Does Systemically Important Bank Status Induce Soft Budget Constraint Syndrome? Evidence From India. *

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Abstract

We test whether the policy of designating some banks as systemically important (SIB) impacts loan performance. Our within a borrower-year between banks tests show that loan delinquency increases by 70% in response to a bank being identified as a 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 via the soft budget constraint syndrome.

Keywords: Systemically Important Banks, Too-big-to-fail, Monitoring, Strategic default, Banking regulation

JEL Codes: G21, G28, E58, H81

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1 Introduction

A prominent policy measure implemented worldwide to address the too-big-to-fail (TBTF) problem of banks (and other financial institutions) is identifying large and well-connected banks as systemically important banks (SIBs) and subjecting them to a higher level of capital requirements and regulatory monitoring.[1] The policy aims to prevent distortionary lending and other practices that could lead to a banking crisis. Although the literature has examined several aspects of the SIB policy, the fundamental question of whether the designation of a bank as systemically important impacts the loan repayment discipline of the borrowers has not been examined.

Theoretically, it is unclear whether the SIB policy leads to an improvement or worsening of the loan repayment discipline of the borrowers. The policy could improve loan performance if higher levels of capital curb risk-shifting incentives and increase banks' effort in screening and monitoring borrowers (Admati and Hellwig (2014)). Strict monitoring by regulators could also have a similar effect.

In contrast, the explicit identification of some banks as SIBs could have a perverse impact on banks: It could induce or exacerbate the soft budget constraint syndrome among the designated SIBs (Kornai et al. (2003); Aghion et al. (1999)), and hence, cause a moral hazard problem. Consequently, SIBs may reduce screening and monitoring efforts. A reduction in screening and monitoring efforts by banks could lead to increased loan delinquency.

Another possibility is that the higher levels of capital and regulatory monitoring, which come along with the SIB designation, disincentivize the evergreening of loans and motivate the SIBs to recognize losses promptly. Even in such a case, the reported defaults will increase in response to a bank being designated as a SIB.

Given the above diverging possibilities, both the direction of loan performance and the likely mechanism need to be empirically investigated. We detect a significant worsening of loan performance in response to a bank being designated a SIB. Evidence suggests that the soft budget constraints caused by lax monitoring is the mechanism at work.

We study the implementation of BASEL III norms relating to SIBs in India. Three major banks–one government-controlled and two private–were designated as SIBs in a staggered manner

[1] See Strahan (2013); Acharya et al. (2016); Favara et al. (2021) for a description of the too big to fail problem.

following the BASEL III norms. The three banks account for 44% of outstanding bank loans in India. The fact that India has both government-controlled and private banks allows us to isolate the impact of SIB policy from pre-existing implicit government guarantees.

Studying the impact of SIB policy on borrower behavior faces two important challenges. First, borrowers of SIBs and non-SIBs could be systematically different and subject to different shocks that covary with the policy. Second, in any country, only a few banks are likely to be designated as SIBs. Therefore, conducting the study at a bank-time level may not be feasible.

We overcome the above challenges by organizing data at a firm-bank-year level and including firm X year fixed effects in the spirit of Khwaja and Mian (2008). Thus, the analysis is within a firm-year and between banks. In addition, we use firm X bank fixed effects to absorb the impact of any special relationship between banks and firms. Finally, the staggered designation of banks as SIBs also helps rule out the influence of correlated shocks.

Using the above framework, we find that the default rate on loans from SIBs is 1.4 percentage points higher than that of non-SIBs. Given the average default rate of 2%, the difference is an economically meaningful 70% of the average default rate. An event study type test helps us rule out the existence of pre-trends.

We investigate the plausible mechanism in the second part of the paper. One possible mechanism is the reduction in monitoring by SIBs (the "lax monitoring" channel) (Diamond (1984)). We define monitoring broadly to include loan recovery efforts. This is possible if the TBTF guarantees induce behavior consistent with soft budget constraints. A second plausible mechanism is the prompt recognition of losses by SIBs due to increased regulatory monitoring (the "loss recognition" channel).

We examine four broad and disconnected categories of evidence. The first set of tests examines the impact of the SIB policy on the tendency to evergreen loans. 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 suggests either no change or a significant increase in evergreening tendencies in response to the SIB designation. We use multiple measures of evergreening of loans, such as (i) direct evergreening - new loans to existing low-quality borrowers (Peek and Rosengren (2005); Caballero et al. (2008); Tantri (2021)); (ii) indirect evergreening - new loans to related parties of existing low-quality borrowers, and movement of funds from the related party that receives the loans to the borrower in trouble (Kashyap et al. (2021)); (iii) increased tendency to restructure loans rather than recognize losses (Mannil et al. (2021)). None of the measures indicate a decrease in evergreening tendency. In fact some of our measures show close to 100% increase in the tendency to evergreen loans. The results are inconsistent with the loss recognition hypothesis and in line with lax monitoring. Further, the results also suggest that the deterioration in loan performance we document is likely to be an underestimation.

The next set of evidence examines activities relating to monitoring and loan recovery. We find a 104% decline in legal cases pertaining to loan recovery, and a 34 to 55% reduction in expenses related to monitoring. Under the "loss recognition" hypothesis, the above expenses are unlikely to decline: if anything, disputes related to recovery of loans and expenses connected with monitoring could increase under loss recognition as borrowers whose loans are declared as nonperforming due to the cleanup may sometimes dispute the status. Thus, the above evidence is consistent with the lax monitoring hypothesis.

The third set of evidence relates to the type of borrowers impacted. We find that the borrowers far away from the lending bank are more likely to default than nearby borrowers in response to the SIB designation of a bank. A large literature in banking shows that the distance between the bank and the borrower impacts monitoring quality (See Granja et al. (2022) and the papers cited therein). The relationship is likely stronger in emerging economies with a higher level of market friction. Given the extant findings, a deterioration in loan performance of far away borrowers is consistent with lax monitoring. More importantly, there is unlikely to be any relationship between loss recognition and distance. In the same spirit, we find that unrated borrowers who are likely to be opaque and require more monitoring default more in response to SIB designation. While the result is consistent with the monitoring channel, it is not entirely inconsistent with loss recognition as it is possible that such borrowers were targets of evergreening before, and a clean-up post the SIB designation leads to higher defaults.

The last category of evidence is related to the stock market reaction to the announcement of increase in banks' non-performing assets (NPA). The adverse market reaction to a higher level of NPAs is likely to be tempered when the increase in NPAs results from a deliberate clean-up rather than reduced monitoring. However, markets are unlikely to be sympathetic to lax monitoring.

We find that the negative market reaction to increase in NPAs is no different when the bank is involved in a SIB. Thus, the evidence is consistent with lax monitoring and inconsistent with loss recognition.

Thus, the evidence, based on symptoms, activities, borrower types, and consequences, indicates that the results are driven by lax monitoring. Our results also suggest that regulators are unable to prevent reduction in monitoring quality by the SIBs. We discuss the possible reasons in detail in Section 7.

In the final part of the paper, we conduct robustness tests and address concerns relating to the interpretation of our results. First, in addition to lax monitoring, the soft budget constraints could also induce lax screening by SIBs. However, lacking loan application-level data, we cannot verify screening efforts. To disentangle the possible impact of SIB status on screening and monitoring, we conduct our primary firm-bank-year level test on a sample of loans that were lent before 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.

Second, given that Indian banking is characterized by a significant presence of government-controlled partially privatized banks (GCBs)—one of the SIBs is also a GCB—a reader may wonder about the potential impact of SIB status in such a setting. An argument could be that GCBs already have an implicit government guarantee, so the SIB status should not make much difference to them. We verify that the tendency of borrowers to default more in response to the SIB status does not depend on the government control of banks. Therefore, it is likely that the result reflects the possibility of SIBs getting first preference in terms of a bailout in an extremely severe crisis where even governments run out of resources to honor all commitments. It is important to note that the option of solving problems by printing additional currency can be highly costly to inflation-prone emerging economies. The fact that the SIB status has bite even in a setting with GCBs shows that our results could be an underestimation of the phenomenon that we point out. The soft budget constraint syndrome could be more severe in other settings dominated by private banks.

Third, we also rule out the possibility of our results being a mechanical reflection of efficient reporting of defaulting cases by SIBs to credit bureaus by comparing the proportion of loans in default reported by SIBs and non-SIBs. Fourth, by exploiting the within-country variation in court efficiency, we rule out the alternative explanation that the results are only due to inefficient law enforcement and thus have extremely limited generalizability. Our results suggest that the loan performance is likely to deteriorate in response to the SIB policy even in regions with efficient courts if banks become lax in monitoring and loan recovery.

Fifth, the design of the policy itself helps rule out the possibility that the "borrower run" phenomenon drives our results (Bond and Rai (2009); Schiantarelli et al. (2020)). Borrower runs occur when firms anticipate a higher chance of failure of a bank. The SIB policy reduces the chances of bank failure. Therefore, the SIB policy cannot induce borrower runs.

Sixth, it is reasonable to worry about the possibility of other confounding policy interventions with a disproportionate impact on large banks, also leading to higher disclosed default rates. For instance, the RBI conducted special audits (Asset Quality Reviews or AQR) between 2015-2019 (Chopra et al. (2021)). Based on the audit findings, the banks were asked to write off loans previously considered standard. To rule out the possibility that our results are due to the audit, we first point out that a firm found to be delinquent to one bank by the audit had to be classified as an NPA by all banks. Thus, the AQR cannot lead to higher defaults at a bank-firm-year level. Nonetheless, we also control for the additional NPAs found by the audit at a bank-year level in our main tests. Our results remain unchanged. Similarly, we also account for other concurrent policy interventions by using suitable proxies and rule out the possibility that our results are due to them.

Finally, there could be a concern that some other unobserved endogenous factors that vary with the size of the banks cause our results. Such a factor, if it exists, should impact banks exactly when they cross the SIB threshold. Given that all banks that crossed the SIB threshold were designated as such, we cannot conduct placebo tests using other banks that crossed the threshold but were not designated as SIBs. Nonetheless, we conduct a placebo test using the next three largest banks as placebo SIBs. We also run a similar placebo test using non-scheduled commercial banks for which the SIB policy was not applied. Our main results do not manifest in placebo tests. Thus, only an endogenous factor that discontinuously impacts banks crossing the SIB threshold from the time when they cross the threshold can affect the interpretation of our results. We cannot think of such endogenous reasons. We also conduct a battery of other false time and false event tests.

We contribute to the strand of banking literature that discusses the implications of banks' Too Big To Fail (TBTF) problem. Strahan (2013) show that the TBTF problem leads to competitive inequity among financial firms and misallocation of credit within the economy. They also discuss potential remedies to the problem. Chari and Kehoe (2016) argue that government bailout of private firms increases risk-taking. Farhi and Tirole (2012) show that TBTF policies can also induce strategic complementarities across risk management choices of banks. Dávila and Walther (2020) show that in environments where bank bailouts are likely, the leverage choices of large banks increase the probability of bailouts. Davies and Tracey (2014) show that the scale economies of large banks are primarily due to the TBTF subsidy. Philippon and Wang (2021) show that a policy that makes government support to banks conditional on their performance can achieve the twin purposes of preventing adverse spillover effects of bank failure and not inducing moral hazard among large banks.

Explicitly designating TBTF banks as systemically important and requiring them to maintain additional capital buffer is one policy measure that is implemented across the globe to counter the TBTF problem (Bongini et al. (2015)). Several recent studies have looked at the impact of the policy. For instance, Iyer et al. (2019) show that systemically important banks corner a higher proportion of uninsured deposits during a crisis at the expense of other banks. Passmore and von Hafften (2019) find the capital surcharges are too less to mitigate the risks. Behn et al. (2019) show that banks manipulate their financial reporting to avoid the capital surcharge associated with the SIB policy. Favara et al. (2021) show that capital surcharges on global systemically important banks (GSIBs) reduce lending by such banks relative to other banks. Firms' total borrowing does not fall as they switch to other banks. To the best of our knowledge, no study has looked at the impact of SIB policy on borrowers' loan repayment behavior. We contribute to this literature by showing that the SIB policy leads to an increase in loan delinquency. One possible reason for the increased delinquency is the soft budget constraints driven reduction in the monitoring of borrowers by banks.

We also contribute to the literature on soft budget constraints in banks (Aghion et al. (1999)). Several studies show that banks either fail to liquidate projects on time or finance bad projects due to the soft budget constraints induced by the possibility of a bailout by governments (Mitchell (1995); Berglöf and Roland (1995); Mitchell (2000)). We show that an explicit policy of identifying SIBs could worsen banks' soft budget constraints problem.

2 Institutional Background

Based on a realization that the policies aimed at 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 explicitly and impose capital surcharges on them. It also requires increased regulatory monitoring of SIBs.

Accordingly, in October 2010, the Financial Stability Board (FSB) advised all member countries to create frameworks to reduce risks from Systemically Important Financial Institutions (SIFIs) in their jurisdictions. 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.[2] The BCBS also required member countries to create frameworks to deal with Domestic Systemically Important Banks (D-SIBs). In addition to the global regulations, several countries increased their supervision of SIBs and imposed additional reporting requirements. For instance, the USA mandated further stress testing for TBTF banks.

Following the BASEL guidelines, the RBI introduced a framework for identifying and regulating D-SIBs in 2014. The framework aims to identify the D-SIBs and impose additional regulatory capital and reporting requirements depending on each D-SIB's degree of systemic risk. Even the methodology of assessing D-SIBs is mainly in line with the G-SIB framework designed by the BCBS. It consists of a two-step process.[3] 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.[4] 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 composite score is calculated using a range of indicators in line with the G-SIB scoring methodology: size, interconnectedness, substitutability, and complexity are the four indicators used.

[2]Source: Basel Committee on Banking Supervision. (2011). Basel III: a global regulatory framework for more resilient banks and banking systems. Bank for International Settlements. `www.bis.org/publ/bcbs189.pdf`

[3]Framework for Dealing with Domestic Systemically Important Banks (D-SIBs). (n.d.). Retrieved April 7, 2022, from `https://rbidocs.rbi.org.in/rdocs/Content/PDFs/FDSIBF220714.pdf`,

[4]Basel III exposure measure is calculated as the sum of the following exposures: (i) on-balance sheet exposures; (ii) derivative exposures; (iii) securities financing transaction exposures; and (iv) off-balance sheet exposures. The specific calculation for each of these sub-items is explained in detail in the BASEL guidelines. Refer `https://www.bis.org/publ/bcbs270.pdf`

The 'size' indicator carries a 40% weightage in the composite score calculation and is determined by the total exposure of the bank measure using the Basel III framework. It considers both on and off-balance sheet exposures of the bank. The 'interconnectedness' indicator carries a weightage of 20%. It is derived using three sub-indicators with equal weight: the three sub indicators are (i) intra-financial system assets held by the bank, (ii) intra-financial system liabilities of the bank, and (iii) total securities issued by the bank.

The third indicator is 'substitutability,' which determines the extent to which other banks can substitute a SIB's services in the event of failure of the SIB. The score carries 20% weight and is calculated using three sub-indicators: assets under custody of the bank, payment activity of the bank, and amount of debt and equity underwritten by the bank. Finally, the 'complexity' indicator gauges the costs and effort needed to revitalize the bank in the event of failure. It is measured using three sub-indicators with equal weightage: the notional amount of OTC derivatives, cross-jurisdictional liabilities, and trade and available for sale securities held by the bank. The details of the composite score calculation used to designate a bank as D-SIB are shown in Panel A of Table A1 in the online appendix and the differences between the BCBS approach of G-SIB identification and RBI's D-SIB identification are shown in Panel B of Table A1 in the online appendix.[5]

The composite systemic importance score of a bank is calculated as the weighted average of the constituent indicator scores: banks that have a composite score above a threshold are classified as D-SIBs. Further, the D-SIBs are allocated into five different buckets depending on the magnitude of the composite score, with higher buckets containing banks with higher systemic importance scores. Bucket 1 (5) consists of banks with the lowest (highest) systemic importance score. Subsequently, D-SIBs in higher buckets attract higher capital requirements (Common Equity Tier 1 or CET1) to cushion against the greater systemic risk posed by such banks. For instance, banks in bucket 1 must maintain an additional CET1 of 0.20% of total risk-weighted assets (RWA), whereas banks in bucket 5 need an additional CET1 of 1.00% of total RWA.

The first set of SIB identification was carried out in the year 2015-2016.[6] 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. Owing to its higher systemic risk, SBI is placed in Bucket-3

[5] Source: `https://www.rbi.org.in/scripts/bs_viewcontent.aspx?Id=2766`

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

and has an excess capital buffer requirement of 0.6%, whereas the other two banks are placed in Bucket-1 and require an additional buffer of 0.2%.

3 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 secured loans which have been registered. A non-registered loan loses certain privileges of secured loans. Therefore, it is reasonable to expect almost all secured loans to be registered. Further, Chopra et al. (2021) show that the MCA database covers more than 50% of all private commercial credit in India. 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.

We obtain loan performance-related data from TransUnion CIBIL, India's largest credit information company. The data covers both defaults and wilful defaults reported by banks to CIBIL. The CIBIL 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 the credit information companies monthly or more frequently. Kashyap et al. (2021) show that loan delinquencies from CIBIL are representative of total corporate non-performing assets in the banking sector.

We match the firm-bank pairs between CIBIL and MCA using the names in both the databases and create a combined panel data of firm-bank pairs with outstanding loans and identify delinquent loans. We add a filter of loan size of Rupees 10 million in all our tests involving loan delinquency as we have loan performance details for only those loans. Further, we obtain accounting information about firms and banks 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.[7] The data include a case identification number, address of the corresponding DRT court, filing date, resolution date, and others. The data are used to obtain the average case pendency rate at the district level.

Our sample spans eleven years, from 2010 to 2020. We have a total of 356,787 firm-bank-year observations pertaining to 21,101 unique firms and 46 unique lenders. In our dataset, 24 out of 46 banks are GCBs. As noted in Section 2, three banks were designated as SIBs, of which one- State Bank of India- is a GCB 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.[8] The unconditional delinquency rate is 2%. Of the total firm-bank-year observations, 12% have a bank designated as SIB. Details of the sample construction and summary statistics are provided in Tables 1 and 2, respectively.

4 Empirical Strategy

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. One way of doing so could be to compare the aggregate borrower behavior at a bank-year level for SIB and non-SIB bank years. 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

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

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

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 an indicator variable that takes a value of 1 if firm i defaults on bank j in year t, 0 otherwise. The indicator variable $SIB_{j,t}$ takes a value of 1 if a bank j is designated as SIB in year t, 0 otherwise. 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 X 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 X year and firm X 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 X 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 X 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 above design leaves us with bank-level time-varying factors as we cannot include bank X year (and bank X firm X 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 X 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, we also test and rule out the existence of pre-existing trends in outcomes. Given these safeguards, if it exists, 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. We think that the possibility of the existence of such a factor is extremely low.

5 Main Result

5.1 SIB and loan delinquency

As discussed in the Introduction, our central question is whether labeling a bank as a SIB improves or worsens the loan repayment behavior of 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. SIBs are also subject to tighter regulatory supervision and reporting requirements. Such measures also could lead to better loan performance by inducing high-quality effort on the part of the bankers.

On the other hand, the SIB designation could exacerbate the perception of too-big-to-fail and thus induce soft budget constraint syndrome due to a higher perceived probability of government support.[9] Subsequently; SIBs may reduce screening and monitoring efforts and consequently experience higher loan delinquencies. Further, it is also possible that SIBs show a higher inclination to promptly recognize losses on loans either because of their improved capital position or due to increased pressure from the regulators.

Therefore, the final outcome depends on the net effect of the two opposing forces described. We test the net effect by estimating the regression specification 1. We present the results in Table 3. Our data are organized at a firm-bank-year level for the sample period from 2010 to 2020. Column 2 in Table 3 presents the results for the full-fledged specification, which includes firm X year fixed effects, firm X bank fixed effects, and bank X year level control variables.

The difference-in-differences (DID) coefficient 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 an economically meaningful 70% of 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.

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

In columns 3 and 4 of the Table, we present the results by limiting the control samples to the private and government-controlled banks, which match with the SIBs in terms of aggregate size. Specifically, we use three GCBs (five privately owned banks) whose combined asset size matches that of the government-controlled SIB (two privately owned SIBs) before the SIB framework was introduced. The idea is to address any residual concerns relating to the time-varying impact of bank size not captured by our control variables that represent the size. As shown in the Table, the results remain similar.

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 a SIB. The revised regression specification is shown below.

$$\begin{aligned} Default_{i,j,t} = &\alpha + \beta_{-5}Pre5 + \beta_{-4}Pre4 + \beta_{-3}Pre3 + \beta_{-2}Pre2 + \beta_0 Post0 + \\ &\beta_1 Post1 + \beta_2 Post2 + \beta_3 Post3 + \beta_4 Post4 + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \end{aligned} \tag{2}$$

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 a 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 0 otherwise. The non-SIBs have a value of zero on all the above variables. *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 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 supporting the thesis that our results in Section 5.1 do not represent a continuation of pre-existing trends.

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 firm-bank-year level results described in Section 5: 1) SIBs become lax at the monitoring and screening of borrowers; 2) they are willing to recognize losses promptly. We discuss both mechanisms below. 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.

6.1 Impact On Evergreening

It is well known that undercapitalized banks engage in risk-shifting behavior by evergreening loans on the verge of default (Acharya et al. (2019); Admati and Hellwig (2014)). Given the above finding, an explanation for our results could be that additional capital surcharges reduce the incentives for risk shifting and lead to timely recognition of losses. Thus, increased defaults on SIB loans could be a mechanical consequence of a reduction in evergreening motivated by the increase in capital adequacy. Hence, under the "loss recognition" hypothesis, the tendency to evergreen should reduce in response to the designation of a bank as a SIB.

Under the lax monitoring channel, the designation of a bank as a 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-level default (Caballero et al. (2008); Tantri (2021)). Thus, the lax monitoring channel predicts either a no change or an increase in the evergreening of loans. Increased defaults are not a mechanical consequence of a reduction in evergreening under this channel.

We examine the above conflicting hypotheses using three measures of evergreening.

6.1.1 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 regression specification for the test.

$$\begin{aligned} New\_loan_{i,j,t} =& \alpha + \beta_1 SIB_{j,t} + \beta_2 firm\_health_{i,t} + \beta_3 SIB_{j,t} \times firm\_health_{i,t} + \beta_2 X_{j,t} \\ &+ \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \end{aligned} \tag{3}$$

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, 0 otherwise. $SIB_{j,t}$ is as defined in Equation 1. $Firm\_health_{i,t}$ of borrower i is defined on the basis of interest coverage ratio (ICR), PBITDA, and profit growth.[10] The health measure *ICR indicator* (*PBITDA indicator*) takes a value of one if ICR is below 1 (PBITDA is less than zero) for the firm i in the respective year t, zero otherwise. 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 whether lending to unhealthy firms is significantly different after a bank is designated as a SIB.

The results are presented in panel A of Table 4. The dependent variable is *new loan* as defined above. The explanatory variable of interest is the interaction between *SIB* and *ICR indicator* (*PBITDA indicator*) in column 1 (2). All variables are defined above. We include bank-year level control variables, firm X year fixed effects, and bank X firm fixed effects in all columns.

We find that the coefficient on SIB remains positive and significant but the coefficient on the interaction term is statistically indistinguishable from zero. Therefore it is reasonable to conclude that banks continue to evergreen loans even after being designated as SIBs.

6.1.2 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 current borrower in trouble, using internal capital markets, in the same year.

We implement specification 1 to test indirect ever-greening. The results are presented panel B

[10]PBDITA is the profit before interest tax depreciation and amortisation

of Table 4. The data are organized at a firm-bank-year level for the sample period from 2010 to 2020. The dependent variable *indirect evergreening indicator* is an indicator variable that takes a value of one if a bank indirectly evergreens the firm's loan during the year under consideration and zero otherwise. The main explanatory variable is *SIB* which is 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 4. 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. This is an economically meaningful 100% of the unconditional rate of indirect evergreening. The result is qualitatively and quantitatively similar even after controlling for the interaction between *SIB* and *Default*. Thus, we find that banks are, in fact, more likely to indirectly evergreen loans after being designated as SIBs.[11]

6.1.3 Loan Restructuring:

Our third measure of evergreening is based on loan restructuring. 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 the complicated steps involved in the loan recovery process.

We test the above thesis by applying specification 1. The dependent variable–*Restructuring indicator*—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 4. The data are organized at a firm-bank-year level for the sample period from 2016 to 2020.[12] 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,

[11] In untabulated results, we find that results also hold for a sub-sample of the post-forbearance period - 2016 to 2020.

[12] The period between 2010 to 2015 was dominated by the forbearance period when RBI allowed the banks to restructure bad assets as a response to the global financial crisis. The forbearance was withdrawn in 2015. The period between 2010 to 2015 saw an exponential increase in the restructuring of loans (Mannil et al. (2021)). So we limit our analysis to the post-forbearance period of 2016 to 2020. However, our results are qualitatively similar for the full sample period from 2010 to 2020.

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 of the banks increases the probability of restructuring by 3.4 percentage points. This is an economically meaningful 37% of the unconditional restructuring rate of 9%. 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.

Overall, the above results rule out the possibility of a decrease in (direct or indirect) evergreening as an explanation for an immediate 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.

6.2 Exercising Creditor Rights and Loan Monitoring Expenses

Under the "lax monitoring" hypothesis, banks that monitor less are expected to exercise creditor rights for loan recovery less aggressively than other banks. Similarly, such banks should also record lower monitoring expenses than other banks. However, under the "loss recognition" hypothesis, banks that actively monitor their borrowers should file higher loan recovery cases given loan defaults and should correspondingly not experience a decrease in loan monitoring expenses. We test the above consequences of the competing hypotheses empirically.

6.2.1 Loan recovery court cases

In India, loan recovery cases are filed in specialized Debt Recovery Tribunal (DRT) courts which have jurisdiction over the firm's location (Vig (2013)). We test whether the probability of being involved in a legal dispute with the borrowers differs for SIBs compared to other banks. We use the following specification.

$$Legal\_dispute_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 X_{j,t} + \gamma_i + \delta_j + \tau_t + \epsilon_{i,j,t} \quad (4)$$

where $Legal\_dispute_{i,j,t}$ is an indicator 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-yer level control variables as discussed in Equation 1.

We present the results in Panel A of Table 5. 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. In column 2 of Panel A, which uses the full-fledged specification, 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 point lower when the bank is a SIB than when the bank is not. The coefficient is economically meaningful since it represents 104% of the unconditional probability of filing a loan recovery case in the DRT court. The result is consistent with the lax monitoring hypothesis.

6.2.2 Loan monitoring expenses

Next, we test whether expenses related to monitoring change significantly after the bank is designated SIB. Specifically, we examine *consulting expenses* and *communication expenses.* An increase in monitoring efforts requires higher outsourcing expenses associated with consulting and a higher frequency of communication with the borrowers. Banks' expenditure on legal and other consultancies relating to loan recovery is considered under consulting expenses. We test whether the above listed expenses decrease after a bank is designated as a SIB using the following bank-year level regression specification.

$$Expense_{j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 X_{j,t} + \gamma_j + \delta_t + \epsilon_{j,t} \tag{5}$$

Where $Expense_{j,t}$ represents natural logarithm of monitoring expenses of bank j in year t. As mentioned earlier, we use two measures of expenses - *consulting expenses* and *communication expenses.* $SIB_{j,t}$ is as defined in Equation 1. γ_j and δ_t represent bank and year-level fixed effects, respectively. $X_{j,t}$ represents the bank-year level control variables as listed in Equation 1.

We present the results in panel B of Table 5. The data are organized at bank-year level for the period 2010 to 2020. The dependent variable in columns 1 and 2 (3 and 4) is the natural logarithm of consulting expenses (communication expenses). The explanatory variable is *SIB* as defined above. We include the bank-year level control variables in the regression models of even-numbered columns. We also include bank and year-level fixed effects in the regression models of all columns. In column 2, we find that there is an economically significant 55% decrease in consulting expenses for SIBs. In column 4 we find that there is also a 34% decline in communication expenses of SIBs. The above results indicating a reduction in consulting and communication expenses are consistent with the "lax monitoring" but not with the "loss recognition" mechanism for the decline in default by SIBs.

6.3 Distant and Unrated borrowers

Under the lax monitoring hypothesis, it is reasonable to expect that firms requiring higher monitoring levels default more on SIBs than non-SIBs. We identify such firms in two ways - 1) firms that are located far from the bank and 2) firms that are unrated and thus more opaque.

6.3.1 Impact of distance between borrowers and SIB on default

Extant literature has shown that distant borrowers require a higher level of monitoring than the borrowers located in the vicinity (Granja et al. (2022); Agarwal and Hauswald (2010)). Thus, we expect the increase in default due to SIB designation to be higher for more distant borrowers if the default is driven by a decline in monitoring. We use the following firm-bank-year level specification to test whether the increase in the probability of default on SIBs is driven by distant borrowers.

$$Default_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 Distant_{i,j,t} + \beta_3 Distant_{i,j,t} \times SIB_{j,t} + \beta_4 X_{j,t} + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \quad (6)$$

Where indicator variables $Default_{i,j,t}$ and $SIB_{j,t}$ are as defined in Equation 1. The indicator variable $Distant_{i,j,t}$ takes a value of one if the bank and firm are headquartered in different states, and zero otherwise. $\gamma_{i,t}$ and $\delta_{i,j}$ represent firm $\times$ year and firm $\times$ bank-level fixed effects, respectively. $X_{j,t}$ represents the bank-year level control variables as listed in Equation 1. The coefficient of interest is β_3 which estimates the differential tendency of distant borrowers to default on SIBs.

We present the results in columns 1 and 2 of Table 6. The data are organized at a firm-bank-year level for the sample period from 2010 to 2020. The dependent variable is $Default$ as defined above, and the main explanatory variable is an interaction between SIB and $Distant$. We include bank-year level control variables in the regression model of column 2. We also have firm $\times$ year and firm $\times$ bank fixed effects in the regression models of all columns. The coefficient on the interaction term, $SIB \times Distant$, is positive and significant, while the coefficient on SIB turns insignificant. Thus, the increase in delinquencies on SIBs appears to be completely driven by borrowers that are headquartered in a different state than the bank.

The above results indicate that the distant borrowers tend to default more on the banks after they are designated as systematically important. The result is consistent with the "lax monitoring" hypothesis. Note that the above result is inconsistent with the competing "loss recognition" mechanism because the distance between a bank and borrower is unlikely to be related to loss recognition. In fact, it may be easier to evergreen loans lent to borrowers located closer due to stronger relationships. Therefore, if loss recognition is the mechanism at work, the increased default should have been driven by borrowers located closer to the banks.

6.3.2 Unrated borrowers and loan defaults

External credit ratings help predict loan defaults and are helpful in loan monitoring activities (Nakamura and Roszbach, 2018). Thus, borrowers that credit rating agencies do not rate require higher monitoring efforts by lenders. If SIBs indeed reduce monitoring efforts, then we expect to find higher defaults by unrated borrowers towards SIBs than other banks. We test the above hypothesis using the following specification.

$$Default_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 SIB_{j,t} \times Unrated_{i,t} + \beta_3 X_{j,t} + \gamma_{i,t} + \delta_{j,t} + \epsilon_{i,j,t} \quad (7)$$

where *Default* and *SIB* are as defined in Equation 1. *Unrated* is an indicator variable which is set to one if the borrower is not rated by any external credit rating agency, zero otherwise. $X_{j,t}$ is the set of control variables used in Equation 1. $\gamma_{i,t}$ and $\gamma_{i,t}$ represent firm-year and firm-bank level fixed effects, respectively.

We present the results in columns 3 and 4 of Table 6. The data are organized at a firm-bank-year level and span 2010 to 2020. Focusing on column 3, we find that the interaction term of *SIB* and *unrated* is positive and significant. Thus, loan defaults towards SIBs are higher in the cross-section of unrated firms, which are difficult to monitor. In terms of economic magnitude, an unrated borrower has a 95% higher probability of defaulting on a SIB than a non-SIB. Therefore, our results are consistent with the "lax monitoring" hypothesis.

6.3.3 Market reaction to loan defaults

Stock markets, on average, react negatively to a decline in bank health. However, if the decline in health results from proactive clean-ups due to higher "loss recognition", we expect the markets to react less negatively to the decline in health. The lower negative reaction is likely due to a reduction in information asymmetry. When banks' health deteriorates due to lax monitoring, there is no positive signal for the markets to react less negatively. Therefore, we do not expect a softer treatment by the stock markets when deterioration in bank health is due to lax monitoring.

We test whether the markets react less negatively to the announcement of loan defaults of SIBs compared to other banks to disentangle the two mechanisms. We use the following specification at a bank-quarter level.

$$Y_{j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 Bank\_health_{j,t} + \beta_3 SIB_{j,t} \times Bank\_health_{j,t} + \gamma_j + \delta_t + \epsilon_{j,t} \tag{8}$$

Where $Y_{j,t}$ represents the market-adjusted returns of a bank's stock. The indicator variable $SIB_{j,t}$ is as defined in Equation 1. *Bank_health* is proxied by *NPA increase* and *ROA decrease*. *NPA increase* is an indicator variable that takes a value of one if NPA increases compared to the previous quarter and zero otherwise, while *ROA decrease* is an indicator variable that takes a value of one if ROA decreases compared to the previous quarter and zero otherwise. γ_j and δ_t represent the bank and year-quarter fixed effects, respectively. The coefficient of interest is β_3 which estimates the change in sensitivity of the capital market to bank health after the bank is designated as a SIB.

The results are presented in Table 7. The dependent variable is the cumulative 5-day excess return over the bank nifty index (Bombay Stock Exchange or BSE return) in columns 1 and 2 (3 and 4). The excess returns are then cumulated over -2 to +2 days around the quarterly result announcement date to arrive at the *5-day excess return*. The explanatory variable is an interaction between SIB and *NPA increase* (*ROA decrease*) in column 1 and 3 (2 and 4). We include bank and year-quarter fixed effects in all columns. Across specifications, the coefficient on *NPA increase* and *ROA decrease* indicator variables are significantly negative, while the coefficients on the interaction terms are statistically indistinguishable from zero. The above results imply that while the excess return is negative when bank health worsens, the capital market response is no different for SIB than other banks. Thus, our results are inconsistent with the "loss recognition" hypothesis, suggesting that banks reduce borrowers' monitoring after being designated systemically important.

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

7 Discussion

The SIBs are subject to a higher level of regulatory monitoring. Our results suggest that SIBs reduce monitoring efforts despite increased regulatory scrutiny. Naturally, questions will arise about the ability of the regulators to prevent a reduction in monitoring.

To appreciate the phenomenon we document, it is important to recognize that a large part of monitoring is not verifiable. For instance, it is hard to verify whether the bankers understand the borrowers' business well and have developed the capability to intervene on time. Even when certain activities are verifiable, it is almost impossible for the regulator to follow up on individual cases.

Why can't the regulator use the same proxies we use for assessing lax monitoring? While the evidence we have produced indicates lax monitoring, they are not actionable on their own in a regulatory or legal sense. For instance, the regulator cannot force banks to initiate legal proceedings against borrowers. Banks may contend that, in some cases, they are better off with a negotiated settlement. Similarly, the regulator cannot prevent banks from lending to related parties of an existing borrower in trouble or restructuring loans. Banks may argue that these are genuine business opportunities. Even market reaction cannot be a basis for regulatory action. Similar concerns arise about distant borrowers and the hiring of consultants.

Generally, it is hard for the regulator to act based on symptoms, suggestive evidence, or the consequences of lax monitoring. A regulator can take action when they see banks violating the enshrined rules. For instance, regulators can question banks if they notice that the banks are not sending the required reminders when a loan is overdue. However, it is hard to judge the quality of the recovery effort.

A second reason for the inability of regulators to detect lax monitoring is the lack of effort on the part of the regulators. Even the regulators may become lax in monitoring SIBs, knowing fully well that taxpayers will rescue these banks should they get into trouble. They may focus on other banks.

We cannot cleanly identify the reasons for the regulator's inability to prevent lax monitoring by SIBs. However, our results indicate that the current regulatory arrangement cannot prevent shirking by SIBs. The regulatory apparatus around SIB should consider the possibility of banks shirking in monitoring after being designated as SIBs.

8 Alternate Explanations And Robustness

8.1 Lax Screening

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. However, we disentangle the 'lax monitoring' from the 'lax screening' mechanism by limiting our bank-firm relationships to the period before any of the banks was designated SIB and estimating the regression specification 1 on this sub-sample. The loans in this restricted sample cannot be impacted by lax screening induced by SIB designation.

The results are presented in Table A2 of the online appendix. In columns 1 and 2, we limit the sample to bank-firm relationships before 2016, while in columns 3 and 4, we limit the sample to bank-firm relationships formed before 2010. The results are quantitatively and qualitatively similar to those in Table 3. Since the results hold even when the screening channel is completely blocked, their chances of being driven by lax monitoring further increases.

8.2 Impact of the Government's control over banks

The Indian banking industry has a significant presence of GCBs. Of the 46 scheduled commercial banks in our sample, 24 are GCBs, and 1 out of 3 SIBs is a GCB.[13] In the above setting, the reader might be concerned that given the implicit government guarantee that GCBs enjoy, the potential impact of SIB status should be insignificant for them. We address the concern by showing that our main result is unchanged even after absorbing the ownership status of banks. We implement the following firm-bank-year level specification for the test.

$$Default_{i,j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 GCB_{j,t} + \beta_3 SIB_{j,t} * GCB_{j,t} + \beta_4 X_{j,t} + \gamma_{i,t} + \delta_{i,j} + \epsilon_{i,j,t} \qquad (9)$$

where $Default_{i,j,t}$ and $SIB_{j,t}$ are as defined in Section 4. $GCB_{j,t}$ is an indicator variable that takes a value of one for GCBs, zero otherwise. 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_1 which estimates the causal impact of SIB designation on loan delinquency after absorbing the government ownership status of banks.

We present the results in column 1 of panel A of Table 8. The sample period is 2010 to 2020. The dependent variable is *default*. The main explanatory variable is an interaction between *SIB* and *GCB*. We include the bank-year level control variables as stated in Equation 1. We also include firm X year and bank X firm-level fixed effects.

We find that the coefficient on *SIB* remains statistically and economically significant even after controlling the ownership status of the banks. The coefficient relating to the interaction between *SIB* and *GCB* is statistically indistinguishable from zero. The result indicates that government control does not impact our results significantly.

The above results indicate the possibility that the increase in delinquencies on SIBs due to lax monitoring follows from borrowers' belief in SIBs getting first preference in government bailouts during an extreme systemic crisis. The government resources might be constrained under such circumstances to support all the GCBs. The governments of emerging economies cannot easily get away with printing notes for discharging government liabilities. Our finding that delinquencies

[13] Major banks in India are known as scheduled commercial banks as they are listed in a schedule under the RBI Act. We have data for all 46 such banks.

increase on SIBs even in a setting with a significant presence of GCBs indicates that the problem may be even more exacerbated in environments with only private banks.

8.3 Efficient Reporting and Recovery Practices

As we note in Section 3, the CIBIL database on loan performance is based on the list of defaulters against whom the banks have started recovery proceedings by issuing a notice. The banks supply the data to CIBIL. A skeptic may argue that SIBs experiencing higher loan delinquency is a mechanical consequence of their improved efficiency in issuing recovery notices and providing the required data to the credit bureau.

We address the concern by explicitly testing whether SIBs report a higher proportion of their non-performing assets to the credit bureau. We implement the above test by organizing data at the bank-year level and running the following regression specification.

$$Y_{j,t} = \alpha + \beta_1 SIB_{j,t} + \beta_2 X_{j,t} + \gamma_j + \delta_t + \epsilon_{j,t} \tag{10}$$

Where $Y_{j,t}$ is the ratio between the amount of default reported to CIBIL and the amount reported in the financial statements of banks for a bank j in year t. The indicator variable $SIB_{j,t}$ takes a value of one if a bank j is designated as SIB in year t, zero otherwise. $X_{j,t}$ represents a vector of bank-year level control variables as in Equation 1. γ_j and δ_t represent bank and year fixed effects, respectively. The coefficient of interest is β_1 which estimates the increase in reported default amount as a proportion of non-performing loans after a bank is designated as SIB.

We present the results in Table A3 of the online appendix. We find that the coefficient on *SIB* is statistically insignificant. Thus, we do not find evidence supporting the alternative explanation that our main results are due to efficient recovery and reporting practices of SIBs.

8.4 Borrower Runs

Given that emerging markets are known to experience borrower runs (Bond and Rai, 2009; Schiantarelli et al., 2020; Kashyap et al., 2021), a reader may wonder whether our results reflect an increase in borrower runs on SIBs. We think that the above alternative explanation is implausible. This is because borrower runs occur when borrowers fear that a bank is likely to collapse and hence will not be able to lend in the future. That clearly is not the case with the identification of SIBs. The chances of eventual failure reduce after a bank is designated as a SIB. Therefore, the borrower-run phenomenon cannot explain our results.

8.5 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 the following specification.

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

where $Y_{i,j,t}$ is either $default$. $Default$ is defined in Section 4. $SIB_{j,t}$ is defined in Section 4. $Courtefficiency_i$ is an indicator variable that takes a value of one if the firm i is located in a district with below median pendency in courts, zero otherwise. The bank-year level control variables included in $X_{j,t}$ are as in Equation 1. Variables $\gamma_{i,t}$ and $\delta_{i,j}$ represent firm-year and firm-bank level fixed effects, respectively. The coefficients of interest are β_1 and β_3. The coefficient β_1 represents the causal impact of SIB designation on delinquencies in areas with low court efficiency, while β_3 captures the incremental tendency of default on SIBs in areas with high court efficiency. If the court efficiency has a role to play, we expect the coefficient β_3 to be significantly negative.

We present the results in column 2 of panel A of Table 8. The sample is at a bank-firm-year level for the sample period 2010 to 2020. The dependent variable is *default*. The main explanatory variable is an interaction between *SIB* and *court efficiency*. The variables have been defined above. We include the bank-year level control variables stated in Equation 1. We also include firm X year and bank X firm level fixed effects. We find that the coefficient on *SIB* stays positive and significant, while the coefficient on the interaction term is insignificant.

The above 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.

8.6 Other Government Interventions

There could be a worry that other concurrent regulatory or government interventions could also drive our results. Therefore, 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.

Nonetheless, to address residual concerns about any indirect or lagged effects of such regulations, we account for the impact of other regulations in our main regression Equation 1. Specifically, 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, which measures the association between SIB and loan repayment behavior. 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.

The other regulatory interventions we control for are discussed below:

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. As noted in the Introduction, 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 Panel B of Table 8 show that the coefficient of the SIB indicator variable continues to remain positive and statistically significant. 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 thresholds are based on different measures of loan quality, capital adequacy, profitability, and off-balance sheet exposure. A breach of even one threshold triggers PCA. The restrictions under the PCA regime range from curbs on dividends to outright suspension of new lending: the severity of restrictions is proportional to the level of breach. 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 2 in Panel B of Table 8. We find that the coefficient for SIB continues to be positive and statistically significant.

Restrictions on restructuring: 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. The circular 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 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.

To address the above 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 3 of Panel B of Table 8 suggest that our main finding is unaffected by the implementation of the February 12 circular.

All Interventions Together: Finally, for completion, we include all the variables representing different alternative explanations as control variables in one regression equation and present the results in column 4 in Panel B of Table 8. The result indicating higher delinquency on SIBs continues to hold.

8.7 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 endogenous factors could cause our findings. However, staggered classification of banks as SIB 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 endogenous 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 Table A4 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 GCB 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 A5 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.[14] We run one thousand such iterations of the specification and plot the histogram of the estimated coefficients in Figure A.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.

9 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 loan performance of those banks. 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 induced by soft budget constraints 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 a SIB. The managers of SIBs could display moral hazard independent of lax monitoring by financial markets due to the increased sense of security offered by the SIB policy. We cannot disentangle the two possible sources of moral hazard. Finally, we do not evaluate the policy from a social welfare point of view. Our focus is limited to loan performance.

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

Despite the above caveats, we believe that our findings are helpful for policy. The results clearly show that the capital surcharges and the regulatory framework imposed by the BASEL III norms are inadequate in stemming the moral hazard that is likely due to the implicit protection offered by the SIB policy. While our findings do not afford us to offer any workable solution, we believe it will be useful to know that the SIB norms themselves could sow the seeds of a future crisis.

Figure 1: 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 *pre2*, *pre3*, *pre4*, and *pre5* are one for 2, 3, 4, and 5 years before a bank is categorised 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 categorised 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.

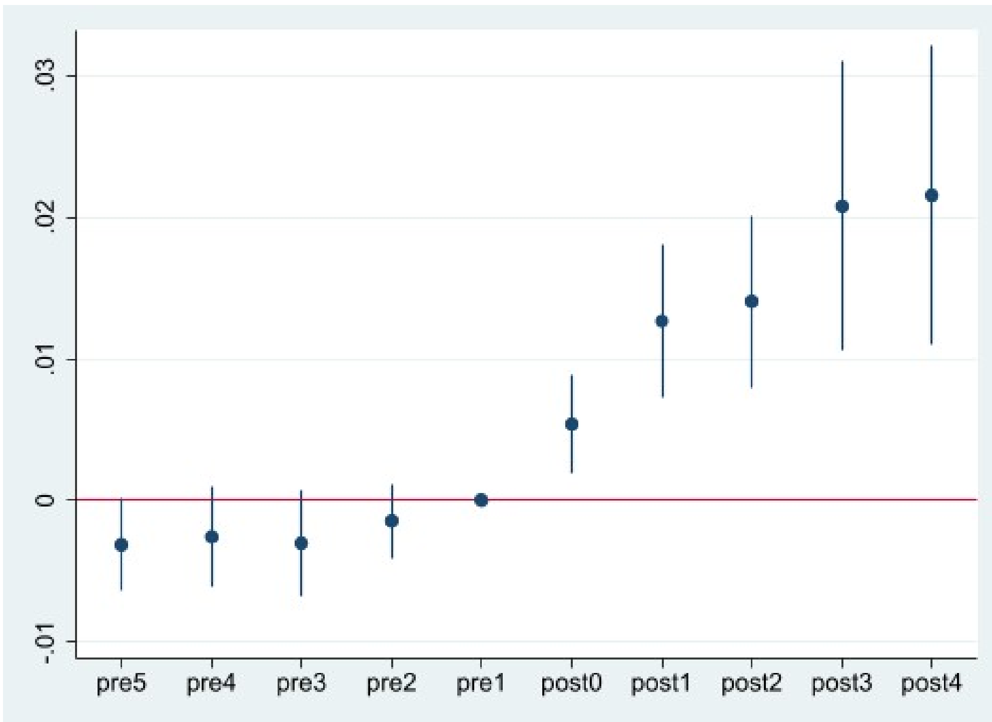

Table 1: Sample construction

Table shows the sample construction.

Sample Construction Table	
Sample Period	FY 2010 - 2020
Number of Banks	46
Number of Firms	21,101
Number of Industry codes	714
Number of firm-bank-year level observations	356,787
Number of firm-bank-year level observations when the Bank is SIB	41,892
Number of firm-bank-year with defaults	5,444
Number of bank-year	500
Number of bank-year when the bank is SIB	13
Number of firm-bank relations	55,966
Number of firm-bank relations with at least 1 default	1724

Table 2: Summary statistics

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

Variable	Obs	Mean	Median	1st %ile	99th %ile	Std dev
Bank-Firm-Year summary statistics						
Default	3,56,787	0.02	0	0	1	0.12
SIB Indicator	3,56,787	0.12	0	0	1	0.32
Public Indicator	3,56,787	0.6	1	0	1	0.49
Restructured Indicator	3,56,787	0.09	0	0	1	0.28
Firm-Year summary statistics						
ICR indicator	2,00,380	0.26	0	0	1	0.44
PBITDA indicator	3,03,021	0.17	0	0	1	0.38
Bank-Year summary statistics						
Capital Adequacy	494	13.5	12.94	8.67	29.2	3.59
GNPA by Assets	494	3.49	2.2	0.16	15.4	3.22
Bank asset size in INR million	494	3.95	1.48	0.03	39.50	7.54
ROA	494	0.55	0.67	-3.14	2.92	1.08

Table 3: SIB and loan delinquency

The table shows the association between default and systemically important status of the 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. 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 columns 1 and 2, we consider all banks, while in columns 3 and 4, the sample is limited to matched control banks based on the size of the treated banks. The matched government-controlled banks are Punjab National Bank, Bank of Baroda, and Bank of India, while matched private sector banks are Yes Bank, IndusInd Bank, Kotak Mahindra Bank, Federal Bank, and Axis Bank. 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 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	0.014***	0.014***	0.009***	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
Control variables	No	Yes	No	Yes
Firm × Year F.E.	Yes	Yes	Yes	Yes
Bank × Firm F.E.	Yes	Yes	Yes	Yes
Observations	234,609	234,358	103,131	103,131
R-squared	0.614	0.616	0.688	0.689

Table 4: 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 Panel A and C and from 2016 to 2020 in Panel B. In Panel A, we further limit the sample to bank-firm relationships that were started before the sample period. 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 *Restructured*, 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. The indicator variable *ICR indicator* (*PBITDA indicator*) 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		Restructure	
	(1)	(2)	(1)	(2)	(1)	(2)
SIB	0.323*	0.446***	0.003***	0.003***	0.034***	0.034***
	(0.190)	(0.168)	(0.001)	(0.001)	(0.009)	(0.009)
Default				-0.001		-0.006
				(0.001)		(0.007)
SIB × Default				0.002		-0.019
				(0.002)		(0.016)
SIB × ICR indicator	0.363					
	(0.321)					
SIB × PBITDA indicator		-0.267				
		(0.306)				
Observations	87,877	91,980	234,358	234,358	114,788	114,788
R-squared	0.540	0.543	0.460	0.460	0.519	0.519
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

Table 5: Mechanism: Creditor right cases and monitoring expenses

The table provides evidence in support of lax monitoring as the underlying mechanism. The data in Panel A are at a bank-firm-year level and spans from 2010 to 2020. In Panel A, the sample 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 Panel B are at a bank-year level and spans from 2010 to 2020. The dependent variable in columns 1 and 2 of Panel B is *Log consulting*, which is the natural logarithm of total consulting outsourcing expenses of the bank in a year. The dependent variable in columns 3 and 4 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 (bank and year) fixed effects in all columns of panel A (B). The standard errors reported in parentheses are clustered at the industry level (bank level) in panel A (B) and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Creditor rights		Panel B: Monitoring expenses			
	Legal dispute		Log consulting		Log communication	
	(1)	(2)	(1)	(2)	(3)	(4)
SIB	-0.033***	-0.024**	-0.806*	-0.799*	-0.333**	-0.425**
	(0.011)	(0.011)	(0.424)	(0.440)	(0.151)	(0.185)
Controls	No	Yes	No	Yes	No	Yes
Firm FE	Yes	Yes	No	No	No	No
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,705	16,705	467	465	465	465
R-squared	0.610	0.611	0.890	0.957	0.946	0.965

Table 6: Mechanism: Firm level heterogeneity

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 is *Default* which is defined in 3. The variable *SIB* is defined in 3. The variable *Distant* is an indicator variable set to one if the borrower and the bank are located in different states, zero otherwise. The variable *Unrated* is an indicator variable set to one if the borrower is not rated by any credit rating agency, zero otherwise. We include the set of control of variables from Table 3 in the even numbered columns. We include firm × year and bank × year fixed effects in all the columns. 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			
	(1)	(2)	(3)	(4)
SIB	-0.000	0.002	0.007***	0.007***
	(0.007)	(0.007)	(0.002)	(0.002)
SIB × Distant	0.016**	0.015**		
	(0.007)	(0.007)		
SIB × Unrated			0.019***	0.019***
			(0.006)	(0.006)
Observations	234,609	234,358	234,609	234,358
R-squared	0.614	0.616	0.614	0.616
Control variables	No	Yes	No	Yes
Firm × Year F.E.	Yes	Yes	Yes	Yes
Bank × Firm F.E.	Yes	Yes	Yes	Yes

Table 7: Mechanism: Capital market reaction to deterioration in bank health

The table tests the difference in the capital market 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 *5-day excess return*. *Excess return* is the return of the bank minus the bank nifty index return (BSE return) on the quarterly result announcement day in columns 1 and 2 (3 and 4). The above calculated excess return is cumulated over 5-days (-2 to +2 days) around the event date to obtain the *5-day excess return*. The indicator variable *SIB* is as defined in Table 3. *NPA increase* (*ROA decrease*) is an indicator variable that takes a value of 1 if GNPA (ROA) increases (decreases) in the quarter compared to the previous quarter. 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.

	Bank nifty		BSE	
	5-day excess return			
	(1)	(2)	(3)	(4)
NPA increase	-0.031***		-0.033***	
	(0.004)		(0.005)	
SIB X NPA increase	0.007		0.010	
	(0.011)		(0.016)	
ROA decrease		-0.030***		-0.030***
		(0.004)		(0.004)
SIB X ROA decrease		0.015		0.016
		(0.012)		(0.018)
SIB	0.011	0.003	0.011	0.005
	(0.014)	(0.016)	(0.020)	(0.022)
Observations	2,430	2,414	2,442	2,426
R-squared	0.128	0.133	0.164	0.164
Bank F.E.	Yes	Yes	Yes	Yes
Year-quarter F.E.	Yes	Yes	Yes	Yes

Table 8: 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. In panel A we present the results for the difference in the association between loan delinquency and SIB designation for GCBs and regions with low court efficiency. In panel B, we test the association after controlling for other government interventions. The dependent variable in both panels A and B is *'Default'* and is defined in Table 3. The main explanatory variable *SIB* is as defined in Table 3. *GCB* is an indicator variable that takes a value of one if the bank is government-controlled, zero otherwise. *Court efficiency* is an indicator variable that takes a value of one if the firm is located in a district with below-median pendency in debt recovery courts, zero otherwise. In column 1 of panel B, we control for GNPA and provisioning divergence as estimated in the asset quality review (AQR), which proxy for the AQR intervention. In column 2 of panel B, we control for the PCAscore calculated following Kashyap et al. (2021), which proxies for the PCA intervention. In column 3 of panel B, 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. Finally, in column 4 of panel B, we control for all the above interventions. 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					
	Panel A		Panel B			
	(1)	(2)	(1)	(2)	(3)	(4)
SIB	0.008**	0.012***	0.016***	0.013***	0.012***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
SIB × GCB	0.008					
	(0.006)					
SIB × Court efficiency		0.010				
		(0.009)				
Observations	225,964	233,365	234,358	230,313	219,327	219,238
R-squared	0.628	0.616	0.616	0.624	0.631	0.631
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

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Internet Appendix

A Figures and Tables

Figure A.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.

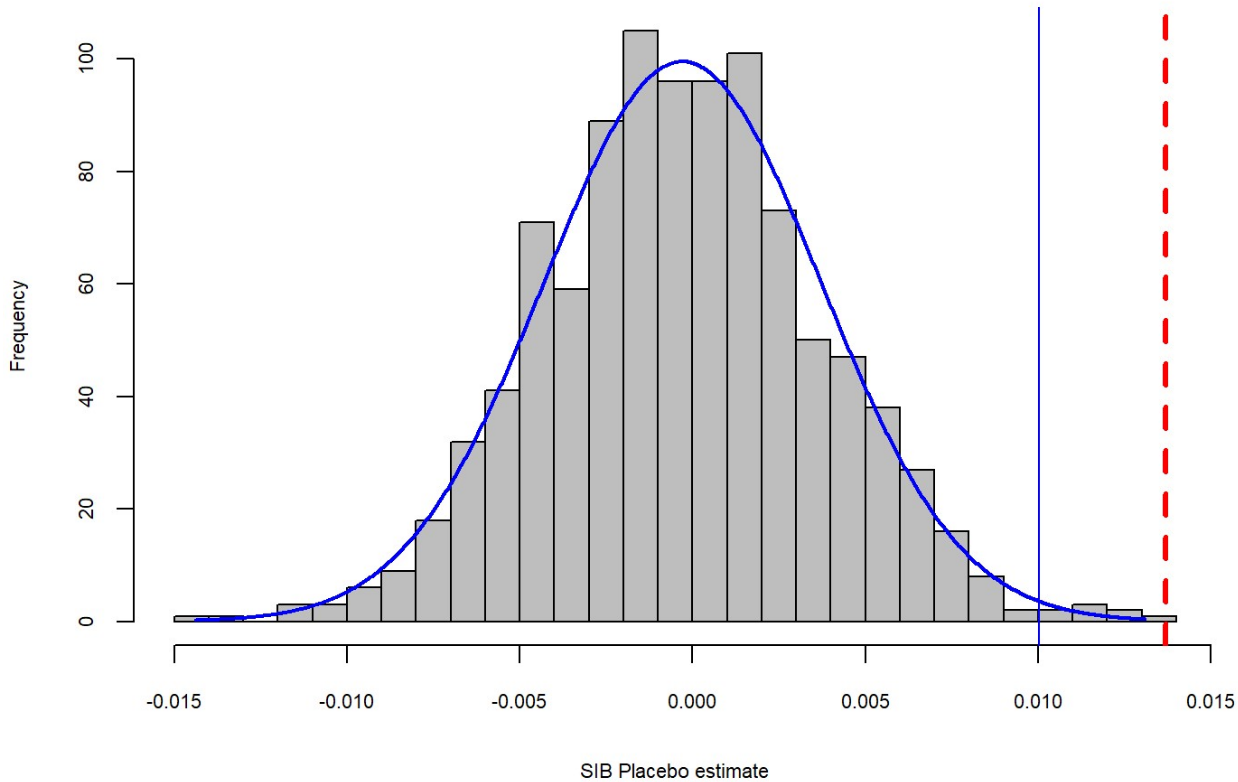

Table A1: Panel A of the table shows the weights of various indicators in the composite score calculation by RBI for designating a bank as D-SIB. Panel B shows the differences between G-SIB identification by BCBS and D-SIB identification by RBI.

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	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 in the sample apart from 75 largest banks.	Banks having size greater or equal to 2% of GDP. Additionally, five largest foreign banks, based on their size, are also added in the sample.
Indicators	Five broad indicators: 1. Cross jurisdictional activity 2. Size 3. Interconnectedness 4. Substitutability 5. Complexity	Four broad indicators: 1. Size 2.Interconnectedness 3. Substitutability 4. Complexity
Indicator weights	All five indicators given equal weight of 20%.	Size is given a weight of 40% and other three indicators are given a weight of 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.

Table A2: Pre Existing Bank-firm relationships.

The table shows the association between default and systemically important status of the banks for a sub-sample of bank-firm relationships. The sample is at 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. Further, in columns 1 and 2 (3 and 4), we limit the data to bank-firm relationships formed before 2017 (2010). The dependent variable is *'default'*, which is defined in Table 3. The main explanatory variable is *'SIB'* as defined in Table 3. The control variables listed in Table 3 are included in the even-numbered columns. We include firm X year and bank X 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	0.014***	0.014***	0.014**	0.014***
	(0.003)	(0.003)	(0.005)	(0.005)
Observations	214,712	214,461	116,589	116,500
R-squared	0.612	0.614	0.619	0.621
Control variables	No	Yes	No	Yes
Firm X Year F.E.	Yes	Yes	Yes	Yes
Bank X Firm F.E.	Yes	Yes	Yes	Yes

Table A3: Reported Default as a proportion of GNPA

The table shows the association between the default amount reported to CIBIL as a proportion of GNPA disclosed in financial statements of banks and the systemically important status of the banks. The sample is at the bank-year level and spans from 2010 to 2020. The dependent variable is *'default by NPA'*, which is the ratio between the default amount reported to CIBIL and the amount of GNPA as per financial statements of banks at a bank year level. The main explanatory variable is *'SIB'* as defined in Table 3. The control variables listed in Table 3 are included in column 2. We include bank and year fixed effects in both 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.

	Default by GNPA	
	(1)	(2)
SIB	-0.010	-0.007
	(0.019)	(0.023)
Observations	355	355
R-squared	0.106	0.111
Controls	No	Yes
Bank F.E.	Yes	Yes
Year F.E.	Yes	Yes

Table A4: 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 SBIs. The data are at the bank-firm-year level and span from 2010 to 2020. In the first 4 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 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 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). 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 controls that are used in Table 3 in columns 2 and 4. We include firm X year and bank X 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				
	Banks				Non-banks
	(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)
Observations	158,785	158,563	158,785	158,563	7,678
R-squared	0.614	0.616	0.614	0.616	0.678
Controls	No	Yes	No	Yes	No
Firm x Bank FE	Yes	Yes	Yes	Yes	Yes
Firm x Year FE	Yes	Yes	Yes	Yes	Yes

Table A5: 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 X year and bank X 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)
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
Firm x Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm x Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes