Preventing Borrower Runs: The Prompt Corrective Action Approach *

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Abstract

We ask whether regulatory intervention in the form of prompt corrective action that seeks to bring troubled banks back to health by imposing temporary restrictions and increasing regulatory monitoring reverses borrower runs. Using the Indian PCA regime and exploiting the sharp discontinuity provided by the entry criteria in a regression discontinuity framework, we find that timely regulatory intervention reduces loan delinquency by way of borrower runs by 93%. Cross-sectional tests based on regional variation in court efficiency and the relationship between economic shocks and delinquency show that a reduction in strategic default leads to improvement in loan performance.

Keywords: Borrower run, Prompt Corrective Action, Strategic Default, Banking regulation

JEL Codes: M41, M48, G21, G28, E58

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1 Introduction

Theory shows the possibility of "borrower runs" in credit markets (Bond and Rai, 2009). Borrower run is a phenomenon where borrowers strategically default on loans lent by lenders that are expected to fail. The reduction in the perceived value of the continued relationship with such lenders drives the phenomenon. In settings where the perceived value of maintaining a relationship with the lenders primarily drives loan repayment behavior, the phenomenon of borrower run is likely to be even more critical. In line with the theory, Schiantarelli et al. (2020) find evidence of borrower runs in Italy. They argue that borrower runs could potentially aggravate banking crises.

Despite the systematic importance of borrower runs, scholars have not examined the ways of mitigating the phenomenon. In particular, we do not know whether regulatory interventions that impose short-term curbs on the troubled lenders to prevent their collapse could mitigate or aggravate borrower runs. We investigate the above question.

Suppose the borrowers expect the actions of the regulators to result in the restoration of a troubled lenders' health. In that case, the tendency to "run" may reduce due to regulatory actions: the borrowers' posterior about the value of continuing the relationship with a troubled lender may increase after the intervention compared to the prior based on the observation of deteriorating health of the lender. Further, the possibility of being under the direct scrutiny of the regulator having powers to influence other lenders may discipline the borrowers.

In contrast, the short-term lending and other curbs imposed by the regulator to restore the health of the lenders may also end up reducing the value of the continued relationship to borrowers, especially to those facing significant credit constraints and in need of credit in the short run. Even the borrowers with present biased preferences are likely to consider the regulatory interventions as reducing the value of continued relationships (Meier and Sprenger (2010)).

Examining the prompt corrective action ("PCA," henceforth) implemented by the Reserve Bank of India ("RBI," henceforth) in the year 2018, we ask whether the intervention helps arrest the borrower run phenomenon.[1][2] Under the PCA framework, banks that breach certain thresholds in terms of five specified accounting and operating parameters face pre-specified and, at times, discretionary regulatory restrictions.[3] 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.

In our study, a straightforward comparison of loan performance of borrowers of banks subjected to PCA and those that are not before and after the regulatory intervention does not work because of the well-known possibility of certain types of borrowers self-selecting into certain types of banks. Thus, any differential loan performance of borrowers of PCA banks could be attributed to the kind of borrowers who borrow from such banks. An acceptable identification strategy should account

[1] We refer to the financial year 2018 (FY 2018), which begins from April 1, 2017, and ends on March 31, 2018, as the 'year 2018'.

[2] Reserve Bank of India is the Indian central bank.

[3] The five parameters are Capital adequacy ratio (CRAR), Tier I capital ratio (CET1), Net non-performing assets ratio (NNPA), Return on assets (ROA), and Leverage. Thresholds are specified for each of the five parameters.

for the above difference.

The PCA framework with sharp discontinuities at arbitrary cut-offs provides a good setting for the use of the regression discontinuity ("RD," henceforth) framework. Further, the fact that all the banks were under a special audit known as the Asset Quality Review ("AQR," henceforth) conducted by the RBI during our sample period substantially alleviates concerns relating to banks manipulating their reported numbers to avoid coming under the PCA radar. Thus, we have an instance where the RD technique can be reliably employed even when the discontinuity is based on the reported accounting numbers.

We follow Manchiraju and Rajgopal (2017) to create a binding running score using the closest of the five parameter values to the cut-off.[4] The spirit of the above method is to eliminate highly healthy and extremely unhealthy banks from the comparison and thus overcome any selection issues. Finally, the McCrary (2008) test rules out the clustering of banks at the cut-off and thus, validates the application of the RD technique.

Thus, the comparison is between similar banks separated by arbitrary levels of the cut-off and not between different types of banks with qualitatively dissimilar borrowers. As an additional layer of identification, following Schiantarelli et al. (2020), we conduct additional RD tests using borrower fixed effects. Effectively, the comparison is within a borrower and between banks, which are similar except with respect to the breach of the PCA cut-off.

We use loan-level data obtained from the Ministry of Corporate Affairs ("MCA," henceforth). The data relating to the performance of loans are obtained from India's largest credit bureau, Transunion CIBIL ("CIBIL," henceforth), which maintains a list of corporate defaults where recovery proceedings have been initiated by banks. The CIBIL records account for 85% of the total Non-performing assets (NPA) disclosed by banks. We show that the omission of nearly 15% of the NPAs does not impact the identification.

All bank-level data are obtained from the Prowess database maintained by the Center For Monitoring Indian Economy (CMIE). We obtain information about the names of the banks that are subjected to the PCA framework from the website of the RBI. Our sample spans a period of 3 years, starting from the year 2018 when the PCA regime was implemented. In total, 12 out of 41 Indian banks were subjected to the PCA treatment during our sample period.

We start with two tests that are in the nature of first stage tests. First, following Schiantarelli et al. (2020), we show that the borrower runs actually exist in India before the rollout of the PCA policy. The test is important given that government-owned banks ("GOBs," hereafter) have a close 47% share of bank loans disbursed in India.[5] Given that GOBs are likely to be rescued eventually by the government, it is not clear whether borrowers consider deteriorating financial performance as a signal of decline in the value of maintaining a connection with such banks. The tests show that the phenomena of borrower runs applies to the GOBs as well. Second, applying the RD framework described above, we find that the flow of fresh credit declines by 34% after a bank enters the PCA

[4] The binding score technique developed by Reardon and Robinson (2012) inspires Manchiraju and Rajgopal (2017) methodology

[5] https://m.rbi.org.in/scripts/PublicationsView.aspx?id=20270

treatment. Thus, the PCA seems to have a direct and immediate impact on lending.

The above results set the stage for our main test regarding the impact of the PCA regime on borrower runs. The RD tests show a discontinuous decline in the delinquency rate on loans lent by banks that enter the PCA regime. The decline is an economically meaningful 93% of the average delinquency rate before the start of the PCA regime. Further, even when we add borrower fixed effects and restrict the examination to within a borrower and between similar banks as in Schiantarelli et al. (2020), we find a similar improvement in loan performance.

Finally, since 11 out of 12 banks that enter into PCA are GOBs, we restrict the sample to borrowers who borrow exclusively from GOBs. The improvement in loan performance due to PCA admission is about 2.8 times of that in the full sample. Thus, the results are not due to GOBs being less impacted by borrower runs.

We conduct several hygiene tests that are required to establish the validity of the RD design. First, as noted before, McCrary test rules out bunching close to the cut-off. Second, we do not observe discontinuities in other borrower-level characteristics. Thus, some other unobserved but correlated factor is unlikely to be at play. Third, the results are robust to placebo tests. Fourth, the results go through even when we account for non-linear slopes of second or third-degree in our RD. Fifth, our results go through even when we use the robust RD framework developed by Calonico et al. (2014).

Finally, we also address concerns relating to the definition of the binding score by (i) redefining the scores; (ii) using OLS models; and (iii) using the Cox proportional hazard model. The results are broadly similar irrespective of the model used.

In the second part of the paper, we examine the nature of loan default that leads to borrower runs. Schiantarelli et al. (2020) find that (i) the borrower run is concentrated in regions of Italy having slow contract enforcement; and (ii) it is not confined to borrowers facing economic shocks. Thus, they conclude that the borrower runs reflect strategic default. In line with their finding, we find that the improvement in loan performance is also (i) concentrated in regions of India with relatively inefficient enforcement of contracts; and (ii) is not concentrated only among borrowers facing shocks. Thus, it is possible to conclude that at least a part of the improvement in loan performance is driven by a reduction in strategic default.

Further, we show that the there is no improvement in loan performance as a result of the PCA when borrowers are more likely to face credit constraints or when borrowers have short-term investment opportunities. The results are in line with our hypothesis outlined above. Such borrowers are likely to value access to finance in the short run relatively more than other borrowers. As discussed before, admission of a bank into the PCA framework results in a significant decline in credit in the short run.

Our paper contributes to the literature in several important ways. First, we contribute to the literature on *borrower runs*. Theoretical studies have shown the existence of an equilibrium in which borrowers strategically default on banks that are expected to fail (Bond and Rai, 2009; Carrasco and Salgado, 2014). Schiantarelli et al. (2020) empirically show that borrowers default selectively more on banks with weak fundamentals. Trautmann and Vlahu (2013) also show in an experimental setting that borrowers are more likely to strategically default during downturns when they expect other borrowers to default and when they have low expectations about bank fundamentals. We show that a regulatory intervention like the PCA helps arrest the borrower run phenomenon.

Second, we contribute to the growing literature on impact of regulatory changes in banking industry (e.g., Kim and Kross (1998), Ahmed et al. (1999), Beatty and Liao (2011), Altamuro and Beatty (2010), Laux and Leuz (2010), Dimitrov et al. (2015), Chircop and Novotny-Farkas (2016), Behn et al. (2016), Ertan et al. (2017), Granja (2018), Liang and Zhang (2019), Corona et al. (2019), Wheeler (2019), Balakrishnan and Ertan (2021)). Most of the studies in this literature focus on analyzing the effects of banking regulations on loan loss provisions, transparency and lending procyclicality among other effects. We contribute to this literature by studying the effect of the PCA framework on borrower runs.[6] To the best of our knowledge, we are the first ones to document impact of a banking regulation on *borrower run* phenomenon. Beatty and Liao (2014) emphasize that majority of the papers focus on studying effects of regulations, which are designed to prevent the previous crisis. We focus on a new regulation, which is forward looking in nature and has received far less attention.[7]

Third, our paper speaks directly to the literature on the importance of financial accounting measures in banking, summarized by Beatty and Liao (2014), Bushman (2014), and Acharya and Ryan (2016). The fact that the PCA framework relies on different accounting and regulatory measures reported by banks makes our paper relevant to this strand of literature. Also, banking regulation outside of the United States is understudied. Leuz and Wysocki (2016) highlight the importance of exploring the impact of regulations in novel settings in other countries. India is the fifth-largest economy in the world and has a vibrant banking sector. The implementation of the PCA framework together with the AQR provides us a unique setting to study its effect on borrower runs.

2 Institutional background

Prompt Corrective Action (PCA) is a regulator-driven framework that imposes restrictions on financially weaker banks and aims to arrest bank collapses at an early stage. One of the first major PCA frameworks was implemented by the US congress vide the Federal Deposit Insurance Corporation Improvement Act (FDICIA) in 1991 following the Savings and Loans crisis. The objective of PCA was to identify undercapitalized banks with deteriorating financials, address the deficiencies by imposing curbs on banks' borrowings and growth, and enforce capital restoration

[6] Aggarwal and Jacques (2001) and Jones and King (1995) study PCA framework in the US setting and find that PCA helped improve capital ratios of banks without increasing credit risk. Kocherlakota and Shim (2007) and Shim (2011) discuss about optimality of prompt corrective actions.

[7] Revised PCA framework in India is a proactive regulation introduced at a time when there was no banking crisis, and not as a response to an existing crisis.

plans.[8] Extant studies (Aggarwal and Jacques (2001), Jones and King (1995)) arrive at a general consensus that FDICIA was effective in improving bank capital and reducing credit risk.

A PCA framework was implemented by the RBI from 2002 to 2017 to identify weak commercial banks and subject them to corrective actions.[9] Under this framework, PCA trigger was based on threshold values for the following three financial parameters. *'CRAR'*, which denotes the capital adequacy ratio, *'NNPA'* defined as the ratio of net NPA (non-performing assets adjusted for provisions) to the net loans and advances, and ROA (return on assets). There were up to three levels of PCA breach. For example, CRAR was required to be at least 6% to avoid level II breach, and NNPA was set to a maximum of 10% to prevent level II breach. Finally, *'ROA'* was expected to be higher than 0.25%. Table A.2 of the online appendix provides details of the various thresholds used for identifying different levels of PCA breach under the old regime.

A bank was expected to be admitted under PCA on the breach of any one of the cut-offs. However, the implementation was largely ineffective because of two reasons. First, commercial banks were allowed to restructure poorly performing loans without creating additional loan-loss provisions, and thus under-report losses (Chopra et al. (2021)). Second, the conditions for PCA were lenient and were rarely triggered. For example, the framework did not include any parameter for limiting off-balance sheet exposures of banks. Further, the *CRAR* measure is a broad measure of capital adequacy. A bank could escape PCA by bolstering *CRAR* through hybrid instruments and subordinated debt without having sufficient Tier I capital. As a result, there were very few banks that were admitted under PCA in 15 years, despite several economic downturns and banking crises.[10]

In the year 2018, the RBI completely overhauled the PCA framework. It redefined the three levels of PCA breach and added two important financial measures, which were motivated by Basel III requirements.[11] The additional thresholds were based on the CET1 ratio and leverage. *'CET1'* is the ratio of Tier I capital to Risk Weighted Assets (RWA) of the bank. *CET1* is the highest quality of regulatory capital. It comprises of common shares, stock surplus, retained earnings, other comprehensive income, and regulatory adjustments.[12] *'Leverage'* is the ratio of Tier I capital to the exposure measure as defined in Basel III. Even off-balance sheet exposures are accounted for. *CET1* and *leverage* thresholds for level II cut-offs were set to a minimum of 5.125% and 3.5% respectively in the year 2018.

The cut-offs for the existing measures were also updated in the revised PCA. *CRAR* threshold was raised to a minimum requirement of 7.75% to prevent level II breach in 2018 as compared to a minimum requirement of 6% in the previous regime. Similarly, the *NNPA* ratio was tightened to

[8]FDICIA classifies FDIC insured depository institutions into 5 levels of capitalization ("well-capitalized," "adequately capitalized," "undercapitalized," "significantly undercapitalized" and "critically undercapitalized") based on levels of leverage, tier I capital ratio, and total capital ratio.

[9]Refer RBI notification `https://rbi.org.in/Scripts/NotificationUser.aspx?Id=1014&Mode=0`

[10]Only three banks were subjected to PCA from 2002 to 2017: "Indian Overseas Bank", "Union Bank of India" and "Dhanlaxmi Bank". These 3 banks account for only 5 out of 531 bank-year observations.

[11]RBI circular for revised PCA `https://rbi.org.in/Scripts/BS_CircularIndexDisplay.aspx?Id=10921`

[12]Refer definition of capital in Basel III `https://www.bis.org/fsi/fsisummaries/defcap_b3.htm`

a maximum allowable limit of 9%, compared to a maximum of 10% in earlier regime, to prevent PCA level II breach. However, the *ROA* criteria for level II breach was now triggered if the bank reported negative *ROA* for three consecutive years. As before, PCA is triggered on the breach of any one of the thresholds.

Although the change in the ROA threshold appears to be a relaxation from the earlier level of .25% in a year, in reality, ROA was rarely a binding constraint leading to a bank entering the PCA. In only 2 out of the 23 PCA bank-year observations, a bank was admitted solely on the basis of ROA criterion. Eventually, the regulator dropped the ROA criterion in the year 2020 as the ROA was derived from the loan loss provisions.[13] The details of the cut-offs for each parameter for each threshold level are presented in Panel A of Table 1.

As discussed earlier, the policy of exemption on provisioning for restructured loans was the major impediment in identifying weak banks. In 2016, the RBI plugged this loophole by discontinuing forbearance, and advising banks to promptly recognize bad loans. In further banking reforms, starting 2016, the RBI initiated the annual "asset quality review" (AQR) exercise, a comprehensive annual audit of bank balance sheets (Mannil et al. (2020)). The purpose of AQR was to identify and disclose the true NPA levels of banks.[14] These regulatory changes made it difficult for banks to manipulate loan-loss provisions, the prominent accrual measure in bank books (Beatty and Liao (2011), Beck and Narayanamoorthy (2013), Akins et al. (2017), Hegde and Kozlowski (2021)). Therefore, it is reasonable to expect improvements in the quality of bank books post the AQR.

Despite a slight relaxation in the *ROA* criterion, it is reasonable to consider the new framework more rigorous and effective because of (i) the institutional changes; (ii) the stringent limits for *CRAR* and *NNPA*; and (iii) the additional triggers for *CET1* and *Leverage*. This is evident from the fact that only three banks were admitted to PCA during the period from 2002 to 2017, but as many as 12 banks were admitted during the sample period (refer Panel B of Table 1).

As alluded to earlier, under the new PCA framework, there are three tiers of severity of breach which have varying consequences. A violation of level I without breaching higher levels is a mild breach and results in minor penalties, such as restrictions on dividend distribution and remittance of profit. On the other hand, the threshold level II has severe consequences such as restriction on branch expansion, higher provisions, and possibly directions from the RBI to reduce certain types of lending. The level II breach results in various degrees of direct and indirect lending curbs on banks. For instance, Allahabad Bank and Dena Bank, which breached level II limits and were placed under PCA in 2019, were subjected to lending restrictions as part of corrective actions.[15] With regard to level III breach, banks face similar curbs as level II breach. Additionally, they face restrictions on management compensation and directors' fee.

We do not use level I threshold breach for identification for two reasons. First, the enforcement

[13] https://www.rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=46165

[14] Speech by the RBI Governor at CII Banking summit https://www.rbi.org.in/SCRIPTS/BS_SpeechesView.aspx?Id=992

[15] https://www.financialexpress.com/industry/banking-finance/rbi-puts-deposit-lending-restrictions-on-allahabad-b 1167248 https://indianexpress.com/article/business/banking-and-finance/rbi-orders-dena-bank-to-stop-lending-restri

of level I breach is discretionary. For instance, in 2018, five banks that breached level I threshold without violating higher thresholds were exempted from the PCA.[16] Second, the corrective actions for a level I breach (without violating level II breach) are mild and do not impact lending.

However, the level II, unlike level I, is strictly enforced. We verify that all banks violating the level II are brought under the correction program (see Panel B of Table 1). Moreover, the violations lead to coercive restrictions. Therefore, the level II of the PCA is binding and provides a precise cut-off to study the treatment effects of PCA. Note that level III breach is a subset of level II breach: there are only 8 occasions when banks violate them. Hence, we consider the breach of level II cut-off as a trigger for PCA admission of banks.

3 Data

We obtain the annual loan-level data from the Ministry of Corporate Affairs ("MCA", henceforth). The MCA data contains all secured loans which have been registered. Bhue et al. (2015) find that approximately three-fourth of all loans in India are secured loans, and Chopra et al. (2021) further show that 50% of all private commercial credit in India is covered by the MCA database. Therefore, it is reasonable to assume that MCA loan data are representative of the corporate loans disbursed in India.

We use TransUnion CIBIL ("CIBIL", henceforth), the largest credit information company in India, for bank-borrower level loan performance data. The CIBIL database maintains a record of all corporate loans in excess of Rupees 10 million, where the bank has initiated legal recovery proceedings after a default. The RBI mandates banks and financial institutions to submit the list of such loan delinquencies to the credit information companies on a monthly or more frequent basis.[17] In Table A.3 of the online appendix, we show that, on average, the loan delinquencies from CIBIL account for roughly 85% of all commercial NPAs disclosed by banks in their financial statements. Hence, loan performance data retrieved from CIBIL provides a fair representation of the population of corporate loan delinquencies.

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 relation pairs and identify delinquent loans, if any. We add an additional filter of loan size of Rupees 10 million to reflect the fact that we have loan performance details for only those loans. Further, we obtain financial data of 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. The RBI's website provides data about the PCA criteria and entry into and exit of banks from the PCA.

Our sample spans three years between 2018 to 2020. The MCA data yields a sample of 127,934

[16] A Credit Suisse report finds that 5 banks breaching threshold level I in FY 2018 were yet to be admitted under PCA `https://economictimes.indiatimes.com/markets/stocks/news/pnb-andhra-bank-could-be-next-on-rbis-pca-framework-credit-suisse/articleshow/64401633.cms?from=mdr`

[17] RBI circular DBOD.No.CID.BC.128 /20.16.003/2013-14 `https://www.rbi.org.in/scripts/NotificationUser.aspx?Id=8969&Mode=0`

firm-bank-year observations pertaining to 21,547 unique firms and 41 unique lenders during this period. Out of the 121 bank-years in the sample period, roughly 20% are PCA bank-years, i.e., when banks were under PCA. Also, 20 out of 41 banks in the data are GOBs. As shown in Table A.3 of the online appendix, 12 banks went under PCA during the sample period, out of which 11 were GOBs. We augment the loan-level data with loan delinquency information available from the CIBIL data, and find that the unconditional delinquency rate is 6%. Details of the sample construction are provided in Panel C of Table 1.

4 Empirical strategy and results

4.1 Borrower run

Our paper tests whether the PCA regime was able to mitigate the likelihood of strategic default in response to deteriorating bank fundamentals in India. Borrowers value the lending relationship with financial institutions for maintaining future access to finance. The threat of discontinuation of this relationship acts as a deterrence to default by the borrowers. Bond and Rai (2009) theoretically show that borrowers' belief that the viability of a financial institution could be threatened by other borrowers' default leads to a decline in the value of lending relationship from the borrowers' perspective. The above scenario may lead to a situation where the value of the relationship falls below a threshold leading those borrowers to default strategically. Bond and Rai (2009) term this phenomenon "borrower run. In their setting, borrowers receive the signal about the viability of financial institutions by observing the repayment behavior of other borrowers.

Schiantarelli et al. (2020) empirically demonstrate the phenomenon in the Italian setting. The difference in their setting, though, is that firms receive a direct signal about the viability of a bank by observing the bank's financial information, as opposed to observing other borrowers. Schiantarelli et al. (2020) use credit registry data to show that the probability of late repayment is positively associated with the share of bad loans in the banks' portfolio in the previous period. The finding is consistent with the "borrower run" phenomenon since firms tend to selectively delay repayment to banks with past loan losses. Our setting is similar to theirs.

Note that the value of future access to finance is even more important in an environment of slow enforcement of contracts and high expected growth in the economy. This is because the slow enforcement of contracts forces banks to rely on the threat of severing lending relations to encourage repayment. Also, the threat is more credible in a high-growth environment where the expected demand for credit is higher in the future. India qualifies on both these fronts. India ranked 163 of 190 countries in the contract enforcement index of the world bank's ease of doing business index, although India's overall ranking improved from 80 to 63 in 2020.[18] Secondly, India's GDP growth was 6.7% in the five years before the pandemic and is expected to be above 7% in the coming decade.[19]

[18]https://www.doingbusiness.org/en/data/exploretopics/enforcing-contracts

[19]https://www.spglobal.com/ratings/en/research/articles/210927-economic-outlook-emerging-markets-q4-2021-vaccina

Nevertheless, we formally test whether "borrower run" is prevalent in India. We do not have access to the credit registry data in India. Instead, we construct a measure of banks' health as the proportion of outstanding loans to firms with interest coverage ratio (ICR) below 1.[20] ICR below 1 represents a scenario where a firm's profit is insufficient to cover the interest expense. We use this measure as the main explanatory variable in the following regression specification:

$$Y_{i,j,t} = \alpha + \beta_1 badfirmshare_{j,t-1} + \beta_2 bankshare_{i,j} + \beta_3 X_{j,t} + \gamma_{i,t} + \delta_j + \epsilon_{i,j,t} \tag{1}$$

where i represents a firm, j represents a bank, t represents a year. $Y_{i,j,t}$ represents loan outcomes. The variables $badfirmshare$ is the proportion of firms with ICR below 1 in bank j's loan portfolio. Consistent with Schiantarelli et al. (2020), we include bank-level vector of controls ($X_{j,t}$) and $bankshare$ which is the exposure of the bank j to firm i. $\gamma_{i,t}$ and δ_j are firm X year and bank fixed effects respectively. Following Schiantarelli et al. (2020), we include firm X year fixed effects which ensure that the estimation is within a firm-year, across banks. The data are restricted to firms with at least two banking relationships.

The results are presented in Table 2. We present the results for complete post-AQR regime (2016-20) (post-AQR to pre-revised PCA regime (2016-18)) in columns 1, 2 & 5 (3, 4 & 6) to test whether the "borrower run" phenomenon was prevalent before the new PCA regime. We include firm X year fixed effects in all columns. We include controls in columns 2, 4, 5 & 6. Consistent with Schiantarelli et al. (2020), we find that a one standard deviation increase in troubled firms' share in a bank's portfolio in the previous year is associated with an 8.5% higher default compared to its unconditional mean. The results suggest that a borrower having multiple banking relationships defaults selectively on the loans from banks with a higher share of bad firms, as compared to other banks.

One concern could be that GOBs dominate Indian banking (Srinivasan and Thampy, 2017), and GOBs are less susceptible to "borrower runs." The expectation of a government rescue may induce borrowers to maintain the relationship with GOBs even when they are in trouble. We allay this concern by restricting our data to GOBs in specification 1. The last two columns of Table 2 show that the results are even stronger for this sub-sample. A one standard deviation increase in troubled firms' share in GOB's portfolio in the previous year is associated with 10.7% higher default compared to its unconditional mean.[21]

4.2 Main result

4.2.1 Hypothesis development

As discussed in Section 2, the revised PCA framework introduced by the central bank tightened the admission criteria for PCA. The restrictions imposed on banks which breach the limit contained

[20] Interest coverage ratio = Earnings before interest and taxes (EBIT)/ Interest expense

[21] The unconditional rate of default is 8% for GOBs.

direct and indirect restrictions on lending. The direct restriction was in the form of discretionary curbs on lending by the RBI. The indirect restrictions involved curbs on branch expansion and the requirement to set aside higher provisions. Additionally, stricter monitoring by the RBI could also result in risk aversion leading to a voluntary decrease in credit supply by banks. The restriction on lending could bring down the threshold for "borrower runs" on banks under the PCA compared to banks with similar fundamentals but not under the PCA.

On the other hand, the regulatory oversight could increase the probability of future turnaround of banks under the PCA. The value of continuing the relationship with these banks compared to other banks in trouble, thus, may increase for firms. Also, the possibility of increased monitoring of PCA banks by RBI may result in borrowers coming under the direct lens of the RBI. Being in the negative list of the RBI could result in the loss of future access to credit from other banks, too.[22] These mechanisms would lead to a lower tendency by firms to default on PCA banks, compared to non-PCA banks with similar fundamentals.

4.2.2 Identification strategy

The revised regulation provides an ideal setting to test the above discussed tension empirically. As discussed in Section 2, the PCA threshold acts as a sharp cut-off for the banks to be placed under the PCA framework. The annual asset quality review (AQR) audits after 2015 also made it difficult for banks to manipulate accounting numbers in order to stay below the PCA threshold. The above factors make the setting ideal for a sharp regression discontinuity (RD) design.

Our main identification challenge is that borrowers who borrow from PCA banks could be systematically different from borrowers who borrow from other banks. We address this concern in the following two ways. First, the sharp RD design ensures that the identification is derived from a very narrow band around the PCA threshold. Thus, the banks on two sides of the cut-off are unlikely to be different. Second, although a sharp RD design does not require fixed effects, we nevertheless include firm fixed effects, which ensure that the identification is within firm (Khwaja and Mian, 2008). Thus, we are able to estimate the repayment behavior of the same firm towards PCA versus non-PCA banks.

For implementing the RD, we need to create a single running variable using the five triggers used to impose the PCA. The five triggers are based on several measures having different scales. For instance, a 0.1 increase in CRAR can be very different from a 0.1 increase in leverage. Therefore we standardize the variables around their respective cut-offs and create a score around zero for each of the variables. The score is calculated as the ratio of the extent of the breach from the specified cut-off to the cut-off value for the financial parameter. For example, NNPA of 10% with respect to a cut-off value of 9% yields a score of 0.11, and is considered as a PCA breach. In comparison, a CRAR of 8.5% corresponding to the cut-off of 7.75% results in a score of -0.10, and is not regarded

[22] Banks may designate borrowers as "wilful defaulters" which can lead to restrictions on accessing credit. Refer RBI circular DBR.No.CID.BC.22/20.16.003/2015-16 (`https://m.rbi.org.in/scripts/BS_ViewMasCirculardetails.aspx?id=9907`)

as a PCA breach. Thus, a positive score denotes a PCA violation, and a negative score indicates that the PCA limit has not been triggered.

Since the PCA is enforced when at least one of the thresholds is violated, we create a binding score that captures all the variables (Manchiraju and Rajgopal, 2017; Reardon and Robinson, 2012). This binding score, *PCAscore*, is defined as the minimum of the positive scores when the bank breaches at least one of the criteria and the maximum of the negative scores when the bank does not breach any criteria. For example, a bank that has scores of 0.1, 0.2, -0.1, -0.2, and -0.2 pertaining to CRAR, CET1, NNPA, Leverage, and ROA, respectively, violates the first two measures and will have a binding score of 0.1. On the other hand, a bank not under PCA and having scores of -0.2, -0.3, -0.4, -0.2, and -0.1 with respect to the five measures, will have a binding score of -0.1.[23] Thus *PCAscore* intuitively captures the effect of all the individual scores and assigns a conservative score which is closest to zero. Details of the summary statistics of the component variables and *PCAscore* are provided in Table 1(Panel D).

We follow Manchiraju and Rajgopal (2017) in using the above scoring technique in a similar setting as theirs. The main motivation behind the scoring technique is to eliminate bank years that have extreme financial parameters on either side of the cut-off. This is in the spirit of RD design because very healthy banks and very low-quality banks should not influence the treatment effect we study. We use following sharp RD specification:

$$\begin{aligned} Y_{i,j,t} = &\alpha + \beta_1 * Treat_{j,t} + \beta_2 * 1_{[-h<PCAscore<h]} * PCAscore_{j,t} + \beta_3 * Treat_{j,t} * PCAscore_{j,t} \\ &+ \gamma_i + \delta_t + \epsilon_{i,j,t} \end{aligned} \tag{2}$$

where $Y_{i,j,t}$ represents loan outcomes such as loan amount and loan repayment. $1_{[]}$ is an indicator function; h is the bandwidth around the cut-off, the running variable *PCAscore* is as defined above, and $Treat$ is an indicator which is 1 for $0 < PCAscore < h$, 0 otherwise. *PCAscore* is by definition standardized so that the cut-off is at 0. γ and δ represent firm and year fixed effects.

4.2.3 Results

We first estimate equation 2 using log loan amount as the dependent variable, $Y_{i,j,t}$, to test whether the loan amount decreases significantly above the cut-off. This is a necessary first-stage test for our identification. The results are shown in Table 3. We show the results for bandwidth of 0.1(0.125)(0.15) around the cut-off in columns 1 & 2 (3 & 4) (5 & 6) . We include firm and year-fixed effects in the even-numbered columns. The Table shows that loan amount reduces by an economically significant 34%. Thus, the regulation is a significant shock to lending by the banks

[23]With regard to ROA, the cut-off is zero, and PCA is triggered when a bank reports negative ROA for three consecutive years. We use the minimum of the positive ROAs when a bank does not violate the PCA on the grounds of ROA conditions. For example, a bank having ROA of 0.1, -0.2, and 0.3 in the last three years will be assigned a score of 0.1. In contrast, we use the maximum of the ROAs when the bank violates the ROA condition. For example, a bank admitted under PCA and having ROA of -0.1, -0.2, and -0.3 in the last three years will be assigned a score of -0.1

that breach the threshold.

We next focus on the loan performance of PCA versus non-PCA banks. We run the specification 2 with an indicator variable which takes the value of 1 if there is a default, 0 otherwise, as the dependent variable, $Y_{i,j,t}$. The results for all firms are presented in Panel A of Table 4. We assume the slope to be linear on both sides of the cut-off in this RD specification. We show the results for bandwidth of 0.1(0.125)(0.15) around the cut-off in columns 1 & 2 (3 & 4) (5 & 6) . We include firm and year fixed effects in the even-numbered columns.

The likelihood of default above the cut-off is lower by 5.6% compared to below the cut-off within a narrow bandwidth of 0.1. This is an economically significant 93% of the unconditional likelihood of default. Firm fixed effects make the estimate within a borrower. The result implies that firms selectively default less to banks which are under the PCA, compared to banks with similar performance but do not breach the threshold.

As stated in Section 3, 11 of 12 banks that went under the PCA framework were GOBs, leading to a concern that the results could just reflect a tendency of firms to default less on GOBs. We find in Table A.4 of the online appendix that, in general, the probability of default to GOBs is not lower than private banks. Nevertheless, in panel B of Table 4, we limit the sample to firms that only borrow from GOBs as at the beginning of the PCA regime. The organization of the panel mimics the organization of Panel A. The results are even stronger for this sub-sample. The likelihood of default above the cut-off is lower by 20.7% compared to below cut-off within a narrow bandwidth of 0.1. This is economically significant 2.8 times the unconditional likelihood of default on government banks.[24]

4.3 RD prerequisites and robustness

4.3.1 McCrary test

A prerequisite for RD is that there shouldn't be any self-selection at the cut-off. Self-selection by banks to stay below the cut-off could result in banks on the two sides of the cut-off being systematically different. Although the asset quality review made it difficult for banks to involve in accounting manipulation, we nonetheless formally investigate the possibility of clustering at the cut-off by conducting the McCrary (2008) test. The result is shown in Figure 1. We find that the difference in density of $PCAscore$ around the cut-off is statistically indistinguishable from zero. The log difference in heights on both sides of the cut-off is -0.8473, and the t-stat for the difference in height is -0.5.

[24] In Table A.5 of the online appendix, we show that the decline in default above the cut-off also holds if we limit our sample to private banks. Columns 1 & 2 of this Table represent bandwidths of 0.125 and 0.15, respectively. We do not include the bandwidth 0.1 in this test because of a lack of power. Note that only one private bank was placed under PCA. Therefore, we do not have sufficient observations for private banks in the narrowest bandwidth of 0.1.

4.3.2 Alternative running score

As described in Section 2, our empirical strategy exactly follows the strategy used in Manchiraju and Rajgopal (2017) for a similar rule. We recognize that defining *PCAscore* as the minimum of the 5 standardized scores could lead to a concern illustrated by the following example. Consider a case where a bank breaches multiple criteria, and all, but one of the breaches is egregious. The remaining one breach is just above the cut-off. Even in such a case of an extreme breach, the bank may end up being classified as just breaching the cut-off and thus a part of our RD sample. Such egregious breaches are rare in our sample, and as explained in Section 2, the main motivation behind our primary scoring method is to eliminate bank years that have extreme financial parameters on either side of the cut-offs.

We address the above concern by redefining our running variable as the maximum of the 5 standardized scores and rerunning specification 2. Thus, in this scoring method, we conservatively use the worst score across all parameters as the *PCAscore* of the bank. The results are shown in Table A.6 of the online appendix for a narrow bandwidth of 0.1. Columns 1 & 2 (3 & 4) are for all firms (limited to firms that only borrow from GOBs). We include firm and year fixed effects in the even-numbered columns. We find a significant decrease in default for PCA banks compared to non-PCA banks. Thus, our results are robust to alternative ways of measuring the binding score.

4.3.3 OLS regression

One limitation of the RD design is that it is by design localized at the cut-off, raising concerns that we cannot extend our results to all banks. We address this by also running an OLS with log loan and default indicator as the dependent variables and an indicator which is 1 for positive *PCAscore* (0 otherwise) as the main explanatory variable. The larger number of observations in the OLS allows us to include firm X-year fixed effects.

We present our results in Table A.7 of the online appendix. Panels A & B show the results with log loan and default indicator as the dependent variable, respectively. In both panels A & B, columns 1 & 2 (3 & 4) are for all firms (limited to firms that only borrow from GOBs), and firm X year fixed effects are included in even-numbered columns. Both loan amount and default probability decrease significantly for bank-firm-years with positive *PCAscore* which is consistent with our RD estimates.

We also run a Cox hazard model for the loans initiated at the start of the new PCA regime. We estimate the hazard ratio of loan default on the PCA indicator, which is 1 for banks that go under PCA in that year. The results presented in Table A.10 of the online appendix corroborate the findings of RD and OLS - there is a significant decline in default rate for PCA firm-bank pairs as compared to non-PCA firm-banks.

4.3.4 Firm performance

The McCrary test alleviates any concerns about clustering near the cut-off. Nevertheless, there could be residual concerns about the difference in default on either side of the cut-off being a reflection of some other unobservable correlated firm-related shocks. If this is the case, other firm-related variables should also show discontinuity around the cut-off.

We test the above hypothesis by estimating the difference between firm performance measures on either side of the cut-off and report the results in Table 5. The results are shown for measures sales growth, EBIT growth, EBITDA margin, and ICR in columns 1,2,3 & 4, respectively. The coefficients on the treated indicator are insignificant across all the firm measures. The results allay the concern regarding any unobservable difference across the cut-off influencing the results.

4.3.5 Robust RD

Calonico et al. (2014) propose a new theory-based confidence interval for RD inferences that are robust to "large" bandwidth choices. Their method corrects for any bias that might creep in a conventional RD under such scenarios. We examine the robustness of our results using the RD robust framework.

We report the results in Table 6. The results are reported for all firms in panel A and for a sub-sample of firms that borrow only from GOBs as of the end of the year 2017 in panel B. In column 1 of the Table, the bandwidth is chosen using the methodology devised by Calonico et al. (2014). In columns 2, 3, and 4, we use the bandwidth of 0.1, 0.125, and 0.15, respectively. The method uses a triangular kernel and the polynomial of degree 1. The Table also reports robust and bias-corrected estimates of the coefficients and standard errors. The results of this test are consistent with the conventional RD results reported in Table 4. We plot the estimated linear fit in Figure 2 using the procedure developed by Calonico et al. (2015), and find a sharp discontinuity at the cut-off.

4.3.6 Higher degree polynomials of $PCAscore$

Another concern could be that if the true relation between the default and $PCAscore$ is non-linear, assuming a linear relationship could induce a bias in favor of finding a treatment effect when there is none. So, we control for the higher degree terms of the running variable to allay this concern. Table 7 reports the estimates after controlling for second and third-degree powers of the running variable using Calonico et al. (2014). These estimates also indicate a significant decrease in default around the cut-off, similar to the linear RD estimates. We plot the estimated second and third-degree polynomial fits in Figure A.1 using the procedure developed by Calonico et al. (2015), and find sharp discontinuities at the cut-off.

4.3.7 Difference in recovery initiations by banks

Recall from Section 3 that CIBIL records data on cases of loan recovery initiations filed by banks, and it accounts for 85% of the NPAs reported by banks. There can be concerns that the reversal of defaults observed in PCA banks is driven by lower recovery initiations by the PCA banks as compared to non-PCA banks and not due to differences in delinquencies. Since the PCA banks are directly monitored by the RBI, such a situation is unlikely.

Nevertheless, we test whether the rate at which the banks initiate recovery procedures is lower for PCA banks. We run an OLS regression where the dependent variable is *Default proportion*, calculated as the ratio of the amount of loans for which recovery proceedings have been initiated in the current year to the previous year NPA of the bank. The independent variable is *Treat*. Note that we do not have sufficient observations to estimate an RD at a bank-year level.

We show the results with (without) control variables in column 1 (2) in Panel A of Table A.9 of the online appendix, and we use both bank and year fixed effects. We find that there is no significant difference in the rate of recovery initiation between PCA and non-PCA banks. In Panel B, we repeat the test with the proportion of 'wilful default' to outstanding NPA as the dependent variable and find similar results. Therefore, the reversal in default observed in our main results cannot be explained by PCA banks having a different recovery initiation rate as compared to the non-PCA banks.

4.3.8 Placebo test

We further strengthen the argument that the observed improvement in loan performance is precisely due to the PCA treatment at the cut-off by conducting placebo tests using false PCA cut-offs. We arbitrarily select false cut-offs above and below the current cut-off and reassign banks to treated and control groups. We then rerun regression specification 2 and report the results in Table A.10 of the online appendix. We find that the results do not hold at the placebo cut-offs. [25]

4.4 Channels of improvement in loan performance

In Section 4.2.3, we show that default by firms decreases on loans from banks under PCA. This reversal in default to weaker banks can be due to two reasons. First, firms reverse strategic default to banks under PCA. Second, the genuinely distressed borrowers may anticipate stringent recovery policies from banks under PCA and thus prioritize repayments to these banks. Schiantarelli et al. (2020) show that the delayed payments to distressed banks are strategic. They support this argument by showing that the phenomenon manifests only in jurisdictions with inefficient legal enforcement; and that the behavior is not limited to distressed borrowers.

If PCA indeed *decreases* strategic default, we should find evidence reversing the above two channels documented by Schiantarelli et al. (2020). That is, we should find that firms in jurisdictions

[25] We can not implement false time placebo tests because none of the banks breached revised PCA limits before 2016 due to the forbearance regime.

with inefficient courts drive the improvement in loan performance, and the improvement is not restricted to distressed borrowers.

4.4.1 Judicial efficiency

As discussed earlier, India ranks low in terms of contract enforcement. Moreover, India exhibits high regional variation in court efficiency (Boehm and Oberfield (2020)). We exploit this regional variation in court efficiency to test whether the decrease in default is driven by firms that are present in states with low court efficiencies.

We construct a measure of court efficiency at the level of Indian states using pendency data (average age of cases) of *high courts* from Boehm and Oberfield (2020).[26] We link this state-level judicial efficiency measure to firms using the state in which the firm is registered. We then run the following regression specification:

$$\begin{aligned}Y_{i,j,t} =&\alpha + \beta_1 * Treat_{j,t} + \beta_2 * Treat_{j,t} * firm\_indicator_{i,t} + \beta_3 * 1_{[-h<PCAscore<h]} * firm\_indicator_{i,t}\\ &+ \beta_4 * 1_{[-h<PCAscore<h]} * PCAscore_{j,t} + \beta_5 * 1_{[-h<PCAscore<h]} * PCAscore_{j,t} * Treat_{j,t}\\ &+ \beta_6 * Treat_{j,t} * PCAscore_{j,t} * firm\_indicator_{i,t} + \gamma_i + \delta_t + \epsilon_{i,j,t}\end{aligned} \tag{3}$$

where $firm\_indicator_{i,t}$ is the judicial inefficiency indicator which is set to 1 for firms registered in states at the top tercile of the average age of cases in the high court and 0 for firms registered in bottom tercile states. Note that the indicator variable $firm\_indicator_{i,t}$ denotes inefficiency in the judicial system. The rest of the variables are as defined in equation 2. The coefficients of interest in this specification are *Treat*, which measures the effect on default to PCA banks in all states, and *Treat*firm_indicator*, which measures the additional effect in states with inefficient courts.

The result is presented in column 1 of Table 8, which shows the result with firm and year fixed effects. We find that the coefficient of *Treat* is statistically indistinguishable from zero. The coefficient of *Treat*firm_indicator* has the value of -17.3% and is statistically significant. The result implies that the decrease in default to PCA is entirely driven by the firms in states with inefficient courts.

4.4.2 Distressed firms

As discussed above, we now test whether the propensity to default on loans from PCA banks is concentrated among distressed borrowers. We run specification 3, where $firm\_indicator$ is an indicator variable set to 1 for firm-years that experience a shock in performance and zero otherwise. We determine shock to firms in two ways. A shock is defined as a decline in operating profits (total tax payments) as per the first (second) measure. Although Operating profit or EBIT measures the overall performance of firms, it can be subjected to earnings management. Therefore we also use a second measure, total tax payment, which is verifiable to a great extent using third-party

[26] *High courts* are the topmost courts in terms of hierarchy in the Indian states.

validation, and thus it is less prone to window-dressing. The rest of the variables are as defined in equation 2. The coefficients of interest are *Treat*, which estimates the default to loans from PCA banks for all firms, and *Treat*firm_indicator*, which estimates the additional defaults to PCA banks when the firm is in distress.

The result using a decrease in operating margin (total tax) as the shock is presented in column 2 (3) of Table 8. Both columns include firm and year fixed effects. In column 2, we find that the coefficient of the interaction term *Treat*Firm shock* is insignificant while the coefficient of *Treat* has a value of -12.2% and is significant. In column 3, the full specification using a decrease in total tax as the shock variable, we observe qualitatively similar results. Thus, our results suggest that the decrease in default due to PCA is not concentrated in distressed firms.

Overall, we find that the reversal of default due to PCA regulation is prevalent for firms that are in states with low court efficiencies and is not dependent on the health of the firms. These two criteria, together, suggest that the default reduction witnessed in the PCA regime is indeed a reduction in strategic default.

4.4.3 Firms with immediate need for credit

As discussed earlier, PCA could exacerbate borrower run, especially in firms that face significant credit constraints in the short run. Such firms have a lower value of continuing relationship with PCA banks. Thus, we expect that the decline in strategic default by the firms which value immediate credit should be lower relative to other firms which value long-term access to credit.

We test this using specification 3, where $firm\_indicator$ is an indicator variable that is set to 1 for firms with an immediate need for credit, 0 otherwise. We identify firms with immediate demand for credit in two ways (i)*credit constrained firms*; and (ii)*high growth firms*.

We recognize firms which have low tangible assets as a proportion of gross fixed asset as credit constrained (Vig, 2013). For this definition, $firm\_indicator$ is 1 for firms in the bottom tercile of the measure, and 0 for firms in the top tercile. We identify high growth firms as firms that have a high EBIT growth rate but a high proportion of whose gross fixed assets have already been depreciated. Using the above measure, $firm\_indicator$ is defined as 1 for the firms with above median EBIT growth and below median non-depreciated gross fixed assets.[27]

The coefficients of interest are *Treat*, which estimates the default to loans from PCA banks for all firms, and *Treat*firm_indicator*, which estimates the additional defaults to PCA banks when the firm has an immediate need for credit.

The results are presented in columns 4 & 5 of Table 8 for credit constrained and high growth definitions, respectively. We include firm and year fixed effects. The coefficient of *Treat* is negative and significant, but the coefficient of *Treat*firm_indicator* is positive and significant in both columns. The coefficient on *Treat*firm_indicator* completely offsets the coefficient on *Treat*. It implies that the effect of PCA on the reversal of borrower run phenomenon is not observed in firms with immediate demand for credit.

[27]Non-depreciated gross fixed assets = (gross fixed assets - cumulated depreciation)/gross fixed assets

4.5 Conclusion

Borrower run, a phenomenon where a borrower defaults selectively to failing institutions, can expedite bank collapse and can aggravate banking crises. Therefore, it is important to study ways to mitigate such a phenomenon. One such way could be to implement the Prompt Corrective Action (PCA) framework, where the undercapitalized banks are kept under the close watch of the regulator and are sanctioned with lending restrictions. We investigate whether the PCA framework can reverse the borrower-run phenomenon using the Indian banking setting.

We first establish that the *borrower run* phenomenon exists in India. Next, we study whether implementation of PCA framework in India alleviates borrower runs. The setting allows us to implement a sharp regression discontinuity design. We find that PCA is successful in reversing borrower runs. Further, the reversal in defaults is concentrated in firms located in inefficient judicial jurisdiction, and the reversal is witnessed in both good and bad firms. The two results indicate that improvement in performance is driven by a decrease in strategic default. However, firms that are highly credit constrained and those that have immediate investment opportunities–a set of firms that are likely to value immediate access to credit more than long-term association- do not reverse borrower runs.

Thus, our findings show that implementation of PCA framework alleviates *borrower runs* and thus can help restore the health of financial institutions. However, it also comes at a cost in the form of a significant decline in lending. We focus on the impact of PCA on strategic default by borrowers and do not do a cost-benefit analysis of the PCA framework. Thus, from a policy perspective, a regulator will do well to weigh the costs of reduced lending in the short run and benefits pointed in this study comprehensively and apply PCA regulation depending on the goals of the implementation.

Figure 1: The figure shows the result of McCrary test for manipulation in a narrow bandwidth around the cut-off. The data are arranged at bank-year level. It shows the distribution of running variable (*PCAscore*) in a bandwidth of 0.1 around the cut-off. *PCAscore* is defined as in Section 4.2.2.

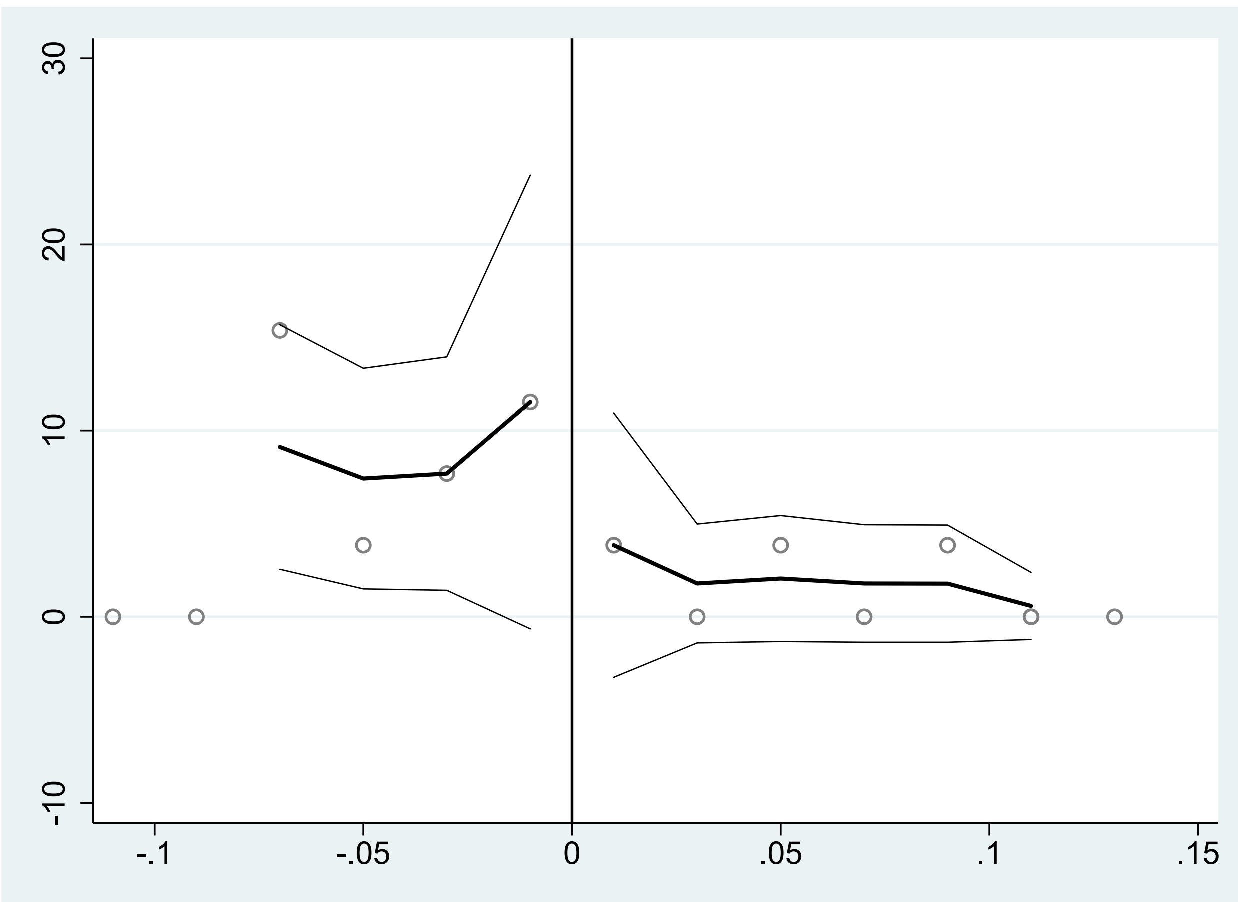
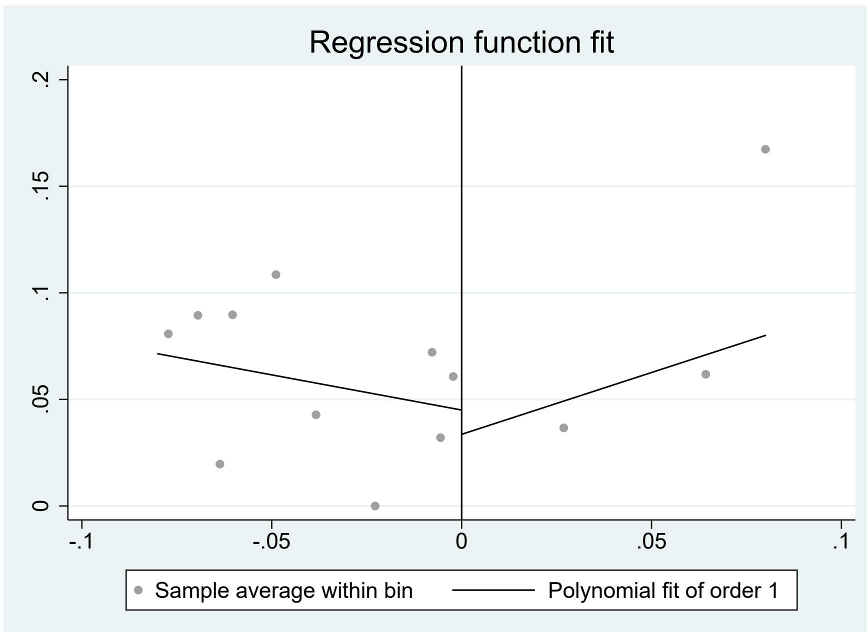


Figure 2: The figures show the RDD plot for the difference in default between treated and untreated bank-firm-years. The data are arranged at bank-firm-year level. The dependent variable *default* is 1 for the bank-firm-years in which the firm defaults to the bank, 0 otherwise. The estimates are presented for 1st degree polynmial function of PCAscore. PCAscore is defined as in Section 4.2.2. Panel A(B) shows the plot for all firms (firms with only government owned banking relations as on end of FY 2017).

(a) Panel A



(b) Panel B

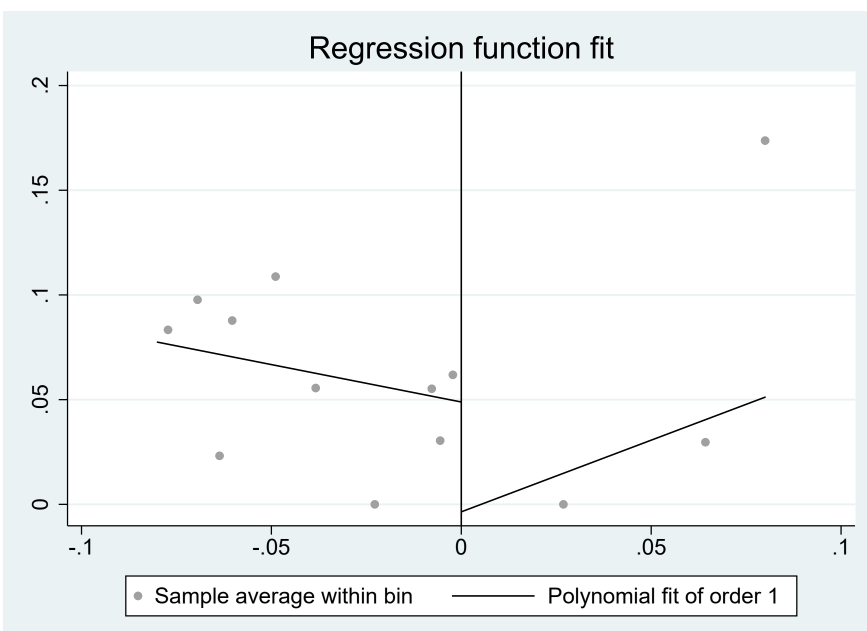


Table 1(Panel A): PCA criteria

In this table, we report the limits of PCA norms for each year for each threshold level, stipulated by the RBI. A bank is admitted under PCA when it breaches any one financial condition under threshold level II. CRAR or the capital adequacy ratio is the ratio of capital to risk weighted assets (RWA) of the bank in a year. CET1 is the ratio of Tier I capital to total RWA as defined in Basel III guidelines. NNPA is the ratio of Net NPA (NPA adjusted for provisions) over net advances of the bank in a year. Leverage is the ratio of Tier I capital to the exposure measure as defined in Basel III. ROA is the return on asset of a bank in a year.

Year	**Threshold Level**	**CRAR**	**CET1**	**NNPA**	**Leverage**	**ROA**
2018	I	<10.25%	<6.75%	>= 6%	<= 4%	Negative for 2 consecutive years
	II	<7.75%	<5.125%	>= 9%	<3.5%	Negative for 3 consecutive years
	III	<6.25%	<3.625%	>= 12%	<3.5%	Negative for 4 consecutive years
2019	I	<10.875%	<7.375%	>= 6%	<= 4%	Negative for 2 consecutive years
	II	<8.375%	<5.75%	>= 9%	<3.5%	Negative for 3 consecutive years
	III	<6.875	<4.25%	>= 12%	<3.5%	Negative for 4 consecutive years
2020	I	<11.5%	<8%	>= 6%	<= 4%	-
	II	<9%	<6.375%	>= 9%	<3.5%	-
	III	<8%	<4.875%	>= 12%	<3.5%	-

Table 1(Panel B): PCA admissions

In this table, we report the number of banks which have breached the PCA limits and the number of banks which were actually admitted under PCA by the RBI. The banks which are admitted under PCA are shown in Table A.1 of the online appendix

Year	**Threshold level**	**Technical breaches**	**PCA admissions**
2018	I	16	11
	II	6	6
2019	I	18	11
	II	11	11
2020	I	15	5
	II	5	5

Table 1(Panel C): Sample Construction

Sample construction table	
Sample period	FY 2018 - 2020
Number of firms	19,389
Numebr of banks	41
Number of bank-year level observations	121
Number of bank-years when the bank is under PCA	23
Numebr of firm-bank relations	39,599
Number of firm-bank-year level observations	1,13,519
Number of firm-bank-years with defaults	6,767
Number of firm-bank-years when the bank is under PCA	22,714

Table 1(Panel D): Summary Statistics

Bank-Year summary statistics						
Variable	**Obs**	**Mean**	**Median**	**1st %ile**	**99th %ile**	**Std dev**
NPA (in bn Rupees)	107	250.35	126.5	3.731	1,727.5	343.42
Commercial NPA (in bn Rupees)	107	213.19	108.24	2.22	1,426.39	293.52
Default (in bn Rupees)	107	143.43	45.488	0.68	1,548.07	249.39
PCAscore	121	-0.34	-0.36	-0.96	0.83	0.42
NNPA	121	5.17	4.87	0.36	16.49	3.95
CET1	121	10.78	9.86	5.61	27.88	3.94
ROA	121	0.1	0.25	-3.48	4.25	1.44
CRAR	121	13.48	12.73	8.69	29.2	3.44
Leverage	117	6.76	5.86	3.33	18.90	2.87
Treated	121	0.19	0	0	1	0.39
Bank-Firm-Year summary statistics						
Variable	**Obs**	**Mean**	**Median**	**1st %ile**	**99th %ile**	**Std dev**
Loan (in mn Rupees)	110,340	2,323	314	10	30,000	28,814
Treated	113,519	0.20	0	0	1	0.40
Default	113,519	0.06	0.22	0	1	0.22

Table 2: Borrower run

The table shows the association between loan default and the previous year proportion of ICR below 1 firms in portfolio of banks. The data is arranged at firm-bank-year level. The dependent variable is *Default*, which takes a value of 1 for the bank-firm-years in which there is a loan default by the firm to the bank, 0 otherwise. The main explanatory variable is the proportion of ICR below 1 firms in portfolio of banks in previous year. We include bank share (which is the exposure of bank to the firm as a proportion of all loans), CRAR, log total asset, deposit to total asset, and cash to total asset as controls in columns 2,4, 5 & 6. In columns 5 & 6 we limit the sample to government owned banks. We include firm X year and bank fixed effects in all columns. The sample is limited to 2016-18 (2016-20) in columns 1, 2 & 5 (3,4 & 6). Standard errors are clustered at industry level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			*Default*			
Proportion of ICR below 1 firms	0.057***	0.028	0.061***	0.050***	0.129**	0.077***
	(0.022)	(0.018)	(0.014)	(0.014)	(0.058)	(0.029)
Bank share		-0.022		-0.027	-0.027	-0.064
		(0.030)		(0.035)	(0.042)	(0.068)
CRAR		-0.006***		-0.000	-0.006**	-0.002**
		(0.002)		(0.000)	(0.002)	(0.001)
Log total asset		-0.045***		-0.032***	0.024	-0.046***
		(0.011)		(0.005)	(0.021)	(0.010)
Deposit to total asset		-0.012		0.077***	0.220***	0.158***
		(0.025)		(0.018)	(0.081)	(0.049)
Cash to total asset		3.282***		0.674	12.362***	4.955***
		(0.824)		(0.561)	(1.922)	(1.351)
Observations	49,549	43,396	123,487	102,410	25,004	53,396
R-squared	0.430	0.374	0.439	0.391	0.393	0.419
Firm X Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: Regression discontinuity: Loan amount

The table shows the difference in loan amount between treated and untreated bank-firm-years in the RD sample around the PCAscore cut-off. The data are arranged at bank-firm-year level and restricted within a bandwidth of 0.1(0.125)(0.15) of PCAscore in columns 1 & 2 (3 & 4) (5 & 6). The dependent variable is log of total loan amount by the bank to the firm in the corresponding year. The estimates are presented for 1st degree polynomial function of PCAscore. *PCAscore* is defined as in Section 4.2.2. *Treated* is an indicator which takes a value of 1 when PCAscore is positive, 0 otherwise. We include firm and year fixed effects in columns 2, 4 & 6. We report robust standard errors in the parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			*Log total loan*			
Treated	-0.421***	-0.512**	-0.137*	-0.039	-0.168**	-0.073
	(0.100)	(0.201)	(0.073)	(0.136)	(0.071)	(0.106)
PCAscore	0.441	-0.023	0.529	-0.016	-0.213	-0.880
	(0.681)	(1.373)	(0.521)	(0.993)	(0.358)	(0.535)
Treated X PCAscore	2.651	5.922**	-3.418***	-1.388	-1.684**	0.096
	(1.839)	(2.733)	(0.766)	(1.456)	(0.656)	(1.051)
Observations	11,199	5,828	14,507	8,658	18,966	14,771
R-squared	0.002	0.446	0.011	0.412	0.010	0.411
Firm F.E.	No	Yes	No	Yes	No	Yes
Year F.E.	No	Yes	No	Yes	No	Yes

Table 4: Regression discontinuity: Default

The table shows the difference in default rate between treated and untreated bank-firm-years in the RD sample around the PCAscore cut-off. The data are arranged at bank-firm-year level and restricted within a bandwidth of 0.1(0.125)(0.15) of PCAscore in columns 1 & 2 (3 & 4) (5 & 6). The dependent variable is *Default*, which takes a value of 1 for the bank-firm-years in which the firm defaults to the bank, 0 otherwise. The estimates are presented for 1st degree polynomial function of PCAscore. *PCAscore* is defined as in Section 4.2.2. *Treated* is an indicator which takes a value of 1 when PCAscore is positive, 0 otherwise. We include firm X year fixed effects in columns 2,4 and 6. Panel A shows the results for all firms while panel B is restricted to firms which only borrow from public sector banks as on end of FY 2018. We report robust standard errors in the parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			*Default*			
Treated	-0.056***	-0.062**	-0.085***	-0.092***	-0.024**	-0.049***
	(0.016)	(0.026)	(0.013)	(0.019)	(0.012)	(0.013)
PCAscore	-0.330***	-0.195	0.122**	0.148	0.151***	0.047
	(0.099)	(0.155)	(0.057)	(0.094)	(0.040)	(0.053)
Treated X PCAscore	2.306***	1.810***	1.954***	1.038***	0.876***	0.602***
	(0.331)	(0.402)	(0.153)	(0.205)	(0.116)	(0.136)
Observations	11,199	5,828	14,507	8,658	18,966	14,771
R-squared	0.008	0.559	0.052	0.530	0.030	0.623
Firm F.E.	No	Yes	No	Yes	No	Yes
Year F.E.	No	Yes	No	Yes	No	Yes

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES			*Default*			
Treated	-0.207***	-0.221***	-0.088***	-0.143***	-0.031*	-0.035*
	(0.040)	(0.070)	(0.021)	(0.051)	(0.018)	(0.021)
PCAscore	-0.357***	-0.227	-0.341**	-0.079	0.128**	-0.105
	(0.135)	(0.344)	(0.133)	(0.310)	(0.060)	(0.103)
Treated X PCAscore	4.408***	4.094***	2.085***	1.990***	0.545***	0.780***
	(0.774)	(0.964)	(0.265)	(0.558)	(0.176)	(0.232)
Observations	4,665	1,986	5,526	2,530	7,952	6,204
R-squared	0.011	0.600	0.023	0.566	0.010	0.658
Firm F.E.	No	No	No	Yes	No	Yes
Year F.E.	No	No	No	Yes	No	Yes

Table 5: Rgression discontinuity: Firm performance

The table shows the difference in firm characteristic between treated and untreated bank-firm-years in the RD sample around the PCAscore cut-off. The data is arranged at bank-firm-year level and restricted within a range of 0.1 around the PCAscore cut-off. The dependent variables are *Slaes growth*, *EBIT growth*, *EBITDA margin* and *ICR below 1* indicator in columns 1,2,3 and 4 respectively. The estimates are presented for 1st degree polynomial function of PCAscore. *PCAscore* is defined as in Section 4.2.2. *Treated* is an indicator which takes a value of 1 when PCAscore is positive, 0 otherwise. We report robust standard errors in the parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	(1) Sales growth	(2) EBIT growth	(3) EBIDTA margin	(4) ICR below 1
Treated	-0.987	-1.240	-0.910	0.011
	(0.707)	(1.245)	(0.859)	(0.041)
PCAscore	4.917	-0.371	5.913	-0.114
	(3.729)	(4.619)	(4.760)	(0.198)
Treated X PCAscore	16.229	-1.310	17.120	-0.322
	(18.445)	(7.940)	(19.580)	(0.607)
Observations	2,764	2,496	2,177	3,272
R-squared	0.524	0.571	0.961	0.678
Firm X Year F.E.	Yes	Yes	Yes	Yes

Table 6: Robust regression discontinuity

This table reports the RD results for the difference in default between treated and untreated bank-firm-years. The data are organized at the bank-firm-year level. Panel A shows the result for all firms while panel B is restricted to firms which only borrow from public sector banks as on end of FY 2017. We use the procedure developed by Calonico et al. (2014) to estimate robust and bias-corrected estimates. The dependent variable $Default$ takes a value of 1 for the bank-firm-years in which the firm defaults to the bank, 0 otherwise. The estimates are presented for a 1st degree polynomial function of running variable PCAscore, which is defined in Section 4.2.2. In column 1, bandwidth selection is based on the method discussed in Calonico et al. (2014) while in columns 2,3 and 4 we use bandwidths of 0.1, 0.125 and 0.15 respectively. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A				
	(1)	(2)	(3)	(4)
VARIABLES	*Default*			
Conventional	-0.026	-0.037**	-0.031**	-0.037***
	(0.016)	(0.015)	(0.012)	(0.011)
Bias-corrected	-0.030*	-0.021	-0.033***	-0.038***
	(0.016)	(0.015)	(0.012)	(0.011)
Robust	-0.030*	-0.021	-0.033*	-0.038**
	(0.017)	(0.018)	(0.017)	(0.016)
Observations	6,680	11,199	14,507	18,966

Panel B				
	(1)	(2)	(3)	(4)
VARIABLES	*Default*			
Conventional	-0.064***	-0.170***	-0.094***	-0.059***
	(0.008)	(0.029)	(0.018)	(0.016)
Bias-corrected	-0.070***	-0.052*	-0.192***	-0.227***
	(0.008)	(0.029)	(0.018)	(0.016)
Robust	-0.070***	-0.052***	-0.192***	-0.227***
	(0.008)	(0.009)	(0.033)	(0.040)
Observations	2,015	4,665	5,526	7,952

Table 7: Robust RD using higher degree polynomial

This table reports the RD results for the difference in default between treated and untreated bank-firm-years. The data are organized at the bank-firm-year level. Columns 1 & 2 show the result for all firms while columns 3 & 4 are restricted to firms which only borrow from government owned banks as on end of FY 2018. We use the procedure developed by Calonico et al. (2014) to estimate robust and bias-corrected estimates. The dependent variable $Default$ takes a value of 1 for the bank-firm-years in which the firms default. The estimates are presented for a 2nd (3rd) degree polynomial function of PCAscore in columns 1 & 3 (2 & 4). The bandwidth selection is based on the method discussed in Calonico et al. (2014). ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES		*Default*		
Conventional	-0.041**	-0.101***	-0.172***	-0.192***
	(0.017)	(0.016)	(0.021)	(0.040)
Bias-corrected	-0.037**	-0.107***	-0.174***	-0.189***
	(0.017)	(0.016)	(0.021)	(0.040)
Robust	-0.037**	-0.107***	-0.174***	-0.189***
	(0.017)	(0.017)	(0.024)	(0.043)
Observations	12,726	38,818	4,839	9,808

Table 8: Inefficient courts, firms in shock, and credit constrained firms

The table shows the association between the firm level cross sectional differences and change in default in a narrow bandwidth around the PCAscore cut-off. The data are arranged at bank-firm-year level and restricted within a range of 0.1 of PCAscore. The dependent variable is *Default*. The estimates are presented for 1st degree polynomial function of PCAscore. We include a triple interaction between *PCAscore*, *Treated* and *Firm level indicator* as explanatory variable. The *Firm level indicatos* include *Court inefficiency* (which takes a value of 1 for firms registered in states with court pendency in top tercile and 0 when it is in bottom tercile), *EBIT change* (which takes a value of 1 when EBIT declines, 0 otherwise), *Tax change* (which takes a value of 1 when total tax declines, 0 otherwise), *credit constrain* (which takes a value of 1 for firms in bottom tercile of ratio of tangible assets to total fixed assets, 0 when it is in top tercile) and *high growth* (which takes a value of 1 when $(grossfixedasset - accumulateddepreciation)/grossfixedasset$ is below median & % EBIT change is above median, 0 otherwise) in columns 1,2,3,4 & 5, respectively. All other variables are as reported in Table 3. We include firm and year fixed effects in all columns. We report robust standard errors in the parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

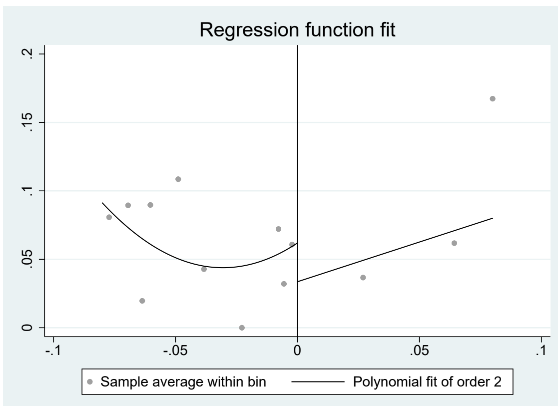
Firm level Indicator	(1) Court inefficiency	(2) EBIT change	(3) Tax change	(4) Credit constrained firms	(5) High growth firms
VARIABLES			*Default*		
Treat	0.083	-0.122*	-0.075*	-0.130**	-0.049*
	(0.051)	(0.071)	(0.043)	(0.060)	(0.025)
Treat * Firm level indicator	-0.173**	0.102	0.076*	0.136**	0.054*
	(0.072)	(0.076)	(0.045)	(0.064)	(0.032)
Firm level indicator		0.001	-0.006	-0.025	0.014
		(0.015)	(0.012)	(0.015)	(0.017)
PCAscore	-0.373	-0.383	-0.078	-0.147	-0.051
	(0.311)	(0.377)	(0.108)	(0.145)	(0.126)
Firm level indicator * PCAscore	-0.450	0.105	-0.225	-0.466*	0.487**
	(0.533)	(0.235)	(0.203)	(0.268)	(0.244)
Treat * Firm level indicator * PCAscore	4.182***	-1.949	-1.305	-1.021	-2.314***
	(1.193)	(1.557)	(0.891)	(1.177)	(0.595)
Observations	1,828	2,496	3,222	2,198	3,158
R-squared	0.568	0.661	0.594	0.582	0.568
Firm F.E.	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes

Internet Appendix

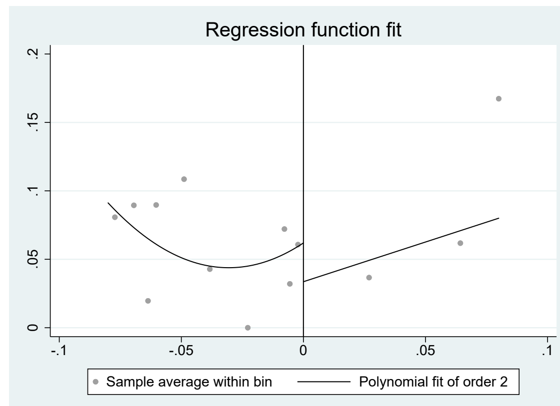
A Figures

Figure A.1: The figures show the RDD plot for the difference in default between treated and untreated bank-firm-years. The data are arranged at bank-firm-year level. The dependent variable default indicator is 1 for the bank-firm-years in which the firm defaults, 0 otherwise. The estimates are presented for 2nd (3rd) degree polynmial function of PCAscore in Panels A & B (C & D). PCAscore is defined as in Section 4.2.2. Panels A & C (B & D) show the plot for all firms (firms with only government owned banking relations as on end of FY 2017).

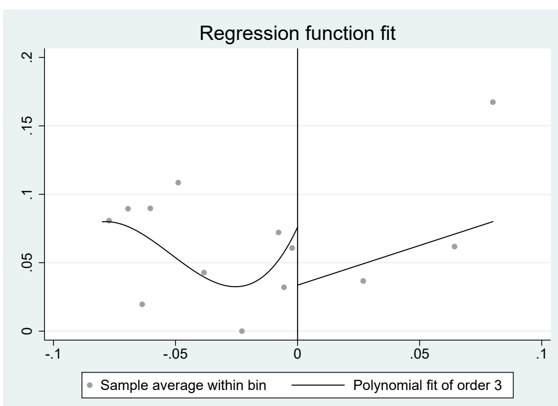
(a) Panel A



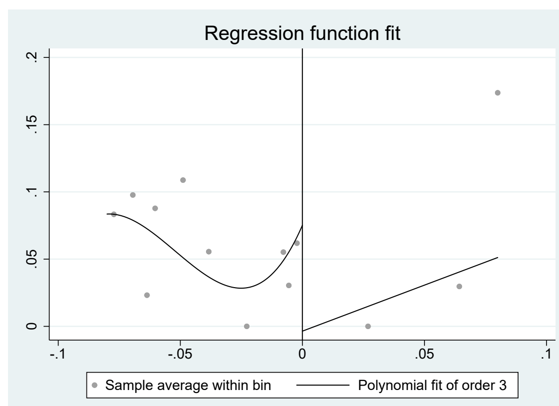
(b) Panel B



(c) Panel C



(d) Panel D



B Tables

Table A.1: Banks under PCA

The table presents all the banks that were admitted under the PCA program between 2018 to 2020 by the RBI.

Banks	**PCA years**
Allahabad Bank	2018 - 2019
Bank of India	2018 - 2019
Bank of Maharashtra	2018 - 2019
Central Bank of India	2018 - 2020
Corporation Bank	2018 - 2019
Dena Bank	2018 - 2019
Indian Overseas Bank	2018 - 2020
IDBI Bank Ltd	2018 - 2020
Oriental Bank of Commerce	2018 - 2019
UCO Bank	2018 - 2020
United Bank of India	2018 - 2019
Lakshmi Vilas Bank Ltd.	2020

Table A.2: PCA criteria (2002 - 2017)

The table presents the cut-off criteria for a bank to be admitted under PCA regime during 2002 to 2017.

Indicator	**Risk threhold level**	**cut-off**
CRAR	1	<9%
	2	<6%
	3	<3%
NNPA	1	>= 15%
	2	>= 10%
ROA	1	<0.25%

Table A.3: Default database NPA coverage

The table shows the average of percentage of defaults from CIBIL database to the NPA reported by banks in the corresponding quarter.

NPA coverage in CIBIL default database (Average of quarterly ratios)	
Default over GNPA	50.3%
Default over GNPA adjusted for agriculutural lending	61.3%
Default over GNPA adjusted for personal lending	73.0%
Default over GNPA adjusted for other non commercial lending	77.0%
Default over GNPA adjusted for commercial lending less than Rs 10 million	85.4%

Table A.4: Default and government owned banks

The table shows the association between firm default and the government ownership of banks. The data is arranged at firm-bank-year level for a sample period 2016-20. The dependent variable is *Default*, that takes a value of 1 for the bank-firm-years in which there is a default by the firm, 0 otherwise. The main explanatory variable is *Public bank*, which is 1 for government owned banks, 0 otherwise. We include *Bank share* (which is the exposure of bank to the firm as a proportion of all loans) as control in columns 2 & 4. We include firm X year fixed effects in columns 3 & 4. Standard errors are clustered at industry level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES		*Default*		
Public bank indicator	0.015***	0.012***	0.002	0.001
	(0.003)	(0.002)	(0.003)	(0.002)
Bank share		-0.166***		-0.079**
		(0.052)		(0.037)
Observations	79,266	73,880	76,022	70,085
R-squared	0.001	0.001	0.345	0.312
Firm X Year F.E.	No	No	Yes	Yes

Table A.5: RD for default in private banks

The table shows the difference in default rate between treated and untreated bank-firm-years in the RD sample around the PCAscore cut-off. The data are arranged at bank-firm-year level and restricted within a bandwidth of 0.125 & 0.15 of PCAscore in columns 1 & 2, respectively. We do not include the bandwidth 0.1 in this test because of lack of observations for private banks in this narrow bandwidth, which also results in relative lack of power of these tests. The sample is limited to private banks. The dependent variable is *Default*, that takes a value of 1 for the bank-firm-years in which the firm defaults, 0 otherwise. The estimates are presented for 1st degree polynmial function of PCAscore. *PCAscore* is defined as in Section 4.2.2. *Treated* is an indicator which takes a value of 1 when PCAscore is positive, 0 otherwise. We include firm X year fixed effects in columns 2,4 and 6. We report robust standard errors in the parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
VARIABLES	*Default*	
Treated	-0.026*	-0.026*
	(0.015)	(0.015)
PCA binding score	0.393***	0.393***
	(0.064)	(0.064)
Treated X PCA binding score	0.000	0.000
	(0.000)	(0.000)
Observations	3,807	3,807
R-squared	0.006	0.006

Table A.6: Alternative running variable

The table shows the difference in default rate between treated and untreated bank-firm-years in the RD sample around the PCAscore cut-off. In this table we use the alternative definition of PCAscore defined in Section 4.2.2. The data are arranged at bank-firm-year level and restricted within a PCAscore bandwidth of 0.1. The dependent variable is *Default*, that takes a value of 1 for the bank-firm-years in which the firm defaults, 0 otherwise. The estimates are presented for 1st degree polynomial function of PCAscore. *Treated* is an indicator which takes a value of 1 when PCAscore is positive, 0 otherwise. We include firm and year fixed effects in columns 2 and 4. Columns 1 & 2 show the results for all firms while columns 3 & 4 is restricted to firms which only borrow from public sector banks as on end of FY 2017. We report robust standard errors in the parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	*Default*			
Treated	-0.146***	-0.241***	-0.242***	-0.296***
	(0.035)	(0.044)	(0.047)	(0.084)
PCAscore	-0.330***	-0.175	-0.357***	-0.221
	(0.099)	(0.155)	(0.135)	(0.344)
Treated X PCAscore	3.688***	4.327***	4.940***	5.147***
	(0.617)	(0.661)	(0.887)	(1.185)
Observations	11,008	5,666	4,656	1,974
R-squared	0.009	0.569	0.011	0.601
Firm F.E.	No	Yes	No	Yes
Year F.E.	No	Yes	No	Yes

Table A.7: OLS

The table shows the association between the default rate and the treatment status of the banks. This table provides the OLS estimates for the full sample from 2018-20. The data are arranged at bank-firm-year level. The dependent variable is *Log total loan* (*Default*, that takes a value of 1 for the bank-firm-years in which the firm defaults to the bank, 0 otherwise) in Panel A (B). PCAscore is defined as in Section 4.2.2. *Treated* is an indicator which takes a value of 1 when PCAscore is positive, 0 otherwise. We include firm X year fixed effects in all columns. We include controls in columns 2 & 4. Columns 1 & 2 show the results for all firms while columns 3 & 4 is restricted to firms which only borrow from public sector banks as on end of FY 2017 in both panels A & B. We report robust standard errors in the parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A

	(1)	(2)	(3)	(4)
VARIABLES	*Log total loan*			
Treated	-0.517***	-0.495***	-0.556***	-0.507***
	(0.047)	(0.045)	(0.042)	(0.046)
Bank share		3.525		-10.531
		(2.308)		(10.309)
Observations	73,938	66,359	18,232	15,619
R-squared	0.404	0.425	0.468	0.494
Firm X Year F.E.	Yes	Yes	Yes	Yes

Panel B

	(1)	(2)	(3)	(4)
VARIABLES	*Default*			
Treated	-0.011***	-0.010***	-0.028***	-0.014*
	(0.004)	(0.003)	(0.009)	(0.007)
Bank share		-0.129**		-0.827*
		(0.050)		(0.471)
Observations	73,938	66,359	18,232	15,619
R-squared	0.426	0.356	0.452	0.416
Firm X Year F.E.	Yes	Yes	Yes	Yes

Table A.8: Cox hazard regression

The table predicts the hazard ratio of loans given by PCA banks with respect to loans given by non PCA banks. The data is at a loan level (firm-bank level) for all the loans that originate before 2018, and records the no of years it takes for the firm to default. In column (1) the length of relation is recorded till the loan defaults or till the relation ends. Whereas in column (2) the relation may also end if the bank is admitted to PCA. The indicator variable *Treated* is set to one when the bank is under PCA in that year, else zero. The coefficient of *Treat* provides the hazard ratio of the loan relation for banks which were admitted to PCA as compared to other loan relations. We also use bank fixed effects in both the columns and provide the 95% confidence interval of the hazard ratio estimates. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)
	Hazard ratio of loan default	
Treated	0.13***	0.10***
	(0.012)	(0.010)
95% CI lower limit	0.10	0.08
95% CI upper limit	0.15	0.12
Bank F.E.	Yes	Yes
Observation	29,635	29,635

Table A.9: Default compared to NPA

The table shows the association between default amount as a proportion of bad loans and the bank's PCA status. The data are arranged at bank-quarter level. The dependent variables in panel A(B) are *Default proportion* (*Wilful default proportion*). *Default proportion* (*Wilful default proportion*) is the ratio of of default (wilful default) loan amount filed for recovery initiation by the bank in the current year as a proportion of non performing asset of the bank in the previous year. The explanatory variable is *Treated* which is 1 for the years in which the bank is placed under PCA framework, 0 otherwise. We include bank level controls including NNPA, CET1, ROA, CCAR and Leverage in column 2 of panels A and B. We include bank and year fixed effects in all columns. Standard errors are clustered at bank level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A		Panel B	
VARIABLES	*Default proportion*		*Wilful default proportion*	
	(1)	(2)	(1)	(2)
Treated	-0.045	-0.024	0.003	0.001
	(0.098)	(0.090)	(0.016)	(0.006)
NNPA		-0.040		-0.004
		(0.037)		(0.003)
CET1		0.003		0.003
		(0.010)		(0.003)
ROA		0.005		0.002*
		(0.004)		(0.001)
CRAR		-0.000		0.000***
		(0.002)		(0.000)
Leverage		0.002		-0.002
		(0.007)		(0.003)
Observations	206	198	305	273
R-squared	0.585	0.592	0.449	0.417
Lender F.E.	Yes	Yes	Yes	Yes
Quarter F.E.	Yes	Yes	Yes	Yes

Table A.10: Placebo test

This table reports the RD results for the difference in default between treated and untreated bank-firm-years for different placebo cut-offs. The data are organized at the bank-firm-year level. Columns 1,3 & 5 (2,4 & 6) shows the result for all firms (firms with only public sector banks as on end of FY 2017). We use the procedure developed by Calonico et al. (2014) to estimate robust and bias-corrected estimates. The dependent variable is $Default$, that takes a value of 1 for the bank-firm-years in which the firms default. The estimates are presented for a 1st degree polynomial function of running variable PCAscore, which is defined in Section 4.2.2. The bandwidth selection is based on the method discussed in Calonico et al. (2014). Columns 1 & 2 (3 & 4) (5 & 6) set the cut-offs at -0.2 (0.3) (0.2). ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	*Default*					
Conventional	0.028***	0.008	0.006	0.025	0.136***	0.053***
	(0.007)	(0.007)	(0.033)	(0.021)	(0.011)	(0.015)
Bias-corrected	0.031***	0.011	-0.036	0.025	0.147***	0.067***
	(0.007)	(0.007)	(0.033)	(0.021)	(0.011)	(0.015)
Robust	0.031***	0.011	-0.036	0.025	0.147***	0.067***
	(0.007)	(0.008)	(0.035)	(0.025)	(0.011)	(0.017)
Observations	16,410	15,702	7,945	5,407	8,349	8,184

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