Does Systemically Important Bank Status Affect Loan Performance? *

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Abstract

We test whether the policy of designating some banks as systemically important (SIB) impacts loan performance. Our tests show that the same borrower is more likely to default on a bank after that bank is identified as an SIB, compared to a non-SIB. Evidence suggests that the increase in loan delinquency is due to a reduction in the monitoring of borrowers by SIBs and not due to their prompt recognition of losses. Thus, our results show that the policy of explicitly identifying systemically important banks could result in moral hazard, where the banks become less diligent in monitoring their borrowers.

Keywords: Systemically Important Banks, Too-big-to-fail, Monitoring, BASEL

JEL Codes: M48, G21, G28, H81

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1 Introduction

The 2008 global financial crisis underscored the risks posed by the failure of too-big-to-fail banks for the broader economy.[1] In response, regulators worldwide created the Systemically Important Bank (SIB) framework, identifying SIBs and subjecting them to higher capital requirements and enhanced supervision.[2] However, by formally designating certain banks as systemically important, regulators may inadvertently signal that these banks will be rescued in a crisis. This creates a fundamental tension in how SIB designation affects bank behavior.

On the one hand, the perceived safety net could encourage moral hazard, inducing SIBs to reduce monitoring, resulting in higher loan delinquencies among SIBs (Dewatripont and Maskin (1995); Qian and Roland (1998)).[3] The above possibility may potentially result in higher loan defaults on SIBs. On the other hand, the additional capital could reduce the risk-taking incentive of SIBs, as they have more skin in the game, while increased regulatory scrutiny might improve loan monitoring (Holmstrom and Tirole (1997), Bhat and Desai (2020)). The above possibility should cause borrowers of SIB to default relatively less on them. These competing theoretical possibilities make the actual impact of SIB designation on loan performance unclear. To the best of our knowledge, our study is the first to systematically examine these effects using detailed loan-level data, providing important empirical evidence on how SIB policies influence loan repayment behavior.

Specifically, this paper addresses the following research question: Does SIB designation

[1]Freixas et al. (2000); Upper and Worms (2004); Iyer and Peydro (2011); Schnabl (2012); Strahan (2013); Acemoglu et al. (2015); Acharya et al. (2016); Favara et al. (2021) describe the too-big-to-fail problem.

[2]The Financial Stability Board (FSB), whose membership includes policymakers from G20 countries and the accounting standard setter IASB, among other organizations, and the Basel Committee on Banking Supervision (BCBS) collaborated to introduce the SIB framework in 2011.

[3]Higher capital requirements might also push banks toward riskier investments as they seek higher yields (Jiménez et al. (2017), Gropp et al. (2014)).

create perverse incentives that worsen loan performance?[4] We exploit the staggered implementation of domestic SIB classification in India to examine the above question. Using a difference-in-differences (DID) design on loan-level data from 2010 to 2020, we find that SIBs witness significantly higher loan delinquencies. The results are consistent with Jiménez et al. (2017) and Gropp et al. (2014), but with crucial differences in setting.[5] We find evidence of lax monitoring as hard-to-monitor borrowers (unrated, distant, weak governance) default more on SIBs. Furthermore, SIBs cut communication expenses (proxy for monitoring) and file fewer legal recoveries. Lastly, SIBs engage in more loan restructuring, suggesting evergreening. Our findings reveal that SIB policies undermine loan quality by distorting monitoring incentives.

The emerging market setting adds urgency to this inquiry. While most SIB studies focus on G-SIBs concentrated in advanced economies (Favara et al. (2021); Behn and Schramm (2021); Degryse et al. (2023)), conditions in markets like India differ. Due to higher state intervention, implicit guarantees are stronger; monitoring costs are higher, given severe information asymmetry and slower judicial processes; and thus, moral hazard effects may be amplified. Our study fills this critical gap. The findings of this paper also advances the debates on delegated monitoring theory (Diamond (1984)) by testing whether banks remain diligent monitors when insulated by SIB protections.

While significant emphasis in the accounting literature has been placed on the benefits of

[4]There is some anecdotal support for the above possibility. For instance, despite being a global SIB (G-SIB), Credit Suisse collapsed in 2023. This suggests that implicit government guarantees induced by SIB designation could worsen the moral hazard problem. If the designation unintentionally increases loan defaults, it could have implications for financial stability.

[5]Jiménez et al. (2017) examines the effects of capital requirements on bank risk, while Gropp et al. (2014) analyzes the consequences of bailout guarantees. Our study builds upon this literature by investigating the effect of SIB designation on bank risk, which operates through three interconnected channels, namely, stronger bailout expectations, stricter capital requirements, and more rigorous monitoring.

higher and dynamic capital buffers to reduce solvency risks and minimize the need for government bailouts (Basel Committee on Banking Supervision (2010), Beatty and Liao (2014), Acharya and Ryan (2016)), surprisingly, no major work in either accounting or finance has looked at the impact of SIB designation on loan performance. This paper attempts to bridge this gap.

The SIB framework was rolled out in India by the Reserve Bank of India (RBI), the nation's central bank, in 2015.[6] Three major banks—one government-controlled and two private—were designated as SIBs in a staggered manner following the SIB framework. These three banks account for 44% of all bank loans in India. The staggered implementation and the availability of firm-bank-time-level data allow us to employ DID. The fact that India has both government-controlled and private banks enables us to isolate the impact of the SIB policy from pre-existing implicit government guarantees.

We find that the default rate on loans from SIBs is 1.4 percentage points higher than that of non-SIBs. This difference is economically meaningful compared to an average default rate of 2% in our sample. The use of firm $\times$ year fixed effects (Khwaja and Mian (2008)) ensures that the analysis is within firm-year and between banks. Thus, the increase in loan defaults of SIBs cannot be explained by any time-varying characteristics of firms. The inclusion of firm $\times$ bank fixed effects further ensures that our results are not due to any special relationship between banks and firms. An event-study-type test helps us rule out the existence of pre-trends. Finally, evidence also suggests that the results are due to the implicit protection that comes from the SIB designation and not due to changes in capital.

The results remain robust under various specifications. First, the results do not change

[6] Refer to: `https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=31680`.

materially with the inclusion or exclusion of firm $\times$ year fixed effects. Second, our results remain similar when we restrict our sample to loans that were disbursed before SIB designation, suggesting that the observed effects are not due to changes in lending policies by banks in response to SIB designation. Third, we verify that our results are unlikely due to endogenous factors that vary with bank size, because restricting the control group to banks closest to SIBs in terms of size does not alter our results.

Further, the firm-bank pair starts from the year in which a loan is made and remains in the panel until the loan is repaid: it does not drop from the panel on the declaration of a non-performing asset (NPA).[7] Thus, NPA recognition does not lead to the right censoring of the data. Nonetheless, for robustness, we estimate our results using the Cox-hazard regression model and obtain directionally similar results as above. We also show that our staggered difference-in-differences event study estimates are robust to the implementation of the correction suggested by Sun and Abraham (2021). Moreover, since the correction restricts the control group to the never-treated cohort, it is also free from the bias introduced due to negative weights in two-way fixed effects estimation (Goodman-Bacon (2021)).

We investigate the underlying mechanism in the second part of the paper. One possible mechanism is the reduction in monitoring by SIBs (Diamond (1984)). We define monitoring broadly to include ex-post activities and efforts involving supervision, management, and loan recovery following lending. An increase in loan delinquencies is possible if the implicit guarantees associated with the SIB designation induce moral hazard on the part of the lenders in monitoring borrowers. A second plausible mechanism is the prompt recognition

[7]We use the terms NPA, default, and loan delinquency interchangeably. A loan is classified as an NPA if the interest and/or principal repayment is overdue for at least 90 days. See section 2.1.2 of the following link: `https://www.rbi.org.in/commonperson/English/Scripts/Notification.aspx?Id=889`

of losses by SIBs, driven by increased monitoring efforts due to higher capital buffers (Bhat and Desai (2020)) and regulatory scrutiny. We refer to this as the “loss recognition” channel.

We examine four disconnected categories of evidence. The first set of evidence examines whether defaults to SIBs are higher among borrowers who are more challenging to monitor. We utilize three proxies motivated by literature to identify such borrowers. First, borrowers without external credit ratings require significantly greater monitoring (Sufi (2007), Ball et al. (2008), Christensen and Nikolaev (2012)). Second, firms with weak internal controls exhibit lower financial reporting quality, necessitating increased monitoring efforts (Costello and Wittenberg-Moerman (2011)). Third, geographical distance between banks and borrowers increases information asymmetry, making borrowers more challenging to monitor (Bushman and Wittenberg-Moerman (2012), Granja et al. (2022)). Consistent with “lax monitoring,” we find that differential loan delinquencies to SIBs compared to non-SIBs are higher in the cross-section of each of these categories of borrowers.

The second set of evidence analyzes the costs of banks’ monitoring and loan recovery activities. Monitoring activities, such as borrower site visits and communication for information requests, are difficult to observe directly and verify using publicly available data. Gustafson et al. (2021) and Minnis and Sutherland (2017) use proprietary data to measure these efforts. In the absence of proprietary data, we proxy such efforts using the communication expenses available in the banks’ audited financial statements.[8] Consistent with “lax monitoring”, we find that SIBs report lower communication expenses than other banks. Additionally, examining legal filings for loan recovery shows a significant drop by SIBs, rejecting

[8]We verify that communication expenses of banks are correlated with the average distances between banks and borrowers - a primary driver of monitoring costs (Bushman and Wittenberg-Moerman (2012),Granja et al. (2022))

the "loss recognition" explanation and further reinforcing the "lax monitoring" narrative.

The third category of evidence pertains to the depositors' to increases in banks' non-performing assets (NPAs). Depositors are likely to be less sensitive to increases in NPAs if SIB designation signals an implicit guarantee to rescue the bank in the event of a failure. We find the above result. The lower response of depositors is also consistent with the moral hazard problem due to lower monitoring by the depositors, inducing the banks to reduce monitoring. The evidence aligns with the "lax monitoring" hypothesis.

The final set of tests examines the impact of the SIB policy on the tendency to evergreen loans—the practice of extending new loans to distressed borrowers to delay the recognition of NPAs. The "loss recognition" hypothesis predicts a reduction in evergreening tendencies. However, under "lax monitoring," a bank may increase evergreening to prevent the spiraling of reported defaults. Evidence based on multiple measures of evergreening developed by the extant literature (Peek and Rosengren (2005); Caballero et al. (2008); Tantri (2021); Mannil et al. (2024); Kashyap et al. (2021)) suggests either no change or a significant increase in evergreening tendencies in response to the SIB designation. The results are inconsistent with the loss recognition hypothesis and in line with lax monitoring.

Thus, evidence of (i) higher defaults by difficult-to-monitor borrowers, (ii) reduced monitoring and loan recovery expenses, (iii) stock market reactions, and (iv) increased evergreening collectively supports the "lax monitoring" hypothesis and potentially rule out the "clean up" hypothesis. We recognize that, in addition to lax *monitoring*, the moral hazard associated with SIB designation could also induce lax *screening* by SIBs. However, distinguishing between ex-ante screening and ex-post monitoring is challenging (Ball et al. (2008), Beatty et al. (2019)), a problem further compounded by the lack of loan application-level data needed to directly verify screening activities. Nevertheless, to disentangle the potential effects of SIB status on screening and monitoring, we rerun our tests on a subset of loans issued prior to the introduction of the SIB policy. Even in this sub-sample, we find a positive association between SIB status and loan defaults. Given that the SIB policy did not impact the screening of these loans, the result is likely to reflect a reduction in monitoring efforts.

Finally, we address concerns related to our findings and explore alternative explanations. First, the results cannot be attributed to a mere shift in loan defaults from non-SIBs to SIBs without any aggregate effects. Second, the relationship between firm performance and loan performance suggests that incremental loan defaults are unlikely to be strategic. The results suggest monitoring by banks added value, and therefore, a reduction in monitoring impacted borrowers' performance and led to higher defaults. Third, we conduct cross-sectional tests to rule out alternative explanations related to (i) inefficient contract enforcement by SIBs, and (ii) other regulatory interventions.

Overall, our results suggest that the SIB policy may have induced moral hazard by reducing banks' incentives to monitor borrowers, resulting in higher loan delinquencies. Our findings are particularly relevant in the context of large bank failures, such as that of Credit Suisse, where implicit guarantees associated with SIB designation may have encouraged moral hazard, weakened risk management, and ultimately contributed to financial instability, despite higher capital buffer requirements.[9] Consequently, our paper underscores the need for policymakers and regulators to implement measures that mitigate the moral hazard effects of SIB designations to safeguard financial stability.

[9]Credit Suisse has been accused of lax risk management despite being a global SIB. See `https://www.businesstimes.com.sg/wealth/bank-crises-and-moral-hazard-regulators-toe-fine-line`

2 Related Literature and Contributions

Our study makes three key contributions. First, we contribute to the growing literature on banking regulatory guidelines, particularly the standards introduced by the Basel Committee on Banking Supervision (BCBS), to enhance global financial stability. The BCBS, an active standard-setting body, has implemented several reforms like Basel I, II, III, and IV, to address emerging risks in banking (Beatty and Liao (2014)). The literature has explored various aspects of these reforms, such as loan-loss provisioning and earnings management (Kim and Kross (1998), Ahmed et al. (1999), Beatty et al. (2002)), fair-value accounting (Chircop and Novotny-Farkas (2016), Kim et al. (2019), Khan and Lo (2019), Bischof et al. (2021)), risk-disclosures (Jorion (2002),Bischof et al. (2022)), treatment of off-balance sheet items (Dou and Xu (2021)), supervisory review and market discipline (Balakrishnan et al. (2021), Bischof et al. (2021)), among other things. We extend this literature by examining the impact of the SIB framework, a policy introduced by BCBS in collaboration with FSB and other policymakers to address systematic risks on loan delinquencies. Although similar to other Basel amendments in its focus on strengthening regulatory capital, we document a novel insight. We find that the SIB designation that was aimed to solve the TBTF problem may actually worsen the TBTF concerns by inducing moral hazard in the respective SIBs.

Second, we contribute to the banking literature that documents the implications of the "too big to fail" (TBTF) problem.[10] Designating TBTF banks as systemically important and imposing additional capital requirements are widely adopted policies to address this issue (Bongini et al. (2015)). However, there is ongoing debate about how higher capital require-

[10] See Farhi and Tirole (2012); Strahan (2013); Davies and Tracey (2014); Gormley et al. (2015); Oliveira et al. (2015); Boyd and Heitz (2016); Chari and Kehoe (2016); Minton et al. (2019); Iyer et al. (2019); Dávila and Walther (2020); Philippon and Wang (2023)

ments affect lending. Studies such as Favara et al. (2021) and Degryse et al. (2023) show that SIBs reduce lending in response to capital surcharges. Furthermore, Bhat and Desai (2020) and Behn et al. (2019) document that higher capital buffers reduce risk-shifting behavior and incentivize borrower screening and monitoring, resulting in higher-quality lending.

In contrast, Jiménez et al. (2017) and Gropp et al. (2014) argue that higher capital can increase risk-taking during normal times as banks search for yield to offset costs. Similarly, Kim and Santomero (1988) and Gale and Özgür (2005) report comparable findings, although the motivating factors vary, ranging from agency frictions to suboptimal risk-sharing between depositors and equity shareholders. We find that SIBs engage in more loan restructuring (loan evergreening), likely driven by moral hazard concerns stemming from TBTF designation. Thus, our findings on lending align with Jiménez et al. (2017), although our setting involves a more comprehensive intervention that combines higher capital requirements with SIB designation.

Finally, our findings contribute directly to the literature on borrower monitoring by banks. Diamond (1984) demonstrates that banks play the critical role of delegated monitors, reducing information asymmetries and lowering financial transaction costs. Subsequent studies have investigated the channels, incentives, and effects of monitoring.[11] Monitoring primarily involves banks' ex-post activities, including site visits and borrower communication, to collect information and evaluate loan performance (Minnis and Sutherland (2017), Gustafson et al. (2021)). Banks gather this information through various channels, such as financial reports, tax statements, and transaction account data (Mester et al. (2007); Norden

[11] See Sufi (2007); Ball et al. (2008); Agarwal and Hauswald (2010); Costello and Wittenberg-Moerman (2011); Christensen and Nikolaev (2012); Bushman and Wittenberg-Moerman (2012); Wang and Xia (2014); Vashishtha (2014); Cerqueiro et al. (2016); Beatty et al. (2019); Shan et al. (2019); Bhat and Desai (2020); Frankel et al. (2020); Gallimberti (2021); Granja et al. (2022)

and Weber (2010); Minnis and Sutherland (2017); Carrizosa and Ryan (2017); Frankel et al. (2020)), and use loan covenants to discipline risky borrowers (Rajan and Winton (1995), Ball et al. (2008), Christensen and Nikolaev (2012)).

Another strand of the monitoring literature examines factors influencing the required monitoring efforts and incentives to monitor. For instance, several studies emphasize that geographical distance between the bank and the borrower is a crucial determinant of monitoring efforts (Sufi (2007); Agarwal and Hauswald (2010); Bushman and Wittenberg-Moerman (2012); Wang and Xia (2014); Granja et al. (2022)). Other studies, such as Costello and Wittenberg-Moerman (2011) and Gallimberti (2021), argue that firms with stronger internal controls and higher financial reporting quality require less monitoring. Similarly, Sufi (2007), Ball et al. (2008), and Christensen and Nikolaev (2012) demonstrate that the availability of external credit ratings substantially reduces monitoring efforts. Finally, the presence of collateral is known to reduce the incentives for monitoring (Rajan and Winton (1995), Cerqueiro et al. (2016)). Our study extends this body of work by identifying another factor that reduces monitoring incentives: moral hazard concerns stemming from SIB status.

3 Institutional Background

Based on a realization that the policies addressing the TBTF problem should consider both the systematic risks posed by the collapse of large financial institutions and the moral hazard stemming from any implicit or explicit government guarantee, the SIB framework was proposed by policymakers worldwide. The framework requires regulators to identify SIBs, impose capital surcharges on them, and increase regulatory scrutiny of the SIBs.

Accordingly, in October 2010, the FSB advised all member countries to create frameworks to reduce risks from Systemically Important Financial Institutions. Further, in November 2011, the Basel Committee on Banking Supervision (BCBS) introduced a framework for identifying the Global Systemically Important Banks (G-SIBs) and increased the capital requirements to safeguard them from insolvency.[12] The BCBS also introduced a similar framework that requires member countries to extend the SIB rules to domestic banks.[13] In addition to the global regulations, several countries increased supervision on SIBs and imposed additional reporting requirements.

Following the BASEL guidelines, the RBI introduced a framework for identifying and regulating D-SIBs in India in 2014.[14] The framework aims to identify the D-SIBs and impose additional regulatory capital and reporting requirements depending on their degree of systemic risk. Even the methodology of assessing D-SIBs is in line with the G-SIB framework designed by the BCBS. It is a two-step process. The first step is to identify SIBs based on the size of the banks relative to the GDP of India. Banks that have a Basel III exposure of more than 2% of the GDP are considered SIB.[15] Second, the banks identified as systemically important are segregated into five different buckets of systemic importance based on a composite score of systemic importance. The details of the composite score calculation for designating a bank as a D-SIB and the differences between the G-SIB and D-SIB identification approaches are provided in Panel A and Panel B of Table A1 in the online appendix, respectively.

[12] See: `https://www.bis.org/publ/bcbs207.pdf`

[13] See: `https://www.bis.org/publ/bcbs233.htm`

[14] See `https://rbidocs.rbi.org.in/rdocs/Content/PDFs/FDSIBF220714.pdf`

[15] Basel III exposure is the sum of on-balance sheet exposures, derivative exposures, securities financing transaction exposures, and off-balance sheet exposures (`https://www.bis.org/publ/bcbs270.htm`)

The first set of SIB identification was carried out in the year 2015-2016.[16] State Bank of India (SBI) and ICICI Bank were the first entrants on the D-SIB list on 31st August 2015. Later, HDFC was listed as a SIB in September 2017. SBI is (ICICI and HDFC are) placed in Bucket-3 (1) and has an excess capital buffer requirement of 0.6% (0.2%).

4 Data

We obtain the annual loan-level and restructuring data from the database maintained by the Ministry of Corporate Affairs (MCA), the government of India. The MCA data covers all registered secured loans. A non-registered loan loses certain privileges of secured loans. Therefore, it is reasonable to expect almost all secured loans to be registered. Consistent with Chopra et al. (2021), we compare the total outstanding loans in the MCA database with the outstanding loans reported in banks' financial statements and find that the coverage of the MCA database is about 68%. Therefore, it is reasonable to assume that MCA data are representative of the corporate loans disbursed in India.

The MCA data contains information about the identity of the lender, the identity of the borrower, the loan amount, the date of loan disbursal, the date of restructuring, if any, and the date of final loan repayment. The database covers loans lent by both banks and non-banks. The database does not provide information about interest rates or loan performance.

Using the MCA data, we create our firm-bank-year level outstanding loan sample in the following way. We start with all the firm-bank pairs with an outstanding lending relationship in the year 2010. Next, a firm-bank pair enters (exits) the sample whenever there is a new

[16]The Indian financial year begins in April and ends in March.

loan extended by the bank to the firm (the firm fully repays the outstanding loan to the bank). The above algorithm gives 397,355 firm-bank-years between 2010 to 2020.[17]

We obtain loan performance-related data from TransUnion CIBIL, India's largest credit information company. The data maintains a record of all corporate loans over Rupees 10 million, where the bank has initiated recovery proceedings after a default. RBI mandates banks and financial institutions to submit the list of such loan delinquencies to credit information companies monthly or more frequently. Kashyap et al. (2021) show that defaults from CIBIL are representative of total corporate non-performing assets in the banking sector.

We next match the firm-bank pairs between CIBIL and the outstanding loan panel created from MCA data using the names in both databases, creating a combined panel of firm-bank pairs with identified delinquent loans. We apply a filter of loan size of at least INR 10 million in tests involving loan delinquency as we have loan performance details for only those loans. The above filter leads to a final firm-bank-year sample of 356,787 observations after excluding foreign banks. The sample construction has been shown in Table 1.

Further, we obtain accounting information about firms and banks and the data related to related party transactions (RPT) from the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE). The Prowess database contains all the audited annual financial statements of banks and firms.

Finally, we obtain the data relating to legal cases filed in Debt Recovery Tribunals (DRT) from their website.[18] The data include a case identification number, address of the corresponding DRT court, filing date, resolution date, and others.

[17] We aggregate all the loans between the bank-firm pairs in the year to arrive at lending between the bank and the respective firm in that year. Henceforth, we call such yearly-aggregated amounts "loans."

[18] Debt Recovery Tribunals were created to facilitate the speedy recovery of debt payable to banks and other financial institutions by their customers (Visaria (2009)).

The final sample of 356,787 firm-bank-year observations pertains to 21,101 unique firms and 46 unique lenders. In this dataset, 24 out of 46 banks are government-controlled. As noted in Section 3, three banks were designated as SIBs, of which one- State Bank of India- is a government-controlled bank and the other two- ICICI Bank and HDFC Bank- are private banks. The three SIBs account for approximately 44% of the total bank assets in 2015.[19] The unconditional delinquency rate is 2% based on the count of defaults.[20] Of the total firm-bank-year observations, 12% have a bank designated as SIB. Detailed summary statistics are provided in Table 2. We have defined all the variables in Table A2 of the online appendix.

5 Main Result

5.1 SIB and loan delinquency

The objective of our study is to gauge the effect of declaring a bank as systemically important on the loan repayment behavior of its borrowers. Banking theory does not provide a clear answer to this question. The SIB qualification is associated with increased capital surcharges. To the extent that a high level of capital leads to higher screening and monitoring efforts by banks and reduces risk-shifting behavior, SIB designation may improve loan performance (Berger and Bouwman (2013), Bhat and Desai (2020)). SIBs are also subject to tighter regulatory supervision and reporting requirements. Such measures could lead to better loan performance by inducing high-quality effort on the part of the bankers (Hirtle et al. (2020)).

On the other hand, the SIB designation could exacerbate the perception of too-big-

[19]In our sample, SIBs make up 26% of the bank-firm relationships.

[20]The delinquency rate in terms of the ratio between the delinquent loan amount and the total assets of the bank is 5%, which is close to the NPA rates reported by banks during the sample period.

to-fail and thus induce moral hazard on the part of the lenders.[21] Further, the TBTF notion can disincentivize market discipline by depositors in curbing the risky behaviour of banks (Cubillas et al. (2017), Kolaric et al. (2021)), exacerbating the moral hazard problem. Consequently, SIBs may reduce screening and monitoring efforts and consequently experience higher loan delinquencies. The problem stated above is similar in nature to the moral hazard induced by deposit insurance or borrower bailouts that trigger moral hazard, resulting in increased risk-taking by banks (Calomiris and Jaremski (2016), Giné and Kanz (2018)).[22] Overall, the final outcome depends on the net effect of the opposing forces described above.

One way to test the hypothesis could be to compare the aggregate borrower behavior at a bank-year level for SIBs and non-SIBs. However, this relatively straightforward approach has two main drawbacks. First, the borrowers banking with SIBs and non-SIBs could be systematically different and exposed to different time-varying shocks that could lead to dissimilar repayment behaviors. The concern is about time-varying shocks that move in the same staggered manner as the SIB implementation. Second, only 3 (13) out of 46 (500) banks (bank-years) are SIBs (bank-years), which is insufficient to derive meaningful inferences.

We overcome the above shortcomings by organizing the data at the bank-firm-year level and implementing a difference-in-differences (DID) design. We use the fixed effects structure to absorb any firm-level time-varying shocks. Our DID specification is as shown below.

$$default_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 X_{j,t} + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \tag{1}$$

where $default_{i,j,t}$ is a variable that takes a value of 1 if firm i defaults on bank j in year t, 0

[21] https://www.federalreserve.gov/aboutthefed/boardmeetings/gsib-methodology-paper-20150720.pdf

[22] Also see: Demirgüç-Kunt and Detragiache (2002). Boyd et al. (2002)

otherwise. The variable $SIB_{j,t}$ takes a value of 1 if a bank j is designated as SIB in year t, 0 otherwise. Note that the variable $SIB_{j,t}$ is a bank-year level variable that denotes the DID interaction term. The bank-year level control variables included in $X_{j,t}$ are non-performing asset ratio (NPA), capital adequacy, and return on assets (ROA). Since we cannot use bank $\times$ year fixed effects, we aim to account for time-varying bank-level endogenous factors using the above variables as these variables proxy health shocks to banks. Variables $\gamma_{i,t}$ and $\delta_{i,j}$ represent firm $\times$ year and firm $\times$ bank level fixed effects, respectively. The coefficient of interest is β_1 which estimates the causal impact of SIB designation on loan delinquency.

The above design reduces the possibility of our estimates being impacted by shocks correlated with SIB treatment assignment. The firm $\times$ year level fixed effects (Khwaja and Mian (2008)) help us compare the repayment behavior of the same firm in a year across SIBs and non-SIBs. Therefore, our inferences are unlikely to be impacted by firm-specific time-varying but correlated shocks. Moreover, the setup provides 41,892 treatment and 314,895 control observations, a reasonable sample to draw credible statistical inferences. Finally, the firm $\times$ bank fixed effects account for factors related to existing special relationships between firms and banks that manifest with SIB designation for reasons other than SIB designation.

The empirical design leaves us with bank-level time-varying factors as we cannot include bank $\times$ year (or bank $\times$ firm $\times$ year) fixed effects. This is because the SIB designation is at a bank-year level, and we do not have cases with multiple loans within a bank-firm-year with variation in the SIB status of the bank. We have two lines of defense to deal with the bank $\times$ year level factors. First, as noted above, we include several variables that account for time-varying bank-level characteristics in the vector of control variables, $X_{j,t}$. Thus, our results remain unaffected to the extent that the control variables absorb the endogenous variable of concern. Second, as we subsequently discuss in section 5.2, we also test and rule out the existence of pre-existing trends in outcomes. Given these safeguards, if they exist, the endogenous variable will have to vary precisely in the same manner as the SIB designation and should be unaccounted for by the control variables and fixed effects. The possibility of such a factor is extremely low.

We present the estimates of specification 1 in Table 3. Our data are organized at a firm-bank-year level for the sample period from 2010 to 2020. Columns 1 and 2 of Table 3 present the results after including the firm $\times$ year and bank $\times$ firm fixed effects, whereas columns 3 and 4 present the results without any fixed effects. Specifically, column 2 presents the estimates for the full-fledged specification with bank $\times$ year level control variables. We cluster the standard errors at the industry level.[23]

The difference-in-differences (DID) coefficient in column 2 suggests that a firm with outstanding loans from both SIB and non-SIB is 1.4 percentage points more likely to default on SIBs. This is economically meaningful compared to the unconditional delinquency rate of 2%. When we compare columns 1 and 2, we notice that the addition of control variables does not significantly change the magnitude of the coefficient of interest. Thus, the possibility of other time-varying bank-level factors influencing the results is low.

Further, as in Khwaja and Mian (2008), the DID estimates generated from the model without using any fixed effects in columns 3 and 4, are similar to those obtained from the fixed effects model. Therefore our results are unlikely to be driven by some other time-varying shock correlated with SIB designation that differentially affects the borrowers of SIBs and

[23]We cluster standard errors at the industry level since there are only a few banks (46) in our study. However, our results remain largely unchanged after clustering at a bank-time level.

non-SIBs. We also find that 56% (27%) of SIB (non-SIB) borrowers in terms of numbers and 89% (72%) in terms of value also borrow from non-SIBs (SIBs). Thus, the observations after the inclusion of fixed effects form a significant fraction of our overall sample.

Finally, as described in Section 4, we do not drop a loan once it becomes an NPA. A loan gets dropped only when it is either repaid or fully written off. Thus, our results are unlikely to be impacted by right censoring. Nonetheless, we validate our results using a Cox hazard regression model in Table A3 of the online appendix.

5.2 Pretrends

To address any concerns relating to the possibility that our results represent a continuation of a pre-existing trend, we modify the DID specification to include variables that account for pre-trends, i.e., indicator variables representing years before and after the bank was labeled as an SIB. The revised regression specification is shown below.

$$Default_{i,j,t} = \alpha + \sum_{n=-5}^{n=-2} \beta_n pre_n + \sum_{n=0}^{n=4} \beta_n post_n + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \tag{2}$$

The indicator variables pre5, pre4, pre3, and pre2 represent 5, 4, 3, and 2 years before a bank is designated SIB, and 0 otherwise. Pre 1, the variable that represents a year before the designation of a bank as an SIB, is in the base. Similarly, post0, post1, post2, post3, and post4 are indicator variables that are set to one for the current year, 1, 2, 3, and 4 years after the bank was designated SIB, respectively, and zero otherwise. All the above variables take a value of zero for non-SIBs. *Default* is the dependent variable. As before, we include firm-year and bank-firm level fixed effects in the regression.

The coefficients corresponding to each indicator variable are plotted in panel A of Figure 1. We do not find any differential default on SIBs compared to non-SIBs before the banks were designated SIBs. The incremental default on SIBs appears to be entirely driven by the period after the banks were defined as SIBs. The figure provides visual evidence that our results in Section 5.1 do not represent a continuation of pre-existing trends.

Sun and Abraham (2021) highlight that the estimates of coefficients that represent different relative time periods in dynamic event studies are potentially contaminated by information from other time periods. For example, the estimate of the coefficient on $pre3$ may be contaminated by the effects in the relative periods other than $pre3$ with some weights on each time period. This may introduce a bias in the estimates. They propose a new estimator that estimates cohort-specific heterogeneous treatment effects and calculates the weighted average of these estimates. Here, a cohort is defined as a group of units that receive treatment at the same time. Sun and Abraham (2021) show that these estimates are free from the above-mentioned bias. In panel B of Figure 1, we show that our staggered DiD event study estimates are robust to the implementation of the correction suggested by Sun and Abraham (2021). Moreover, Goodman-Bacon (2021) show that since TWFE estimate in a staggered setting is a weighted average of various DID estimates, including the ones where previously treated groups act as a control, they could suffer from bias. The above Sun and Abraham (2021) estimate restricts the control group to the never-treated cohort and is free from the bias highlighted by Goodman-Bacon (2021).

5.3 Impact of the Government's control over banks

The government-controlled banks (GCBs) form a significant fraction of the Indian banking industry. Of the 46 scheduled commercial banks, 24 are GCBs, and 1 out of 3 SIBs is a government-controlled bank.[24] A reader might be concerned that given the implicit government guarantee that GCBs enjoy, the potential impact of SIB status should be insignificant for them. To address this concern, we highlight that our specification includes bank-level fixed effects, that absorb any effect due to variation in the type of ownership of banks. Nevertheless, we examine whether the defaults towards a SIB is any different when the SIB is a government-controlled bank. We implement the following specification for the above test.

$$default_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 GCB_j + \beta_3 SIB_{j,t} \times GCB_j + \beta_4 X_{j,t} + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \tag{3}$$

Where the indicator variable GCB_j identifies government-controlled banks. All the other variables are as in Equation 1. The coefficient on $SIB_{j,t}$ captures the effect on loan delinquencies in general, while the coefficient of the interaction term $SIB_{j,t} \times GCB_j$ measures the incremental impact on defaults when the treated bank is a government-controlled bank.

We present the results in column 1 of Table A4 of the online appendix for the sample period 2010 to 2020. We find that the coefficient on $SIB_{j,t}$ remains statistically significant even after controlling the ownership status of the banks. The coefficient on the interaction between $SIB_{j,t}$ and GCB_j is statistically indistinguishable from zero. The result indicates that government control does not impact our results.

The above results indicate the possibility that the increase in delinquencies on SIBs due to

[24] Scheduled commercial banks are listed in a schedule under the RBI Act.

lax monitoring follows from borrowers' belief in SIBs getting first preference in government bailouts during an extreme systemic crisis. Government resources might be constrained under such circumstances to support all the government-controlled banks. The governments of emerging economies cannot easily get away with printing notes to discharge their liabilities. Our finding that delinquencies increase on SIBs even in a setting with a significant presence of government-controlled banks indicates that the problem may be even more exacerbated in environments with only private banks.

6 Mechanism

Having shown that a firm is more likely to default on a SIB than a non-SIB, we next hone in on the mechanism driving the phenomena. We can think of two plausible mechanisms that can explain the results described in Section 5: (1) SIBs become lax at the monitoring and screening of borrowers ("lax monitoring" channel); or (2) they are willing to recognize losses promptly ("loss recognition" channel). We discuss both mechanisms below. As discussed in the Introduction, lacking loan application data, we cannot credibly comment on screening efforts.[25] Our emphasis, therefore, remains on monitoring in detecting moral hazard. We define the word monitoring broadly to include loan recovery practices as well. The evidence relating to the mechanism can be divided into four broad categories discussed below.

[25] Loan screening and monitoring efforts are difficult to disentangle, which is why most studies treat them as a combined construct (Ball et al. (2008), Beatty et al. (2019)). However, to isolate the impact of SIB status on lax monitoring, we conduct a robustness test using a sub-sample of loans screened and lent before the SIB designation, ensuring the results are unaffected by lax-screening motivations (refer Section 7.4).

6.1 Loan Monitoring Efforts

If SIBs experience higher defaults due to lower monitoring efforts, we expect this effect to be more pronounced among borrowers who require more intensive monitoring. We draw on established proxies from the literature to identify such borrowers. Specifically, we focus on borrowers who are not rated by credit rating bureaus (Sufi (2007), Ball et al. (2008)), have poor internal controls (Costello and Wittenberg-Moerman (2011)), and are geographically distant from the lending banks (Bushman and Wittenberg-Moerman (2012), Granja et al. (2022)). These characteristics are indicative of borrowers requiring greater monitoring efforts.

6.1.1 Unrated Borrowers

Our next proxy for measuring bankers' monitoring efforts is the availability of borrowers' credit ratings. The literature emphasizes that external credit ratings are reliable predictors of loan defaults and are often incorporated into covenants to monitor borrowers (Berlin and Loeys (1988), Nakamura and Roszbach (2018)). Banks frequently rely on covenants and pricing grids linked to financial leverage, performance metrics, or credit ratings to effectively oversee their borrowers. Moreover, Ball et al. (2008) and Christensen and Nikolaev (2012) argue that while financial accounting information is a critical tool for debt contracting and monitoring, credit rating-based covenants are particularly valuable when the quality of accounting information for debt contracting is low.

Additionally, Sufi (2007) documents that firms without external credit ratings, require more intense monitoring by their lenders.[26] We leverage this insight to test whether SIB des-

[26] Specifically, Sufi (2007) notes that banks are more likely to lend to *unrated* (hard-to-monitor) borrowers when they are geographically close - an alternative proxy for monitoring efforts as discussed in Section 6.1.3.

ignation reduces monitoring incentives due to moral hazard ("lax monitoring" hypothesis). Specifically, if SIBs engage in less monitoring, we expect *unrated* borrowers to default more on SIBs than non-SIBs. We test the above hypothesis using the following specification.

$$default_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 SIB_{j,t} \times unrated_{i,t} + \beta_3 X_{j,t} + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \tag{4}$$

Here, *default* and *SIB* are as defined in Equation 1. The variable *unrated* is set to one if firm is not rated by any external credit agency in the year, zero otherwise. $\gamma_{i,t}$ and $\delta_{i,j}$ denote the firm $\times$ time and firm $\times$ bank level fixed effects, respectively. The variable $X_{j,t}$ represents the set of bank-time level control variables.

We present the results in Table 4. The data are organized at a firm-bank-year level and span from 2010 to 2020. The outline of the table is similar to Table 6. We find that the interaction term *SIB* $\times$ *unrated* is positive and statistically significant. Thus, loan defaults towards SIBs are higher in the cross-section of unrated firms, which are difficult to monitor. The results are consistent with the "lax monitoring" hypothesis.

6.1.2 Borrowing Firms' Internal Controls

Costello and Wittenberg-Moerman (2011) shows that firms with weak internal controls exhibit lower financial reporting quality, making their financial statements less reliable for debt contracting. In such cases, lenders may resort to more intensive monitoring efforts rather than relying on traditional practices centered on financial statements of borrowers. Consequently, firms with poor internal controls may require greater monitoring, potentially leading to higher defaults under the "lax monitoring" channel for SIBs. To test this, we examine whether defaults on SIBs differ across the cross-section of firms with weak internal controls.

We follow Krishnan (2005) and Goh (2009) to construct measures for internal control strength. For instance, Krishnan (2005) shows that firms with larger and independent audit committees tend to have stronger internal controls. On similar lines, Goh (2009) demonstrates that larger audit committees and independent boards play a critical role in remediating material weaknesses in internal controls. Based on these insights, we classify firms as having poor quality internal controls if their audit committee is disproportionately small relative to the total board size and they have a lower proportion of independent board members. We then use the following specification to test the association of firms' internal controls and their likelihood of defaulting on SIBs.

$$\begin{aligned} default_{i,j,t} =& \alpha + \beta_1 SIB_{j,t} + \beta_2 weak\_internal\_controls_{i,t} + \beta_3 weak\_internal\_controls_{i,t} \\ & \times SIB_{j,t} + \beta_4 X_{j,t} + \gamma_{i,t} + \delta_j + \epsilon_{i,j,t} \end{aligned} \tag{5}$$

This regression specification follows the layout of Equation 4, with the primary difference being how we identify firms that require higher monitoring by lenders. In this case, we identify hard-to-monitor firms using the indicator variable *weak_internal_controls* that is set to one if two criteria are met: (i) the ratio of the size of the firm's audit committee to the size of its overall board is lower than the median value, and (ii) the proportion of independent board members in the firm's overall board is lower than the median value in a year. The rest of the variables in the specification carry their usual meaning.

We present our findings in Table 5. The data is at a firm-bank-year level from years 2010 to 2020. We include firm $\times$ year in all columns, bank fixed effects in columns 1 and 2, and firm × bank effects in columns 3 and 4. The even-numbered column also includes the bank-year level control variables. As expected, the coefficient of the interaction between SIB and $weak\_internal\_controls$ is positive and significant. Consistent with "lax monitoring" hypothesis, SIBs experience significantly higher defaults from firms with weak internal controls (hard-to-monitor) compared to firms with stronger internal controls (easier-to-monitor).

6.1.3 Distant Borrowers

Our first measure for the cost of monitoring is the distance between the borrower and the lender. Extant literature suggests that lower geographical distance between the borrower and the lender can help acquire soft information about borrowers, enhancing the lender's monitoring abilities (Sufi (2007), Agarwal and Hauswald (2010), Bushman and Wittenberg-Moerman (2012), Wang and Xia (2014), Granja et al. (2022)). For instance, Granja et al. (2022) show that an increase in distance between the banks and borrowers before the global financial crisis led to higher risk-taking by banks due to reduced monitoring. This is in line with the view that effective monitoring by lenders involves borrower site visits, which are costlier when the borrower site is farther from the lender (Gustafson et al. (2021)).

We extend this argument to identify firm-borrower pairs that require higher monitoring in our setting. If the increase in defaults on SIBs stems from a decline in monitoring, we expect that these defaults are disproportionately higher in firm-bank pairs that are geographically distant. We use the following firm-bank-year level specification to test the above hypothesis.

$$default_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 distant_{i,j} + \beta_3 distant_{i,j} \times SIB_{j,t} + \beta_4 X_{j,t} + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \tag{6}$$

The indicator variable $distant_{i,j}$ takes a value of one if the bank and firm are headquartered in different states, and zero otherwise (Bushman and Wittenberg-Moerman (2012)). $\gamma_{i,t}$ and $\delta_{i,j}$ represent firm $\times$ year and firm $\times$ bank-level fixed effects, respectively. The rest of the variables are as defined in Equation 1. The coefficient of interest is β_3 which estimates the differential tendency of distant (i.e., costly to monitor) borrowers to default on SIBs.

We present the results in Table 6. The data are organized at a firm-bank-year level for the sample period from 2010 to 2020. We include bank-year level control variables in the even-numbered columns. We employ firm $\times$ year fixed effects across all columns to absorb any time-varying firm-level heterogeneity. We include bank fixed effects in columns 1 and 2, and firm $\times$ bank fixed effects in columns 3 and 4, respectively. In column 4, which presents the full-fledged specification, we find that the coefficient on the interaction term, $SIB_{j,t} \times distant_{i,j}$, is positive and significant, while the original DID coefficient $SIB_{j,t}$ turns insignificant.[27] Thus, the increase in delinquencies on SIBs appears to be entirely driven by borrowers located farther from the bank, who inherently require higher monitoring efforts.

6.2 Exercising Creditor Rights and Loan Monitoring Efforts

In this section, we analyze the impact of the SIB status on loan recovery efforts by banks. Under the "loss recognition" hypothesis, banks should pursue loan recovery cases against delinquent borrowers more aggressively after SIB designation. In contrast, the "lax monitoring" hypothesis suggests that SIBs exercise creditor rights less aggressively due to increased loan evergreening. Additionally, we analyze the impact of SIB designation on banks' moni-

[27] Although the coefficient on $SIB \times distant$ in column 2 is statistically insignificant, the result is qualitatively similar. The coefficient has a positive sign with a large magnitude and p-value of less than 0.15.

toring efforts, as reflected in the monitoring expenses they incur. According to the "lax monitoring" ("loss recognition") channel, SIBs should incur lower (higher) monitoring expense than non-SIBs. We test the above consequences of the competing hypotheses empirically.

6.2.1 Loan Recovery Efforts

In India, loan recovery cases are filed in specialized Debt Recovery Tribunals (DRT) with jurisdiction over the firm's location (Vig (2013)). We test whether SIBs are less likely to file a court case against borrowers compared to non-SIBs using the following specification.

$$legal\_dispute_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 X_{j,t} + \gamma_i + \delta_j + \tau_t + \epsilon_{i,j,t} \tag{7}$$

where $legal\_dispute_{i,j,t}$ is a variable set to one if there is a loan recovery case filed in a DRT court involving borrower i and bank j in the year t, zero otherwise. $SIB_{j,t}$ is as defined in Equation 1. Variables γ_i, δ_j, and τ_t represent firm, bank, and year level fixed effects, respectively. $X_{j,t}$ represents the bank-year level control variables as discussed in Equation 1.

We present the results in columns 1 and 2 of Panel A of Table 7. The data are at a bank-firm-year level for the sample period from 2010 to 2020. We limit the sample to observations where the firm has defaulted on loan repayments to the bank in the year since loan recovery related *legal disputes* can occur only in such scenarios. In column 2 of Panel A, we find that the coefficient on *SIB* is negative and statistically significant. Thus, the probability of filing a loan recovery case is 2.4 percentage points lower when the bank is a SIB than when the bank is not, an economically meaningful 104% of the unconditional probability of filing a loan recovery case. The result is consistent with the lax monitoring hypothesis.

In an alternative test, we also examine whether the expenses related to loan recovery efforts change significantly after banks are designated as SIBs. We proxy for expenses incurred towards loan recovery efforts using the line item *Legal expenses* reported by banks in their financial statements. *Legal expenses* constitute the expenses incurred by the banks towards legal teams, lawyers, court case filings, and related consultancy fees. Such costs mimic activities that are related to court filings and legal disputes. Thus, an increase in loan recovery efforts should reflect in higher *Legal expenses* for banks. We test this hypothesis using the following bank-year level DID specification.

$$Legal\_expense_{j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 X_{j,t} + \gamma_j + \delta_t + \epsilon_{j,t} \tag{8}$$

Here $Legal\_expense_{j,t}$ represents the logarithm of legal expenses of bank j in year t. $SIB_{j,t}$ is defined in Equation 1. γ_j and δ_t represent bank and year fixed effects, respectively. $X_{j,t}$ represents the bank-year level control variables listed in Equation 1.

We present the results in columns 3 and 4 of panel A of Table 7. The data are organized at a bank-year level for the period 2010 to 2020. We include the bank-year level control variables in the even-numbered columns. We also include bank and year-level fixed effects in all columns. In column 2, we observe an economically significant 61% decline in *legal expenses* incurred by SIBs. Thus, our findings rule out the "loss recognition" hypothesis.

6.2.2 Loan Monitoring Efforts

Next, we investigate whether SIBs exert lower monitoring efforts. Monitoring activities involve periodic information requisitions and communication with borrowers. Such data are rarely disclosed. Gustafson et al. (2021) and Minnis and Sutherland (2017) use proprietary data of communications between banks and borrowers to measure monitoring. In the absence of such data, we employ *communication expenses* reported by banks as a proxy for motoring activities by banks. *Communication expenses* include telephone expenses, postage and courier charges, and other related expenses - costs that are usually related to communication with clients. The intuition is that an increase in monitoring efforts should reflect in higher expenses associated with communication. We then test whether the communication expenses decrease after a bank is designated as an SIB using the specification equation 8.

We document the findings in panel B of Table 7. The layout is similar to columns 3 and 4 of Panel A, with the key difference being that the dependent variable in Panel B is the natural logarithm of *communication expenses*. Consistent with the "lax monitoring", we find that banks experience a significant (34%) decline in communication expenses.

Overall, the above results reinforce the "lax monitoring" narrative - SIB designation induces moral hazard, reducing banks' monitoring efforts.

6.3 Depositors' Response to SIB Performance

Depositors, on average, react negatively to a decline in bank health (Iyer et al. (2016)). However, if the SIB designation increases the perceived safety net, then it should have two implications. First, SIBs should witness an increase in deposits relative to other banks, as depositors may prioritize SIBs, assuming their funds are implicitly guaranteed. Second, if depositors assume their money is safe regardless of the SIBs' financial health, they should become less responsive to the health of SIBs. We test the above hypotheses using the following specification at a bank-quarter level.

$$Y_{j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 NPA\_indicator_{j,t} + \beta_3 SIB_{j,t} \times bank\_health_{j,t} + \gamma_j + \delta_t + \epsilon_{j,t} \quad (9)$$

Where $Y_{j,t}$ represents the log of bank deposits. The indicator variable $SIB_{j,t}$ is as defined in Equation 1. *NPA_indicator* is proxied by an indicator variable based on NPA of the previous quarter. The variable *NPA indicator* takes a value of one if the NPA of the bank in the previous quarter is greater than the median NPA across all banks and zero otherwise. The variables γ_j and δ_t represent the bank and year-quarter fixed effects, respectively. The coefficients of interest are β_1, which estimates the change in deposits after SIB designation, and β_3, which estimates the change in sensitivity of the deposits to bank health after SIB designation.

The results are presented in Table A5 of the online appendix. The dependent variable is the log of bank deposits. The explanatory variable is the interaction between SIB and *NPA indicator*. We include bank and year-quarter fixed effects in all columns. The first noteworthy result is that across specifications, the coefficient on *NPA indicator* is negative and statistically significant. This implies that deposits decline when bank health worsens, in general. Furthermore, in the full-fledged specification of column 2, the coefficient on *SIB* is positive and statistically significant. This implies that SIB witnesses an increase in deposits relative to other banks after SIB designation. Most importantly, the coefficient on the interaction between SIB and *NPA indicator* is positive and statistically significant. This implies that deposits become less sensitive to the declining bank health of SIB. Thus, our results are consistent with the increase in the perceived safety net due to SIB designation. The above result implies that depositors monitor the banks less after SIB designation, plausibly inducing moral hazard and "lax monitoring."

6.4 Impact On Loan Evergreening

Loan evergreening is the practice of banks extending new or restructured loans to financially distressed borrowers to prevent defaults, typically to delay recognition of non-performing loans. Undercapitalized banks are known to engage in this risk-shifting behavior by evergreening loans nearing default (Acharya et al. (2019); Admati and Hellwig (2014)). Based on this, an explanation for our results could be that additional capital surcharges on SIBs reduce the incentives for risk shifting and lead to timely recognition of losses. Thus, the increase in defaults on SIB loans could be a mechanical consequence of a reduction in evergreening by SIBs. Hence, under the "loss recognition" hypothesis, the tendency to evergreen should reduce in response to the designation of a bank as an SIB.

Under the lax monitoring channel, the designation of a bank as an SIB does not lead to a reduction in evergreening practices. On the contrary, banks that reduce monitoring efforts may be motivated to increase the evergreening of loans to prevent a sudden deterioration of loan performance. The extant literature shows that evergreening eventually leads to a higher levels of loan delinquencies (Caballero et al. (2008); Tantri (2021)). Thus, the lax monitoring channel predicts either a no change or an increase in the evergreening of loans. We examine the above conflicting hypotheses using three measures of evergreening.

6.4.1 New loan to troubled borrower (Direct Evergreening)

Under the first measure of evergreening, which we call direct evergreening, a bank lends a new loan directly to the borrower in trouble with the understanding that the proceeds will be used to settle an existing loan. No formal restructuring is involved (Tantri (2021)).

We test whether banks are more likely to directly transfer loans to troubled existing borrowers, which can then be used to settle an existing loan. We use the following specification.

$$\begin{aligned} new\_loan_{i,j,t} = &\alpha + \beta_1 SIB_{j,t} + \beta_2 firm\_health_{i,t} + \beta_3 SIB_{j,t} \times firm\_health_{i,t} \\ &+ \beta_2 X_{j,t} + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \end{aligned} \tag{10}$$

Where $new\_loan_{i,j,t}$ is the natural logarithm of the value of a new loan by bank j to firm i in year t. $SIB_{j,t}$ is as defined in Equation 1. $firm\_health_{i,t}$ denotes whether the borrower i is in poor health in year t and is defined on the basis of interest coverage ratio (ICR) and profits before interest depreciation, tax, and amortization (PBITDA). The variable $firm\_health$ takes the value of one if the interest rate coverage (ICR) of firm i in a year t is less than 1, zero otherwise. An ICR below one indicates the incapability of the firm to meet the interest payments. Alternatively, it takes the value of one if the PBITDA of a firm i in a year t is negative, zero otherwise. Negative PBITDA denotes firms that are experiencing operating losses and, thus, face difficulty in repaying loans. The bank-year level control variables included in $X_{j,t}$ are as described in Equation 1. Variables $\gamma_{i,t}$ and $\delta_{i,j}$ represent firm-year and firm-bank level fixed effects, respectively. The coefficient of interest is β_3, which estimates differential lending to unhealthy firms after a bank is designated as a SIB.

The results are presented in panel A of Table 8. The explanatory variable of interest is the interaction between $SIB_{j,t}$ and $firm\_health_{i,t}$ in column 1 (2). We include bank-year level control variables, firm × year fixed effects, and bank × firm fixed effects in all columns.

In column 1 of Panel A of Table 8, the coefficients on SIB and $SIB \times firm\_health$ are positive and significant. Thus, banks seem to increase the suspected evergreening activities after being designated as SIBs. In column 2, with PBITDA as a measure of firm health, the coefficient on SIB remains positive and significant, and the coefficient of the interaction term is positive but statistically insignificant. Therefore, it is reasonable to conclude that banks continue evergreening even after being designated as SIB. In untabulated results, we find that our conclusions remain unchanged after including bank × year fixed effects.

6.4.2 Indirect Evergreening

Next, we follow Kashyap et al. (2022) in defining indirect evergreening: a loan is considered to be indirectly evergreened if an unhealthy bank lends to the related firm of its existing borrower in trouble, and the related firm that receives the new loan transfers funds to the troubled borrower, using internal capital markets, in the same year. The term related party is defined by law. It includes associations such as having common key managerial personnel and common ownership. We describe the term in Table A2 of the online appendix.

We implement the DID specification shown in Equation 1 to test indirect ever-greening. The results are presented in panel B of Table 8. The data are organized at a firm-bank-year level for the sample period from 2010 to 2020. We also limit the sample to firm-bank relations, which were initiated before our sample period. The dependent variable *indirect evergreening* is a variable that takes a value of one if a bank indirectly evergreens the firm's loan during the year and zero otherwise. The main explanatory variable is *SIB* as defined in

Equation 1. To test whether the tendency to indirectly evergreen deferentially is limited to non-defaulting loans, in column 2, we also include the interaction between *SIB* and *default*, which are defined in section 5. The control variables included in all columns are as listed in Equation 1. We also include firm-year and bank-firm level fixed effects in all columns.

We find that the SIB designation of the banks increases the probability of indirect evergreening by 30 basis points which is an economically meaningful 30% of the unconditional rate of indirect evergreening. Thus, we find that banks are, in fact, more likely to indirectly evergreen loans after being designated as SIBs.

6.4.3 Loan Restructuring

Our third measure of evergreening is based on loan restructuring in the spirit of Caballero et al. (2008). They identify evergreening through loan restructuring indirectly by examining the amount spent by firms on loan servicing. The MCA data allow us to observe loan restructuring directly.

While it is not possible to characterize every case of restructuring as an evergreening transaction, it is also true that restructuring is a way of postponing recognition of losses. Loan restructuring also allows banks to delay exerting effort on loan recovery. Lazy banks are likely to tread the easy path of restructuring instead of a harder loan recovery process.

We test the above thesis by applying the DID specification 1. The dependent variable–*loan restructuring*—takes the value of one if a bank restructures a loan borrowed by a firm in the respective year and zero otherwise. The results are presented in panel C of Table 8. The data are organized at a firm-bank-year level for the sample period from 2016 to 2020.[28]

[28]The period between 2010 to 2015 was dominated by forbearance when RBI allowed the banks to restructure bad assets as a response to the global financial crisis. The period saw an exponential increase in

The main explanatory variable is *SIB* which is defined in Equation 1. The control variables included in all columns are as listed in Equation 1. We also include firm-year and bank-firm level fixed effects in all columns. In column 2, we include an interaction between *SIB* and *default*. The purpose is to test whether the tendency to restructure differentially is limited to non-defaulting loans. In such a case, the incentive to default diminishes.

We find that the SIB designation increases the probability of restructuring by 3.4 percentage points, an economically meaningful 37% of its unconditional mean. However, as shown by the coefficient of the interaction term, the tendency to restructure does not vary with loan performance. It appears that the SIBs show a higher preference for restructuring all types of loans, including loans in default, rather than initiating loan recovery procedures.

The above results rule out the possibility of a decrease in evergreening as an explanation for an increase in default on SIBs. Thus, it is unlikely that the results are a mechanical consequence of increased capital leading to prompt recognition of losses.[29]

Overall, the above independent pieces of evidence support the "lax monitoring" channel for an increase in default in response to SIB designation and rule out "loss recognition."

7 Alternative Explanations And Robustness

7.1 Strategic or Selective defaults

A reader may wonder if the link between lax monitoring and loan performance could be driven by two alternative explanations. First, it could be the case that even healthy firms

the restructuring of loans (Mannil et al. (2024)). So we limit our analysis to the post-forbearance period of 2016 to 2020. However, our results are qualitatively similar for the period from 2010 to 2020.

[29] We also verify that there are no significant differences between SIBs and non-SIBs in their tendency to evergreen loans during the pre-SIB period.

strategically default on SIBs helped by “lax monitoring.” Second, one could argue that the relationship banks add value by leveraging their expertise to monitor borrowers and improve borrowers' project payoffs. Therefore, the relationship banks can help prevent loan delinquencies. However, if SIB designation triggers “lax monitoring”, the banks are less likely to leverage their expertise to prevent borrowers from selecting bad projects, resulting in the worsening of borrowers' health. Hence, in the above scenario, we expect to observe that the increase in delinquencies is significantly higher for observably unhealthy borrowers.

We test the above thesis by implementing specification equation 10 with $default$ as the dependent variable. If the delinquency rate increases after SIB designation, irrespective of the health of the defaulting borrowers, the delinquencies are highly likely to be strategic in nature. On the other hand, if unhealthy firms are more likely to be delinquent, the results could be driven by the second argument stated above.

We show the estimates in Table A6 of the online appendix and find that the coefficient on SIB is statistically indistinguishable from zero while the coefficient on the interaction term $SIB \times firm\_health$ is positive and statistically significant. The result implies that the increase in default is indeed driven by unhealthy firms. Thus, the increase in delinquencies is less likely to be driven by the strategic behavior of borrowers, irrespective of their health.

Second, firms that would have defaulted anyway due to poor health choose to default on SIBs. The implication of the above channel would be a shifting of default from SIBs to non-SIBs with no aggregate impact. However, as shown in section 5, our results related to the association between loan performance and SIB designation are largely similar without firm × year fixed effects. Thus, the results hold across borrowers as well as within borrowers. Moreover, in panel A of Table A7 of the online appendix, we show that the main results are largely unchanged in a sub-sample limited to firms with exclusive relationships with SIB banks. Thus, it is not the case that firms shift loan delinquencies from non-SIBs to SIBs.

7.2 Matched sample

As discussed earlier, our identification does not allow us to include bank × time fixed effects. Thus, there could be a concern that SIBs are systematically different from non-SIBs. The concern can impact our results if some other time-varying shocks correlated with SIB designation could have affected large banks and are not absorbed by our fixed effect structure. We limit the sample of non-SIBs to the ones that are comparable in size with SIBs and show that our results remain largely unchanged in Panel B of Table A7 of the online appendix.

7.3 Increase in capital

A concern could be that the deterioration in loan performance is due to the designation of a bank as an SIB and the implicit guarantee that comes with it or due to an increase in capital requirements. As described in detail in Section 2, a strand of literature on the impact of bank capital shows that, under some circumstances, an increase in bank capital could lead to increased risk-taking and, consequently, worse loan performance (Jiménez et al. (2017), Kim and Santomero (1988), and Gale and Özgür (2005)). We attempt to disentangle the effects of the two causes by estimating the following specification.

$$\begin{aligned} default_{i,j,t} =& \alpha + \beta_1 SIB_{j,t} + \beta_2 \Delta capital_{j,t} + \beta_3 SIB_{j,t} \times \Delta capital_{j,t} + \beta_4 X_{j,t} \\ & + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \end{aligned} \tag{11}$$

here $\Delta capital$ denotes the year-on-year change in capital adequacy ratio of the bank. The ratio is calculated as per the BASEL III norms. All the other variables are the same as mentioned in Equation 1. The coefficient $\Delta capital$ estimates the effect of an increase in capital adequacy on loan delinquency of the borrowers, whereas the coefficient SIB estimates the effect of moral hazard from the SIB designation. The coefficient of the interaction term measures the differential impact of the increase in capital of SIBs on loan delinquencies.

We present the results in Panel A of Table A8 of the online appendix. Column 2 shows that the coefficient of SIB is very close to the estimates shown in Table 3. Both $\Delta capital$ and its interaction with SIB have coefficients that are close to zero. The result implies that the deterioration in loan performance is most likely due to the designation of banks as SIBs and the implicit guarantee that comes with it and not due to increased capital requirements.

7.4 Lax screening

As discussed in the Introduction, it is difficult to isolate lax screening from the lax monitoring efforts of banks. An alternative mechanism responsible for the increase in default after SIB designation could be the lax screening of loan applications by the SIBs. The lack of loan-application level data constrains us from explicitly testing the 'lax screening' mechanism. Nevertheless, we empirically examine whether the results are due to changes in lending policies post the SIB designation of banks. We ask - are our results solely due to SIBs lending to low-quality borrowers? To answer the above question, we limit the sample to loans that were issued before the SIB designations and rerunning specification 1. The results presented in Panel B of Table A8 of the online appendix are similar to the original estimates in Panel

A. Thus, the loan performance of existing borrowers deteriorates after SIB classification, and the results are not due to a change in the composition of borrowers or lax screening.

7.5 Inefficient courts

Given the inefficient law enforcement mechanism in emerging economies, a reasonable alternative explanation could be that the inefficiency of courts might drive a higher default on SIBs. Thus, a critique may argue that these results are limited to countries having inefficient law enforcement infrastructure. If the above explanation is correct, even within India, the phenomenon should be less prevalent in regions having efficient courts.

We examine the above hypothesis by implementing equation 6 with $default$ as the dependent variable and an interaction between SIB and a variable representing the measure of court efficiency as the explanatory variable. The court efficiency measure $inefficientcourt$ is a variable that takes a value of one if the firm i is located in a district with below median pendency in courts, zero otherwise.

We present the results in column 2 of Table A4 of the online appendix. The sample is at a bank-firm-year level for the sample period 2010 to 2020. We find that the coefficient on *SIB* stays positive and significant, while the coefficient on the interaction term $SIB \times inefficientcourt$ is insignificant. The results indicate that the efficiency of the courts does not seem to play a role in the incremental default after a bank is designated as a SIB.

7.6 Other Government Interventions

There could be a worry that other concurrent regulatory interventions could drive our results. We control for other interventions and discuss the results in section B of the online appendix.

7.7 Placebo tests

We also conduct a battery of false banks and false time placebo tests and discuss the results in section C of the online appendix.

8 Conclusion

The paper shows that a policy of explicitly identifying some in spirit too big to fail banks as systemically important and imposing capital surcharges on them leads to deterioration in their loan performance. The economic setting studied is India, where three large banks were designated as systemically important following the BASEL III norms. The comparison is within a firm-year and between SIBs and non-SIBs. Evidence suggests that the forces of moral hazard on the part of the lenders dominate the likely positive effect of increased capital and regulatory supervision. The evidence further suggests that at least a part of the moral hazard manifests in the form of lax monitoring of borrowers by banks.

Some caveats are in order here. First, we cannot verify the possibility of moral hazard spilling over to screening as we do not have access to loan applications. Therefore, we cannot present the total impact of the SIB policy on lending. Our focus is limited to the performance of loans that are already screened. Second, while we find moral hazard in the form of lax monitoring, we cannot pinpoint the exact determinant of the same. Evidence suggests that monitoring by the financial market reduces due to a bank being identified as an SIB.

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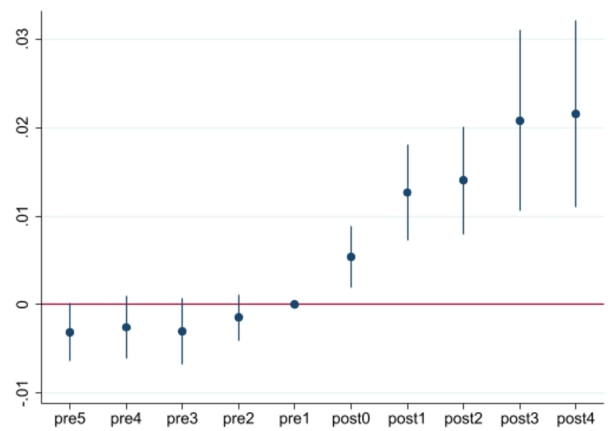
Figure 1: Pretrend Analysis

In panel A, the figure plots the coefficients of the dynamic version of the difference-in-differences design of the main regression. The sample is at the bank-firm-year level and spans from 2010 to 2020. The dependent variable is '*default*,' an indicator variable that takes a value of one if the firm defaults on a bank in the year and zero otherwise. The explanatory variables *pre1*, *pre2*, *pre3*, *pre4*, and *pre5* are one for 1, 2, 3, 4, and 5 years before a bank is categorized as SIB respectively, and zero otherwise. *post0*, *post1*, *post2*, *post3*, and *post4* are one for current year, 1, 2, 3, and 4 years after a bank is categorized as SIB respectively, zero otherwise. The dots represent the point estimates of the coefficient, while the span of the lines represents a 95% confidence interval. We include firm-year and bank-firm level fixed effects. The standard errors are clustered at the industry level. In panel B, the figure plots the coefficients from the event study estimating the impact of SIB designation on loan delinquency. In the model, we use the "interaction-weighted" estimator suggested by Sun and Abraham (2021) for estimating the dynamic treatment effects. The period 0 indicates the year in which the first set of banks are designated as SIB.

(a) Panel A: Conventional



(b) Panel B: Sun and Abraham Estimator

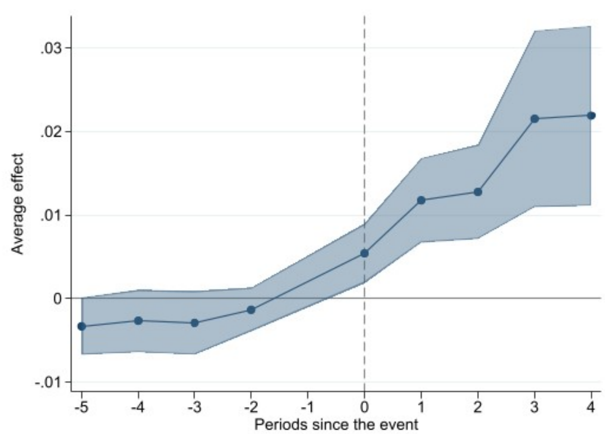


Table 1: Sample construction

Table shows the sample construction at firm-bank-year, bank-year, and firm-year levels.

Particulars	Count
Firm-bank-year level	
Sample period	2010-20
Number of firm-bank-years with an outstanding loan	397,355
Number of firm-bank-years with an outstanding loan above INR 10 million	380,593
Number of firm-bank-years with an outstanding loan above INR 10 million after dropping foreign banks	356,787
Number of distinct firms	21,101
Number of dictinct banks	46
Number of firm-bank-years with a default	5,444
Number of firm-bank-years where bank is designated as SIB	41,892
Bank-year level	
Number of bank-year level observations	494
Number of SIB bank-years	13
Firm-year level	
Number of firm-years with at least one outstanding loan	160,408
Number of firm-years with interest rate data	97,649

Table 2: Summary statistics

Table shows the descriptive statistics for bank-firm-year, firm-year, and bank-year level variables.

Variable	Obs	Mean	Median	1 %ile	99 %ile	Stdev
Bank-Firm-Year summary statistics						
Default	356,787	0.02	0	0	1	0.12
SIB	356,787	0.12	0	0	1	0.32
GCB	356,787	0.6	1	0	1	0.49
New loan (INR million)	356,787	161	0	0	3310	1620
Indirect evergreening	356,787	0.01	0	0	1	0.06
Distant	356,787	0.76	1	0	1	0.42
Loan restructure	356,787	0.09	0	0	1	0.28
Legal dispute	17,102	0.02	0	0	1	0.15
Firm-Year summary statistics						
Low ICR (ICR <1)	200,380	0.26	0	0	1	0.44
Low PBITDA (PBITDA <0)	303,021	0.17	0	0	1	0.38
Unrated	181,554	0.60	1	0	1	0.49
Interest rate	97,649	9.84	9.70	0	52.07	7.37
Bank-Year summary statistics						
Capital adequacy ratio	494	13.5	12.94	8.67	29.2	3.59
Log Deposits	1,530	14.06	14.16	11.32	16.70	1.12
Non-performing asset (NPA) ratio	494	3.49	2.2	0.16	15.4	3.22
Bank asset size (INR million)	494	3.95	1.48	0.03	39.50	7.54
Legal expenses (INR million)	467	574	86	0.80	8166	1543
Communication expenses (INR million)	465	707	322	7	5156	1093
Regulatory actions	465	0.91	1	0	5	1.27
ROA	494	0.55	0.67	-3.14	2.92	1.08
Bank-Quarter summary statistics						
NPA increase	1,777	0.57	1	0	1	0
ROA decrease	1,762	0.48	0	0	1	1
Firm-level cross sectional summary statistics						
Court efficiency	50,883	0.14	0	0	1	0.34

Table 3: SIB and loan delinquency

The table shows the association between default and systemically important status of the banks using a DID specification. The sample is at a bank-firm-year level and spans from 2010 to 2020. The data are restricted to bank-firm pairs with outstanding loans exceeding INR 10 million. The dependent variable is *'default'*, which is an indicator variable that takes a value of one if the firm defaults on loan repayments to the bank in the year, zero otherwise. The main explanatory variable is *SIB* which is one for the bank-years when a bank is designated as a systemically important bank, zero otherwise. Note that *SIB* is a bank-year level variable denoting the DID term. The bank-year level control variables included in the even-numbered columns are capital adequacy ratio, natural logarithm of asset size, and ROA. We include firm $\times$ year and bank $\times$ firm fixed effects in columns 1 and 2. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default			
	(1)	(2)	(3)	(4)
SIB	0.014***	0.014***	0.015***	0.013***
	(0.003)	(0.003)	(0.002)	(0.002)
Capital Adequacy Ratio		0.000**		-0.000
		(0.000)		(0.000)
Log Assets		-0.017***		0.003***
		(0.002)		(0.000)
ROA		-0.002***		-0.009***
		(0.000)		(0.001)
Firm $\times$ Year F.E.	Yes	Yes	No	No
Bank $\times$ Firm F.E.	Yes	Yes	No	No
Observations	234,609	234,358	356,787	356,478
R-squared	0.614	0.616	0.002	0.010

Table 4: Mechanism: Unrated Borrowers

The table shows the association between loan defaults and the types of borrowers for SIBs versus non-SIBs. The data is at a Bank-Firm-Year level spanning from 2010 to 2020. The dependent variable *default* and the variable *SIB* are defined in 3. The variable *Unrated borrower* is set to one if the borrower is not rated by any credit rating agency in that year, zero otherwise. We include the set of control of variables from Table 3 in the even numbered columns. We include firm × year fixed effects in all the columns. Columns 1 and 2 (3 and 4) also include bank-level (bank-firm-level) fixed effects. The standard errors reported in parentheses are clustered at the industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default			
VARIABLES	(1)	(2)	(3)	(4)
SIB	-0.000	0.000	0.007***	0.007***
	(0.001)	(0.001)	(0.002)	(0.002)
SIB × Unrated borrower	0.031***	0.031***	0.019***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
Controls	No	Yes	No	Yes
Firm × Year F.E.	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	Yes	Yes
Firm × Bank F.E.	No	No	Yes	Yes
Observations	242,001	241,750	2,34,609	2,34,358
R-squared	0.379	0.381	0.614	0.616

Table 5: Mechanism: Borrowers with Internal Control Weakness

The table shows the association between loan defaults and the borrowers with weak internal controls for SIBs versus non-SIBs. The data is at a Bank-Firm-Year level spanning from 2010 to 2020. The dependent variable *default* and the variable *SIB* are defined in 3. The variable *Weak internal controls* is set to one if the borrower has lower than median level of proportion of independent directors in the overall board, and has lower than median level of proportion of size of audit committee to the overall board size. We include the set of control of variables from Table 3 in the even numbered columns.We include firm × year fixed effects in all the columns. Columns 1 and 2 (3 and 4) also include bank-level (bank-firm-level) fixed effects. The standard errors reported in parentheses are clustered at the industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default			
VARIABLES	(1)	(2)	(3)	(4)
SIB	0.002	0.002	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)
SIB × Weak internal controls	0.013***	0.013***	0.010**	0.010**
	(0.004)	(0.004)	(0.005)	(0.005)
Controls	No	Yes	No	Yes
Firm × Year F.E.	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	Yes	Yes
Firm × Bank F.E.	No	No	Yes	Yes
Observations	242,001	241,750	234,609	234,358
R-squared	0.378	0.380	0.614	0.616

Table 6: Mechanism: Distant Borrowers

The table shows the association between loan defaults and the types of borrowers for SIBs versus non-SIBs. The data is at a Bank-Firm-Year level spanning from 2010 to 2020. The dependent variable *default* and the variable *SIB* are defined in 3. The variable *distant* is set to one if the borrower and the bank are located in different states, zero otherwise. We include the set of control of variables from Table 3 in the even numbered columns. We include firm × year fixed effects in all the columns. Columns 1 and 2 (3 and 4) also include bank-level (bank-firm-level) fixed effects. The standard errors reported in parentheses are clustered at the industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default			
VARIABLES	(1)	(2)	(3)	(4)
SIB	0.002	0.004	-0.000	0.002
	(0.002)	(0.004)	(0.007)	(0.007)
SIB × Distant borrower	0.009*	0.008	0.016**	0.015**
	(0.005)	(0.005)	(0.007)	(0.007)
Distant borrower	0.003*	0.003**		
	(0.002)	(0.002)		
Controls	No	Yes	No	Yes
Firm × Year F.E.	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	Yes	Yes
Firm × Bank F.E.	No	No	Yes	Yes
Observations	242,001	241,750	2,34,609	2,34,358
R-squared	0.375	0.375	0.614	0.616

Table 7: Mechanism: Creditor right cases, loan recovery expenses, and monitoring expenses

The table examine the impact of SIB designation on court filings, legal expenses, and communication expenses incurred by banks in a DID sense. The data in columns 1 and 2 of Panel A are at a bank-firm-year level and spans from 2010 to 2020. The sample in columns 1 and 2 is limited to observations where a firm has defaulted on repayment of loans to a bank in a year. The dependent variable in Panel A is *Legal dispute*, which is an indicator variable set to one if the firm and bank are involved in a legal dispute in DRT court in the year, zero otherwise. The data in rest of the columns are at a bank-year level and spans from 2010 to 2020. The dependent variable in columns 3 and 4 of Panel A is *Log legal expense*, which is the natural logarithm of total expenses incurred by the banks towards legal teams, lawyers, and related consultancy fees in a year. The dependent variable in columns 1 and 2 of Panel B is *Log communication*, which is the natural logarithm of the total communication expenses of the bank in a year. The indicator variable *SIB* is as defined in Table 3. We use the set of control variables from Table 3 in the even numbered columns. We include firm, bank and year columns 1 and 2 of Panel A. We include bank and year fixed effects in rest of the columns. The standard errors reported in parentheses are clustered at the industry level (bank level) in the first two columns (rest of the columns) and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Loan Recovery effort				Panel B: Monitoring effort	
	Legal dispute		***Log(Legal expense)***		***Log(Communication expense)***	
	(1)	(2)	(3)	(4)	(1)	(2)
SIB	-0.033***	-0.024**	-1.154**	-0.933**	-0.333**	-0.425**
	(0.011)	(0.011)	(0.460)	(0.418)	(0.151)	(0.185)
Controls	No	Yes	No	Yes	No	Yes
Bank F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Firm F.E.	Yes	Yes	-	-	-	-
Observations	16,705	16,705	467	465	465	465
R-squared	0.610	0.611	0.706	0.940	0.946	0.965

Table 8: Mechanism: Change In Loan Evergreening

The table shows the the association between tendency of banks to evergreen loans and their systemically important status. The data are at the bank-firm-year level and span from 2010 to 2020 in Panels A and B, and from 2016 to 2020 in Panel C. In Panel B (C), we further limit the sample to bank-firm relationships that were started before 2010 (2016). The dependent variable in Panel A is *Log (new loan)*, which is the natural logarithm of new loans extended by the bank to the firm. The dependent variable in Panel B is *indirect evergreen*, which takes the value of one if the bank indirectly evergreens the firm's loan in that particular year, zero otherwise. Indirect evergreening is defined following Kashyap et al. (2022). The dependent variable in Panel C is *loan restructure*, an indicator variable which takes a value of one if the bank restructures the loan of the firm in the year and zero otherwise. The indicator variables *SIB* and *default* are as defined in Table 3. In column 1(2) of Panel A *firm health* is an indicator variables that takes a value of one if ICR is below 1 (PBITDA is less than zero) for the firm in the respective year, zero otherwise. The indicator variable *SIB* is as defined in Table 3. We include control variables from Table 3 in all columns. We include firm × year and bank × firm fixed effects in all columns. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Direct evergreening		Panel B: Indirect evergreening		Panel C: Restructuring	
	log (new loan)		***indirect evergreen***		***loan restructure***	
	(1)	(2)	(1)	(2)	(1)	(2)
SIB	0.393**	0.463***	0.003**	0.003**	0.034***	0.034***
	(0.173)	(0.151)	(0.001)	(0.002)	(0.010)	(0.010)
SIB X firm health	0.348*	0.066				
	(0.201)	(0.235)				
Default				-0.000		-0.006
				(0.001)		(0.007)
SIB X Default				0.001		-0.020
				(0.002)		(0.015)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Bank × Firm F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	179,438	188,242	116,500	116,500	94,924	94,924
R-squared	0.557	0.560	0.422	0.422	0.514	0.514

Internet Appendix

A Figures and Tables

Table A1: D-SIB designation criteria

Panel A of the table shows the weights of various indicators in the composite score calculation by RBI for designating a bank as D-SIB. Panel B shows the differences between G-SIB and D-SIB identification methodology. The details of the D-SIB framework are published by RBI (see `https://www.rbi.org.in/scripts/bs_viewcontent.aspx?Id=2766`)

Panel A

Indicator	Sub-indicator	Indicator weight
Size	–	40%
Interconnectedness	Intra-financial system assets	6.67%
	Intra-financial system liabilities	6.67%
	Oustanding Securities	6.67%
Substitutability	Assets Under Custody	6.67%
	Payments made using RTGS and NEFT [a]	6.67%
	Underwritten transactions in capital markets	6.67%
Complexity	Notional amount of OTC Derivatives	6.67%
	Cross Jurisdictional Liabilities	6.67%
	Securities held For Trading and available for Sale	6.67%

Panel B

Point of difference	G-SIB Identification by BCBS	D-SIB Identification by RBI
Sample of banks	75 largest global banks based on Basel III leverage ratio exposure. Additionally, national supervisors have the discretion to add any bank outside this sample.	Banks having size greater or equal to 2% of GDP. Additionally, the 5 largest foreign banks (based on size) are also added to the sample.
Indicators	1. Cross jurisdictional activity 2. Size 3. Interconnectedness 4. Substitutability 5. Complexity	1. Size 2.Interconnectedness 3. Substitutability 4. Complexity
Indicator weights	All five indicators are given an equal weight of 20%.	Size - 40% and each of the other three indicators - 20% each
Sub-indicators	Three sub-indicators for Complexity indicator: 1. Notional amount of OTC derivatives 2. Level 3 assets 3. Trading and Available For Sales Securities	Cross jurisdictional liabilities sub-indicator used instead of level 3 assets. Rest all sub-indicators same as G-SIB.

[a] RTGS stands for real time gross settlement and NEFT stands for national electronic fund transfer. Both are electronic fund transfer systems used by banks in India.

Table A2: Variable Definitions

The table presents the definitions of the variables.

Variable	Definition
default	A variable which identifies if the firm has failed to repay loans partially or fully to the bank in the year, zero otherwise. A defaulted loan is also referred to as an NPA loan or a delinquent loan.
SIB	A (bank-year level) variable which identifies if the bank is designated as systemically important bank in the year, zero otherwise. This variable is equivalent to the conventional DID term denoting whether the bank is treated (gets SIB status) or not.
GCB	Stands for government-controlled banks. A variable which denotes whether the bank is (partially) under government control.
new loan	Value of the loan extended by the bank to the firm in the year.
log(new loan)	Natural logarithm of one plus the value of loan extended to the firm by the bank in the year.
ICR	Stands for Interest cover ratio, which is calculated as the ratio of operating profit to interest expense of the firm. An ICR below one indicates inability of the firm to meet interest payments using operating profits.
PBITDA	Stands for profit before interest, tax, depreciation and amortisation reported by the firm in the year. It is a measure of operating profit of the firm in the year.
firm health	Indicator variable that identifies if a firm has poor health in a year based based on two criteria: (i) ICR is less than one, or (ii) PBITDA is negative.
direct evergreening	A loan is said to be directly evergreened loan if it is extended by the bank to a low quality firm in the year.
indirect evergreening	A variable set to one if the bank *indirectly evergreens* loans to the firm in the year, zero otherwise. Indirect evergreening is defined following Kashyap et. al (2022). Specifically, a loan to a firm is said to be indirectly evergreened, if an unhealthy bank extends a new loan to a related party of its existing borrower in trouble. Further, the related firm that receives the new loan transfers funds to the current borrower in trouble, using internal capital markets, in the same year.
loan restructuring	A variable set to one if the bank restructures a loan to the borrower in the year, zero otherwise.
capital adequacy	Ratio of banks' equity capital to total risk weighted assets, calculated as per Basel guidelines.

Table A2 (Continued): Variable Definitions

Variable	Definition
NPA	NPA stands for non-performing assets ratio of the bank in the year.
size	Value of total assets of the bank in the year.
ROA	Stands for return on assets ratio reported by the bank in the year.
DRT	Stands for Debt Recovery Tribunal courts which settle disputes between borrowers and banks for recovery of collateral. Each district has a DRT court and each firm falls under the jurisdiction of a DRT court based on the location of the firm.
inefficient court	A variable set to one for firms which are located in districts with lower than median level of pendency ratio in DRT courts, and zero otherwise. Pendency ratio of DRT court is calculated as the ratio of pending number of court cases at the year end to total cases.
legal dispute	A variable which denotes whether the firm and the bank are involved in a loan recovery case filed in the DRT court in the year.
legal expense	Total value of expenses incurred by the bank towards legal teams, lawyers, court case filings, and related consultancy fees in the year. It is reported in line item number VIII under schedule 16 (operating expenses) in the audited annual report of the bank.
communication expense	Total value of expenses incurred by the bank towards telephone expenses, postage and courier expenses, web hosting and conference expenses, and other related communication expenses in the year. It is reported in line item number IX under schedule 16 (operating expenses) in the audited annual report of the bank.
distant	The variable is defined at firm-bank level and takes a value of one if the firm and bank are headquartered in different states, zero otherwise.
unrated	The variable takes a value of one if the firm is rated by at least one rating agency in the year, zero otherwise.
weak internal control	The variable takes a value of one if the borrower has lower than median level of proportion of independent directors in the overall board, and has lower than median level of proportion of size of audit committee to the overall board size, zero otherwise
NPA increase	A variable set to one if the NPA of the bank increases compared to the previous quarter.
ROA decrease	A variable set to one if the ROA of the bank decreases compared to the previous quarter.

Table A2 (Continued): Variable Definitions

Variable	Definition
AQR	Stands for Asset Quality Review. It is an annual audit exercise conducted by the RBI to determine the true Gross NPA (GNPA) or loan provisions of the bank. The AQR findings are than compared with the GNPA and loan provisions reported by the bank in the financial statements. Banks are mandated to report a high divergence in GNPA or loan provisions in their revised financial statements.
GNPA divergence	The difference between the bank reported Gross NPA and the AQR reported Gross NPA of the bank in the year.
provision divergence	The difference between the bank reported loan provisions and the AQR reported loan provisions of the bank in the year.
PCA	Stands for Prompt Corrective Action, a regulation where a bank is admitted to strict supervision and monitoring by RBI if it breaches financial thresholds based on capital adequacy ratio, NPA, leverage, tier I capital ratio, or ROA. Several banks were admitted to PCA during 2017 to 2020.
PCA score	The score for each bank which represents the distance to admission of the bank into Prompt Corrective Action (PCA). The PCAscore is calculated following Kashyap et. al (2021b). It is the maximum of the five standardized score caluclated based on thresholds for capital adequacy ratio, tier I capital ratio, net non performing assets, leverage, and ROA of the bank.
regulatory actions	The variable represents the number of supervisory actions initiated by regulators against a bank in a given year. These regulators include the RBI, SEBI (akin to the SEC in the US), depository institutions, the Central Bureau of Investigation (CBI, akin to the FBI in the US), and the Financial Intelligence Unit (FIU, which monitors financial fraud). Regulatory charges are typically related to non-compliance with guidelines or fraudulent activities, and actions can range from monetary penalties to the eviction or imprisonment of bank officers involved in fraud.
interest rate	The effective interest rate paid by the firm to the banks in a year. It is the ratio of total interest paid to the total value of loans owed to all the banks in the year.
SIB exposure	A firm-year level variable which identifies whether the firm has more than median level of proportion of loans taken from SIB.

Table A3: Cox hazard model

The table presents the rate of loan default on SIBs using a cox hazard regression model. The data are arranged at a borrower level and is limited to the borrowers who have not defaulted on loan repayments until the SIB regulation came into effect. The model uses the years to default for each borrower. The independent variable is SIB which is one for firms which borrow from at-least one SIB, and zero otherwise. In column 2 we also include industry fixed effects. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Hazard ratio of loan default	
	(1)	(2)
SIB	1.310***	1.319***
	(0.086)	(0.089)
Industry f.e.	No	Yes
95% lower CI	1.153	1.155
95% upper CI	1.490	1.506
Observations	16,695	16,695

Table A4: Government-Controlled Banks

The table presents the differential change in defaults for government-controlled banks after SIB designation. The data are organized at a bank-firm-year level and span from the years 2010 to 2020. The dependent variable is *'default'* and is defined in Table 3. The main explanatory variable *SIB* is as defined in Table 3. *GCB* is a variable that takes a value of one if the bank is government-controlled, zero otherwise. *Inefficient court* is a variable that takes a value of one if the firm is located in a district with below-median pendency in DRT courts, zero otherwise. Additionally, we include control variables as stated in Table 3 in all the columns. We include firm × year and bank × firm fixed effects in all the columns. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default	
	(1)	(2)
SIB	0.008**	0.012***
	(0.003)	(0.003)
SIB × *GCB*	0.008	
	(0.006)	
SIB × *inefficient court*		0.010
		(0.009)
Control variables	Yes	Yes
Firm × *Year F.E.*	Yes	Yes
Bank × *Firm F.E.*	Yes	Yes
Observations	225,964	233,365
R-squared	0.628	0.616

Table A5: Mechanism: Depositors' reaction to deterioration in bank health

The table tests the difference in the depositor's reaction to the decline in performance for SIBs and non-SIBs. The sample is at the bank-quarter level and spans from 2010 to 2020. The dependent variable is *Log Deposits*. *Log Deposits* is the log of deposits for a bank in a quarter. The indicator variable *SIB* is as defined in Table 3. *NPA indicator* is an indicator that takes a value of one if the NPA of the bank in the previous quarter is greater than the median NPA. We include bank and year-quarter fixed effects in all the columns. The standard errors reported in the parentheses are clustered at the bank level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log deposits	
	(1)	(2)
SIB × NPA indicator	0.210***	0.195***
	(0.074)	(0.055)
SIB	0.170	0.119**
	(0.127)	(0.057)
NPA indicator	-0.104***	-0.045***
	(0.036)	(0.016)
Bank Controls	No	Yes
Bank F.E.	Yes	Yes
Year-Quarter F.E.	Yes	Yes
Observations	1,530	904
R-squared	0.962	0.972

Table A6: Default and firm health

The table shows the association between loan delinquency on SIBs and firm health. The data are at the bank-firm-year level and span from 2010 to 2020. The dependent variable is *default* as defined in Table 3. The indicator variables *SIB* is as defined in Table 3. In column 1(2) *firm health* is an indicator variable that takes a value of one if ICR is below 1 (PBITDA is less than zero) for the firm in the respective year, zero otherwise. We include control variables from Table 3 in all columns. We include bank $\times$ firm fixed effects in all columns. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default	
	(1)	(2)
SIB	0.000	-0.001
	(0.001)	(0.001)
Firm health	-0.000	0.008***
	(0.001)	(0.001)
SIB X Firm health	0.009***	0.036***
	(0.003)	(0.006)
Control variables	Yes	Yes
Firm X Bank F.E.	Yes	Yes
Year F.E.	Yes	Yes
Observations	211,837	270,250
R-squared	0.425	0.435

Table A7: Sub-sample Analysis

The table shows the association between default and the systemically important status of the banks for a sub-sample of firms exclusively borrowing from SIBs and matched banks. The sample is at a bank-firm-year level and spans from 2010 to 2020. The data are restricted to bank-firm pairs with outstanding loans exceeding INR 10 million. In panel A (B), the data are limited to a sub-sample of firms exclusively borrowing from SIBs in 2015 (a sub-sample of SIBs and matched control banks). The matched government-controlled banks are Punjab National Bank, Bank of Baroda, and Bank of India, and matched private sector banks are Yes Bank, IndusInd Bank, Kotak Mahindra Bank, Federal Bank, and Axis Bank. The dependent variable is *'default'*, which is an indicator variable that takes a value of one if the firm defaults on loan repayments to the bank in the year, zero otherwise. The main explanatory variable is *SIB* which is one for the bank-years when a bank is designated as a systemically important bank, zero otherwise. The bank-year level control variables included in the even-numbered columns are capital adequacy ratio, natural logarithm of asset size, and ROA. We include no (year and bank × firm) fixed effects in columns 1 and 2 (3 and 4) of panel A. We include firm × year and bank × firm fixed effects in panel B. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default					
	Panel A: Firms with exclusive relations with SIBs				Panel B: Matched banks	
	(1)	(2)	(3)	(4)	(1)	(2)
SIB	0.029***	0.019***	0.014***	0.012***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Control variables	No	Yes	No	Yes	No	Yes
Firm X Year F.E.	No	No	No	No	Yes	Yes
Year F.E.	No	No	Yes	Yes	Yes	Yes
Bank X Firm F.E.	No	No	Yes	Yes	Yes	Yes
Observations	38,411	38,407	38,082	38,078	103,131	103,131
R-squared	0.012	0.021	0.473	0.474	0.688	0.689

Table A8: Alternative explanations

The table attempts to rule out alternative explanations for an increase in loan delinquencies on SIBs. The sample is at a bank-firm-year level and spans from 2010 to 2020. The data are restricted to bank-firm pairs with outstanding loans exceeding INR 10 million. The dependent variable is *'default'*, which is an indicator variable that takes a value of one if the firm defaults on loan repayments to the bank in the year, zero otherwise. In Panel A the regression model is estimated for the whole sample. In column 1 (2) of Panel B, we restrict the sample to bank-firm relationships that existed in 2016 (2010). The main explanatory variable is *SIB* which is one for the bank-years when a bank is designated as a systemically important bank, zero otherwise. The variable $\Delta Capital$ is the year-on-year change in capital adequacy. The bank-year level control variables included in the even-numbered columns of Panel A are capital adequacy ratio, natural logarithm of asset size, and ROA. We also include the above listed control variables in all columns of Panel B. We include firm × year and bank × firm fixed effects in all columns. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Change in capital		Panel B: Pre-existing relations	
	default			
	(1)	(2)	(1)	(2)
SIB	0.015***	0.015***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.005)
$\Delta capital$	0.001***	0.001***		
	(0.000)	(0.000)		
SIB × $\Delta capital$	-0.001***	-0.001***		
	(0.000)	(0.000)		
Control variables	No	Yes	Yes	Yes
Firm × Year F.E.	Yes	Yes	Yes	Yes
Bank × Firm F.E.	Yes	Yes	Yes	Yes
Observations	234,260	234,260	214,461	116,500
R-squared	0.614	0.616	0.614	0.621

B Other Government Interventions

To address residual concerns about any indirect or lagged effects of other government regulations, we account for the impact of other regulations in our main regression Equation 1. We carefully review such regulations and government actions implemented during our sample period. Given that the SIB classifications were implemented in a staggered manner and we do not observe any pre-trends, there is a low likelihood that any of these concurrent regulations impact the SIBs differently than non-SIBs. Nevertheless, we examine other interventions and create control variables that proxy the degree of impact of other regulations on banks. We then include these variables in our main specification. If the main coefficient relating to the SIB indicator variable remains largely unchanged, we can rule out the alternative explanation that our results are due to other regulations.

Asset Quality Review: The central bank conducted asset quality reviews (AQR) between 2016 and 2019 to unearth the true levels of non-performing assets. Subsequently, the RBI directed banks to report additional NPAs based on the audit findings. The AQR thus cleaned up the balance sheet of firms. A critic may argue that the AQR impacted SIBs more than non-SIBs and may have resulted in higher defaults on SIB loans. Specifically in this special audit, a borrower account found to be delinquent on one bank in the audit had to be classified as an NPA by all banks having a lending relationship. Thus, AQR is unlikely to affect our firm-bank-year level tests.

Nonetheless, we address the concern by controlling for AQR findings in our main specification Equation 1. Specifically, we follow Chopra et al. (2021) and control for the divergence between reported NPAs and the audit findings and divergence between reported provisions and revised provisions in Equation 1. Results reported in column 1 of Table B1 of the online appendix show that the coefficient of the SIB indicator variable continues to remain positive and statistically significant. Moreover, we also restrict the sample to control banks with similar AQR divergences as the SIBs. Results reported in column 2 of Table B1 show that the coefficient of the SIB indicator variable continues to remain positive and statistically significant in the restricted sample. Thus, the AQR disclosures are unlikely to drive our results.

Prompt Corrective Action (PCA): The RBI implemented the PCA in the financial year 2018. Under the PCA framework, banks that breach well-defined thresholds regarding five specified accounting and operating parameters face pre-specified and, at times, discretionary regulatory restrictions. The objective of the PCA was to arrest bank collapses at an early stage and implement remedying actions. In total, 12 out of 46 Indian banks were subject to the PCA treatment during our sample period. Kashyap et al. (2021) show that the PCA intervention reduced strategic default on unhealthy banks that were subject to PCA regulation.

Following Kashyap et al. (2021), we create a PCA score based on the five measures and include it as a control variable in Equation 1. We present the results in column 3 of Table B1. We find that the coefficient for SIB continues to be positive and statistically significant.

Restrictions on restructuring (Feb 12 circular): On February 12, 2018, the RBI issued a circular that directed banks to aggressively recognize stressed assets and create provisions. The circular also directed banks to implement the resolution and restructuring plans in a time-bound manner. It took away banks' discretion in restructuring loans by directing them to refer the defaulting borrowers who fail to stick to the resolution plan to bankruptcy courts. Thus, the banks could not continue evergreening loans endlessly. The circular and its impact is discussed in detail by Chari et al. (2021). The circular was in force till June 2019, when the Supreme court of India struck it down. Given the circular's impact on loan loss recognition, a reader may worry that our results are due to a higher impact of the circular on SIBs.

Please note that figure 1 shows that the increase in default on SIB banks coincides perfectly with SIB designation in 2016, two years before the circular was implemented. Nevertheless, to address any residual concern, we first identify banks more impacted by the circular. Since the circular had a higher impact on banks with a higher proportion of restructured loans, we identify banks with a higher proportion of restructured loans as banks more impacted by the circular. Specifically, we include a control variable representing the proportion of restructuring at a bank year level and its interaction with the period during which the February 12 circular was in force, in Equation 1. The results shown in column 4 of Table B1 suggest that our main finding is unaffected by the implementation of the February 12 circular.

Loan Restructuring schemes: The RBI introduced two restructuring schemes in 2016: the Strategic Debt Restructuring (SDR) scheme and the Scheme for Sustainable Structuring of Stressed Assets (S4A), to enable banks to manage stressed assets. The SDR scheme allowed banks to convert a portion of overdue loans into equity while refinancing the rest under certain conditions. The S4A scheme also permitted banks to restructure large corporate debts without provisioning for them.

There might be a concern that these restructuring schemes were disproportionately used by SIBs compared to non-SIB banks, resulting in observed differences in NPAs. However, this concern is misplaced, as both schemes were repealed in 2018 and thus are unlikely to have had a significant impact throughout the entire sample period. Nevertheless, we address this concern by examining whether the restructured loans reported by banks changed differently for SIBs compared to non-SIB banks. We fail to find any significant change in restructured assets of SIBs following the introduction of the restructuring schemes (see Table B2). Thus, the increase in NPAs experienced by SIBs is unlikely to be due to differences in the adoption of these restructuring schemes compared to non-SIBs.

Table B1: Alternative explanations

The table presents the evidence ruling out alternative explanations. The data are organized at a bank-firm-year level and span from the years 2010 to 2020. The dependent variable is *'default'* and is defined in Table 3. The main explanatory variable *SIB* is as defined in Table 3. In column 1, we control for GNPA and provisioning divergence as estimated in the asset quality review (AQR), which proxy for the AQR intervention. In column 2, we restrict the control banks to banks with similar GNPA divergence as the SIBs. In column 3, we control for the PCAscore calculated following Kashyap et al. (2021), which proxies for the PCA intervention. In column 4, we control for the proportion of restructured assets and its interaction with the indicator variable representing the period of enforcement of the February 12 circular by the RBI. Additionally, we include control variables as stated in Table 3 in all the columns. We include firm × year and bank × firm fixed effects in all the columns. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default			
	(1)	(2)	(3)	(4)
SIB	0.016***	0.012***	0.013***	0.012***
	(0.003)	(0.004)	(0.003)	(0.003)
Control variables	Yes	Yes	Yes	Yes
Firm × Year F.E.	Yes	Yes	Yes	Yes
Bank × Firm F.E.	Yes	Yes	Yes	Yes
Observations	234,358	47,352	219,327	219,238
R-squared	0.616	0.706	0.631	0.631

Table B2: Alternative explanations: Loan Restructuring Schemes

The table presents the evidence ruling out alternative explanations. The data are organized at a bank-year level and span from 2010 to 2017. The dependent variable, *log restructuring*, is the natural logarithm of the amount of loans restructured in the respective year. The variable *SIB bank* is an indicator variable that takes a value of one for SIBs and zero otherwise. The variable $Post\_SDR$ ($Post\_S4A$) takes a value of one after 2015 (2016) and zero otherwise. We include bank and year fixed effects in all the columns. The standard errors reported in the parentheses are clustered at the bank level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log(restructuring)			
	(1)	(2)	(3)	(4)
SIB banks × *Post_SDR*	-0.042	-0.045		
	(0.352)	(0.365)		
SIB banks × *Post_S4A*			-0.018	-0.046
			(0.367)	(0.363)
Control variables	No	Yes	No	Yes
Bank F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	327	327	327	327
R-squared	0.917	0.920	0.917	0.920

C Placebo tests

Finally, readers might have residual concerns that endogenous factors related to the characteristics of SIBs may be driving our results. For example, the endogenous factors could be related to the size of the banks, and since the largest banks were designated SIB by definition, these factors could cause our findings. However, staggered classification of banks as SIBs requires these endogenous factors to kick-in in correlation with the timings of SIB implementation, which seems implausible. Nevertheless, we conduct a battery of placebo tests to rule out the presence of such factors.

First, we restrict our sample to all non-SIBs and designate the three largest banks from the restricted sample as placebo SIB-banks. We keep the sample period between 2010 to 2020, and the timing of the staggered implementation matches the actual SIB designation years. We implement specification 1 in this setting, and present the results in Panel B of Table C1 of the online appendix. In columns 1 and 2, we designate the largest 3 banks from the restricted sample as placebo SIBs, while in columns 3 and 4, we designate the largest government-controlled bank and largest 2 private banks as placebo SIB. We include bank-year level control variables in all columns. We also include firm-year and bank-firm level fixed effects in all columns. In column 5, we restrict the data to non-banks and designate the top 3 non-banks as placebo SIBs. We find that the coefficient on *SIB* is insignificant across specifications. Thus, the results are not driven by an endogenous factor related to bank size.

Second, we conduct placebo tests by assigning banks the SIB treatment at false times. We restrict the data to the time period before our main sample - 2002 to 2010 - and designate false treatment years from 2003 to 2010. We designate different years as false treatment years in different placebo tests. We, however, retain the three actual SIBs as treated banks. We now re-run the main specification 1 for each of the above placebo years and present the results in Table C2 of the online appendix. The coefficients on *SIB* in all the columns is negative and largely insignificant, which suggests that the increase in default towards SIBs was witnessed only after the banks were labeled as SIBs and not at other points in time.

Finally, we also document placebo tests based on false treatment bank years. We randomly generate 13 bank years out of the 500 bank years as treated and run the main specification 1 to estimate the DID coefficient.[30] We run one thousand such iterations of the specification and plot the histogram of the estimated coefficients in Figure C.1 of the online appendix. As shown in the figure, the actual coefficient (0.014) observed in our main results far exceeds the 99th percentile of the distribution (0.01). That is, we can reject the null hypothesis that the rate of default of borrowers on loans borrowed from treated banks is not increasing. Overall, the placebo tests make it highly implausible that the observed results are due to endogenous factors other than the SIB designation of banks.

[30] The 13 bank-years match the actual count of treated bank-years in our sample.

Figure C.1: The figure plots the distribution of coefficients from 1000 iterations of a simulation, randomly labeling 13 bank years as treated and estimating the main coefficient in Equation 1. The blue vertical line shows the 99^{th} percentile of the distribution, and the red vertical line shows our estimated coefficient.

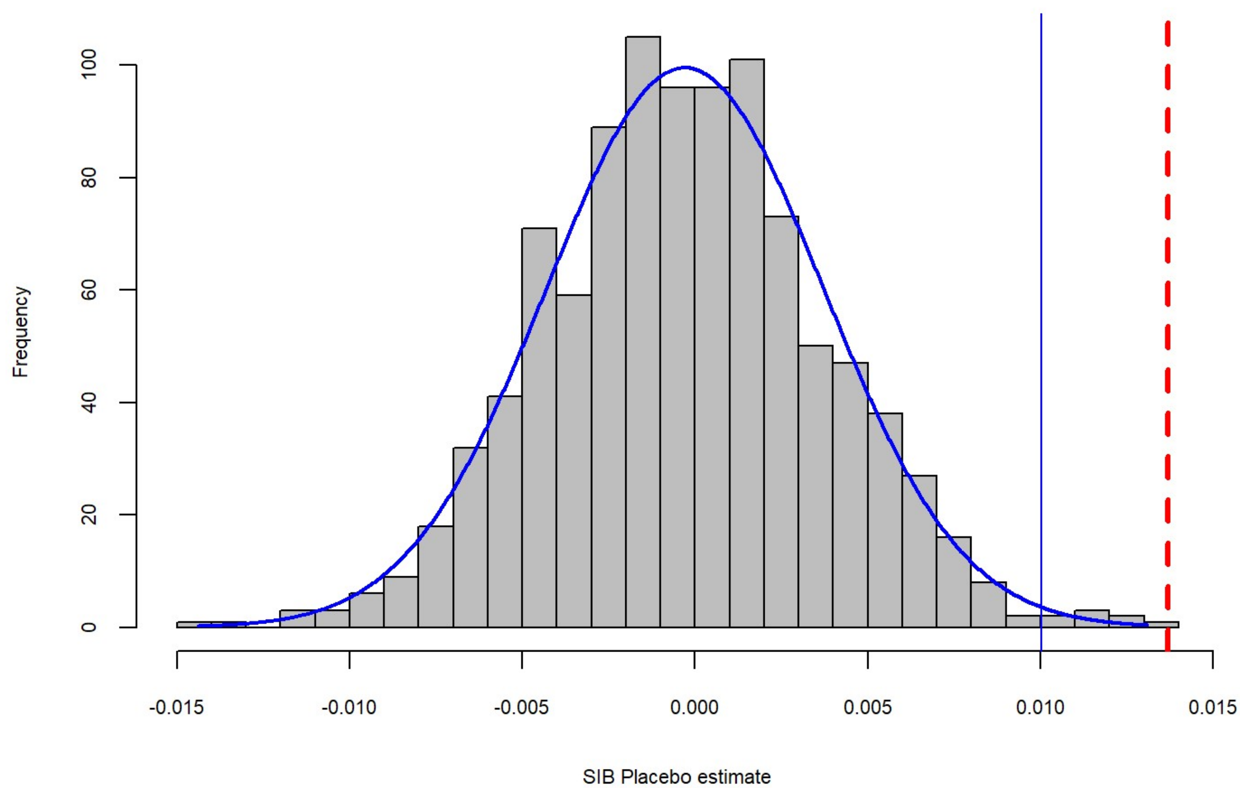


Table C1: False bank placebo test

The table shows the placebo estimates of the association between default and systemically important status allocated to other large banks that were not classified as SIBs. The data are at the bank-firm-year level and span from 2010 to 2020. In the first four columns, we restrict the data to scheduled commercial banks; in column 5, we restrict the data to non-banks. The dependent variable is *Default* which is an indicator variable as defined in 3. The indicator variable *SIB* is an indicator variable that takes a value of one from the year in which the banks are allocated placebo treatment, 0 otherwise. The banks which are assigned false SIB treatment are Bank of Baroda, Punjab National Bank, and Bank of India (Bank of Baroda, Axis Bank, and Yes Bank) in columns 1 and 2 (3 and 4) of Panel B. The top three non-banks are assigned false treatment in column 5. We remove the true SIBs from our data. We include the same set of control variables that are used in Table 3 in even-numbered columns. We include firm × year and bank × firm fixed effects in all columns. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default				
	(1)	(2)	(3)	(4)	(5)
SIB	0.006	0.001	0.003	0.003	-0.003
	(0.005)	(0.005)	(0.004)	(0.004)	(0.018)
Control variables	No	Yes	No	Yes	No
Firm × Year F.E.	Yes	Yes	Yes	Yes	Yes
Bank × Firm F.E.	Yes	Yes	Yes	Yes	Yes
Observations	158,785	158,563	158,785	158,563	7,678
R-squared	0.614	0.616	0.614	0.616	0.678

Table C2: False time placebo test

The table shows the placebo estimates of the association between default and systemically important status allocated at random times before the start of our sample period. The placebo test data is at the bank-firm-year level and spans from 2002 to 2010. The dependent variable is *Default* which is an indicator variable as defined in Table 3. The explanatory variable is *SIB*. *SIB* is an indicator variable that takes a value of one from the year in which the banks are allocated placebo treatment, 0 otherwise. The placebo treatment is allocated in the years 2003, 2004, 2005, 2006, 2007, 2008, and 2009 in the columns 1, 2, 3, 4, 5, 6, 7, and 8, respectively. We include firm × year and bank × firm fixed effects in all columns. The standard errors reported in the parentheses are clustered at the industry level and are adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	default							
Placebo treat year	2003	2004	2005	2006	2007	2008	2009	2010
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SIB	-0.010	-0.006**	-0.002	-0.002	-0.002	-0.001	-0.001	0.000
	(0.010)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.000)
Firm × Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	69,591	69,591	69,591	69,591	69,591	69,591	69,591	69,591
R-squared	0.705	0.705	0.705	0.705	0.705	0.705	0.705	0.705