis. Coleman and Feler (2015) show that in Brazil, after the global financial crisis, government bank lending mitigated an economic downturn, but this lending was inefficiently allocated and reduced productivity growth.

Unlike private banks, whose lending behaviour is more procyclical due to reliance on market-driven funding and risk-averse strategies, government banks are backed by the sovereign, which enables them to prioritize macroeconomic stability (Iannotta et al., 2013). However, while countercyclical lending by government banks mitigates economic shocks, it is often associated with inefficiencies such as lending under political pressures, leading to resource misallocation and weaker long-term returns (Shen and Lin, 2012). The inability of government-owned banks to balance economic stabilization with financial performance raises concerns about their use as a short-term countercyclical tool.

In this paper, we examine whether government-owned banks can operate efficiently while fulfilling their mandate to reduce the impact of economic downturns. To address these questions, we analyze and compare the performance of government and private banks in India around the Covid-19 crisis. When the Covid-19 pandemic spread globally in late 2019 and early 2020, most governments imposed lockdowns that severely slowed economic activity.[2] Covid-19 induced economic crisis was as an exogenous shock to the banking system. We use it to study how lending and performance of government banks and private banks

[1] World Bank - Bank Regulation and Supervision Survey - 2016.

[2] https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200331-sitrep-71-covid-19.pdf

compare before, during and after the crisis.

We believe India provides an ideal setting for studying the efficiency of government banks' countercyclical lending policy for the following three reasons. First, the Indian government has a significant presence in the banking sector (62% share in lending right before the pandemic), making a large section of its banking system immensely vulnerable to the government's influence in lending decisions. Second, the government of India implemented the strictest lockdown in the world to curb the spread of the Covid-19 pandemic.[3] As a result, the Indian economy shrunk drastically by 24% in quarter one of the Financial Year (FY[4]) 2020-21 and remained subdued in the following three quarters. Third, the banking system in India underwent a series of reforms in the years preceding the crisis, which presents us with a rare opportunity to examine the impact of these reforms on efficient lending practices.

To compare the performance of government and private banks, we gather annual financial data for all scheduled commercial banks two years before and after FY 2020–21, the peak of the economic crisis. Using difference-in-differences (DD) regressions with two-way fixed effects on bank-year panel data, we find that government-owned banks significantly outperformed private banks in the post-crisis period. Specifically, government banks increased their return on assets by 0.92 percentage points. They increased credit growth by 3.46 percentage points relative to private banks while reducing operating expenses by 9.5 percentage points. This superior performance was also evident in the stock market, where government banks saw a remarkable 25.76 percentage points increase in returns over their private counterparts compared to the pre-crisis period.

To check if government banks allocated increased credit counter-cyclically, we utilize detailed loan-level data sourced from the Ministry of Corporate Affairs (MCA), Government of India. We construct a firm-state-year panel capturing annual secured loans taken by a firm across different states[5] in any given year. We augment this panel with Google's mobility data,

[3] See Figure 17-k of Hale et al. (2020)

[4] Note that financial year in India runs from April 1 of a given year to March 31 of next year. So, Financial year 2020-21 runs from April 1, 2020 to March 31, 2021.

[5] India has 28 states and 8 union territories.

a location-specific and time-varying indicator of lockdown stringency that serves as a proxy for economic disruption during the pandemic. Using regressions that interact government bank dummy with lockdown intensity, we find evidence indicating that government banks indeed disproportionately extended credit in regions experiencing greater economic distress attributable to Covid-19 related lockdowns.

This finding prompts an important question: Was the observed lending growth driven by supply-side or demand-side factors? One possibility is that during the pandemic, certain sectors such as healthcare—relatively resilient or even thriving—were more likely to be clients of government-owned banks, while severely affected sectors like hospitality were predominantly served by private banks. Such sectoral matching between firms and banks could partly explain the divergence in credit growth. To investigate whether firm-bank matching accounts for the observed patterns in credit growth, we adopt a regression design in the spirit of Khwaja and Mian (2008). Specifically, we rearrange the loan-level MCA data into a firm-bank-year panel, capturing the amount of new secured lending issued to each firm by each bank in a given year. Using a difference-in-differences approach while controlling for both time-variant and invariant firm characteristics, we find that firms were more likely to receive a new loan from government-owned banks during the crisis and also in the subsequent years of recovery.

Cole (2009) shows that banks in India provided low-quality financial intermediation after the government acquired many of them in 1980. Naturally, we must compare the quality of loans lent by government and private banks in our sample. Using DD regressions at the bank-year level, we find that government banks reduced their non-performing loans by 2.77 percentage points in the post-crisis period compared to private banks. We then examine whether these banks mask their bad loans to show improved balance sheet quality (Acharya et al., 2021).

We conduct three tests to evaluate the quality of lending. First, we use the availability of the credit rating of a firm as a proxy for its quality and find that compared to private banks; government banks directed their increased lending toward credit-rated firms rather than lower-quality (unrated) firms during the post-pandemic period. Second, we checked if government banks were more likely to increase lending to distressed firms. We find that government banks lent more to distressed firms only during the crisis year (FY 2020-21) but did not continue this pattern in later years. This pattern appears in line with the mandate of government banks to help distressed firms recover from the crisis (La Porta et al., 2002). Third, we compare firm-level outcomes and observe that borrowers from government banks reported higher profits and reduced receivables, signalling stronger financial health. These findings suggest that despite their crisis-related interventions, government banks followed prudent lending practices by targeting firms with good long-term prospects, even if those firms were temporarily distressed.

We augment the above analysis by studying the lending technologies used by government banks to achieve sustainable countercyclical lending. We explore two such technologies: relationship lending and banks' adoption of digital technologies. We hypothesize that banks likely refined their lending practices by strengthening screening and monitoring processes. One such practice could be the expansion of relationship lending (Beck et al. (2018)). Relationship banking is effective in improving the monitoring of loans and screening out low-quality firms (Boot and Thakor, 2000). Using the MCA firm-bank-year data, we define relationship banks based on relationship length, average loan size, and number of repeat borrowers. Banks with above-median relationship length, loan size, and number of repeat borrowers are classified as relationship banks. Using triple difference regressions, we find that government banks that follow relationship banking lent more during the crisis and the recovery years.

Banks could have also relied on digital technologies to strengthen their screening and monitoring processes (Mishra et al. (2022)). We classify banks into high and low adoption of digital technologies based on the frequency of digital banking-related terms mentioned in their annual statements in the five years preceding the crisis. We use this measure as a proxy for the bank's adoption of digital lending technologies. Again, using the triple difference regression design, we find that government banks that showed higher adoption of digital technologies lent more during the crisis and the recovery years. We also find that these banks show higher improvement in returns on assets and stock market returns in the crisis and recovery phases.

Next, we move on to study the policy interventions that plausibly enabled government banks to practice countercyclical lending profitably. One plausible intervention is the clean-up undertaken by the banking regulator in India (Reserve Bank of India or RBI) in the years preceding the Covid-19 crisis. As most of the banks that required cleanup were government banks, these banks improved their lending practices, which likely showed up in their profits during and after the crisis period.

The regulator implemented two prominent measures to clean up bank balance sheets in the years preceding the crisis. First, RBI ran an extensive audit exercise called the Asset Quality Review or AQR (Chopra et al., 2021) starting in 2016, which uncovered massive bad loans, majorly in government banks. Second, RBI intervened in the functioning of several bank boards through a supervisory intervention called the Prompt Corrective Action or PCA (Kashyap et al., 2022) that was revised in 2018. More than half of the government-owned banks went through this exercise during the pre-crisis period.[6]

We hypothesize that together, the clean-up measures improved the quality of bank balance sheets substantially, which shows up in subsequent lending practices (Bonfim et al., 2020). To test this hypothesis, we calculate the drop in bad loans from 2016 to 2020, as these reforms started in 2016 and continued until the pandemic hit in 2020. The banks that showed an above median drop in non-performing loans to net advances ratio are termed high clean-up banks. We analyse credit growth and non-performing loans using triple difference regressions on government bank dummy, crisis period, and high clean-up banks to find that more cleaned government banks increased credit growth more while reducing non-performing loans in the post-pandemic period. To support this analysis, we also verify that banks with greater exposure to regulatory reforms (AQR and PCA) significantly improved

[6]https://economictimes.indiatimes.com/markets/stocks/news/banks-under-pca-framework-drop-despite-recap-package-heres-why/articleshow/62645887.cms

their recognition of bad loans between 2016 and 2020, leading to cleaner balance sheets. This improvement was particularly pronounced for government-owned banks.

As a result of the regulator's clean-up exercises, banks' capital diminished, and hence, they reduced lending in the pre-pandemic years (Chopra et al., 2021). However, the Government of India recapitalised its banks before the crisis. In the bank-year panel, using triple difference regressions, we show that government banks that were recapitalized more than the median led the charge of absolute as well as incremental lending in the post-crisis period. This finding shows that the bank balance sheet cleanup backed by capital support from the sovereign prepares government banks for sustainable countercyclical lending.

We run several tests to check for alternate explanations of our results. First, we check if government banks received more deposits than private banks during the crisis, which could have led to increased lending (Ivashina and Scharfstein, 2010). Granja et al. (2022) have documented an increase in risky lending by banks that suddenly receive large deposits. As government banks have an implicit bail-out guarantee from the government, unlike private banks, depositors are likely to believe that their money is secure with the government banks (Demirgüç-Kunt et al., 2014). The government banks, in turn, likely used this enhanced liquidity to lend more. We do not find any differential lending growth from banks that had higher deposit growth in a triple interaction regression setting with government banks and post-crisis dummies.

Second, it is likely that government banks command more trust against failure (Mishra et al., 2023), and hence attract income from other sources like asset management services. We find that non-banking income does not explain the increase in government bank profitability and returns. Third, we find that government banks do not increase interest rates compared to private banks, and hence, their net interest margin also does not explain the outperformance of government banks. Fourth, we removed the largest government bank, the State Bank of India (SBI), and the results went through. We also verify whether our primary results are driven by too-big-to-fail banks but find no evidence for that.

One more concern could arise in the reader's mind about the timing of the shift in government banks' performance. If the clean-up started in 2016 and continued till 2019 and even later for some banks, why did the performance shift of government banks occur suddenly during the pandemic? It is likely that though the regulator and the government were cleaning up government banks, its effect would be showing up gradually. When the Covid-19 lockdown induced a crisis unexpectedly, government banks took up the lead in lending more to the economy. Our thesis is that the increased lending volumes combined with cleaner balance sheets and disciplined lending practices led to higher profitability, which translated into higher market returns.

We primarily contribute to two strands of literature. One that studies countercyclical lending (Coleman and Feler (2015), WorldBank (2012), Burgess and Pande (2005)) often led by government-owned banks (La Porta et al. (2002), Sapienza (2004), Andrianova et al. (2008)), and the other strand that studies the regulatory reforms in banking and their corresponding policy implications (Agarwal et al. (2014), Diamond and Rajan (2011), Chopra et al. (2021), Tantri and Vishen (2024)).

Our paper contributes to the literature by demonstrating that lenders can perform well, even while engaging in countercyclical lending. This finding presents an exception to the traditional view that countercyclical lending is always loss-making (Khwaja and Mian, 2005, Megginson, 2005). We add to the debate which highlights government banks' stabilizing role in downturns (Bertay et al., 2015) while presenting novel evidence that shows that it is possible to mitigate inefficiencies of government-owned banks (La Porta et al., 2002, Micco et al., 2007) that often lead to poor loan quality and low profitability (Cornett et al. (2010), Iannotta et al. (2007)). Contrary to the established findings, our analysis during the Covid-19 crisis shows that countercyclical lending can achieve both economic support and financial efficiency.

Second, this paper adds to the literature on the long-term effects of regulatory reforms in the banking sector (Bertrand et al. (2007), Angelini and Cetorelli (2003)). While many studies have focused on the isolated impacts of reforms such as the Asset Quality Review (Chopra et al. (2021)) or the reforms in bankruptcy laws (Lilienfeld-Toal et al. (2012), Kulkarni et al.

(2019)), we show that regulatory interventions collectively strengthened government banks by cleaning up their balance sheets as theorized by Diamond and Rajan (2011). Our findings indicate that pre-crisis regulatory measures significantly contributed to the improved financial health and disciplined lending practices of government banks, which helped them fulfil their mandate more effectively during the pandemic without suffering losses. This study suggests that a combination of regulatory actions is likely required to keep lenders prepared for countercyclical lending.

Additionally, this study contributes to the ongoing debate about loan evergreening practices in banks (Bonfim et al., 2020, Kashyap et al., 2023). Past research has shown that weaker financial institutions are often pressured to lend to politically connected or distressed firms, particularly during election years (Dinç (2005), Sapienza (2004)). However, our analysis based on firm-level data demonstrates that government banks under regulatory oversight shift their lending focus toward firms with strong potential to recover from a crisis rather than zombie or politically favored firms (Caballero et al. (2008), Claessens et al. (2008)). This new evidence provides policy insight that even weak lenders may adopt prudent lending technologies and refrain from engaging in evergreening practices after undergoing regulatory reforms.

The remainder of the paper proceeds as follows. Section 2 outlines the institutional context of our study and Section 3 describes the sample. Section 4 draws out the empirical research design and defines the corresponding variables. Section 5 presents the results of the empirical analysis. Section 6 focuses on the potential mechanism. We wrap up the paper with the conclusion in Section 7.

2 Institutional Setting

While the trend toward privatization has reduced government stakes in banks over recent decades, state ownership in the banking sector remains substantial in many parts of the world. In at least one hundred countries, governments continue to maintain a notable presence in the banking industry, with public sector banks accounting for an average of 20.53% of total banking assets. See Tables A2 and A3 of the online appendix.[7] As per an estimate given by Cull et al. (2017), government-owned banks collectively manage approximately 18% of global banking assets. Yet, this global average masks considerable variation across regions. In several emerging markets—particularly in South Asia, as well as parts of the Middle East and North Africa—the footprint of state-owned banks is significantly larger. In fact, in a diverse group of countries ranging from Indonesia and Turkey to India and Brazil, government banks control over 30% of banking system assets.[8]

Though government banks are often inefficient, their role in dealing with large-scale economic crises remains crucial. During the Global Financial Crisis of 2008, government banks were instrumental in stabilizing distressed banking systems by providing liquidity and capital, even in regions such as Europe and other developed economies (Iannotta et al. (2013), Cull et al. (2017)).

We are interested in studying the performance of lenders that engaged in countercyclical lending during the large-scale economic crisis induced by the Covid-19 pandemic. India offers a compelling setting to study the role of government-owned banks (GoBs) during the Covid-19 crisis for three reasons. First, India has the highest level of government ownership in banking globally, with government banks holding 74% of assets as per Cull et al. (2017). Using another data source released by RBI in February 2020, we see a 62% share of government banks in lending right before the pandemic.[9] Second, India imposed one of the world's strictest lockdowns, leading to a sharp 24% GDP contraction in Q1 2020-21.[10] Third, recent banking reforms likely enhanced resilience to economic shocks. Together, these factors make India a natural case for evaluating government banks' responses to an exogenous crisis.

It is easy to visualize the year-wise intensity of the Covid-19 induced economic crisis in

[7] World Bank - Bank Regulation and Supervision Survey - 2016.

[8] Based on Cull et al. (2017), countries where governments owned more than 30% of banking assets in 2010 include Indonesia, Germany, Iceland, Slovenia, Turkey, Belarus, Russia, Argentina, Brazil, Costa Rica, Suriname, Uruguay, Venezuela, Bangladesh, Bhutan, India, Maldives, Sri Lanka, Burundi, and Seychelles.

[9] See Feb-2020 data for Public/(Public + Private) Sector Banks in `https://data.rbi.org.in/` − > Statistics − > Banking- Assets and Liabilities − > Bank Group-wise Business of Scheduled Banks in India.

[10] See Figure 17-k of Hale et al. (2020); Statista

Figure A2 of the online appendix. It plots the change in human traffic at transit stations like railway and bus stations compared to a baseline of February 2020 (when lockdowns were not initiated), as reported by Google Mobility Reports. We use this change to gauge the intensity of lockdown and, hence, the intensity of crisis for different financial years. The plot shows that FY 2020-21 was the worst hit due to lockdowns. It saw an average drop in mobility of 22 percentage points. With some ups and downs, the subsequent years saw a recovery in mobility and, presumably, in economic activity.

India has twelve government-owned banks and twenty-one private banks. In this study, we ignore the foreign banks which are relatively small compared to Gogovernment banksBs and private banks. Government banks have 59.53% per cent of the total loan value in the country on their balance sheet in 2024[11]. Historically, government banks have been inefficient, which is evident in the Price to Book ratio of 0.84 for the largest government-owned bank (State Bank of India) in March 2020, while the largest private bank (HDFC Bank) had a significantly higher Price to Book ratio of 2.76. Clearly, the stock-market participants value the assets of government banks less than their book value. This difference in the market's view of the balance sheet quality of government banks shows that they were in dire need of reforms.

The Indian banking sector accumulated significant non-performing assets (NPAs) between 2006 and 2016 due to aggressive lending, poor credit assessments, adverse global conditions, and a very long forbearance period from 2008 to 2014 (Mannil et al., 2024).[12] To address these issues and clean up the banking system, the Reserve Bank of India (RBI) and the Government of India implemented two prominent measures. First, RBI initiated the Asset Quality Review (AQR) in 2016 to audit banks' books (Chopra et al., 2021). Second, RBI enforced the Prompt Corrective Action (PCA) framework (Kashyap et al., 2022), revised in 2018, which forced the struggling banks to preserve capital. More than half of government-owned banks were treated under PCA.[13]

[11] https://www.ibef.org/industry/banking-india

[12] https://indianexpress.com/article/business/banking-and-finance/full-text-of-raghuram-rajans-note-to-parliamentary-estimates-committee-on-bank-npas-5351153/

[13] https://economictimes.indiatimes.com/markets/stocks/news/banks-under-pca-framework-drop-despite-

The AQR is an audit exercise, designed to uncover hidden stress in banks' balance sheets. It revealed that many banks were under-reporting NPAs by restructuring loans. This forced banks to accurately classify stressed assets, improving transparency and trust in the banking system. The AQR pushed banks to resolve bad loans through recoveries or write-offs[14].

The PCA framework, first introduced in 2002 and revised in 2017, allowed RBI to intervene in banks showing signs of financial weakness, such as low capital adequacy or high NPAs. The framework imposed restrictions on bank operations and could mandate management changes. In 2018, 11 out of 12 banks under PCA were government-owned. This framework prevented the unhealthy banks from taking excessive risks, restricted their growth, and encouraged them to conserve capital by limiting operations. It helped prevent further deterioration in bank health by enforcing strict regulatory measures until their financial position improved (Acharya, 2018).

The unintended consequence of the above-mentioned clean-up exercises was the erosion of the capital base of the Government banks in India. To adhere to Basel III capital adequacy standards, the Government of India undertook significant recapitalization efforts to strengthen its banks. As per the FY19 Union Budget presented in the parliament, during 2016-19, government banks underwent recapitalization totalling INR 3.19 trillion. This included INR 2.5 trillion infused by the government and over INR 660 billion raised by the government banks themselves (Chari et al., 2019).

Meanwhile, during 2015-20, India's banking sector underwent significant digital transformation, enhancing operational efficiency and lending practices[15]. The adoption of digital platforms enabled lenders to assess creditworthiness more effectively, especially for small businesses lacking traditional credit histories (Alok et al., 2024). By 2020, digital loans accounted for 0.7% of India's GDP, a tenfold increase from 2017 (Khera, 2023). Though historically, government banks have been slower to adopt new technologies (Mishra et al.,

recap-package-heres-why/articleshow/62645887.cms

[14] https://www.livemint.com/Politics/syAma4MN15oNf0MMXr2GTN/Raghuram-Rajans-RBI-tenure-Three-years-that-packed-a-punch.html

[15] https://www.bis.org/review/r240828p.pdf

2023), the Indian banking system overall has actively implemented Artificial Intelligence and Machine Learning algorithms for enhanced credit risk assessment (Agarwal et al., 2025, Tantri, 2021).

3 Data

We run our primary analysis on bank-year level panel data. This data is sourced from ProwessDx database of Center for Monitoring Indian Economy (CMIE). ProwessDx records annual financial statements of 54,817 firms in India. There are 34 government-owned and private Scheduled Commercial Banks (SCB) in India[16], out of which 33 are in our sample.[17]

Our primary period of analysis is a five year period between Financial Year (FY) 2018-19 to FY 2022-23. We consider FY 2020-21 as the year of Covid-19 induced economic crisis when the lockdown was most stringent. The Covid-19 pandemic continued after this year as well, but the lockdowns were not as stringent, and hence the economy did not suffer as much. We consider FY 2018-19 and 2019-2020 as the pre-crisis period, and FY 2021-22 and 2022-23 as the post crisis period.

In Panel A of Table 1, we report that there are 33 banks in our sample, out of which 12 are government-owned, and 21 are private banks. In Panel A of Table A4, we summarize the financial characteristics of these banks for the entire sample period. The average bank has assets worth INR 5 trillion and makes profits of INR 26 billion. The average return on assets in this period is 0.5% with an average non-performing loans ratio (NNPA) of 3.2% and net interest margin (NIM) of 2.9%. The banks in our sample returned 12.6% average stock market returns in this period.

In Table 3, we compare the financials of government and private banks before and after the Covid-19 crisis and report the difference between private and government banks. Notice

[16]https://www.rbi.org.in/hindi1/Upload/content/PDFs/APPEH23102021_AP1.pdf

[17]We drop IDBI bank as it converted from government-owned to private bank during our sample period. https://www.livemint.com/economy/post-strategic-sale-idbi-bank-to-continue-as-indian-private-sector-bank-dipam-11669554987165.html

that government banks increased their assets, stock returns, and profits relative to private banks in the post-Covid period while reducing their relative NPAs. The relative position of government and private banks does not change much regarding net interest margin, loans to deposit, and employee compensation ratio.

The secondary dataset of our paper is organized at a firm-bank-year level. We collect loan-level information from the Index of Charges website of the Ministry of Corporate Affairs, Government of India. On this website, banks register charges or claims on collateral associated with a loan given to each firm. They record the firm name, date of loan disbursal, loan amount, and location of the bank branch. We organize this data into a firm-bank-year panel. In Panel B of Table 1, we report that we have collected data on 188,471 secured loans taken by 148,645 firms spread across 14 industries in our sample period of five years. We also report the number of active firm-bank relationships in the dataset.

However, we do not have the financial details of all these firms. We collect financial details of firms from CMIE ProwessDx, which has 54,817 firms as reported in Panel A of Table 1. These firms are profitable on average and have large amount of receivables. We want to draw the readers' attention towards the Interest Coverage Ratio of these firms being high on average, but the 5th percentile score below one on this metric. Hence, there are a substantial number of distressed firms in the sample.

4 Empirical Strategy

In this paper, we first measure the relative lending behaviour of government-owned banks and privately-owned banks during the COVID-19-induced economic crisis with the pre-crisis lending pattern of the two types of banks. To do so, we run difference-in-differences regression of the following type on bank-year panel data:

$$\begin{aligned} Y_{bt} = {} & \beta_1 \mathrm{GoB}_b \times \text{During Covid}_t + \beta_2 \mathrm{GoB}_b \times \text{Post Covid}_t \\ & + \beta' \mathbf{X}_{bt} + \delta_b + \theta_t + \varepsilon_{bt} \end{aligned} \tag{1}$$

In the above equation, the subscript b represents a *bank*, and t represents a *year*. *GoB* is an indicator variable that equals one for a government-owned bank, and zero for private banks. *During Covid* is also an indicator variable that equals one for FY 2020-21 and zero for all other years. It represents the worst phase of the Covid-19-induced economic crisis as evident from Figures A1 and A2 of the online appendix. *Post Covid* is another indicator variable that equals one for FY 2021-22 and 2022-23, and zero for all other years. While these years also saw widespread Covid-19 outbreaks, lockdowns were less stringent relative to FY 2020-21, leading to a milder economic slump and some phases of recovery.

Our primary outcome variable represented by Y_{bt} in the above equation is Stock Returns. In the same setup, we also examine performance measures: Return on Assets (RoA), Net Non-Performing Assets (NNPA) ratio, Expenses ($log(Expenses)$), and Credit Growth ($log(Loan_t/Loan_{t-1})$). We control for all macroeconomic variations that are specific to a year, which can potentially affect all banks by introducing year fixed effects (θ_t). Additionally, we control for time-varying bank-level annual financial characteristics like bank size *(log(Total Assets))*, their liquidity (*Loans to Deposit Ratio*), financial health (*Capital Adequacy Ratio*), and management salary (*Employee Compensation Ratio*) represented by $\mathbf{X}_{bt}$ in the above equation. We also control for all observable and unobservable time-invariant bank characteristics using bank fixed effects (δ_b).

To eliminate this concern of firm-bank matching explaining the credit growth story, we rely on Khwaja and Mian (2008) style regression design. Using this regression design, we can disentangle the bank lending channel from the firm demand channel, which can exist simultaneously. So, to check if the bank lending channel can explain the change in the relative performance of government-owned versus private banks, we organize the data in a firm-bank-year level panel and run variations of the following regression equation:

$$\begin{aligned} Y_{fbt} = {} & \beta_0 + \beta_1 \text{GoB}_b + \beta_2 \text{During Covid}_t + \beta_3 \text{Post Covid}_t + \beta_4 \text{GoB}_b \times \text{During Covid}_t \\ & + \beta_5 \text{GoB}_b \times \text{Post Covid}_t + \delta_b + \gamma_{ft} + \varepsilon_{fbt} \end{aligned} \tag{2}$$

In the above equation, the subscript f represents a *firm*, b represents a *bank*, and t represents a *year*. *GoB*, *During Covid*, and *Post Covid* are indicator variables as defined in equation 1. In this equation, we also include firm × year fixed effects (γ_{ft}), and bank fixed effects (δ_b). Firm-year fixed effects control for all time-varying and time-invariant characteristics of firms, and bank fixed effects control for all time-invariant characteristics of banks.

5 Results

5.1 Government-owned vs Private Banks

We examine how the government banks performed relative to private banks during the Covid-19 induced economic crisis by estimating regression equation 1 on the bank-year level panel dataset of government-owned and privately owned scheduled commercial banks in India. This dataset runs from FY 2018-19 to 2022-23, where FY 2020-21 is the year of the Covid-19 crisis. We report the results for Annual Stock Returns, Return on Assets (RoA), Net Non-performing Assets as a percentage of Net Advances (NNPA ratio), Annual Expenses ($log(Expenses)$) and Credit Growth ($log(Loan_t/Loan_{t-1})$) as the dependent variables in Table 4.

In column 1, we report the coefficient estimates for Stock Returns (%) as the dependent variable. These results show that the stock returns of government banks rose 26 percentage points higher than those of private banks from pre- to post-crisis years. The increase in relative returns is clearly economically significant and showcases the extraordinary flip in investor confidence in government-owned banks. This result is also evident from Figure 2, which plots the year-on-year value-weighted portfolio returns of banking stocks. Note that the difference in portfolio returns of government-owned and private banks in the pre-crisis period does not predict the drastic outperformance of government-owned observed during the pandemic.

Column 2 records a similar effect in terms of RoA, where the difference in RoA of government banks relative to private banks also shows a rise of 9.21 percentage points in the post-Covid period. Column 3 presents the reduction in NNPA of government banks in this period. Government banks reduced the difference in NNPA with private banks by 2.77 percentage points in the post-crisis period. Column 4 reports that government banks also reduced their operating expenses compared to private banks in the post-period by 9.5 percentage points.

In column 5, we report the coefficient estimates for Credit Growth as the dependent variable. The result shows that compared to private banks, government banks increased lending growth by 4.5 percentage points during the worst phase of the Covid-19 crisis and 3.5 percentage points in the recovery phase. Together, these results show that relative to private banks, government-owned banks improved their stock market performance and return on assets while increasing countercyclical lending, and reducing bad loans and operating expenses.

All the above results include two-way fixed effects at the bank and year level and also include bank-level time-varying controls, *viz.*, Bank Size (log(Total Assets)), Capital Adequacy and its first lag, Loans to Deposit Ratio, and Employee Compensation Ratio. We reproduce these results after dropping bank fixed effects to see the coefficients of government banks in the pre-period. Table A19 of the online appendix reports these results, which are similar to the ones with bank fixed effects. Results go through even when we run a modified version of equation 1 where we introduce a *Too Big to Fail* dummy ($TBTF$) to make it a triple difference regression. Here, is the triple difference regression equation with two post periods:

$$\begin{aligned} Y_{fbt} = {} & \beta_1 \text{GoB}_b \times \text{During Covid}_t + \beta_2 \text{GoB}_b \times \text{Post Covid}_t + \beta_3 \text{TBTF}_b \times \text{During Covid}_t \\ & + \beta_4 \text{TBTF}_b \times \text{Post Covid}_t + \beta_5 \text{GoB}_b \times \text{TBTF}_b \times \text{During Covid}_t \\ & + \beta_6 \text{GoB}_b \times \text{TBTF}_b \times \text{Post Covid}_t + \delta_b + \gamma_{ft} + \varepsilon_{fbt} \end{aligned} \tag{3}$$

In this triple difference or difference-in-differnce-in-difference (DDD) regression, *During*

Covid and *Post Covid* variables are absorbed by firm $\times$ time fixed effect (γ_{ft}), and pre-period *GoB*, *TBTF*, and their interaction are absorbed by bank fixed effects (δ_b). Table A6 of the online appendix presents the results and rules out the possibility that these results are driven only by large banks.

Table A19 documents that government banks were underperforming private banks on stock returns, return on assets, and non-performing loans in the pre-crisis period but were similar in expenses. We also see that government banks were lending more in the pre-crisis period than private banks and increased it further during the Covid-19 crisis. This result validates the findings in the literature that government banks lend countercyclically. The counter-cyclical lending result can also be seen in Figure 1, which depicts the increase in lending by government banks relative to private banks coinciding with the stock market crash in March 2020. We further show this in Table A7 of the online appendix by creating Firm-State-Year panel data for the years FY 2019-20 to 2022-23 and tagging the primary lender of the firm in that state as a government-owned or private bank. As lockdowns' intensity depended on state-level administration, this panel captures the new loans borrowed by firms in different geographic regions in different years from government or private banks. We run the following regression:

$$\begin{aligned} Y_{fst} = {} & \beta_0 + \beta_1 \text{GoB}_{fst} + \beta_2 \text{Lockdown Stringency}_{st} \\ & + \beta_3 \text{GoB}_{fst} \times \text{Lockdown Stringency}_{st} + \theta_t + \gamma_f + \sigma_s + \varepsilon_{fst} \end{aligned} \tag{4}$$

In the above equation, the subscript s represents a *state*, f represents a *firm* and t represents a *year*. θ_t represents year fixed effects, γ_f represents firm fixed effects and σ_s represents state fixed effects. *Lockdown Stringency* varies across states and years and is measured using the annual aggregated value of change in mobility at railway and bus stations compared to pre-crisis values as reported in Google Mobility Reports. The higher the drop in human mobility in a region, the stricter the lockdown. We find that β_3 is positive and statistically significant, which means that government banks increased lending in regions and periods where the crisis was more severe.

Next, we find the correlation between bank performance (RoA) and potential drivers like credit growth, non-performing loans, and net interest margin. We run an ordinary least squares regression of RoA on these three factors and report the results in Table A8 of the online appendix. The results show that higher credit growth and higher net interest margin, along with lower non-performing loans, are correlated with bank profitability in this period. This result, combined with the relative rise in credit growth by government banks, encouraged us to explore the credit growth story further.

5.2 Bank Lending Channel

Is the observed growth in lending driven by supply-side factors or demand-side factors? To answer this question and rule out firm-bank matching as the primary driver of the government banks' credit growth story, we run regression equation 2 on a firm-bank-year panel dataset, and report the results in Table 5.

In column 1, the dependent variable is *log(1+New Loan Amount)* and in column 2 it is an indicator variable *New Loan* that equals one in a year when the given firm had borrowed a new loan from the given bank, and zero otherwise. We report coefficient estimates as per equation 2, which runs Khwaja and Mian (2008) style regressions. We see that government banks lent less in the pre-crisis period but increased it during the crisis and recovery years. Here, we want to highlight that all banks increased lending during the crisis, but government banks increased more than private banks and continued this practice even in the following years. For firms with borrowing histories from both government-owned and private banks, the lending increase by government-owned banks is even more pronounced. These results confirm the presence of a bank lending channel, as we have taken out all time-varying and time-invariant observable and unobservable firm-level characteristics, including loan demand and bank preferences. Therefore, we conclude that the observed lending is primarily a supply push by government banks.

One concern could be that the largest bank in India, the State Bank of India (SBI), is a government-owned bank and is single-handedly driving the lending pattern. However, when we run the above test after dropping SBI from the sample, the results remain similar. These results are reported in Table A9 of the online appendix. We include several variations of fixed effects, but the results remain similar.

5.3 Borrowing Firms' Quality and Performance

In section 5.1, we documented that government banks improved their poor performance compared to private banks on non-performing loans in the post-Covid period. One could argue that government banks obscured their non-performing loans as supervisory oversight likely weakened during the crisis, effectively "evergreening" bad loans and inflating reported profits in the short run. We check if government banks mask their bad loans to show improved balance sheet quality.

To check for any attempt to mask bad loans, we examine the quality and performance of firms that received new loans during this period. We first check if government banks were more likely to increase lending to distressed firms. We find that they lent more to distressed firms than private banks during the crisis year (FY 2020-21) but did not continue this pattern in later years. Using the firm-bank-year panel dataset, we regress *log(1+New Loan Amount)* as the dependent variable in a modified version of equation 2 where we introduce triple difference (DDD) regressions as described in equation 3 after replacing *TBTF* with *Distressed Firm* which is an indicator variable that equals one when interest coverage ratio (ICR) of a firm is less than one, and zero otherwise. We report the results in columns 1 and 2 of Table 6 and find that government banks increased lending to distressed firms during the crisis year of FY 2020-21 but did not continue this trend in the post-Covid period. Column 1 has no fixed effects; column 2 introduces firm x year and bank fixed effects which control for all time-varying and time-invariant characteristics of firms and time-invariant characteristics of banks.

Moreover, not all loans lent to distressed firms can be called zombie loans; a bank could lend to a distressed firm that can recover once the crisis subsides. Only because government banks lent more to distressed firms, we can not claim that their quality of lending is poor. We conduct two more tests to evaluate the quality of lending. First, we use the availability of a credit rating as a proxy for firm quality and transparency. Using triple difference regressions, we find that compared to private banks, government banks directed their increased lending toward credit-rated firms rather than lower-quality (unrated) firms during the post-pandemic period. We report these results in Columns 3 and 4 of Table 6. Column 3 has no fixed effects; column 4 introduces firm $\times$ year and bank fixed effects

Second, firms that received loans from government-owned banks during the pandemic reported higher profits and reduced receivables, indicating improved financial health compared to firms that borrowed predominantly from private banks. These findings collectively suggest that government banks were prudent in lending to firms with strong potential for profitability, leading us to reject the hypothesis of evergreening by government banks. In a triple difference regression setting, we regress profits and receivables on post-Covid dummy, GoB dummy, and treatment dummy. The *Treatment* dummy equals one for a firm that borrowed a secured loan during the FY 2020-21 and zero otherwise. In Table 7, we report the coefficient estimates of this regression and find that firms that predominantly received loans from government banks during the worst phase of crisis outperform their peers afterwards.

These results together indicate that government banks not only lent more during the pandemic, but they did so with prudence, resulting in improved balance sheets and profitability in the post-pandemic period.

6 Potential Mechanism

6.1 Lending Technology

We hypothesize that banks enhanced their lending practices during the crisis period by improving their screening and monitoring capabilities. One key channel through which this may have occurred is the adoption of digital technologies. Digital tools can support more effective credit evaluation, risk assessment, and borrower monitoring, particularly during periods of heightened uncertainty (Mishra et al., 2022).

To measure banks' adoption of digital technologies, we analyze the frequency of digital banking-related terms in their annual reports over the five years preceding the crisis. This frequency serves as a proxy for each bank's level of digitization. Based on this measure, we classify banks into high and low digital adopters.

We then apply a triple-difference regression framework to examine whether highly digitized government banks exhibited differential lending and profitability patterns during the crisis. In our empirical specification, we modify equation 3 by replacing the $TBTF$ indicator with a *High Digitization Bank* dummy. To analyze profitability, we use the Bank-Year panel and include a third interaction term for *High Digitization Bank* in equation 1.

The results indicate that government banks with higher levels of digital adoption extended more credit during the crisis and recovery period and experienced a greater increase in return on assets (RoA). Lending results are presented in column 1 of Table 9, and profitability result in column 2.

Another important mechanism through which banks may have refined their lending strategies is the expansion of relationship lending. Relationship banking enables financial institutions to leverage informational advantages and provide credit based on long-term borrower relationships (Boot and Thakor, 2000). Such relationships are associated with superior screening and monitoring, making them particularly valuable in times of economic stress (Beck et al., 2018, Bolton et al., 2016).

Using MCA data, we classify banks as relationship lenders based on three criteria: average relationship length with borrowers, average loan size, and the number of repeat borrowers. Banks exceeding the median on all three dimensions are identified as relationship banks. Applying the triple-difference estimation strategy, we find that government banks with stronger relationship banking practices showed significantly higher lending growth during the crisis. These findings are documented in Table A11 of the online appendix.

6.2 Bank Balance Sheet Cleanup

We hypothesize that the regulatory reforms improved the functioning of government-owned banks in the pre-crisis period, which is reflected in their improved performance during the crisis. We start by verifying whether the regulatory reforms had an effect on the recognition of non-performing loans in the pre-crisis period. As described in Section 2, there are two prominent reforms that could have potentially affected the lending practices of government banks: Asset Quality Review (AQR) and Prompt Corrective Action (PCA).

If these practices were effective, we should see an increased recognition of non-performing loans by banks more exposed to these reforms in the pre-crisis period. We choose the period of 2015 to 2020 to study the bank cleanup. AQR started in 2015, and a revised PCA was implemented in 2018. Starting in 2015, and before 2020, using the bank-year panel data, we regress the Net Non-performing Assets to Net Advances (NNPA ratio) of banks on the GoB dummy and its interaction with *AQR Exposure* variable, as well as *PCA* dummy, and present the results in Table A10 of the online appendix. We followed Chopra et al. (2021) to define *AQR Exposure* measure as the maximum deviation in provisioning disclosed by the bank from that found in RBI's audit in this period. If there was no deviation, this measure equals zero. *PCA* is an indicator variable that equals one for a bank if RBI implemented the Prompt Corrective Action framework on the bank during this period. The results indeed show an increased recognition of non-performing loans by the banks exposed to regulatory interventions. This effect is pronounced for the government banks.

Having established that banking interventions by RBI led to higher disclosure of bad loans by government banks before the crisis, we move on to check if this clean-up led to improved efficiency of these banks in the post-crisis period. We run the regression equation 3 after replacing *TBTF* with *High Cleanup Bank* on bank-year panel with two-way fixed effects. *High Cleanup Bank* is an indicator variable that saw above median drop in NNPA ratio between 2016 and 2020, and zero otherwise. Table 8 presents the result for the above regression on credit growth and NNPA ratio using the bank-year level panel data. We find that government-owned banks that were cleaned up more during the pre-crisis period increased their lending growth and deposit growth more and reduced their NPAs more compared to private banks from the pre- to post-crisis period.

6.2.1 Recapitalization

Following the clean-up exercise, government banks experienced significant capital erosion, leading to reduced lending activity. To meet Basel III capital adequacy norms, the Government of India initiated a large-scale recapitalization program. To check if recapitalization had a role to play in the countercyclical lending growth of government banks, we use the bank-year panel and run triple difference regressions after incorporating *High Capital Infused Bank* dummy. This variable takes a value of 1 for banks that underwent an above median capital infusion in the pre-crisis period: FY 2016-17 to 2019-20. We report the results in Table A12. Columns 1 and 2 present results for contemporaneous and next year's total lending by the bank, while column 3 reports credit growth from this year to the next. The analysis tests whether higher capital infusion influenced lending behaviour, using the change in the capital received from FY2016 to FY2020. We find that equity infusion by the government, indeed, enabled banks to recover from their capital deficiency and increase lending during the crisis.

6.2.2 Alternate Explanations

We run several tests to check for alternate explanations of our results. First, we check if government banks received more deposits than private banks during the crisis, which could have led to increased lending. As government banks have an implicit bail-out guarantee from the government, unlike private banks, depositors are likely to believe that their money is secure with the government banks. The government banks, in turn, likely used this enhanced liquidity to lend more. We do not find any differential lending growth or profitability from banks that had higher deposit growth in a triple interaction regression setting with government banks and post-crisis dummies on the bank-year panel. The results are reported in Table A13 of the online appendix.

Second, it is likely that government banks command more trust, especially, during a crisis, and hence attract income from other sources like asset management services. We run regressions as per equation 1 with non-interest income as a proportion of total income as the dependent variable and report the results in Table A14 of the online appendix. We find that non-interest income did increase during crisis, but this increase did not sustain in the post-crisis period. Third, using lending interest rates from RBI's website on quarterly bank-wise lending rates, we find that government banks do not increase interest rates compared to private banks, and hence, their net interest margin also does not explain the outperformance of government banks. These results are reported in Tables A15 and A16 of the online appendix, respectively.

7 Conclusion

This study provides novel insights into efficient countercyclical lending. We look at credit growth and financial performance of Government-owned Banks (GoBs) which are mandated to lend more during economic downturns like the one induced by the Covid-19 pandemic. In this period, government-owned banks in India increased credit growth more relative to private banks while reducing non-performing loans and improving stock market returns. We find that the improved profitability despite countercyclical lending can be explained by the pre-crisis regulatory reforms that strengthened government banks' balance sheets and refined their lending practices. The countercyclical lending role of government banks during the crisis, while maintaining or even improving asset quality, demonstrates that government banks can act as stabilizing agents in times of economic distress without compromising efficiency. This implies that policymakers can utilize government banks as instruments for economic policy, particularly in downturns, provided these banks are adequately capitalized and have undergone essential clean-up measures beforehand.

Our findings carry significant policy implications, suggesting that governments could adopt similar regulatory frameworks to strengthen banking systems to prepare for future economic shocks. If state-owned banks can operate efficiently while maintaining economic stability, then banks, even the weak ones in other economies, under robust regulatory oversight could be prepared to play a stabilizing role during downturns without compromising on efficiency and profitability.

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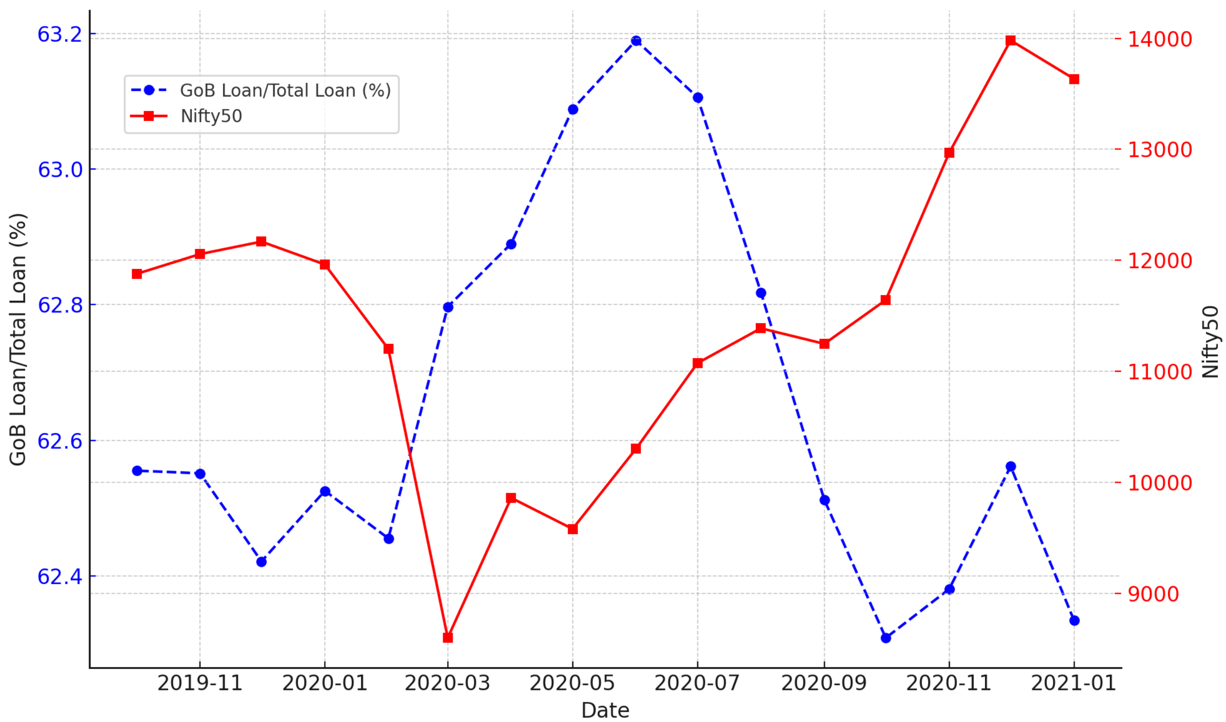

Figure 1: Countercyclical Lending by Government-owned Banks: Here, we plot month-on-month percentage of GoB lending as a percentage of total lending by GoB and private banks on the left y-axis, and Nifty50 on the right y-axis. Nifty50 is India's primary stock market index. We obtain GoB and private banks lending data from RBI's website: https://data.rbi.org.in/ $->$ Statistics $->$ Banking- Assets and Liabilities $->$ Bank Group-wise Business of Scheduled Banks in India.

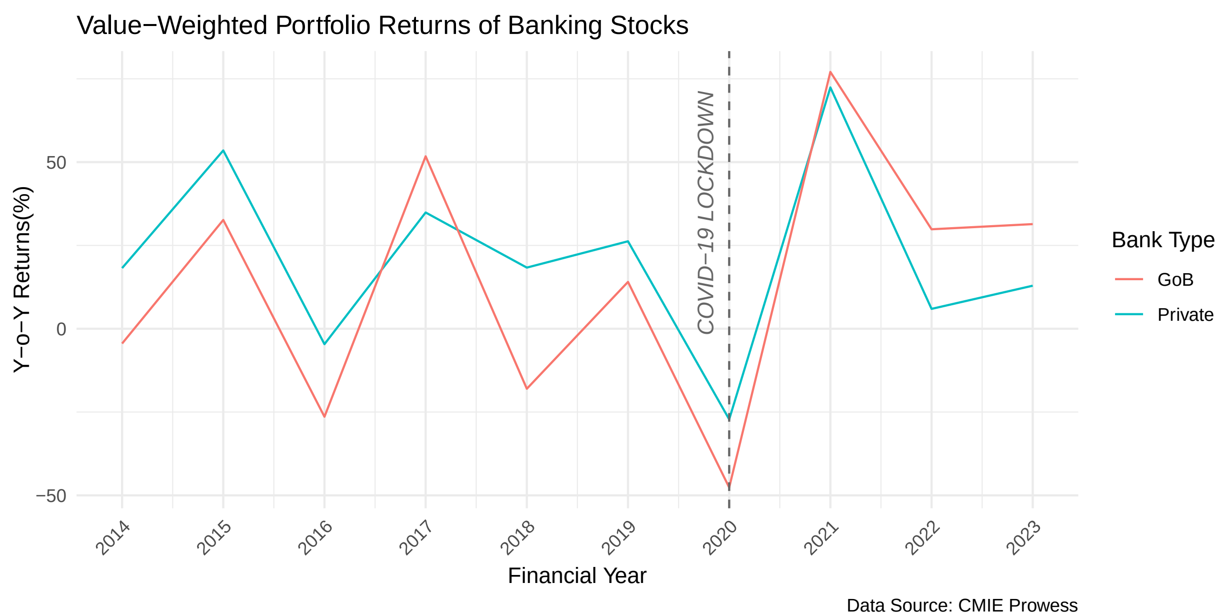

Figure 2: Value-Weighted Portfolio Returns of Banking Stocks: This plot illustrates the year-on-year percentage returns of value-weighted portfolios for Government-Owned Banks (GoBs) and Private Sector Banks during the period 2014-2023. The impact of the COVID-19 lockdown is observable, with GoBs outperforming Private Sector Banks post-lockdown. Data is sourced from CMIE Prowess.

TABLE 1: **Data Coverage Summary**: This table provides a summary of data coverage from two sources: Panel A presents data from the Prowess database (CMIE), and Panel B presents data from the Index of Charges, Ministry of Corporate Affairs (MCA). The table includes the number of Government-owned Banks (GoBs), Private Sector Banks (PVBs), firms, non-financial firms, industries (based on 2-digit NIC classification), and the number of years covered in the dataset for each data source. The coverage spans five financial years (FY) from FY 2018-2019 to FY 2022-23.

Data Source	
Panel A: Prowess, CMIE	**Value**
Number of Government Banks (GoBs)	12
Number of Private Banks (PVBs)	21
Number of Firms	54,817
Number of Industries (2 Digit NIC)	14
Number of Years	5
Panel B: Index of Charges, MCA	**Value**
Number of Firms	148,645
Number of Industries (2 Digit NIC)	14
Number of Years	5
Number of Loans in Sample Period	188,471
Number of Active Firm-Bank Relationship	194,471

TABLE 2: **Summary Statistics** for key financial variables of Banks and firms over the five financial years of the sample from FY 2018-19 to FY 2022-23. Panel A presents the statistics of the key variables for Banks, and Panel B for Firms. For each variable, we report the Mean, Standard Deviation (SD), Minimum (Min), Maximum (Max), 5th Percentile (P5), Median (P50), and 95th Percentile (P95).

Panel A: Banks							
	Mean	SD	Min	Max	P5	P50	P95
Assets(In Trillion INR)	5.16	8.35	0.08	55.28	0.12	2.49	15.88
PAT(In Billion INR)	26.41	85.69	-164.18	502.32	-56.41	6.03	210.78
Expenses(In Billion INR)	372.18	534.47	5.70	3232.07	10.60	205.75	1125.18
ROA(%)	0.51	1.03	-210.49	0.91	-45.89	0.24	1.33
Net Interest Margin(%)	2.86	1.25	-5.56	7.97	1.89	2.71	4.55
NNPA Ratio(%)	3.25	4.01	0.25	35.02	0.41	2.29	7.73
Loans to Deposits Ratio	0.43	0.05	0.29	0.62	0.34	0.43	0.51
Employee Compensation Ratio	0.13	0.04	0.06	0.30	0.07	0.19	0.21
Stock Returns(%)	12.58	55.69	-91.73	175.25	-68.99	8.30	118.67

Panel B: Firms							
	Mean	SD	Min	Max	P5	P50	P95
EBITDA(In Billion INR)	1.01	13.27	-439.15	1214.41	-0.02	0.02	2.29
Cash Profit(In Billion INR)	476.49	733.45	-316.67	591.72	-0.10	0.02	1.46
Delta Receivables(In Billion INR)	0.35	5.59	-239.07	235.77	-0.85	0.02	2.05
Interest Coverage Ratio(%)	34.16	2242.79	-16.11	341620.40	0.62	2.39	44.08

Panel C: Loan Variables							
	Mean	SD	Min	Max	P5	P50	P95
Loan Amount(In Trillion INR)	417.10	10,540.00	0.00	4,624,000.00	0.00	0.00	840.00
Loan Dummy	0.22	0.42	0.00	1.00	0.00	0.00	1.00
Average Relationship Days (Till 2020)	273.12	75.89	0.00	1061.76	138.94	278.34	333.46
Composite Relationship Measure	0.04	0.04	0.00	0.53	0.01	0.02	0.10
High Relationship Banking Dummy	0.55	0.49	0.00	1.00	0.00	1.00	1.00

TABLE 3: **Comparison of Key Financial Metrics** Between Government Owned Banks and Private Sector Banks During the Pre-COVID Period (FY 2018-19 to FY 2019-20) and Post-COVID Period (FY 2021-22 to FY 2022-23). The variables reported include Assets (in Trillion INR), Profit After Tax (PAT) (in Billion INR), Net Interest Margin(%), Net Non-Performing Assets (NNPA) Ratio(%), Loans to Deposits Ratio, Employee Compensation Ratio and Stock Returns(%). This analysis captures differences in these variables across bank types, reflecting the difference during the pre-COVID period in Panel A and the post-COVID period in Panel B. We report the difference in means ($\mu_1 - \mu_0$), where μ_1 refers to the mean value of the financial metric for the Public Sector Banks and μ_0 refers to that of Private Sector Banks. p-values are also presented, with significance levels denoted by $*p < 0.05$, $**p < 0.01$, and $***p < 0.001$.

Panel A: Pre-COVID	GoB(μ_1)	Private(μ_0)	$\mu_1 - \mu_0$	p
Assets (Trillion INR)	18.746	15.450	3.296*	0.027
PAT (Billion INR)	60.606	100.532	-39.926**	0.003
Net Interest Margin (%)	2.486	3.675	-1.189***	0.000
NNPA Ratio (%)	11.920	7.846	4.074***	0.000
Loans to Deposits Ratio	0.752	0.812	-0.060***	0.000
Employee Compensation Ratio	0.063	0.054	0.009	0.245
Stock Returns (%)	11.192	22.473	-11.281	0.244

Panel B: Post-COVID	GoB(μ_1)	Private(μ_0)	$\mu_1 - \mu_0$	p
Assets (Trillion INR)	27.253	19.873	7.380**	0.003
PAT (Billion INR)	67.547	48.690	18.857	0.490
Net Interest Margin (%)	3.056	4.120	-1.064***	0.000
NNPA Ratio (%)	7.040	6.420	0.620*	0.024
Loans to Deposits Ratio	0.749	0.795	-0.046***	0.000
Employee Compensation Ratio	0.064	0.049	0.015	0.168
Stock Returns (%)	28.896	8.620	20.276*	0.047

TABLE 4: Bank Performance: This table presents coefficient estimates for regression equation 1. We show results for five dependent variables as Stock Returns in column (1), Return of Total Assets (ROA) in column (2), Net Non-Performing Assets Ratio Credit growth variable in column (3), Logarithm of Total Operating Expenses in Column (4), and Credit growth variable in column (5). Variables used in the regression are described in Section 3. The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centred around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. All regressions have Bank-fixed effects, Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Capital Adequacy and its first lag, Loans to Deposit Ratio, and Employee Compensation Ratio.

	(1) Stock Returns	(2) ROA	(3) NNPA Ratio	(4) ln(Expenses)	(5) ln(L(t)/L(t-1))
GoB × During COVID	-2.718	0.236	-1.971***	-0.00132	0.0451**
	(21.39)	(0.465)	(0.478)	(0.0558)	(0.0182)
GoB × Post COVID	25.76**	0.921**	-2.768***	-0.0948**	0.0346**
	(9.406)	(0.406)	(0.422)	(0.0449)	(0.0146)
Bank Level Controls	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Adjusted R^2	0.610	0.916	0.948	0.995	0.939
Observations	158	170	170	170	170

Standard errors are clustered at the bank level and reported in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE 5: Bank Lending Channel: This table presents coefficient estimates for regression equation 2. We show results with log(1+Amount) as the dependent variable in columns (1) and with Loan Dummy in columns (2). All columns include Firm $\times$ Year and Bank fixed effects. Variables used in the regression are described in Section 3. The data used for the analysis is organized as a firm-bank-year panel, obtained from the Ministry of Corporate Affairs (MCA) database, and includes firms over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centered around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown.

	log(1+Amount)	Loan Dummy
	(1)	(2)
GoB $\times$ During COVID	2.968***	0.0871***
	(0.295)	(0.00888)
GoB $\times$ Post COVID	1.367***	0.0372***
	(0.229)	(0.00714)
Firm $\times$ Year FE	YES	YES
Bank FE	YES	YES
Observations	345027	345027
Adjusted R^2	0.097	0.104

Standard errors are clustered at the industry level and are reported in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE 6: Lending Quality: This table presents coefficient estimates for regression equation 3 after replacing *TBTF* with *Distressed Firm* and *Unrated Firm* indicator variables. We show results with log(1+Amount) as the dependent variable in columns (1) and (2), focusing on distressed firms. "Distressed Firm" is a dummy variable that takes a value of 1 if the firm's interest coverage ratio (ICR) is less than 1, indicating financial distress. We show results based on firm's rating availability in columns (3) and (4), with the dependent variables being log(1+Amount). "Unrated Firm" is a dummy variable, which takes a value of 1 if the firm has not been assigned a rating by any rating agency. Column (1) and (3) do not include any fixed effects, column (2) and (4) includes Firm x Year and Bank fixed effects. Variables used in the regression are described in Section 3. The data used for the analysis is organized as a firm-bank-year panel, obtained from the Ministry of Corporate Affairs (MCA) database, and includes firms over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centred around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown.

	log(1+Amount)			
	(1)	(2)	(3)	(4)
GoB	-3.750***		-6.819***	
	(0.298)		(0.589)	
During COVID	1.120***		0.199	
	(0.287)		(0.391)	
Post COVID	-0.554**		-0.540	
	(0.261)		(0.493)	
GoB × During COVID	1.645***	2.833***	7.374***	7.176***
	(0.342)	(0.285)	(0.999)	(1.271)
GoB × Post COVID	0.453*	1.490***	3.781***	3.047***
	(0.217)	(0.257)	(0.439)	(0.779)
Distressed Firm	-1.454***			
	(0.487)			
GoB × Distressed Firm	-0.372	2.749***		
	(0.447)	(0.456)		
During COVID × Distressed Firm	0.0149			
	(0.429)			
Post COVID × Distressed Firm	0.978**			
	(0.403)			
GoB × During COVID × Distressed Firm	2.736***	2.861*		
	(0.490)	(1.429)		
GoB × Post COVID × Distressed Firm	0.890	-1.526		
	(0.685)	(1.015)		
Unrated Firm			17.54***	
			(0.692)	
GoB × Unrated Firm			1.129	2.838***
			(0.686)	(0.626)
During COVID × Unrated Firm			2.017***	
			(0.268)	
Post COVID × Unrated Firm			0.579	
			(0.459)	
GoB × During COVID × Unrated Firm			-3.218***	-4.184***
			(0.841)	(1.020)
GoB × Post COVID × Unrated Firm			-3.556***	-2.269***
			(0.684)	(0.659)
Firm × Year FE		YES		YES
Bank FE		YES		YES
Observations	825543	345027	237366	119822
Adjusted R^2	0.018	0.097	0.136	0.312

Standard errors are clustered at the industry level and are reported in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE 7: Firm Performance: This table presents coefficient estimates for borrower-level performance based on firm-year data obtained from the CMIE Prowess database. The dependent variables are EBITDA in column (1), Cash Profit in column (2), and Delta Receivables in column (3). "Treatment" is a dummy variable that takes the value of 1 for the firms which have obtained a secured loan during the financial year FY 2020-21. The interaction terms "Treatment × Post COVID" and "Treatment × Post COVID × GoB", which capture the differential impact of the COVID-19 lockdown on treated firms and government-owned banks (GoBs). Firm controls are included in all specifications and the variables used in the regression are described in Section 3. The data is organized as firm-year panel data over six years, with three years pre- and three years post-lockdown. We use an event window [-3, 3] centred around the onset of the COVID-19 lockdown (t=0).

	(1) EBITDA	(2) Cash Profit	(3) Delta Receivables
Treatment × Post Covid	507.0***	406.1***	389.3
	(143.5)	(129.5)	(248.1)
Treatment × Post Covid × GoB	441.0**	617.6***	-1214.4***
	(219.2)	(207.8)	(277.7)
Firm Controls	YES	YES	YES
Year FE	YES	YES	YES
Firm FE	YES	YES	YES
Adjusted R^2	0.841	0.749	0.172
Observations	11643	11620	4167

Standard errors are clustered at the industry level and reported in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE 8: BANK CLEANUP: This table presents coefficient estimates for regression equation 3 after replacing *TBTF* with *High Cleanup Bank*. We show results for two dependent variables Credit growth variable in columns (1) and (2), Net Non-Performing Assets Ratio in columns (3) and (4). The results are based on bank clean-up, testing the hypothesis by calculating the drop in non-performing assets ratio (NNPA) from 2016 to 2020, as the bank clean-up reforms began in 2016 and continued until the onset of the pandemic in 2020. The banks that exhibited an above-median drop in the non-performing loan to net advances ratio are classified as high clean-up banks. The "High Cleanup Bank" is a dummy variable, taking a value of 1 for banks that underwent a higher clean-up, resulting in a below-median NNPA (Net Non-Performing Assets) ratio in the pre-crisis period up to FY 2019-2020. The base period for comparison is FY 2016-17. Variables used in the regression are described in Section 3. The data is organized as a bank-year panel and includes the financial years (FY) from FY 2016-2017 to FY 2019-2020. The DDD analysis using a firm-bank-year panel dataset covers the financial years from FY 2018-2019 to FY 2022-23.

	$\ln\left(\frac{L_t}{L_{t-1}}\right)$ (1)	NNPA Ratio (2)
GoB × During COVID	0.137*	-1.656**
	(0.0787)	(0.801)
GoB × Post COVID	0.0180	-2.349***
	(0.0514)	(0.547)
During COVID × High Cleanup Bank	-0.0705	0.676
	(0.0430)	(0.735)
Post COVID × High Cleanup Bank	-0.0559	0.460
	(0.0389)	(0.400)
GoB × During COVID × High Cleanup Bank	0.0386	-1.780*
	(0.0984)	(0.981)
GoB × Post COVID × High Cleanup Bank	0.189***	-1.973***
	(0.0608)	(0.676)
Bank Controls	YES	YES
Bank FE	YES	YES
Year FE	YES	YES
Adjusted R^2	0.455	0.947
Observations	167	167

Standard errors are clustered at the bank level and reported in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE 9: Bank Digitization: This table presents coefficient estimates for regression equation 3 after replacing *TBTF* with *High Digitization Bank*. We show results for two dependent variables log(1+Amount) and Return on Assets in columns (1) and (2) respectively. This table presents the digitization emphasis of banks over five years in the pre-crisis period FY 2015-2016 to FY 2019-2020. The "High Digitization Bank" is a dummy variable that takes the value of 1 for banks that demonstrated above-median usage of digitization-related terminology in their annual financial reports during the pre-COVID period, measured by the difference in word usage between FY 2019-2020 and FY 2015-2016. The DDD analysis using a firm-bank-year panel dataset covers the financial years from FY 2018-2019 to FY 2022-23 in column (1) and using a bank-year panel dataset in column (2).

	log(1+Amount)	ROA
	(2)	(3)
GoB × During COVID	2.561***	-0.986
	(0.387)	(0.726)
GoB × Post COVID	1.010***	-0.021
	(0.302)	(0.438)
During COVID × High Digitization Bank	-1.825***	-0.606*
	(0.288)	(0.314)
Post COVID × High Digitization Bank	-0.871**	-0.326
	(0.370)	(0.403)
GoB × During COVID × High Digitization Bank	4.221***	2.390***
	(0.335)	(0.734)
GoB × Post COVID × High Digitization Bank	3.281***	1.174*
	(0.363)	(0.597)
Bank Controls	NO	YES
Bank FE	YES	YES
Year FE	NO	YES
Firm × Year FE	YES	NO
Adjusted R^2	0.077	0.653
Observations	286622	135

Standard errors are clustered at the industry level and reported in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$

Appendix

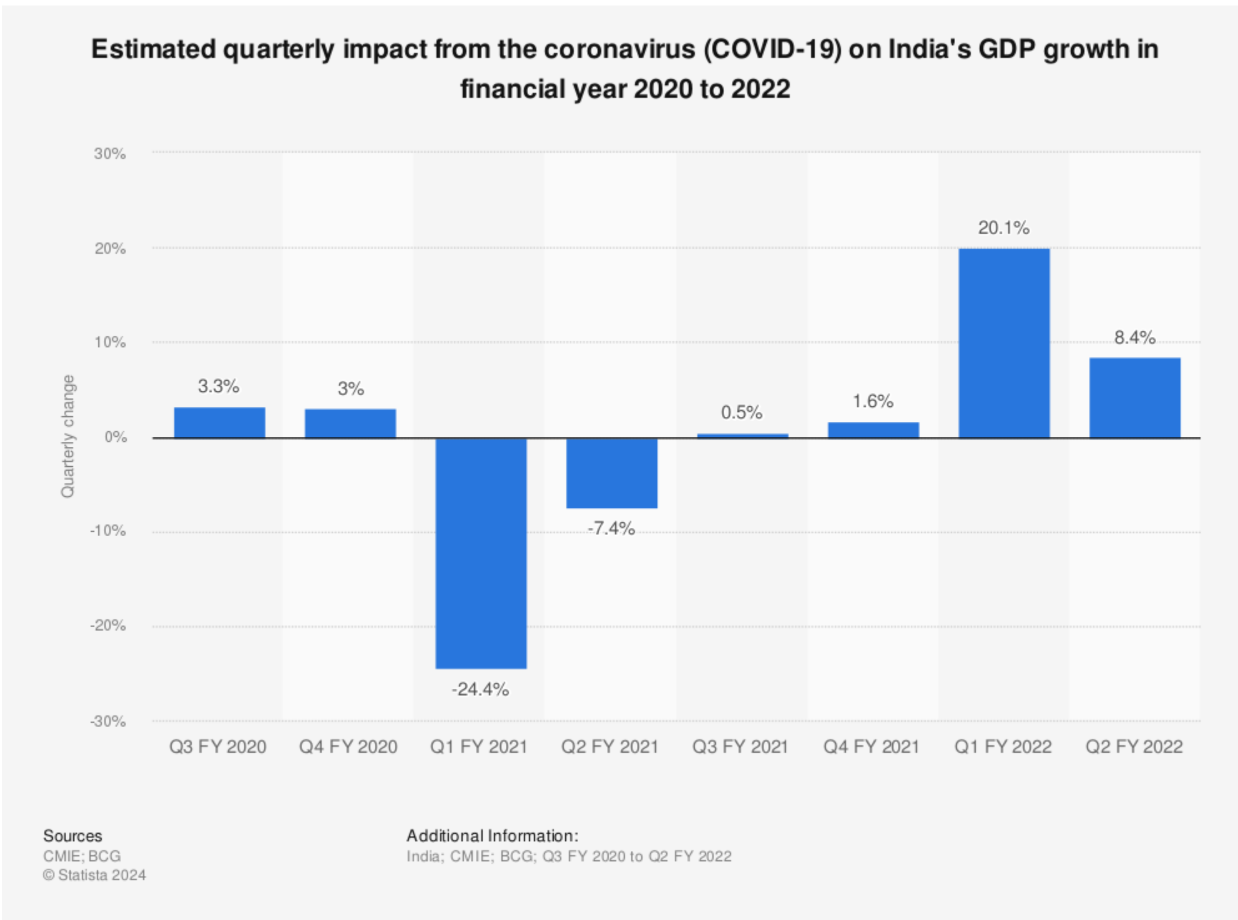

Figure A1: ECONOMIC SHOCK: Estimated quarterly impact from the coronavirus (COVID-19) on India's GDP growth in the financial year 2020 to 2022. Source:https://www.statista.com/statistics/1103120/india-estimated-impact-on-gdp-growth-by-coronavirus-epidemic/

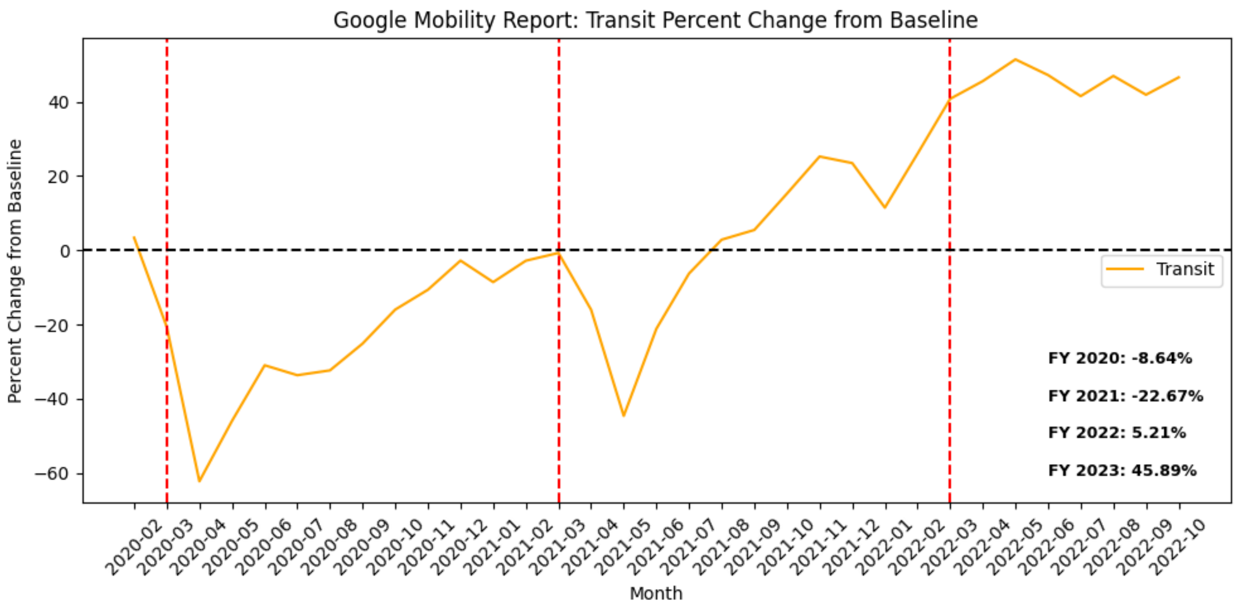

Figure A2: STAGES OF CRISIS: Using Google Mobility Reports, which measure the human traffic at transit stations like railway and bus stations, we gauge the intensity of lockdown and hence the intensity of crisis for different financial years in the sample period. The percentages represent the average of state-wise change in mobility compared to that in February 2020, i.e., before the crisis started. The red vertical lines represent the change to a new financial year.

TABLE A1: Description of Variables

Variable Name	Description	Type
Dependent Variables		
Stock Returns	Year-on-Year stock returns	Continuous
ROA	Return on total assets	Continuous
NNPA Ratio	Net non-performing assets to total advances ratio	Continuous
Credit Growth	Logarithmic difference of lending between the current fiscal year and previous fiscal year, calculated as $log(\frac{L_t}{L_{t-1}})$ denoting the growth in loans and advances	Continuous
Deposit Growth	Logarithmic difference of deposits obtained between the current fiscal year and previous fiscal year, calculated as $log(\frac{D_t}{D_{t-1}})$ denoting the growth in deposits	Continuous
log(1+Amount)	Natural logarithm of the charge amount lent to firms in a year	Continuous
Indicator Variables		
GoB	Dummy variable, which equals one if the lender is a public sector bank and zero in case of a government-owned bank	Binary
Pre COVID	Indicator variable taking a value of zero before the lockdown in 2020	Discrete
During COVID	Indicator variable taking a value of one during 2020, covid-19 lockdown	Discrete
Post COVID	Indicator variable taking a value of two post 2020, after covid-19 lockdown	Discrete
High COVID Impact	Dummy variable, takes a value of 1 for firms operating in industries significantly affected by the COVID-19 pandemic, such as Manufacturing, Construction, Hotels etc. and zero otherwise	Binary
High Capital Infused Bank	Dummy variable, which equals one if the lending bank underwent an above median capital infusion in the pre-crisis period and zero otherwise	Binary
High Cleanup Bank	Dummy variable, which equals one if the lending bank underwent an above median asset clean up excercise in the pre-crisis period and zero otherwise	Binary
High Digitization Bank	Dummy variable, which equals one if the lending bank demonstrated above- median usage of digitization-related terminology in their annual financial reports during the pre-COVID period, measured by the difference in word usage between FY 2019-2020 and FY 2015-2016 and zero otherwise	Binary
PCA	Dummy variable, which equals one if the lender bank is under the Prompt Corrective Action (PCA) of the Reserve Bank of India (RBI) and zero otherwise	Binary
Distressed Firm	Dummy variable, which equals one if the firm has an Interest Coverage Ratio (ICR) < 1 and otherwise	Binary
Relationship Banking	Dummy variable, takes a value of 1 for above median firm-bank relationship score and zero otherwise	Binary

Continued on next page

TABLE A1: (Continued) Description of Variables

Variable Name	Description	Type
Unrated Firm	Dummy variable, which equals one if the firm has not been rated by any of the credit rating agency and zero otherwise	Binary
TBTF	Dummy variable, which equals one if the lender is a TOO-BIG-TO-FAIL bank and zero otherwise	Binary
Bank Controls		
Size	Natural logarithm of the total assets of a bank	Continuous
Loans-to-deposits ratio	Loans issued in the current fiscal year scaled upon the deposits accumulated in the previous fiscal year	Continuous
Employee compensation ratio	Employee compensation in the current fiscal year scaled upon the income generated in the previous fiscal year	Continuous
AQR Measure	Net NPA Divergence scaled by total assets; where net means the difference in the financial years between FY 2019-20 and FY 2016-17	Continuous
Firm Variables		
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization. It is a key financial metric used to assess a firm's operating performance	Continuous
Cash Profit	Cash Profit refers to the actual cash earnings of a firm after accounting for non-cash expenses like depreciation and amortization but before considering financing costs and taxes. It represents the firm's ability to generate cash from operations.	Continuous
Delta Receivables	Change in firm's receivables refers to the outstanding amounts that a firm is yet to receive from its customers or clients for goods sold or services rendered on credit.	Continuous

TABLE A2: Sumary: Government Ownership of Banks across the World: Percent of the banking system's assets held by banks that were government-controlled (i.e. where government-owned 50% or more equity). Source: World Bank - Bank Regulation and Supervision Survey - 2016.

	All	With non-zero values
Number of Observations	144	100
Mean	14.26	20.53
Std Dev	18.92	19.66
Min	0	0.06
Max	100	100
Percentile		
10	0	0.2
25	0	4.7
50	4.9	15
75	22.5	30.1
90	44.6	49

TABLE A3: Countries with Government Owned Banks: This table lists countries where the banking system has a presence of government-controlled banks (i.e., banks with at least 50% government equity). Source: World Bank – Bank Regulation and Supervision Survey (2016).

Angola	Argentina	Armenia	Austria
Azerbaijan	Bangladesh	Belarus	Belgium
Belize	Benin	Bhutan	Bolivia
Bosnia and Herzegovina	Botswana	Brazil	British Virgin Islands
Burkina Faso	Burundi	Cabo Verde	Chile
Colombia	Costa Rica	Cote d'Ivoire	Croatia
Curaçao	Cyprus	Czech Republic	Dominican Republic
Ecuador	El Salvador	France	Gambia, The
Germany	Ghana	Guatemala	Guinea-Bissau
Haiti	Hungary	Iceland	India
Indonesia	Ireland	Kazakhstan	Kenya
Korea, Rep.	Kuwait	Kyrgyz Republic	Lesotho
Liberia	Liechtenstein	Luxembourg	Macao SAR, China
Maldives	Mali	Marshall Islands	Mauritius
Mexico	Morocco	Namibia	Netherlands
New Zealand	Niger	North Macedonia	Pakistan
Panama	Paraguay	Peru	Philippines
Poland	Portugal	Qatar	Romania
Russian Federation	Rwanda	Samoa	San Marino
Saudi Arabia	Senegal	Serbia	Seychelles
Slovenia	Spain	Sri Lanka	Sweden
Switzerland	Taiwan, China	Tajikistan	Tanzania
Thailand	Togo	Tonga	Trinidad and Tobago
Tunisia	Turkey	Uganda	Ukraine
United Kingdom	Uruguay	Vietnam	Zimbabwe

TABLE A4: **Summary Statistics** for key financial variables of Government-owned and Private Sector Banks over the pre-crisis financial years, FY 2018-19 to FY 2019-20. Panel A presents the statistics for Government-owned Banks, and Panel B for Private Sector Banks. The variables reported include Assets (in Trillion INR), Profit After Tax (PAT) (in Billion INR), Net Interest Margin(%), Net Non-Performing Assets (NNPA) Ratio(%), Loans to Deposits Ratio, Employee Compensation Ratio and Stock Returns(%). For each variable, we report the Mean, Standard Deviation (SD), Minimum (Min), Maximum (Max), 5th Percentile (P5), Median (P50), and 95th Percentile (P95).

Panel A: Government-owned Banks

	Mean	SD	Min	Max	P5	P50	P95
Assets(In Trillion INR)	5.812	8.628	0.085	39.514	0.135	2.955	36.809
Expenses(In Billion INR)	480.624	635.453	11.983	2891.875	75.569	279.053	2825.791
PAT(In Billion INR)	-25.539	47.091	-151.163	144.881	-99.755	-24.142	8.622
Net Interest Margin(%)	1.994	1.376	-5.560	3.374	1.302	2.168	2.685
NNPA Ratio(%)	6.597	5.456	2.190	35.020	2.230	5.565	10.810
Loans to Deposits Ratio	0.399	0.036	0.315	0.449	0.336	0.407	0.441
Employee Compensation Ratio	0.121	0.025	0.077	0.168	0.078	0.125	0.166
Stock Returns(%)	-33.029	31.693	-84.610	28.350	-69.980	-35.390	10.380

Panel B: Private Sector Banks

	Mean	SD	Min	Max	P5	P50	P95
Assets(In Trillion INR)	2.516	3.687	0.081	15.305	0.118	0.919	11.011
Expenses(In Billion INR)	216.729	286.553	6.556	1125.183	10.419	81.332	835.780
PAT(In Billion INR)	14.386	63.737	-164.180	262.573	-28.642	4.318	79.308
Net Interest Margin(%)	3.182	1.112	1.693	7.965	1.892	3.042	4.079
NNPA Ratio(%)	2.523	2.017	0.360	10.040	0.580	1.910	5.770
Loans to Deposits Ratio	0.459	0.058	0.326	0.619	0.375	0.454	0.559
Employee Compensation Ratio	0.112	0.041	0.062	0.241	0.066	0.109	0.191
Stock Returns(%)	-21.748	40.681	-91.730	52.250	-80.160	-19.160	44.540

TABLE A5: MAIN RESULT: This table presents coefficient estimates for regression equation 1. We show results for five dependent variables as Stock Returns in column (1), Return of Total Assets (ROA) in column (2), Net Non-Performing Assets Ratio Credit growth variable in column (3), Logarithm of Total Operating Expenses in Column (4), and Credit growth variable in column (5). Variables used in the regression are described in Section 3. The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centred around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. All regressions have Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Capital Adequacy and its first lag, Loans to Deposit Ratio, and Employee Compensation Ratio.

	(1) Stock Returns	(2) ROA	(3) NNPA Ratio	(4) ln(Expenses)	(5) ln(L(t)/L(t-1))
GoB	-17.42*	-1.150***	2.718***	0.0686	0.0560**
	(8.742)	(0.397)	(0.559)	(0.0647)	(0.0234)
GoB × During COVID	5.241	0.333	-1.168	-0.0794	0.0765**
	(20.96)	(0.505)	(0.697)	(0.0681)	(0.0316)
GoB × Post COVID	30.59***	1.012***	-2.253***	-0.126**	0.0412*
	(10.23)	(0.360)	(0.454)	(0.0566)	(0.0208)
Bank Level Controls	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES
Adjusted R^2	0.606	0.851	0.891	0.986	0.811
Observations	159	176	176	176	176

Standard errors are clustered at the bank level and reported in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A6: Too Big to Fail: Regression results for banks classified by the Reserve Bank of India (RBI) as Domestic Systemically Important Banks (D-SIBs), or "Too Big to Fail" (TBTF) banks. The TBTF dummy variable takes a value of 1 for banks in the SBI Group, HDFC, and ICICI. This table presents results based on a Difference-in-Differences-in-Differences (DDD) framework, interacting TBTF banks with Government-Owned Banks (GoB) during and after the COVID-19 pandemic. The dependent variables across the columns are as follows: Column (1) Stock Returns, Column (2) Return on Assets (ROA), Column (3) Credit Growth, Column (4) Net Non-Performing Assets (NNPA) ratio, Column (5) log(Expenses). The triple interaction terms assess the impact of being a TBTF bank, and a GoB, and the effects of COVID-19 on these banks. Each specification includes year and bank fixed effects. Variables used in the regression are described in Section 3. The sample is obtained from CMIE Prowess database and organized as a bank-year panel. The analysis uses a five-year event window [-2, 2], centered around the COVID-19 lockdown during the financial year April 2020 to March 2021 (t=0).

	(1) Stock Returns	(2) ROA	(3) $\ln\left(\frac{L_t}{L_{t-1}}\right)$	(4) NNPA Ratio	(5) ln(Expenses)
GoB × During COVID	3.644	0.486	0.0585***	-2.895***	-0.116*
	(0.16)	(1.03)	(2.87)	(-4.15)	(-1.96)
GoB × Post COVID	32.25***	1.188***	0.0533***	-3.920***	-0.169***
	(4.03)	(2.99)	(3.08)	(-6.58)	(-2.80)
During COVID × TBTF	-26.72	1.718	0.0902***	-2.383***	-0.193**
	(-1.22)	(1.64)	(5.50)	(-5.92)	(-2.36)
Post COVID × TBTF	-0.486	0.831**	0.0590*	-1.804***	-0.174***
	(-0.03)	(2.17)	(1.81)	(-2.80)	(-3.47)
GoB × During COVID × TBTF	24.10	-1.401	-0.109***	2.394***	0.165*
	(0.85)	(-1.22)	(-4.93)	(3.25)	(1.74)
GoB × Post COVID × TBTF	-0.854	-1.110*	-0.0740**	3.180***	0.197***
	(-0.05)	(-1.97)	(-2.03)	(3.59)	(2.96)
Year FE	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES
Adjusted R^2	0.666	0.918	0.932	0.888	0.992
Observations	159	184	184	184	170

t statistics in parentheses. Standard errors are clustered at the bank level.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A7: Countercyclical Lending: This table examines whether government-owned banks (GoBs) responded counter-cyclically to local economic disruptions during the Covid-19 pandemic by extending more credit in regions experiencing stricter lockdowns. We use detailed loan-level data from the Ministry of Corporate Affairs (MCA) to construct a firm-state-year panel of secured loans. To capture local economic conditions, we incorporate Google's location-specific lockdown stringency index. The dependent variable in the first pair of columns is the log amount of credit sanctioned, and in the second pair, an indicator for whether a new loan was issued. The key interaction term—GoB × Lockdown Stringency—is positive and significant across all specifications, suggesting that GoBs disproportionately extended credit in more stringently locked-down regions. All regressions include year and state fixed effects, and some include firm fixed effects as indicated. Standard errors are clustered at the state level.

	log(1 + Loan Amount)		New Loan Dummy	
	(1)	(2)	(3)	(4)
GoB	-0.795**	-1.583***	-0.0472**	-0.106***
	(0.315)	(0.220)	(0.0194)	(0.0142)
Lockdown Stringency	0.0057	-0.0170***	0.0002	-0.0011***
	(0.0137)	(0.0047)	(0.0007)	(0.0003)
GoB × Lockdown Stringency	0.0103**	0.025***	0.0007***	0.0016***
	(0.0040)	(0.0032)	(0.0002)	(0.0002)
Year FE	YES	YES	YES	YES
Firm FE		YES		YES
State FE		YES		YES
Observations	336722	329254	336722	329254
Adjusted R^2	0.002	0.238	0.003	0.217

Standard errors in parentheses and are clustered at the state level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE A8: COVARIATES OF GOB RETURNS: This table presents the coefficient estimates for Return on Assets (ROA), based on Fixed Effects Regression. The dependent variable is the Return on Assets (ROA). The sample is obtained from CMIE Prowess database for banks over a 5-year period from FY 2018-19 to FY 2022-23. Column (1) presents results with year fixed effects, while Column (2) includes both year and bank fixed effects. Independent variables include credit growth rate (ln(L(t)/L(t-1))), Net Non-Performing Assets (NNPA) Ratio, Net Interest Margin (NIM), log of total assets, employee compensation ratio, capital adequacy ratio (current and lagged), and loans to deposits ratio.

	(1)	(2)
	RoA	
GoB	-0.755**	
	(0.369)	
ln(L(t)/L(t-1))	8.235***	8.078**
	(2.239)	(3.261)
NNPA Ratio	-0.229***	-0.141**
	(0.0524)	(0.0612)
NIM	0.492***	0.744**
	(0.0861)	(0.297)
ln(Total Assets)	0.0969	-0.564
	(0.0919)	(0.510)
Employee Compensation Ratio	-6.848**	-7.324
	(2.933)	(7.846)
Capital Adequacy Ratio	0.0657***	0.0717***
	(0.00578)	(0.0113)
L.Capital Adequacy Ratio	-0.104***	-0.105***
	(0.00597)	(0.00683)
Loans Deposits Ratio	-8.661**	-7.421
	(3.895)	(4.959)
Year FE	YES	YES
Bank FE		YES
Adjusted R^2	0.911	0.938
Observations	176	170

Standard errors are clustered at the bank level and reported in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A9: Bank Lending Channel without SBI: This table presents coefficient estimates for regression equation 2. The dependent variable across all columns is log(1+Amount). Column (1) includes Year fixed effects, Column (2) includes Industry fixed effects, Column (3) includes Industry x Year fixed effects, Column (4) includes Firm fixed effects, Column (5) includes Firm x Year fixed effects, and Column (6) includes Firm x Year and Bank fixed effects. The sample is obtained from the Ministry of Corporate Affairs (MCA) database, organized as a firm-bank-year panel spanning the financial years April 2018 to March 2023. Variables used in the regression are detailed in Section 3. The analysis uses a five-year event window [-2, 2], centered around the COVID-19 lockdown during the financial year April 2020 to March 2021 (t=0).

	log(1+Amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
GoB	-4.159***	-4.156***	-4.143***	-5.866***	-5.696***	
	(-15.27)	(-15.81)	(-15.98)	(-15.85)	(-12.46)	
During COVID		1.155***		1.102***		
		(4.75)		(5.24)		
Post COVID		-0.375*		-1.123***		
		(-1.86)		(-10.05)		
GoB × During COVID	2.335***	2.332***	2.284***	3.087***	3.962***	3.433***
	(6.89)	(7.01)	(7.00)	(12.63)	(8.47)	(7.65)
GoB × Post COVID	0.806***	0.853***	0.796***	2.909***	2.544***	1.761***
	(4.78)	(5.19)	(4.91)	(17.05)	(8.19)	(5.44)
Year FE	YES					
Industry FE		YES				
Ind. × Year FE			YES			
Firm				YES		
Firm × Year FE					YES	YES
Bank FE						YES
Adjusted R^2	0.027	0.021	0.029	0.126	0.058	0.094
Observations	736210	736210	736210	728122	297742	297742

t statistics in parentheses. Standard errors are clustered at the industry level.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A10: Regulatory Intervention and NPA Recognition: This table presents the coefficient estimates of the effects of "Average Exposure" measure on the Net Non-Performing Assets (NNPA) Ratio for banks. The analysis is conducted using a bank-year panel, obtained from the CMIE Prowess database, covering the financial years from FY 2016 to FY 2020. The dependent variable is the NNPA Ratio, which reflects the share of non-performing assets in relation to the bank's total assets. The primary explanatory variables include Government-Owned Banks (GoB), and interaction terms between GoB and the average exposure measures. Control variables such as Size, Employee Compensation Ratio, Capital Adequacy Ratio, and Loans to Deposits Ratio are included to account for bank-specific characteristics. Year fixed effects are used to control for time-specific shocks affecting all banks.

	NNPA Ratio	
	(1)	(2)
GoB	1.536**	1.680**
	(2.15)	(0.822)
AQR Exposure	2.421**	
	(2.19)	
GoB × AQR Exposure	4.879***	
	(2.86)	
GoB× PCA		2.915***
		(0.794)
Bank Level Controls	YES	YES
Year FE	YES	YES
Adjusted R^2	0.800	0.798
Observations	208	162

Standard errors are clustered at the bank level and reported in parenthesis
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A11: RELATIONSHIP BANKING: This table presents coefficient estimates for regression equation 3 after replacing *TBTF* with *Relationship Banking* indicator variable. We show results based on the impact of relationship banking on firm-bank interactions, using a newly constructed composite relationship measure. The variable, "Relationship Banking", is a dummy variable that takes a value of 1 if the bank's relationship score exceeds the median for all firm-bank pairs before the COVID-19 lockdown. The composite relationship measure captures three dimensions: the average number of firms per interaction, the average relationship duration (in days) until 2021, and the average loan amount (in millions). These dimensions reflect the strength and depth of banking relationships across firms. Column (1) includes Year fixed effects, column (2) includes Industry fixed effects, column (3) includes Industry x Year fixed effects, column (4) includes Firm fixed effects, column (5) includes Firm x Year fixed effects, and column (6) includes Firm x Year and Bank fixed effects. Variables used in the regression are described in Section 3. The data used for the analysis is organized as a firm-bank-year panel, obtained from the Ministry of Corporate Affairs (MCA) database, and covers the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centred around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown.

	log(1+Amount)					
	(1)	(2)	(3)	(4)	(5)	(6)
GoB	-4.547***	-4.538***	-4.540***	-8.066***	-7.123***	
	(0.349)	(0.341)	(0.340)	(0.503)	(0.511)	
During COVID		2.135***		2.021***		
		(0.330)		(0.303)		
Post COVID		0.831***		-0.0804		
		(0.273)		(0.192)		
GoB × During COVID	0.599	0.599	0.579	1.615***	1.214**	1.197***
	(0.369)	(0.368)	(0.355)	(0.274)	(0.443)	(0.392)
GoB × Post COVID	-0.693***	-0.612**	-0.687***	2.006***	0.773**	0.477
	(0.233)	(0.230)	(0.231)	(0.195)	(0.314)	(0.289)
Relationship Banking	0.848***	0.846***	0.838***	-0.188	0.134	
	(0.138)	(0.141)	(0.143)	(0.213)	(0.264)	
GoB × Relationship Banking	0.840***	0.828***	0.866***	3.569***	2.807***	
	(0.179)	(0.173)	(0.179)	(0.328)	(0.259)	
During COVID × Relationship Banking	-1.783***	-1.781***	-1.771***	-1.696***	-1.828***	-1.770***
	(0.261)	(0.262)	(0.260)	(0.229)	(0.444)	(0.416)
Post COVID × Relationship Banking	-2.372***	-2.353***	-2.368***	-1.938***	-2.578***	-2.433***
	(0.213)	(0.206)	(0.211)	(0.157)	(0.313)	(0.283)
GoB × During COVID × Relationship Banking	2.146***	2.149***	2.086***	1.750***	3.365***	3.196***
	(0.291)	(0.292)	(0.301)	(0.250)	(0.482)	(0.434)
GoB × Post COVID × Relationship Banking	2.210***	2.160***	2.180***	1.061***	1.885***	1.936***
	(0.161)	(0.159)	(0.162)	(0.146)	(0.199)	(0.191)
log_firm_age	-0.815***	-0.939***	-0.898***	-12.95***		
	(0.135)	(0.149)	(0.143)	(0.516)		
Year FE	YES					
Industry FE		YES				
Ind. × Year FE			YES			
Firm				YES		
Firm × Year FE					YES	YES
Bank FE						YES
Adjusted R^2	0.031	0.026	0.033	0.126	0.063	0.088
Observations	800420	800420	800420	792325	332254	332254

Standard errors are clustered at the industry level and reported in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A12: CAPITAL INFUSION: This table presents coefficient estimates for regression equation 3 after replacing *TBTF* with *High Capital Infused Bank*. We show results for two dependent variables of lending in columns (1) and (2), as well as the credit growth variable in columns (3). The results are based on bank capital infusion, testing the hypothesis of whether capital infusion has driven lending by calculating the increase in Capital Infusion from 2016 to 2020. The banks that exhibited an above-median increase in the capital infusion are classified as high capital infusion banks. The "High Capital Infused Bank" is a dummy variable, taking a value of 1 for banks that underwent a higher capital infusion above-median in the pre-crisis period up to FY 2019-2020. The base period for comparison is FY 2016-17. The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centred around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. Variables used in the regression are described in Section 3. All regressions have Bank-fixed effects, Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Capital Adequacy Ratio.

	(1) log(L(t))	(2) log(L(t+1))	(3) ln(L(t)/L(t-1))
GoB × Post COVID	-0.0289	-0.0112	0.0203
	(0.0263)	(0.0188)	(0.0648)
GoB × Post COVID × High Capital Infused Bank	0.0585**	0.0717**	0.119**
	(0.0272)	(0.0313)	(0.0575)
Bank Controls	YES	YES	YES
Bank FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	135	131	135
Adjusted R^2	0.999	0.997	0.399

Standard errors in parentheses are clustered at the bank level.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A13: DEPOSIT GROWTH: This table presents coefficient estimates for regression equation 3 after replacing *TBTF* with the deposit growth computed as $ln(D(t)/D(t-1))$. We show results for three dependent variables of Stock returns, Return on Assets (ROA) and Lending Growth Variable in columns (1), (2) and (3) respectively. The results are based on the increased deposit growth in banks, testing the hypothesis whether increase in deposits drives lending and other bank performance measures during and aftermath the pandemic. The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centered around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. Variables used in the regression are described in Section 3. All regressions have Bank-fixed effects, Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Employee Compensation Ratio, Loans to Deposit Ratio, Capital Adequacy Ratio and its first lag.

	(1) Stock Returns	(2) ROA	(3) ln(L(t)/L(t-1))
GoB × During COVID	19.22	0.642	0.0564***
	(27.01)	(0.575)	(0.0194)
GoB × Post COVID	6.522	1.294**	0.0552***
	(21.86)	(0.601)	(0.0183)
ln(D(t)/D(t-1))	109.5	8.889***	0.297***
	(96.21)	(2.006)	(0.0479)
GoB × ln(D(t)/D(t-1))	-55.39	-0.328	0.269***
	(59.99)	(3.775)	(0.0832)
During COVID × ln(D(t)/D(t-1))	194.1*	-2.565	-0.0639
	(110.1)	(2.846)	(0.151)
Post COVID × ln(D(t)/D(t-1))	-150.0	-0.0739	-0.0284
	(111.2)	(2.929)	(0.0973)
GoB × During COVID × ln(D(t)/D(t-1))	-167.3	-1.739	-0.202
	(140.9)	(4.708)	(0.149)
GoB × Post COVID × ln(D(t)/D(t-1))	213.9	-2.851	-0.259*
	(206.9)	(5.125)	(0.139)
Bank Controls	YES	YES	YES
Bank FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	158	170	170
Adjusted R^2	0.613	0.929	0.947

Standard errors in parentheses are clustered at the bank level
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A14: Non-Interest Income: This table presents coefficient estimates for regression equation 1. We show results for Non-Interest Income as the percentage of total income as the dependent variable in column (1). The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centered around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. Variables used in the regression are described in Section 3. All regressions have Bank-fixed effects, Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Capital Adequacy and its first lag, Loans to Deposit Ratio.

	$\frac{\text{Non-Interest Income}}{\text{Total Income}}$ (1)
GoB × During COVID	0.0524**
	(0.0252)
GoB × Post COVID	0.0374
	(0.0481)
Year FE	YES
Bank FE	YES
Observations	113
Adjusted R^2	0.082

Standard errors in parentheses are clustered at the bank level.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A15: LENDING RATES: This table presents coefficient estimates for regression equation 1. We show results for Benchmark Rate in column (1), Demand Rate for 5 per cent and 60 per cent or more business originated in columns (2) and (4), respectively, and Term Rate for 5 per cent and 60 percent or more business in columns (3) and (5), respectively, as the dependent variable. The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database and the RBI database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centered around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. Variables used in the regression are described in Section 3. All regressions have Bank-fixed effects, Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Capital Adequacy and Loans to Deposit Ratio.

	(1) Benchmark	(2) Demand Rate 5%	(3) Term Rate 5%	(4) Demand Rate 60%	(5) Term Rate 60%
GoB × During COVID	-0.0751	-0.418	-0.419	-0.0338	-0.786
	(0.0746)	(0.792)	(0.950)	(0.385)	(0.933)
GoB × Post COVID	-0.153	-0.460	-0.224	-0.487	-1.491
	(0.144)	(0.820)	(0.988)	(1.078)	(1.002)
Bank Controls	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
Observations	135	132	128	133	132
Adjusted R^2	0.839	0.840	0.663	0.394	0.465

Standard errors in parentheses are clustered at the bank level.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A16: Net Interest Margin: This table presents coefficient estimates for regression equation 1. We show results for Net Interest Margin (NIM) as the dependent variable in column (1). The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centered around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. Variables used in the regression are described in Section 3. All regressions have Bank-fixed effects, Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Capital Adequacy and its first lag, Loans to Deposit Ratio, and Employee Compensation Ratio.

	(1) NIM
GoB × During COVID	0.0965
	(0.153)
GoB × Post COVID	0.0557
	(0.187)
Bank Level Controls	YES
Bank FE	YES
Year FE	YES
Adjusted R^2	0.923
Observations	170

Standard errors are clustered at the bank level and reported in parentheses.
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A17: Main Result Without Merged Banks.: This table presents coefficient estimates for regression equation 1. We show results for five dependent variables as Stock Returns in column (1), Return of Total Assets (ROA) in column (2), Net Non-Performing Assets Ratio Credit growth variable in column (3), Logarithm of Total Expenses in Column (4), and Credit growth variable in column (5). Variables used in the regression are described in Section 3. The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centred around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. All regressions have Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Capital Adequacy and its first lag, Loans to Deposit Ratio, and Employee Compensation Ratio.

	(1) Stock Returns	(2) ROA	(3) NNPA Ratio	(4) ln(Expenses)	(5) ln(L(t)/L(t-1))
GoB	-18.73*	-1.080*	3.461***	0.137	0.0286
	(10.09)	(0.533)	(0.773)	(0.0887)	(0.0299)
GoB × During COVID	20.65	0.729	-2.791***	-0.105	0.0691**
	(24.20)	(0.737)	(0.615)	(0.0778)	(0.0278)
GoB × Post COVID	27.34**	1.152**	-3.373***	-0.207***	0.0791***
	(11.24)	(0.472)	(0.575)	(0.0739)	(0.0219)
Bank Level Controls	YES	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES
Adjusted R^2	0.590	0.498	0.697	0.982	0.751
Observations	129	136	136	136	136

Standard errors are clustered at the bank level and reported in parentheses.

$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A18: MAIN RESULT WITH MERGER DUMMY AND AMALGAMATED BANK DATA: This table presents coefficient estimates for regression equation 1. We show results for four dependent variables as Return of Total Assets (ROA) in column (1), Net Non-Performing Assets Ratio Credit growth variable in column (2), Logarithm of Total Expenses in Column (3), and Credit growth variable in column (4). Variables used in the regression are described in Section 3. The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centred around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. All regressions have Year-fixed effects, and bank-level controls that include Bank Size (log(Total Assets)), Capital Adequacy and its first lag, Loans to Deposit Ratio, and Employee Compensation Ratio.

	(1) ROA	(2) NNPA Ratio	(3) ln(Expenses)	(4) ln(L(t)/L(t-1))
GoB	-0.677	2.805***	0.0433	-0.0121
	(0.422)	(0.542)	(0.0771)	(0.0386)
During COVID × GoB	0.553	-1.565**	-0.158**	0.145***
	(0.428)	(0.590)	(0.0659)	(0.0486)
Post COVID × GoB	0.820**	-2.409***	-0.155***	0.116***
	(0.332)	(0.430)	(0.0516)	(0.0264)
Bank Level Controls	YES	YES	YES	YES
Bank FE	NO	NO	NO	NO
Year FE	YES	YES	YES	YES
Observations	173	173	173	173
Adjusted R^2	0.498	0.676	0.986	0.609

Standard errors in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$

TABLE A19: MAIN RESULT WITH PRICE TO BOOK RATIO: This table presents coefficient estimates for regression equation 1. We show results for P/B Ratio as the dependent variable. Variables used in the regression are described in Section 3. The data used for the analysis is organized as bank-year panel data, obtained from the CMIE Prowess database, and includes Scheduled Commercial Banks over the financial years (FY) from FY 2018-2019 to FY 2022-2023. For analysis, a five-year event window [-2, 2] is considered, centred around FY 2020-21 (t=0), aligning with the onset of COVID-19's first wave and the subsequent lockdown. All regressions have Year-fixed effects, and bank-level controls that include Bank Size as (log(Total Assets)), Capital Adequacy, Loans to Deposit Ratio, and Employee Compensation Ratio.

	P/B Ratio
GoB × During COVID	-0.0637
	(0.150)
GoB × Post COVID	0.293*
	(0.153)
Size	-0.275
	(0.255)
Employee Compensation Ratio	-2.108
	(2.119)
Capital Adequacy Ratio	-0.0198
	(0.0126)
Loans Deposits Ratio	0.0949
	(0.423)
Bank FE	YES
Year FE	YES
Observations	120
Adjusted R^2	0.929

Standard errors are clustered at the bank level and reported in parentheses
$*p < 0.1, **p < 0.05, ***p < 0.01$