Preventing Strategic Defaults In Response to Deteriorating Bank Health: The Prompt Corrective Action Approach

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Abstract

We ask whether regulatory intervention in the form of prompt corrective action (PCA), which seeks to bring troubled banks back to health by imposing temporary restrictions and increasing regulatory monitoring, reverses strategic defaults. 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 strategic defaults by 1.1 times its unconditional mean. Evidence suggests that the mechanism is the intervention's ability to credibly signal to the borrowers about the likely restoration of bank health and continuation of banking relationships.

Keywords: Strategic default, Borrower run, Banking regulation

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

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1 Introduction

Theory shows the possibility of borrowers strategically defaulting when lenders are expected to curtail credit in the future due to their deteriorating health (Bond and Rai (2009)). Such strategic defaults are more likely to occur in economic settings where the expectations of obtaining bigger loans in the future primarily drive loan repayment behavior. These are economic settings having weak contract enforcement capabilities and domination of relationship banking. Schiantarelli et al. (2020) find evidence of strategic defaults in response to deteriorating health of the banks in Italy. They argue that such defaults could potentially aggravate banking crises.

Despite the systemic importance of strategic defaults caused by deteriorating lender health, scholars have not examined how to halt them. We do not know whether piecemeal regulatory interventions such as enhancement of creditor rights, bank clean-ups and stress tests, bankruptcy reforms, and others work, or a more comprehensive regulatory approach, that involves short-term curbs on bank activity, is required.

The prompt corrective action (PCA) framework implemented by the Reserve Bank of India (RBI, the Indian Central Bank) in the financial year 2018 is one such comprehensive regulatory measure. Under the PCA framework, banks that breach well-defined thresholds in terms of 5 specified accounting and operating parameters face pre-specified and, at times, discretionary regulatory restrictions. The thresholds are based on accounting measures of loan quality, capital adequacy, profitability, and off-balance sheet exposure reported in the banks' financial statements. A breach of even one threshold triggers the PCA. The restrictions under the PCA range from curbs on dividends to suspension of lending. The aim is to restore banks' health before they are let out of the PCA. However, the time required for the restoration of bank health is uncertain. Using the above intervention as an economic setting, we ask whether it helps halt strategic defaults in response to deteriorating bank health.

In the first part of the paper, following Schiantarelli et al. (2020), we examine whether strategic defaults in response to deteriorating bank health exist in India. For this purpose, we conduct a test modelled on Schiantarelli et al. (2020), by organizing the data at a bank-firm-quarter level and including firm $\times$ quarter fixed effects. We use data relating to loan performance compiled by CIBIL, the largest credit bureau in India. We create measures of bank health based on shocks to borrower health and not on loan performance. For instance, a measure of bank health is based on the proportion of borrowing firms having their loan restructured in the last quarter. Identifying bank health based on borrowers' health reduces concerns about reverse causality that may arise from using loan performance as a measure of banks' health and the outcome variable of interest. A firm-bank level measure can cause reverse causality when it is used to identify bad banks and the outcome. However, firm-level measures that we use cannot cause such mechanical reverse causal effects as we include firm $\times$ quarter fixed effects. The evidence suggests that strategic defaults in response to bank health exist in India.

Our main analysis is focused on examining whether the PCA policy is effective in halting strategic defaults in response to lenders' deteriorating health. Ex-ante, it is unclear whether a regulatory action such as PCA could lead to a decline in strategic defaults. Suppose the borrowers expect the restrictions imposed under PCA to result in the restoration of a troubled lender's health. In that case, the tendency to default wilfully may reduce due to PCA: the borrowers' posterior about the value of continuing the relationship with a troubled lender may be higher after the intervention compared to the prior. 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 relationships with the lenders. The above consideration may result in an increased tendency to default. Thus, the question requires an empirical investigation.

We first use the bank-firm-quarter level OLS model, similar to the model used by Schiantarelli et al. (2020) to test whether strategic defaults reverse because of PCA. To this end, we introduce an interaction term between a bank health measure and the variable representing the PCA intervention to the OLS model used by Schiantarelli et al. (2020). We find that one standard deviation deterioration in a bank's health decreases the probability of loan delinquency by 2 percentage points when the bank is admitted to PCA. The effect is economically meaningful because the improvement represents 67% of the unconditional loan delinquency rate. Firm $\times$ quarter fixed effects rule out the possibility that the results are due to borrower level time-invariant or time-varying factors. Bank-level fixed effects absorb the bank-level time-invariant factors. We also rule out pre-existing trends by showing that the probability of loan delinquency reduces only after a bank's admission into the PCA, not before.

Although the OLS model accounts for the systematic differences between borrowers of PCA and other banks by using firm $\times$ quarter fixed effects, the possibility of the two types of banks themselves being systematically different remains. Such differences could be time-varying and also influence borrower behavior. To absorb such differences, we cannot include bank $\times$ quarter fixed effects in the OLS model. Fortunately, the PCA framework with sharp discontinuities at arbitrary cut-offs provides a good setting for using the regression discontinuity (RD) framework. Time-varying bank-level shocks are unlikely to be systematically different on either side of an arbitrary cut-off. Observing sharp discontinuities at PCA thresholds helps us link the results directly to the PCA.

We use the robust RD methodology developed by Calonico et al. (2014) to examine the impact of the PCA. The robust RD is advantageous as it uses an objective bandwidth selection methodology and corrects for biases due to bandwidth selection. We also verify the robustness of our results using the conventional RD tests that include firm $\times$ quarter fixed effects.

For the RD tests, we organize data at a firm-bank-quarter level. The value of the running variable is based on the closeness of the bank in every firm-bank-quarter pair to PCA qualification. We follow Reardon and Robinson (2012) and Manchiraju and Rajgopal (2017) to create a bank-quarter level binding running score using the maximum of the standardized values of the 5 parameters. The standardized scores are defined in a way such that an increase in their values brings banks closer to PCA qualification. Thus, firm-bank-quarter observations where the bank under consideration narrowly qualifies for PCA (narrowly misses PCA) in a quarter form the treatment (control) group. Thus, within the same firm-quarter, there could be a difference in treatment status based on the health of the bank involved. We conduct required hygiene tests, including the McCrary (2008) test, for a valid application of the RD design. The fact that threshold levels for the same criterion change more than once within our sample period helps us further rule out self-selection and other identification concerns.

The RD tests show a discontinuous decline in delinquency rate on loans lent by banks that enter the PCA regime. The decline is an economically meaningful 1.1 times the unconditional delinquency rate before the intervention. In line with Schiantarelli et al. (2020), we further show that the halting of loan delinquencies due to PCA is concentrated in regions of India having more inefficient legal infrastructure and is unrelated to shocks faced by borrowing firms. Thus, it is possible to conclude that PCA intervention halts strategic defaults.

To learn about the broad contours of regulatory interventions that can potentially stem strategic defaults in response to deteriorating bank health, it is essential to understand what aspects of the PCA led to the reversal of the phenomenon. It is clear that any intervention, to be effective, should credibly reverse borrowers' expectations about the bank's likely inability to continue lending in the future. In other words, borrowers should believe that the intervention will restore bank health and lead to the continued flow of credit in the future.

We provide three pieces of evidence to show that the PCA regime credibly signaled to the borrowers that the banks' health would eventually be restored. The evidence we discuss is ex-ante, based on the program's design. However, we also present ex-post outcomes that are in line with the ex-ante expectations.

First, the RBI can intervene under PCA promptly only if the financial statements of banks are reliable. Realizing the importance of acting based on credible information, the

RBI conducted an asset quality review (AQR) before enforcing the PCA regime (Chopra et al. (2021)). Therefore, there is a reason for the borrowers to believe, ex-ante, that the RBI acted based on credible data about bank health and promptly before banks' health deteriorated beyond repair.

The data suggest that the reversal in strategic defaults happens only in those cases where the RBI intervened immediately after a mild breach of the PCA thresholds. In cases where the RBI intervened after an egregious violation of thresholds- cases where banks suddenly jumped from outside PCA threshold to deep inside- we do not find a reversal in strategic defaults even when the banks are placed in PCA. The result suggests that borrowers believe that the PCA can rescue banks only when they are admitted into the regime at an early stage of worsening in their health and not after a substantial deterioration. The AQR significantly increased the possibility of prompt intervention, making the PCA regime more credible. Expectedly, we also find a significant improvement in bank health when they are in PCA. The visible improvement in borrower health during the PCA treatment also strengthens the ex-ante belief about it's likely positive effects. Further, the sharp discontinuous decline in strategic defaults at the PCA threshold suggests that the reversal is not just because of AQR.

Second, the PCA created an alignment between the objectives of the regulators and the interests of the political class in working towards restoring PCA banks' health. A significant limitation of regulatory actions in emerging economies that are subject to strategic defaults is the inability of regulators to enforce the regulations in true spirit: political interests or slow-moving courts come in the way. For instance, actions taken by regulators to improve loan repayment discipline over the years can be potentially nullified by a politically motivated large-scale debt waivers (Mukherjee et al. (2018); Giné and Kanz (2018)) or dilution of creditors' rights (Tantri (2018)).

Under the PCA, the RBI could direct the PCA banks to curb lending and also impose restrictions on branch expansions. Thus, the regulation can impose short-term political costs by slowing down economic growth in the short term, especially during election times. It is not easy for politicians to undo the impact of actions taken under the PCA due to the above powers of the RBI under the PCA regime. Also, communicating to the voters that their economic problems are due to the central bank's actions is hard. Thus, the PCA incentivizes the political class to work towards reviving PCA banks and not obstructing the process. The ex-post evidence is in line with the ex-ante expectation: we find a sharp reduction in politically motivated lending by PCA banks.

Third, one common way banks dodge regulatory actions is by evergreening loans (Caballero et al. (2008); Peek and Rosengren (2005); Kashyap et al. (2022)). For instance, regulations requiring a higher level of capital can be nullified by evergreening, which reduces the burden of provisioning. Therefore any intervention, that can potentially curb evergreening can improve banks' health. The PCA regime also had the component of strict monitoring by the RBI which increases financial reporting transparency of banks (Costello et al. (2019)). The RBI looked at lending activity, the sectoral composition of loans, and the restructuring practices of banks frequently and had the power to ask banks to modify or stop certain types of practices. Here too, the ex-post evidence is in line. We find a significant decline in the evergreening of loans by PCA banks.

Thus, more than the label, the credible design of the PCA program seems to have made the difference. It sends a credible signal because the regulator shows a willingness to absorb the costs of displeasing the political class. The ex-post evidence only reinforces the ex-ante expectations.

In the last part of the paper, we address concerns about our inferences and identification strategy and conduct robustness tests. A critic may argue that if the PCA policy is effective in stemming strategic defaults, then strategic defaults on all unhealthy banks should cease immediately. The argument goes as follows. Every bank must cross the PCA threshold on its way to failure. Suppose the borrowers anticipate the above path clearly and trust that the PCA treatment will enable banks to continue banking relationships in the long run. In that case, they will stop the strategic defaults as soon as the PCA policy is implemented.

In a detailed discussion presented in Section 7.3, we argue that it makes sense for borrowers to distinguish between banks already under PCA and those likely to breach the PCA threshold in the future due to at least three reasons. First, as pointed out above, the effectiveness of PCA depends on the stage of deterioration in bank health at the time of intervention. Borrowers cannot be sure that in the future, banks will be admitted to PCA before their health deteriorates significantly. Second, the track record of the RBI justifiably creates uncertainty about whether current non-PCA banks will be placed under PCA if and when they breach the thresholds. Finally, given that more than a quarter of the banking system was placed under the PCA simultaneously, borrowers have reason to believe that the short-term costs of placing more banks under PCA may be more than the long-term benefits, and hence, the regulator may forbear from enforcing PCA.

Our tests also rule out some other plausible alternative mechanisms and address residual concerns. First, we examine other important regulatory interventions between the years 2016-2021. These include (i) a clean-up exercise in the form of an asset quality review; (ii) enhancement of creditor rights; and (iii) bankruptcy reform. Evidence suggests that none of the interventions led to a reduction in strategic defaults. Second, we conduct placebo tests that rule out the possibility that the reversal of strategic defaults is due to reasons other than the PCA intervention. Third, we also rule out the possibility that our results are only due to lax reporting of defaulting cases by PCA banks by comparing the amount of NPAs covered by the CIBIL database and the amount of NPAs reported in bank financial statements between PCA and non-PCA banks. Finally, we show that the significant presence of government-controlled banks (GCBs) does not impact the interpretation of our results, as even GCBs reduce lending in the face of health shocks due to capital constraints. Thus, the pre-condition required for the kind of strategic defaults we study exists for GCBs as well.

We do not claim that PCA did not impose costs. The PCA negatively impacted lending in the short term. On a further investigation, we find that lending decline is mostly driven by a reduction in practices bordering on evergreening. We do not detect a decrease in investments by borrowers borrowing from PCA banks. Instead, we find a significant decline in the related party transfers made by such firms to the management and controlling shareholders. Thus, a substantial part of the lending practice seems to be due to a decline in the practices that led to the banking crisis in India (Chopra et al. (2021), Chari et al. (2021)).

However, we acknowledge that our tests can only detect average effects. We cannot rule out the possibility that some firms face difficulties in the short term. It is also possible that the decline in credit in the short run could encourage some borrowers to default strategically. Borrowers who cannot clearly read the long-term signals may engage in such behavior.

While considering the generalizability of our findings, it is crucial to keep in mind that strategic defaults in response to deteriorating bank health occurs only in economic settings where contract enforcement is weak. Thus, even the reversal we point out is limited to such settings. Our results show that a credible regulatory action aimed at restoring bank health where the regulator has some control over the path to recovery can halt strategic defaults in other comparable settings as well.

Our paper contributes to the literature in several important ways. We contribute to the literature on strategic defaults in response to deteriorating bank health. 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 strategic defaults. We also show that several piecemeal regulatory interventions that have components of the PCA are not as effective as the PCA.

Second we contribute to the growing literature on impact of regulatory change in banking industry (e.g., Kim and Kross (1998), Ahmed et al. (1999), Aggarwal and Jacques (2001), Kocherlakota and Shim (2007), Mayes et al. (2008), Altamuro and Beatty (2010), Laux and Leuz (2010), Beatty and Liao (2011), Repullo and Suarez (2013), Dimitrov et al. (2015), Chircop and Novotny-Farkas (2016), Behn et al. (2016), Ertan et al. (2017), Nicoletti (2018), Corona et al. (2019), Wheeler (2019), Anderson et al. (2019), Gropp et al. (2019), Boyer and Kempf (2020), Balakrishnan et al. (2021), Balakrishnan and Ertan (2021), Gopalan (2022)). Studies in this literature mostly focus on impact of banking regulations on loan loss recognition, lending activities, deposits, bank risk taking, disclosures, and financial reporting among others. Some studies also debate on the efficiency of regulations, especially capital regulations, with regards to banking failures and systemic risks. We contribute to this literature by studying the effect of regulator driven PCA framework on strategic defaults. To the best of our knowledge, we are the first to document impact of a banking regulation on *strategic default* behaviour of borrowers.

Finally, our paper also contributes to the literature highlighting the role of financial reporting in the banking sector (Beatty and Liao (2014), Bushman (2014), Acharya and Ryan (2016)). Particularly, Acharya and Ryan (2016) underscores the importance of banks' financial reporting in enhancing the stability of the financial system. The fact that the PCA framework, which relies on accounting measures reported in banks' financial statements, halts borrower runs supports the above view.

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 plans. Extant studies (Aggarwal and Jacques (2001), Jones and King (1995)) find that FDICIA was effective in improving bank capital and reducing credit risk. Thus, the regulatory tool that we examine has been used by regulators worldwide at different times and does not represent an India specific specialized approach.

A weak version of the PCA framework for banks was initially introduced in India in financial year 2002.[1] Although it gave the RBI formal powers to place restrictions on un-

[1] The Indian financial year starts in April and ends in March. For example, Financial Year 2018 covers the period beginning from the calendar month of April 2017 to March 2018.

healthy banks, in practice, several banks with egregious violations were not placed under PCA. For example, IDBI Bank and Dena Bank breached the net non-performing asset ratio (NPA) requirement by close to 30% and 10% in 2017, respectively, but were not placed under PCA. Similarly, United Bank of India and Central Bank of India violated return-on-asset (ROA) thresholds by roughly 400%, but were exempted from being placed under PCA. Despite having objective criteria, the RBI used discretion in deciding whether to invoke PCA or not.[2]

Further, India introduced regulatory forbearance on provisioning requirements on restructured loans and continued the policy for seven years between 2008 and 2015 (Mannil et al. (2020)). Due to the forbearance policies, even unhealthy banks reported healthy numbers and dodged the PCA thresholds. Therefore, the old PCA regime does not provide a good setting to examine the impact of the PCA policy.

Realizing the old PCA framework was not working, the RBI introduced a new PCA framework in 2018 after withdrawing forbearance and conducting an asset quality review (AQR).[3] The new regulation aimed at placing unhealthy banks under RBI supervision and implementing remedial measures promptly. More importantly, the RBI relied on objective criteria rather than judgment while invoking the PCA. Thus, for all practical purposes, the new PCA regime can be considered equivalent to the introduction of the PCA regime.

The 2018 PCA framework introduced specific criteria for placing banks in PCA. The framework defines thresholds based on five bank health measures: capital adequacy ratio (CRAR), common equity tier I capital ratio (CET1), net non-performing asset ratio (NPA), leverage ratio and ROA. These measures are motivated by Basel III requirements and include both on-balance sheet as well as off-balance sheet metrics. The health parameters are defined in Table 1 (Panel A).[4]

Under the new PCA framework, there are three tiers of the severity of the breach, which have varying consequences. Table 1 (Panel B) describes the thresholds for the three levels of PCA. Note that the threshold level for each parameter may vary across years. For example, the minimum CRAR required to avoid level II breach is 7.75%, 8.375%, and 9% in the year

[2]The old PCA regime had three criteria for PCA admission based on net non-performing asset ratio (NPA), capital adequacy ratio (CRAR), and return on assets (ROA). NNPA had two thresholds. Level I threshold for NNPA was breached when NNPA was between 10% to 15%, whereas Level II threshold was breached when NNPA was higher than 15%. CRAR level I (II) (III) threshold was triggered when CRAR was between 9% and 6% (between 6% and 3%) (below 3%). ROA had a single threshold which was triggered at below 0.25%

[3]RBI conducted a special audit - Asset Quality Review (AQR) - of the banks every year starting 2016 to unearth the actual state of affairs of banks. The banks were asked to report revised NPAs make additional provisions based on the audit findings.

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

2018, 2019 and 2020, respectively. Violation of threshold for any one of the health parameters leads to admission of the bank into PCA.

In terms of restrictions under the PCA, a violation of level I alone results in minor penalties, such as restrictions on dividend distribution and remittance of profit. On the other hand, the breach of threshold level II has severe consequences such as restrictions 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. 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 of level I breach is discretionary. For instance, in 2018, five banks that violated the level I threshold without violating higher thresholds were exempted from the PCA.[5] Second, the corrective actions for a level I breach (without violating level II breach) are mild and do not impact lending.

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

3 Data

We obtain the quarterly loan-level data from the MCA. The MCA data contain all registered secured loans. Bhue et al. (2015) find that approximately three-fourths of all loans in India are secured loans. Chopra et al. (2021) further show that the MCA database covers 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 contain 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 CIBIL, India's largest credit information

[5] 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`

company. The CIBIL maintains a record of all corporate loans over Rupees 10 million, where the bank has initiated legal 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. We find that, on average, the loan delinquencies from CIBIL account for roughly 85% of all non-priority sector NPAs of banks.[6] Hence, loan performance data retrieved from CIBIL provides a fair representation of corporate loan delinquencies in general.

We match the firm-bank pairs between CIBIL and MCA using firm and bank names in both the databases and create a combined panel data of firm-bank pairs and identify delinquent loans. We add a 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 accounting information about banks from the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE). The RBI's website provides data about the PCA criteria and entry into and exit of banks from the PCA.

India has fast-track courts called Debt Recovery Tribunals (DRT), that deal with loan recovery cases (Visaria, 2009). We obtain the data relating to cases filed in DRT courts from their website. We use the data to assess the efficiency of relevant courts at a regional level. Finally, our data for district-level total outstanding credit and total outstanding credit to agriculture comes from the Database for Indian Economy (DBIE) maintained by the RBI.

Our sample spans four financial years, from 2018 to 2021. We have 608,500 firm-bank-quarter observations pertaining to 22,027 unique firms and 41 unique lenders. Out of the 580 bank-quarters in the sample period, roughly 18% are PCA bank-quarters. Also, 20 out of 41 banks in the data are government controlled banks (GCBs). Twelve banks went under PCA during the sample period, out of which 11 were GCBs. The NPA rate in the sample is 3%. The sample construction and summary statistics are provided in Table 2 (Panel A) and Table 2 (Panel B), respectively.

4 Strategic Defaults in Response to Deteriorating Bank Health

Our paper tests whether the PCA regime can mitigate the likelihood of strategic default in response to deteriorating bank fundamentals in India. Borrowers value the lending relationship with financial institutions to maintain future access to credit. The threat of

[6] In India, lending to agriculture, and micro, small and medium enterprises (MSME) are considered as priority sector lending. RBI mandates commercial banks to lend at-least 40% of their overall credit to the priority sector. MCA data does not cover the priority sector advances.

discontinuation of banking relationships acts as a deterrence to default by the borrowers in economic settings where formal contract enforcement mechanisms are inefficient. Bond and Rai (2009) theoretically show that a borrower's belief that the viability of a financial institution could be threatened by other borrowers' default could lead to a decline in the value of the lending relationship from the borrower's perspective. They find an equilibrium where borrowers default strategically in response to a decline in the value of the lending relationship below a threshold. They term the phenomenon "borrower run."

Borrower runs happen when expectations about bank failures form a contagion that flows through borrower networks (Bond and Rai (2009), Guiso et al. (2013), Pérez-Cavazos (2019), Trautmann and Vlahu (2013)). We note that strategic defaults in response to deteriorating bank health could happen even when there is no contagion in the sense of Bond and Rai (2009). Borrowers who independently expect a reduction in future access to credit due to the deterioration of their bank's health have incentives to default strategically. The tendency is likely to be higher in economic environments having inefficient contract enforcement mechanism and the dominance of relationship banking. Accordingly, in the Italian setting, Schiantarelli et al. (2020) empirically demonstrate that borrowers strategically default on troubled lenders. They show that the probability of late repayment is positively associated with the share of bad loans in a bank's portfolios in the previous period. Our setting is similar to theirs.

4.1 Indian institutional setting and strategic defaults

As discussed above, the value of future access to finance is higher in environments having slow enforcement of contracts, high expected growth, dominance of relationship banking and significant credit constraints. 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 impactful in a high-growth and credit-constrained environment where the expected demand for credit is higher in the future. India qualifies on these fronts. India is ranked 163 of 190 countries in the contract enforcement index of the World Bank's Ease of Doing Business rankings, although India's overall ranking improved from 80 to 63 in 2020. On the growth dimension, India's GDP grew by 6.7% in the five years before the COVID-19 pandemic and is expected to be above 7% in the coming decade.[7] Indian firms face significant credit constraints as well (Banerjee and Duflo (2014)).

The dependence on relationship banking due to frictions makes strategic defaults in

[7] https://www.spglobal.com/ratings/en/research/articles/210927-economic-outlook-emerging-markets-q4-2021-vaccination-progress-and-policy-decisions-remain-key-to-growth-12122390

response to deteriorating bank health less costly. Even if a borrower repays loans and maintains their credit profile, it is not easy to obtain credit from other lenders in such environments as other lenders lack the specialized knowledge required to lend to the borrower (Rajan (1992)). Thus, the impact of a decline in credit score on future access to credit is likely to be muted in this setting. The above four properties of the Indian setting make it ideal for the presence of strategic defaults.

4.2 The Existence of Strategic Defaults And Their Reversal Due to PCA

Next, we empirically test whether "strategic defaults" in response to deteriorating health of the bankers are prevalent in India and do they reverse due to the PCA policy. We start with an OLS based test inspired by Schiantarelli et al. (2020). Specifically, we test whether borrowers default selectively on loans lent by unhealthy banks and whether such defaults reverse when banks get admitted to the PCA.

Schiantarelli et al. (2020) note that measures of bank health that are based on the proportion of loans of a bank in default are susceptible to reverse causality: loan defaults by borrowers itself can lead to the identification of a bank as a bad bank. Moreover, for a firm that defaults on one bank and does not default on another at the same time, firm $\times$ time fixed effects may not alleviate reverse causality. There could be other endogenous unobserved factors at firm-bank-quarter level (unrelated to bank health) that cause default.

To address the concerns relating to reverse causality, we construct a measure of banks' health based on the health of their borrowers. For instance, our primary measure considers a borrower as unhealthy if any of its loan has been restructured by any lender in the previous quarter. Note that previous research has shown that due to the prevalence of a forbearance policy and lack of timely recapitalization, banks in India increasingly resorted to restructuring to hide loan defaults (Chopra et al. (2021), Mannil et al. (2020)). Therefore, restructuring of a loan is a credible signal of a borrower being in trouble in the Indian context during our sample period. The proportion of outstanding loans from such borrowers at a bank-quarter level is our measure of deterioration in bank health. For robustness, we vary the definition of unhealthy borrowers by considering other characteristics like interest coverage ratio and accounting losses.

Since our measure is based on the inherent health of the firm and is not dependent on the actual delinquency event towards any bank(s), firm $\times$ quarter fixed effects can significantly mitigate the reverse causality. The threat to the above identification can only come from a firm-bank-quarter level unobserved factor that is not related to firm health or bank health but which leads to deterioration of firm health and causes default only on unhealthy banks. The chance of existence of such a factor is remote. In addition, the outcome variable of interest is not the same as the variable used to measure bank health.

We, therefore, use the following OLS regression specification for identifying strategic defaults and their reversal:

$$\begin{aligned} Y_{i,j,t} =& \alpha + \beta_1 \times badfirmshare_{j,t-1} + \beta_2 \times PCA_{j,t} + \beta_3 \times badfirmshare_{j,t-1} \\ & \times PCA_{j,t} + \beta_4 \times X_{j,t} + \gamma_{i,t} + \delta_j + \epsilon_{i,j,t} \end{aligned} \tag{1}$$

Where i represents a firm, j represents a bank, and t represents a year-quarter. The dependent variable $Y_{i,j,t}$ represents $default$, which is an indicator variable set to one when the firm i defaults on loan repayment to bank j in the quarter t, zero otherwise. The variable $badfirmshare_{j,t-1}$ is the proportion of loans lent to unhealthy firms in bank j's loan portfolio during the previous year-quarter $t-1$. Consistent with Schiantarelli et al. (2020), we include a one year lagged bank-year level vector of control variables in ($X_{j,t}$) - natural logarithm of total assets, deposit to total assets ratio, cash to total assets ratio, and exposure of the bank j to firm i. The sample spans years 2018 to 2021.

$\gamma_{i,t}$ and δ_j are firm $\times$ quarter and bank fixed effects, respectively. Therefore, the estimation is within a firm-quarter and across banks (Khwaja and Mian (2008)). The above fixed-effect structure restricts the data to firms with at least two banking relationships within the year-quarter. Standard errors are clustered at the industry level.[8]

The results are presented in columns 1 and 2 of Table 3. We first consider the coefficient of the explanatory variable $badfirmshare$, which indicates the relationship between bank health and loan performance for banks not in PCA. 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 quarter is associated with an 8% higher default compared to its unconditional mean among the non PCA banks. The results confirm the existence of strategic defaults in India.

To test the reversal of strategic defaults, we interact the dummy variable representing the qualification of a bank into PCA (PCA) with the variable representing a deterioration of bank health ($badfirmshare$). A positive coefficient on the bank health variable and a negative coefficient on the interaction term indicates the (i) existence of strategic defaults; and (ii) their reversal due to PCA.

In columns 1 and 2 of Table 3, the coefficient on the interaction term between PCA and $badfirmshare$ is significantly negative, implying that strategic defaults towards unhealthy

[8]We cluster standard errors at the industry level since there are only a few banks (41) in our study. However, our results remain qualitatively similar after clustering at the bank level.

banks decline after they are placed under PCA. The coefficient on the interaction term $PCA \times badfirmshare$ is -0.05 and the standard deviation of $badfirmshare$ is 0.4. Thus, one standard deviation increase in $badfirmshare$ is associated with 2 percentage points reduction in default towards PCA banks, which is economically meaningful 67% the total rate of default on loans. The results support our thesis that strategic defaults in response to deteriorating bank health reverse due to the PCA.

Further, we vary the definition of firm health and show that our results are robust to the alternate definitions. We define firm health in two additional ways - 1) we consider a firm as unhealthy if one of its loan has been restructured in the past quarter and its interest coverage ratio (ICR) is below one, and 2) we consider a firm as unhealthy if the firm reports a loss in the previous quarter.[9] We then redefine $badfirmshare$ as the proportion loans lent by the bank to unhealthy firms based on above two definitions. We estimate Equation 1 using the redefined $badfirmshare$ and present the results in Table A.1 of the online appendix. The results are qualitatively similar to our main specification.

4.3 Test of Pre-Trends

There could be a concern that the reversal in default that we find after PCA admission is a continuation of a pre-existing trend. To test pre-trends, we extend the data by 4 quarters and estimate a regression equation of the following form:

$$\begin{aligned} Y_{i,j,t} =& \alpha + \beta_1 \times badfirmshare_{j,t-1} + \beta_2 PCA_{j,t} + \sum_{n=1,n\neq 3}^{n=6} \beta_{3,n} \times Pre_{n,j} \times badfirmshare_{j,t-1} \\ &+ \beta_4 \times badfirmshare_{j,t-1} * PCA_{j,t} + \beta_5 \times X_{j,t} + \gamma_{i,t} + \delta_j + \epsilon_{i,j,t} \end{aligned} \tag{2}$$

Where $Pre_{n,j}$ is an indicator variable that takes a value of one n quarters before bank j is placed under PCA regulation, zero otherwise. The other variables are as defined above in Equation 1.

We present the results in columns 3 and 4 of Table 3. The organization of the columns mimics the organization of columns 1 and 2. Notice that coefficients of all the interaction terms involving indicator variables representing the pre-PCA period are statistically indistinguishable from zero. The co-efficient of $badfirmshare$ and its interaction with the PCA largely remain unchanged as compared to the results presented in columns 1 and 2. Given the above results, it is reasonable to rule out the alternative explanation that our results are

[9]ICR is the ratio between earnings before interest and tax (EBIT) and the interest expense. Thus, the value of ICR being below one represents a scenario where the profit of the firm is unable to meet its loan commitments.

due to the continuation of pre-existing trends.

5 The Reversal of Strategic Defaults- The RD Test

The OLS specification that we used in Section 4.2 can be criticized on the grounds that it does not consider time-varying bank-level shocks that move with the PCA designation. Given that the designation of a bank as a PCA varies at a bank-quarter level, we cannot use bank $\times$ quarter fixed effects in a firm-bank-quarter panel structure. To address the above concern, we use a sharp RD design where we compare firm-bank-quarters where the bank under consideration narrowly meets the PCA criteria with firm-bank-quarters where the bank under consideration narrowly misses them. Given the closeness of their fundamental characteristics, the chances of the two types of banks being subject to a time-varying endogenous shock differently reduce substantially.

Three features of the regulation make it ideal for the use of a sharp RD design - i) as discussed in Section 2, the PCA has well-defined thresholds; ii) the annual AQR audits made it difficult for banks to manipulate accounting numbers to stay below the thresholds; and (iii) as discussed in Section 2, the threshold levels for each parameter vary during the sample period, which further randomizes the treatment thresholds, lending more credibility to the RD design. For example, the level 2 threshold for CRAR (CET1) was 7.75% (5.125%) in 2018 and 8.375% (5.75%) in 2019.

To implement the RD design, we need to create a single running variable from 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 is very different from a 0.1 increase in leverage. Therefore, following Reardon and Robinson (2012) and Becht et al. (2016), we standardize the variables around their respective cut-offs and create a score around zero for each variable. 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. While assigning a sign to the standardized score, we consider whether an increase or decrease in the criterion under consideration leads to PCA qualification. We create the score so that a positive score denotes a PCA violation, and a negative score indicates that the PCA limit has not been triggered. For instance, in the case of net NPA, the applicable cut-off is 9%, and an increase in values leads to PCA qualification. Therefore, an NNPA level of 10% gets a standardized score of 0.11 ((10-9)/9). Similarly, in the case of CRAR, the applicable cut-off is 7.75%, and a decrease in values leads to PCA qualification. Therefore, a CRAR level of 8.5% gets a standardized score of -0.1 ((7.75-8.5)/7.75).

Since the PCA is enforced when at least one of the thresholds is violated, we create a binding score based on all five variables (Becht et al., 2016; Reardon and Robinson, 2012). This binding score (*PCAscore*) is defined as the maximum of the five standardized PCA scores. For example, a bank with scores of 0.1, 0.2, -0.1, -0.2, and -0.2 on CRAR, CET1, NNPA, Leverage, and ROA, respectively, violates the first two measures and will have a binding score of 0.2.[10] This way of scoring ensures that all bank quarters with a PCA breach or miss are correctly identified. Therefore, the use of sharp RD design in justified. Details of the summary statistics of the component variables and *PCAscore* are provided in Table 2 (Panel B).

We use the RD robust methodology developed by Calonico et al. (2014). It is a preferred method of employing RD design to estimate the average treatment effect for the following reasons. First, it uses an objective data-driven criterion to choose a bandwidth around the cut-off, unlike traditional RD methods' ad-hoc manual selection of bandwidths. Second, the rdrobust estimator corrects any bias that may result from large bandwidth selected around the cut-off and thus provides robust bias-corrected confidence intervals.

For the robust RD tests, we organize the data at a bank-firm-quarter level. The dependent variable represents $default$ as in Equation 1. The running variable *PCAscore* is as defined above. The sample period is 2018 to 2021.

We present the results in Table 4. The three columns present the conventional, bias-corrected, and robust RD coefficients. We focus on column 3. The reported RD coefficient is 3.4% and has a negative sign. In other words, the admission of a bank into the PCA leads to a sharp decline in default rates. In economic terms, the likelihood of default above the cut-off is lower by 3.4 percentage points than below the cut-off. This is an economically significant 1.1 times the unconditional likelihood of default. We also plot the estimated linear fit for all firms in panel A of Figure 1. As shown in the figure there is a sharp discontinuity at the cut-off. Thus, firms selectively default less to PCA banks compared to comparable non-PCA banks.

A note on the bandwidth and other choices made is in order here. Our main analysis uses the default options prescribed in Calonico et al. (2014). For instance, the rdrobust package provides several options to choose from different bandwidth selection procedures, and the default option used is the "mserd" bandwidth selection process. The mserd option specifies the mean squared error based optimal bandwidth selector for estimating the treatment effect.

Additionally, the package also provides flexibility to use other available bandwidth selection procedures such as msetwo, msesum, etc.[11] Our RD inferences are robust to all the

[10]The ROA cut-off is zero, and PCA is triggered when a bank reports negative ROA for three consecutive years. We use the minimum of the last three years' ROAs as an input for calculating the standardized ROA score.

[11]Refer Calonico et al. (2017), and the stata manual for the rdrobust package with the complete list of

available bandwidth selection methodologies. Similarly, the package uses a triangular kernel function as the default option to construct the local polynomial estimators, but it also provides options to use uniform or epanechnikov as alternative kernel functions. In unreported results, we find that the choice of kernel function does not have any impact on our observed results. Finally, our results are also robust to all methodologies available in the package to compute standard errors, which are adjusted for heteroskedasticity.

5.1 Conventional RD With Firm × Time Fixed Effects

As a robustness measure, we also estimate a convention RD design of the following form:

$$\begin{aligned} Y_{i,j,t} =& \alpha + \beta_1 \times Treat_{j,t} + \beta_2 \times 1_{[-h<PCAscore<h]} \times PCAscore_{j,t} \\ &+ \beta_3 \times Treat_{j,t} \times PCAscore_{j,t} + \gamma_{i,t} + \epsilon_{i,j,t} \end{aligned} \tag{3}$$

Where i represents a firm, j represents a bank, and t represents a year-quarter. The dependent variable $Y_{i,j,t}$ represents $default$ as in Equation 1. $1_{[]}$ is the indicator function; h is the bandwidth around the cut-off, the running variable *PCAscore* is as defined above, and $Treat$ is an indicator variable which is 1 for $0 < PCAscore < h$, 0 otherwise. The sample period is 2018 to 2021. $\gamma_{i,t}$ represents firm × quarter fixed effects. Standard errors are clustered at the industry level.

We assume a linear slope on both sides of the cut-off and present the results in Table 5. Columns 1 and 2 (3 and 4) (5 and 6) shows the result for bandwidth 0.1 (0.125) (0.15) around the cut-off.[12] We include firm × quarter fixed effects in even-numbered columns.

The likelihood of default above the cut-off is lower by 5.9 percentage points than below the cut-off within a narrow bandwidth of 0.125. This is an economically significant 1.97 times the unconditional likelihood of default. The inclusion of firm × quarter fixed effects makes the estimation within a borrower-quarter. Thus, the results from conventional RD tests using firm × quarter fixed effects are in line with the results obtained using the robust RD methodology.

5.2 Hygiene Tests

We conduct basic hygiene tests that are essential for a valid application of the RD design.

The McCrary Test: Self-selection to stay below the cut-off could result in banks on the two sides of the cut-off being systematically different, and hence, make the use of RD

available options.

[12]The bandwidth 0.15 represents the 25th percentile of the PCAscore, conditioned on the PCAscore being positive

design inappropriate. Although the AQR 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 panel B of Figure 1. We find that the difference in density of *PCAscore* around the cut-off is statistically indistinguishable from zero.[13]

Test For Discontinuity in Other Variables: There could be concerns about the difference in default at the cut-off being a reflection of some other unobservable correlated firm-related time-varying shocks that are specific to a banking relationship. Other firm-related variables are also likely to show discontinuity around the cut-off if this is the case. We test the above hypothesis by estimating the difference between firm performance measures on either side of the cut-off using the RD specification from Equation 3 and report the results in Table A.2 of the online appendix. The results are shown for the measures - natural logarithm of sales, profit margin, financial leverage, and current ratio in columns 1,2, 3, and 4, respectively. The coefficients on the treated indicator variables are statistically indistinguishable from zero across all the measures.

Second Degree Polynomial of The PCAscore: A concern could be that if the true relation between 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 2nd-degree terms of the *PCAscore* in Equation 3 to allay this concern. Results presented in panel A of Table A.3 of the online appendix show that the RD estimates do not change significantly.

Donut-hole RD test: Another issue with RD design could be that the estimates are sensitive to heaping in the running variable close to the cut-off (Barreca et al. (2016), Barreca et al. (2011)). To allay the above concern, we implement a "donut-hole" RD approach recommended by Almond and Doyle (2011) and Barreca et al. (2011). We exclude a subset of the sample around the PCA cut-off where manipulation is likely to happen. Specifically, we drop observations within the donut-hole bandwidth of 0.01, 0.015, 0.02, and 0.03 and re-run the RD specification. Results presented in panel B of Table A.3 of the online appendix indicate that the RD coefficients still remain statistically and economically significant.

Placebo Test: We further strengthen the argument that the observed improvement in loan performance is due to PCA treatment at the cut-off by conducting placebo tests using false PCA cut-offs. We run 100 iterations of the RD Equation 3 by arbitrarily selecting cut-offs, and plot the coefficients in Figure A.1 of the online appendix. The blue lines show the 95th percentile of the distribution on either side of the mean, while the red line shows our main RD coefficient with cut-off as zero. We find that our coefficient lies beyond the

[13]The coefficient of log difference in heights is -1.03 with a standard error of 0.64

95th percentile of the distribution. Thus, we can reject the null hypothesis that there is no differential decline in default on PCA banks.

5.3 Further Evidence On Strategic Default

To establish that the observed increase in default is indeed strategic in nature, Schiantarelli et al. (2020) show that they are more prevalent in regions with inefficient courts and are not related to firm performance. We follow Schiantarelli et al. (2020) to establish that the reduction in loan default that we document is indeed a reduction in strategic default.

First, we exploit the variation in legal efficiency in India using the pendency of cases filed at Debt Recovery Tribunals (DRTs) and test whether the reversal in loan defaults is concentrated in regions with inefficient courts.[14] Specifically, we interact the treatment variable of the RD specification mentioned in Equation 3 with a firm-level court inefficiency measure and estimate the following regression:

$$\begin{aligned} Y_{i,j,t} = &\alpha + \beta_1 \times Treat_{j,t} + \beta_2 \times Treat_{j,t} \times CourtInefficiency_i \\ &+ \beta_3 \times 1_{[-h<PCAscore<h]} \times CourtInefficiency_i + \beta_4 \times 1_{[-h<PCAscore<h]} \\ &\times PCAscore_{j,t} + \beta_5 \times 1_{[-h<PCAscore<h]} \times PCAscore_{j,t} \times Treat_{j,t} \\ &+ \beta_6 \times Treat_{j,t} \times PCAscore_{j,t} \times CourtInefficiency_i + \gamma_{i,t} + \epsilon_{i,j,t} \end{aligned} \tag{4}$$

where $CourtInefficiency$, is a firm level indicator variable, which is set to one if the firm is located in the jurisdiction of a DRT which is in top tercile in terms of pendency of cases, and set to zero if the corresponding DRT court is in the bottom tercile of pendency of cases. All the other variables and fixed effects used are similar to the ones used in the RD specification in Equation 3. We cluster the standard errors at industry level. The sample period is 2018 to 2021. Results are reported in column 1 of Table 6. We find that the coefficient on $Treat$ becomes insignificant, while the coefficient on the interaction term $Treat \times CourtInefficiency$ is negative and significant. As expected, we find that the reduction in default is driven by firms located in regions having inefficient courts.

Second, in subsequent columns of Table 6 we show that measures of firm performance are unrelated to the reversal in default. We consider the indicator variables representing year on year negative growth in earnings, negative growth in EBITDA, and negative growth in indirect tax expense as measures of shock to firm performance in columns 2, 3, and 4, respectively. We use indirect tax growth as a proxy for performance because tax data are verifiable using third-party records (Pomeranz (2015)). Overall, we find no significant

[14] DRT courts are bankruptcy courts where loan recovery related cases are filed (Lilienfeld-Toal et al. (2012)).

difference in the reversal of strategic defaults based on firm performance in a specification similar to Equation 4. The above results indicate that initial high default and its reversal are induced by strategic considerations rather than the performance of the firms.

6 Underlying mechanism

This section attempts to understand how the PCA intervention halts strategic defaults in response to deteriorating bank health. Bond and Rai (2009) and Schiantarelli et al. (2020) show that borrowers' perception that a struggling bank will not be able to continue lending in the future incentivizes strategic defaults. Thus, a prerequisite for halting strategic defaults is reversing the borrowers' belief that a bank is unlikely to lend in the future. Such a reversal can happen if borrowers believe that banks' health will be restored.

Therefore, the question of mechanism boils down to what makes borrowers believe that the PCA intervention will eventually restore bank health. Therefore, we highlight the aspects of the PCA intervention that potentially influence borrower beliefs. Our primary evidence is based on the ex-ante aspects of program design and analysis, although we also provide some ex-post evidence that reinforce the ex-ante expectations.

6.1 Timely Intervention

A regulatory intervention, such as the PCA, aimed at curing unhealthy banks can be successful only when the health of banks is diagnosed accurately ex-ante. For instance, if an unhealthy bank can hide its true health via asset misclassification or earnings management, then it may escape or delay the PCA intervention. If most unhealthy banks can thus dodge the regulation, then PCA is likely to be ineffective in restoring overall bank health. In the absence of reliable financial statements, banks may get into PCA after exhausting all earnings management opportunities. It may be too late to treat such banks. Thus, the accuracy and reliability of financial statements are crucial for PCA to be successful. Recognizing the importance of the issue, the RBI first conducted a detailed asset quality review (AQR) before enforcing the PCA policy. The AQR exercise revealed that banks, on average, underreported NPAs by 52%. Consequently, banks were asked to increase loan loss provisions by 30%.

The Indian AQR was not a one-time event. The RBI conducted AQRs from 2016 to 2020. Thus, admission to PCA was based on financial statements audited and verified by the RBI. Such stringent verification before PCA admission increases the possibility of timely admission into the PCA. In other words, even a minor breach can be identified quickly as it is relatively difficult for banks to manage their numbers to escape the PCA. To the extent that timely detection and early treatment are associated with an increased probability of recovery, the RBI's approach of conducting an AQR before the PCA intervention is likely to appear credible to the borrowers.

Evidence: We test the above thesis by comparing the reaction of borrowers to PCA admissions that happen on a relatively small violation of the PCA threshold and those that occur after an egregious violation. We estimate the following regression specification.

$$\begin{aligned} Y_{i,j,t} =& \alpha + \beta_1 \times MarginalBreach_j + \beta_2 \times EgregiousBreach_j + \beta_3 \times X_{j,t} \\ &+ \gamma_{i,t} + \epsilon_{i,j,t} \end{aligned} \tag{5}$$

where $MarginalBreach_j$ ($EgregiousBreach_j$) is an indicator variable that takes a value of one if bank j's violation of $PCAscore$ is in the bottom 25 percentiles (top 75 percentiles) at the time of its entry into the PCA, zero otherwise. Note that an egregious breach does not mean laxity in enforcing PCA or the use of discretion by the RBI in implementing PCA. These are cases where the values for financial parameters of the banks show a sudden jump from below the threshold to significantly above the threshold. For instance, a bank may witness NNPA jump from 8.9%, which is just below the threshold level, to 13% in the next period and thus qualify as an egregious breach. The dependent variable, control variables, and fixed effects are as in Equation 1.

We present the results in columns 1 and 2 in Table 7. The coefficient of $MarginalBreach_j$ ($EgregiousBreach_j$) is significantly negative (positive), which suggests that reversal of default is witnessed in banks which violate the PCA criteria narrowly and thus have a higher probability of recovery. The results also indicate that admitting banks into PCA after a substantial decline in their health does not seem to help.

Thus, the evidence suggests that the timely intervention by the RBI, which the AQR partly facilitated, contributed to enhancing borrower confidence about the restoration of health of PCA banks, and, hence contributed to the reversal of strategic defaults.

6.2 Alignment between regulator's and the government's interests

It is often seen in emerging economies that actions taken by regulators to infuse loan repayment discipline among the borrowers get nullified by political interventions in credit markets. For instance, when the Indian bank regulator was trying to increase credit bureaus' coverage and improve the country's credit culture, the government announced a large-scale debt waiver. Several studies have shown that the Indian debt waiver fuelled moral hazard (Giné and Kanz (2018); Kanz (2016); De and Tantri (2014); Mukherjee et al. (2018)). The intervention by one of the state governments in India, which effectively banned almost all loan recovery practices of micro-finance institutions, also had a similar effect (Tantri (2018)). Given the above history, regulations that create a conflict between their intended objectives and short-term political interests are unlikely to be successful: the political class is likely to make efforts to neutralize such regulations.

The PCA regulation is different because it gave full powers to the RBI to control lending and other operations of banks. Under the PCA, the RBI can order banks to completely stop lending to some or all sectors. In other words, the RBI gets powers to nullify the negative impact of political interventions. The regulator can curb politically motivated lending by banks under the PCA.

Also, by curtailing lending, the PCA has the potential to impose political costs. Suppose the lower flow of credit leads to lower investments and unemployment. In that case, the political leaders are likely to find it challenging to convince the electorate that the economic distress is due to the actions taken by the regulators. Also, given the powers of RBI under the PCA, it is not easy for the executive to nullify the effect created by PCA.

Thus, it is in the political class's interest to work with the regulators to get the banks out of PCA. The alignment of interests between the regulators and the government makes PCA different from other regulations. The alignment also has the potential to reverse strategic defaults by changing borrower expectations about the eventual health of the banks.

Further, under the PCA, the RBI has powers to impose restrictions on banks' dividend payments, management compensation, and related party transactions (RPT). These restrictions could curtail the tendency of controlling shareholders to extract private benefits at the expense of minority shareholders. Therefore, it may become easier for PCA banks, including private banks in PCA, to raise capital from capital markets.

Evidence: We provide four pieces of ex-post evidence that reinforce the ex-ante expectations based on the design of the PCA. The spirit of the evidence is that the PCA policy leads to a decline in lending, especially politically important types of lending.

First, we investigate whether overall credit by PCA banks declines after the banks are placed under PCA restrictions. We use the following specification for the test.

$$Y_{i,j,t} = \alpha + \beta_1 \times PCA_{j,t} + \beta_3 \times X_{j,t} + \gamma_{i,t} + \delta_j + \epsilon_{i,j,t} \tag{6}$$

Where $Y_{i,j,t}$ is the natural logarithm of loan extended by bank j to firm i in year-quarter t. The indicator variable PCA is as defined in Section 4.2. We include bank-level vector of control variables, ($X_{j,t}$), as defined in Equation 1. The coefficient of interest is β_1. It represents the change in lending under the PCA regime.

We present the results of the above specification in panel A of Table 8. We include control variables in both columns. Firm × quarter and bank fixed effects are also included in all columns. Across specifications, we find a negative association between PCA and lending. The above result implies that PCA restrictions indeed result in a decline in lending by the banks placed under the regulation.

Second, we ask whether the decline in lending by PCA banks results in a decline in overall credit to regions dominated by them. We estimate the following regression equation.

$$Y_{k,t} = \alpha + \beta_1 \times DistrictPCAexposure_{k,t-1} + \gamma_k + \delta_t + \epsilon_{k,t} \tag{7}$$

Here the data are at a district-year level. The dependent variable $Y_{k,t}$ is the natural logarithm of credit outstanding in district k in year t. *DistrictPCAexposure* is an indicator variable set to one when the district lies above the median in terms of proportion of credit from PCA banks in year $t-1$, and zero otherwise. The data spans 2016-2021. Results are presented in column 1 of Panel B of Table 8. As expected, the coefficient of the interaction term in column 1 is negative and significant, suggesting that total credit to impacted districts declines due to the PCA regulation. The coefficient on the variable $districtPCAexposure$ is -5.3%. Thus, lending to districts highly exposed to PCA banks declines by 5.3 percentage points after the banks are placed under PCA regulation, which is economically significant 83% of the average lending growth.

Third, we examine whether agricultural credit also declines. Nearly half of India's population depends on agriculture, so credit flow to agriculture is highly politically sensitive (Cole (2009)). We estimate the regression Equation 7 and report the results relating to the flow of agriculture credit in column 3 of panel B of Table 8. The coefficient on the variable $districtPCAexposure$ is -4.5%. Thus, agricultural lending to districts highly exposed to PCA banks declines by 4.5 percentage points after the banks are placed under PCA regulation, which is economically significant 47% of the average agricultural lending growth.

Finally, we ask whether the decline in credit due to the PCA reverses during elections. Cole (2009) shows that bank lending close to elections is politically more significant than lending during non-election years. Therefore, if PCA banks lend as much as other banks during elections, the political costs discussed above may be muted. On the contrary, if PCA banks continue to lend less even during elections, the political costs of reduced lending may get amplified.

We test the differential impact of the PCA regime on lending during elections by modifying the regression Equation 7. We introduce a new indicator variable, *election*, that takes the value of one if the state to which the district is under consideration has a scheduled state-level election during the year and zero otherwise. As noted by Cole (2009), the timing of the scheduled state-level elections in India is exogenous. We estimate a interaction regression involving *election* and *districtPCAexposure*.

We present the results in columns 2 and 4 of panel B of Table 8. Notice that coefficient on *districtPCAexposure* continues to be negative and statistically significant. The interaction between *election* and *districtPCAexposure* has a co-efficient that is statistically indistinguishable from zero. The result suggests that the PCA regime leads to reduced lending even during elections. The political class seems unable to force PCA banks to reverse their slower lending during elections.

We test for existence of pretrends by including indicator variables $pre2$, $pre3$, and $pre4$ in the Equation 7. The variables represent 2, 3, and 4 years before the districts have above median value of exposure to PCA banks for the first time, respectively. We present the results in columns 1 and 2 of Table A.4 of the online appendix for natural logarithm of total credit and natural logarithm of agricultural credit as dependent variables, respectively. We do not find any evidence of the existence of pretrends, while the coefficients on *districtPCAexposure* continue to be negative and significant.

Given the political costs, the ruling party that controls the government has an incentive to work with the central bank to ensure that the banks are out of the PCA. Note that Chopra et al. (2021) point out that the AQR does not lead to the recapitalization of banks. The ability to impose high political costs makes the PCA different in its ability to force the government to act on further clean-ups and recapitalization. Therefore, ex-ante borrowers are likely to factor this aspect of the PCA in their decision to default strategically on unhealthy banks.

The evidence presented in Figure A.2 and Table A.5 of the online appendix is in line. We find a 4.3 percentage points increase in PCA banks' capital adequacy ratio. We also see a significant improvement in other PCA parameters, including CET1, NNPA, ROA, and off-balance sheet exposures.

Thus, the ex-post evidence is in line with the ex-ante expectation that arises from the design of the PCA program. It is crucial to note that even the ex-post evidence manifests when the banks are under PCA. These developments may reinforce borrowers' beliefs about the overall effectiveness of PCA in restoring bank health eventually and leading to continued lending in the future.

6.3 Potential To Curb Evergreening

In the context of Indian banking, it is important to note that indiscriminate evergreening, facilitated by regulatory forbearance, was one of the root causes of the banking crisis (Chopra et al. (2021); Mannil et al. (2020); Chari et al. (2021)). Further, Kashyap et al. (2022) show that banks continued to evergreen loans even after the withdrawal of the forbearance regime. Evergreening can help banks circumvent the provisioning requirements and thereby window dress bank health. As shown by the literature on the Japanese banking crisis (Caballero et al. (2008); Peek and Rosengren (2005)), evergreening can only postpone the eventual failure of banks. In fact, it increases the chances of eventual bank failure. Therefore, increased evergreening of loans could fuel borrower expectations about eventual bank failure and incentivize strategic defaults.

Given the above situation, it is important to detect and prevent evergreening to reverse strategic defaults. Most ex-post regulatory tools fail to detect and prevent the evergreening of loans, as regulators do not have control over day-to-day lending. The PCA framework includes rigorous monitoring of lending activities by the regulator. It empowers the regulator to order the PCA banks to stop some or all types of lending practices anytime. Therefore, the borrowers have reasons to believe that the PCA intervention has the potential to stem the decline in bank health by detecting and preventing evergreening. Such beliefs of borrowers could potentially reverse strategic defaults.

Evidence: We examine whether the PCA intervention was indeed successful in preventing evergreening. We estimate the following regression equation.

$$Y_{i,t} = \alpha + \beta_1 \times PCAexposure_{i,t-1} + \gamma_i + \delta_t + \epsilon_{i,t} \tag{8}$$

Here, the data are organized at a firm-year level. The dependent variable $Y_{i,t}$ takes the value of one if a firm's loan is evergreened during a year. We use two measures of evergreening. The first measure, which we call direct evergreening, is in the spirit of Caballero et al. (2008). Here a loan is considered evergreened if a bank restructures a loan of a borrower. Our second measure is based on Kashyap et al. (2022). Their measure of indirect evergreening is based on the use of related parties of an insolvent borrower by a bank to channel funds to the insolvent borrower.[15]

The independent variable $PCAexposure_{i,t-1}$ is an indicator variable set to one when the firm i has higher than the median level of exposure to PCA banks in the year $t-1$, zero otherwise. We include firm and year fixed effects. The sample period is 2016 to 2021.

The results are presented in columns 1 and 2 of Table 9. In column 1, the dependent variable is $Directevergreenloan$, which is the natural logarithm of total restructured loans

[15] An insolvent firm is said to engage in loan evergreening if its current banker extends a fresh loan to a healthy related party which in turn transfers the loan funds to the insolvent firm. Eventually, the funds are used to repay the original loans. Thus, the bank ends up funding repayment of its old loan in trouble. They call such transactions indirect evergreening. They also show that indirect evergreening is dominant and difficult to detect way of evergreening loans in India.

of the firm in the year. Here the coefficient on $PCAexposure$ is negative and significant. The result suggests that firms that banked extensively with PCA banks witnessed a 39% decline in direct evergreening after the banks were placed under PCA regulation.

Next, we test whether the close monitoring of PCA banks by RBI deterred the indirect evergreening of loans to zombie firms. In column 2 of Table 9, we use $Indirectevergeening$ as the dependent variable, which is set to one if the firm is involved in indirect evergreening in that year and zero otherwise. Results suggest that firms having high exposure to PCA banks have a lower probability of engaging in evergreening after the PCA regulation is enacted. The coefficient is economically meaningful because it represents a 100% reduction in evergreening compared to the unconditional possibility of loan evergreening.

Further, to contain the NPA crisis, it is also essential to ensure that the funds extended by banks are utilized for their intended purpose and are not expropriated. The RBI advises banks to monitor the utilization of loan proceeds and to keep a close watch on the diversion of funds through RPTs. We, therefore, test whether the PCA framework addresses the misutilization of funds by examining its impact on RPTs. We present the results in columns 3 and 4 of Table 9. The dependent variable in column 3 (4) is the logarithm of a firm's total RPT amount (Net RPT outflow) to its controlling stakeholders and managers in a year. Here, Net RPT outflow is calculated as the total RPT outflow from the firm adjusted for RPT inflows into the firm from controlling stakeholders and managers. As conjectured, we find that Total RPT and Net RPT outflow to key stakeholders of the firms with above median exposure to PCA banks indeed reduce by approximately 3.5% and 4.6%, respectively after the banks were placed under PCA intervention.

We test for existence of pretrends by including indicator variables $pre2$, $pre3$, and $pre4$ in the Equation 8. The variables represent 2, 3, and 4 years before the firms have above median value of exposure to PCA banks for the first time, respectively. We present the results in columns 3, 4, 5, and 6 of Table A.4 of the online appendix for evergreening of loans, indirect evergreening of loans, and RPT flows. We do not find any evidence of the existence of pretrends, while the coefficients on $PCAexposure$ continue to be negative and significant.

Thus, the PCA intervention seems to have addressed the root cause of the NPA crisis by (i) reducing loan evergreening through restructuring by PCA banks, (ii) reducing indirect evergreening by PCA banks, and (iii) curtailing PCA bank borrowers' tendency to divert the funds raised by way of loans for the private benefit of controlling shareholders and the management of such firms. Although the above evidence is ex-post, on an ex-ante basis, the RBI's ability to monitor and prevent distortionary lending practices under the PCA framework sends credible signal that the bank health will eventually improve under PCA.

7 Discussion On Issues Relating To The PCA

In this section, we discuss several issues relevant to our thesis that the PCA caused a decrease in strategic default.

7.1 Other Alternative Explanations

Here we consider some alternative mechanisms and examine whether they explain the halting of strategic defaults in response to the PCA regulation.

7.1.1 Other Interventions

There could be a residual concern that the reversal in strategic defaults could be due to other interventions of the regulator that coincided with the PCA and not because of PCA. In response, we draw the attention of the reader to the sharp discontinuities that we observe at the PCA limits and no significant discontinuity at placebo limits. It is unlikely that other interventions lead to sharp discontinuities precisely at the PCA cut-offs. None of the other interventions had the same cut-offs.

Nonetheless, to address residual concerns, we examine the impact of four important regulatory interventions that aimed at reducing bank delinquency during the sample period on strategic defaults: (i) The Asset Quality Review (AQR) (ii) Scheme for Sustainable Structuring of Stressed Assets (S4A) which allowed the lenders to restructure and segregate the stressed borrower's debt into sustainable and unsustainable portions, and treat them differently, (iii) Strategic Debt Restructuring Scheme (SDR) which was aimed towards reduction of NPAs of banks by allowing them to acquire a controlling stake in defaulting debtors, and participate in the boards of borrowers, and (iv) implementation of Feb-2012 circular, which required even a single day's default in debt servicing to be reported to the RBI followed by implementation of resolution plan. Any failure to implement the resolution plan within six months led to compulsory initiation of bankruptcy proceedings.

(i) The AQR

We first take up the concern that clean-up of bank balance sheets due to the AQR caused a reduction in strategic default. It is important to highlight the finding of Chopra et al. (2021), who showed that the AQR did not lead to the recapitalization of banks. They also find that the unhealthy banks continued zombie lending even after the AQR. Therefore, it is unlikely that the AQR in itself reversed strategic defaults.

Nonetheless, to address the alternative explanation, following Chopra et al. (2021), we collect data about the divergence in NPA between the reported numbers and the audit findings at a bank-year level. The variable so created is the measure of the impact of the AQR. We include the variable and its interaction with PCA dummy in Equation 1. We present the results in Table A.6. Our coefficient of interest remains largely unchanged even after controlling for the impact of AQR. Thus, we rule out the AQR as an alternative explanation.

(ii) Other Interventions

To rule out the alternative explanation that our results due to other regulatory interventions, we estimate following regression equation for all the tests.

$$\begin{aligned} Y_{i,j,t} =& \alpha + \beta_1 \times Post_t + \beta_2 \times badfirmshare_{j,t-1} + \beta_3 \times Post_t \\ & \times badfirmshare_{j,t-1} + \beta_4 \times X_{j,t} + \gamma_{i,t} + \tau_j + \epsilon_{i,j,t} \end{aligned} \tag{9}$$

Where $Y_{i,j,t}$ is $default$ as in Equation 1. The data are at the firm-bank-quarter level and we consider a window of one year before and after the interventions. SDR, S4A, and Feb-12 were implemented in the years 2016, 2017, and 2019, respectively. Thus, the sample periods considered are 2015 to 2016, 2016 to 2017, and 2018 to 2019, and $post_t$ takes a value of 1 after years 2016, 2017 and 2019 for SDR, S4A, and Feb-12 circular, respectively. The variable $badfirmshare$ is as defined in Equation 1. The main explanatory variable is an interaction between $post$ and $badfirmshare$ as defined above. $X_{j,t}$ is a vector of bank-year level control variables as in Equation 1. $\gamma_{i,t}$ and τ_j represent firm $\times$ quarter and bank fixed effects, respectively.

The results are presented in Table A.7 of online appendix. Columns 1,2, and 3 show the result for SDR, S4A, and Feb-12 circular, respectively. The coefficients on the interaction terms are insignificant across all columns. Thus, we do not find a decrease in default by the borrowers because of the above interventions by RBI indicating that other interventions were not successful in preventing strategic defaults.

The PCA is different because it combines early intervention, strict monitoring by RBI, significant restrictions on banks, and a clear roadmap towards restoring bank health. However, we acknowledge that our evaluations of RBI interventions are limited to the tools deployed by RBI and there may be other possible interventions which can potentially curb tendencies to default strategically.

7.1.2 Lax 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. The banks supply the data to CIBIL. A skeptic may argue that PCA banks experiencing lower loan delinquency is a mechanical consequence of their laxity in issuing recovery notices and providing the required data to the credit bureau. Note that, laxity in reporting is unlikely because PCA banks are closely monitored by the RBI.

Nevertheless, we explicitly test whether PCA banks report a lower proportion of their non-performing assets to the credit bureau. We implement the above test by organizing data at the bank-quarter level and estimating the following regression specification.

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

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 quarter t. The indicator variable $PCAadmission$ takes a value of one if the bank is under PCA regulation, zero otherwise. $X_{j,t}$ represents a vector of bank-quarter level control variables - NNPA, CET1, ROA, CRAR and Leverage. γ_j and δ_t represent bank and quarter fixed effects, respectively. The coefficient of interest is β_1 which estimates the differential reporting of default amount as a proportion of non-performing loans after a bank is placed under PCA framework.

We present the results in Table A.8 of the online appendix. We find that the coefficient on $PCAadmission$ is statistically insignificant. Thus, we do not find evidence supporting the alternative explanation that our main results are due to lax recovery and reporting practices of PCA banks.

7.2 Strategic Default In The Presence of Government Owned Banks

A critic may argue that the dominance of government-controlled partially privatized banks in India (GCBs) could nullify the other factors that support strategic defaults. This is because the survival of GCBs is implicitly guaranteed. Therefore, it is possible to argue that strategic defaults may not manifest in India despite the weaknesses in the law enforcement system.

In this context, it is essential to note that a bank's perceived inability to lend because of its ill-health incentivizes strategic defaults and not just its failure to survive. In other words, even if unhealthy banks survive but cannot lend as before, strategic defaults could occur. The above is the case with GCBs. While governments protect the depositors and ensure no default on deposits, they often do not recapitalize the unhealthy GCBs to the extent required to reach the level of lending of healthy banks (Chopra et al., 2021). We verify the above argument empirically using the below specification.

$$\begin{aligned} Y_{j,t} = \alpha + \beta_1 \times LowQualityBank_{j,t-1} + \beta_2 \times GCB_j + \beta_3 \times GCB_j \\ \times LowQualityBank_{j,t-1} + \delta_j + \theta_t + \epsilon_{j,t} \end{aligned} \tag{11}$$

where j represents a bank and t represents year-quarter. The dependent variable $Y_{j,t}$ represents natural logarithm of the total deposits or total advances of the banks in a quarter. The variable *Low quality Bank* is the NPA ratio of the bank in the previous quarter. GCB is an indicator variable that takes a value of one if bank j is a GCB, zero otherwise. δ_j and θ_t represent bank and quarter fixed effects. The coefficient of interest is β_3, which represents the additional effect of bank health on deposits or advances in GCBs.

We present the results in Table A.9. As expected, the coefficient on *Low quality Bank* is negative in both columns 1 and 2, which indicates that an increase in the NPA ratio is associated with a decline in both deposits and lending activities in the next quarter. On the other hand, in column 1, the coefficient on the interaction term, *GCB* $\times$ *Low quality Bank*, is positive and significant, which suggests that the decline in deposits in response to health shocks is lower for GCBs. The Wald test for joint significance of $\beta_1+\beta_3$ in the Equation 11 shows that the combined value of coefficients is statistically indistinguishable from zero. Therefore, it is reasonable to claim that the flow deposits into GCBs is unaffected by the health shocks they face.

Interestingly, the coefficient of the interaction term in column 2 is negative, indicating that deterioration of bank health is associated with a decline in lending irrespective of banks' type of ownership. Thus, although GCBs have a high probability of survival, they still reduce lending when their health deteriorates.

Further, Banerjee et al. (2008) show that loan officers of GCBs reduce lending when the risk of being subjected to anti-corruption inquiries becomes salient. A decline in bank health could lead to allegations of corruption and investigations (Tantri, 2021). The fact that GCBs are more prone to such inquiries may make their lending more sensitive to deterioration in their health and end up incentivizing strategic defaults. Thus, overall the evidence suggests that the advantage due to a higher chance of survival may be offset by the lack of recapitalization and reduction in lending due to fear of prosecution. Hence, GCBs could be susceptible to strategic defaults.

We have shown above that despite the implicit guarantee, GCBs reduce lending when they are in trouble. Therefore, it is likely that the strategic defaults will reverse even when a GCB is put under the PCA and even among borrowers who borrow exclusively from GCBs. In Table A.10 of the online appendix, we use the OLS Equation 1 to show that the reversal of strategic defaults in response to the PCA intervention manifests even when we restrict the sample to GCBs. Similarly, in Table A.11 of the online appendix we show that our results for the GCB sample are robust to the RD design as well.

7.3 Borrowers' ex-ante expectations: PCA versus non-PCA banks

A reader may wonder – why do borrowers reduce default more on PCA banks compared to other banks? The question follows from the rationale that every bank with deteriorating health will be placed under PCA at some time on its journey to failure. Thus, the borrowers should expect PCA to reduce the likelihood of failure of all banks. This should discourage borrowers from strategically defaulting on all unhealthy banks, not just those under PCA restrictions. We provide three responses countering this line of argument.

First, as noted in Section 6.1, the evidence suggests that the PCA is effective in stemming strategic defaults only when the PCA admission happens relatively early in terms of breach of thresholds; when banks enter the PCA after a sudden and an egregious breach, the treatment fails to halt strategic defaults. It is difficult for a borrower to know whether a bank will enter the PCA with a mild or egregious breach. Thus, ex-ante, there is uncertainty regarding the effectiveness of PCA.

Second, under the old PCA regime, the RBI did not admit some banks that breached the old PCA thresholds. Therefore, some borrowers may think that even under the current PCA regime, some banks may not be admitted into PCA despite breaching the thresholds. Thus, it may be rational for borrowers to distinguish between banks already in PCA and other banks that are likely to enter after a deterioration in their health.

Finally, it is important to reiterate that 12 out of 41 banks were placed under the PCA framework. These banks accounted for about 27% of the total outstanding bank loans in India in 2017. We have already shown in Section 6.2 that PCA restrictions lead to a decline in credit by the banks, imposing a cost on the economy. The borrowers might be concerned that after a point, the costs associated with PCA imposition might surpass the benefits, and the regulator might decide against placing more unhealthy banks under the PCA framework.

Thus, it is reasonable to believe that the borrowers are likely to distinguish between PCA and non-PCA banks while forming expectations about the continued flow of credit.

7.4 Bank Health After Exiting The PCA

To Evaluate the PCA policy, it is important to understand whether the improvements in bank health during the PCA are temporary or continue even after banks exit the PCA. The answer to the above question is likely to inform the reader about whether the changes during the PCA are only due to intense monitoring and enforcement by the regulator or do they represent structural changes within banks that are likely to be long-lasting.

We test whether strategic defaults continue to decline after banks come out of the PCA using the following specification:

$$
\begin{aligned}
Y_{i,j,t} =& \alpha + \beta_1 \times badfirmshare_{j,t-1} + \beta_2 \times PCAadmission_{j,t} + \beta_3 \\
& \times PostPCA_{j,t} + \beta_4 \times badfirmshare_{j,t-1} \times PCAadmission_{j,t} \\
& + \beta_5 \times badfirmshare_{j,t-1} \times PostPCA_{j,t} + \beta_6 \times X_{j,t} + \gamma_{i,t} + \delta_j + \epsilon_{i,j,t}
\end{aligned} \tag{12}
$$

where $PCAadmission$ takes a value of one when the banks are under the PCA regime, and zero otherwise; while $PostPCA$ takes a value of one after the bank exits PCA, and zero otherwise. The other variables are as explained in Equation 1. The data are at the bank-firm-quarter level. The sample period is between 2018 and 2021. Results presented in Table A.12 of the online appendix show that the coefficients on the both the interaction terms involving *PCAadmission* and *postPCA*, are negative and significant. The result suggests that the decline in default continues even after the banks are out of PCA. Thus, the reversal of strategic defaults is not just a temporary phenomenon due to intense RBI monitoring.

7.5 Importance of the Phenomenon and the Solution

A reader may wonder whether strategic default in the nature of borrower runs that we study are important enough from a macroeconomic point of view. In other words, is the phenomenon significant enough to attract the attention of the regulators and researchers? Schiantarelli et al. (2020), who, to the best of our knowledge, are the first to examine the phenomenon empirically, argue that such strategic defaults can potentially cause a large-scale financial crisis. They study the banking crisis in Italy. Such impacts are possible in other similar settings as well. As we have noted in Section 1, despite the importance of the phenomenon, no study has examined the ways of preventing it.

A critic may also argue that it is not surprising that a regulatory intervention such as the PCA curbs strategic defaults. In this context, it is important to note that it is not clear, ex-ante, that the PCA framework is likely to curb strategic default for several reasons.

First, it is not clear whether the PCA framework will be implemented true to its spirit. The same set of factors that lead to slow enforcement of contracts may also impede the implementation of the PCA. It is important to note that the RBI could not implement the old PCA framework. Second, as pointed out in Section 1, a decline in credit in the short run due to PCA may exacerbate strategic defaults if the regulator does not sufficiently anchor borrower expectations about eventual improvement in PCA banks' health. Third, the evergreening of loans contribute to deterioration in banks' health, and the deterioration in bank health triggers strategic default. It is not clear from the design of the PCA that it can prevent the evergreening of loans on a sustained basis. Research shows that previous interventions in India have failed to curb the evergreening of loans.

Therefore, it is reasonable to conclude that our finding that the PCA intervention can curb strategic defaults is important to regulators and researchers.

7.6 Other Costs and Benefits

Although the purpose of our paper is to focus on the impact of PCA on strategic default behavior, it is important to point out to the reader that PCA can impose costs as well. As discussed in Section 6.2, one of the costs of PCA regulation is that it led to decline in lending by unhealthy banks. The reduction in lending can negatively impact borrowers who are in genuine need of credit and can be costly in a credit-constrained economy like India. However, we also find that decline in lending was driven by decrease in loan evergreening practices - the primary reason for the banking crisis in India. The RBI thus had two choices - either allow the default to spiral for the short-term gain of higher credit or to take firm steps to reduce NPAs for the long-run revival of the credit cycle. The RBI chose the latter.

Nevertheless, we conduct tests to analyze whether the decline in lending adversely affected investments made by firms. We use a specification similar to Equation 8, where the dependent variable is investments made by the firm. Our results tabulated in Table A.13 of the online appendix show that investment measured in terms of change in gross fixed assets; change in property, plant, and equipment; and change in plant and machinery do not change significantly for firms more exposed to PCA banks after the banks are placed under PCA.

In contrast, we find a significant decline in RPTs to the firm's key management personnel when the firm has higher exposure to PCA banks (refer columns 3 and 4 in Table 9). These findings show that a reduction in lending during the PCA regime was accompanied by a significant reduction in distortionary lending practices that led to the banking crisis in the first place. Thus, the costs of reduced short-term lending need to be compared with these short-term benefits and the long-term benefits from sustainable improvement in bank health.

An important caveat is in order here. Our tests relating to real effects on firms can only detect average effects: we cannot rule out that some firms experience difficulties in short run. We also acknowledge that we do not provide a comprehensive assessment of all benefits and costs of PCA.

8 Conclusion

Strategic default in response to deteriorating bank health is a phenomenon where a borrower defaults selectively on unhealthy banks seen incapable of lending in the future. It is well known that in countries having inadequate contract enforcement infrastructure, a bank's implicit promise to continue lending in the future is one major incentive for prompt loan repayment. Thus, in such settings, the borrowers' apprehension about an unhealthy bank's ability to continue banking relationships drives strategic defaults. Given that strategic defaults can expedite bank collapse and aggravate banking crises, 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 strategic defaults using the Indian banking setting.

We first establish that *strategic defaults* in response to deteriorating bank health exist in India. Next, we study whether implementing the PCA framework reduce such strategic defaults. The setting allows us to implement a sharp RD design. We find that PCA is successful in reversing such strategic defaults. Evidence also suggests that the reduction in strategic defaults is due to the signaling effect of the regulatory intervention: the PCA intervention credibly signals to the borrowers that a bank is likely to come out healthy and continue banking relationships. Thus, the incentive to default strategically on unhealthy banks diminishes due to the intervention.

Therefore, our findings show that implementation of the revised PCA framework alleviates *strategic defaults* in response to deteriorating bank health and can help restore the health of financial institutions. We acknowledge that PCA comes at a cost in the form of a significant decline in lending in the short run. We focus on the impact of PCA on strategic defaults 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 out in this study comprehensively and apply PCA regulation depending on the goals of the implementation.

Further, we recognize that phenomenon of strategic defaults in response to deteriorating bank health apply mostly to parts of the world with poor quality of legal enforcement. Also, we do not claim that PCA is the only way of halting such strategic defaults. The long-term sustainable cure for the problem lies in improving law enforcement infrastructure, strengthening creditor rights, improving bank and borrowing firm governance, and other measures. Nevertheless, as strategic defaults in response to deteriorating bank health are observed in several settings and implementing the above long-term measures can be a lengthy process, the PCA intervention can serve well as a quick remedy to arrest strategic defaults and restore bank health.

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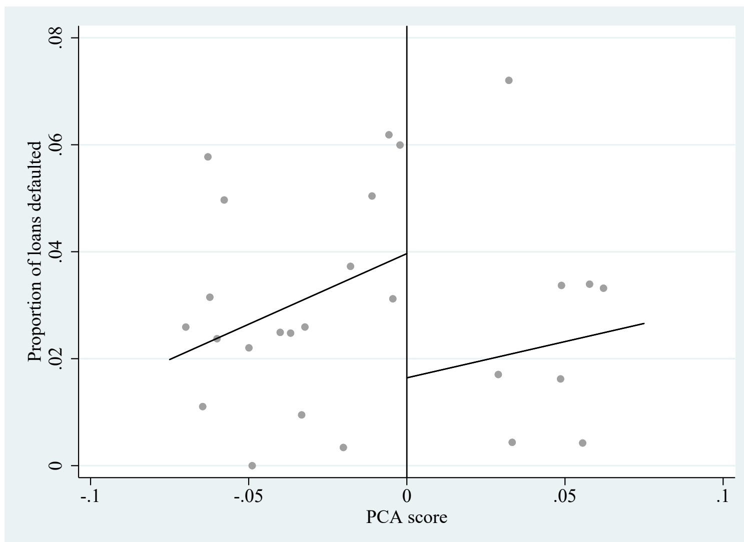
Figure 1: Panel A of the figure shows the RD plot for the difference in default between observations marginally below and marginally above the PCA threshold. The bandwidth is estimated using the procedure developed in Calonico et al. (2014). The data are organized at a bank-firm-quarter level. The x-axis represents the running variable *PCAscore*, which is as defined in Section 5. The y-axis represents the average of *Default* for each bin of observations. The plot uses a first order local polynomial to present the fitted values on both sides of the PCA cut-off. Panel B of the figure shows the McCrary test for manipulation in a narrow bandwidth around the cut-off. The data are organized at a bank-quarter level. The x-axis represents the running variable *PCAscore* and the y-axis represents the distribution of bank-quarter observations. The figure plots the density of bank-quarter observations below and above the cutoff together with their respective 95% confidence intervals.

(a) Panel A



(b) Panel B

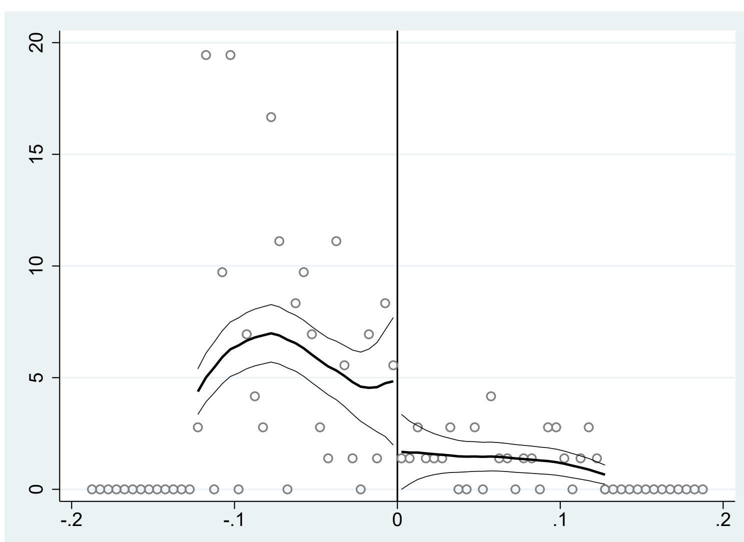


Table 1 (Panel A): PCA Parameters

In this table, we define all the financial variables used to determine the threshold violations under the PCA policy.

Financial parameter	Definition
CRAR	It denotes the capital adequacy ratio of bank and is calculated as ratio of total capital to total risk weighted assets (RWA) of the bank in a year.
CET1	It is the ratio of Common Equity Tier I capital to the total RWA as defined in Basel III guidelines.
NPA	It is the ratio of Net NPA (NPA adjusted for provisions) over net advances of the bank in a year.
Leverage	It is the ratio of Tier I capital to the total exposure of the bank as defined in Basel III. Total exposure also comprises of off-balance sheet exposures of the bank.
ROA	It is the ratio of Net income to the total asset of the bank in a year.

Table 1 (Panel B): PCA cut-offs

In this table, we report the limits of PCA norms for each year for each threshold level. A bank is admitted under PCA when it breaches any one financial parameter. The parameters have been defined in panel A above.

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 C): PCA Admissions

In this table, we report the number of banks which breached the PCA limits and the number of banks which were actually admitted under PCA by the RBI.

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
2021	I	6	2
	II	2	2

Table 2 (Panel A): This table describes the sample used in our tests. It specifies the number of unique firms, banks, bank-quarters, firm-bank pairs, and firm-bank-quarters used in different levels of main analysis. It further enumerates the number of bank-quarters under PCA regime, number of firm-bank-quarters where the firm defaults on the bank, and the number of firm-bank-quarters under PCA regime.

Sample construction table	
Sample period	FY 2018 - 2021
Number of firms	22,027
Number of banks	41
Number of bank-quarter level observations	580
Number of bank-quarters when the bank is under PCA	107
Number of firm-bank relations	48,202
Number of firm-bank-quarter level observations	608,500
Number of firm-bank-quarters with defaults	17,028
Number of firm-bank-quarters when the bank is under PCA	96,221

Table 2 (Panel B): This table provides the summary statistics at bank-quarter and firm-bank-quarter levels. The bank-quarter level variables include value of non-performing asset (*NPA*), the running variable *PCAscore* as defined in Section 5, net non-performing asset as a proportion of outstanding loan *(NNPA*), ratio between common equity tier 1 capital and risk weighted assets (*CET1*), return on asset (*ROA*), capital adequacy ratio (*CRAR*), ratio of tier I capital to total exposure (*Leverage*), the indicator variable *PCA* as defined in Section 4.2, and *Badfirmshare* as defined in Section 4.2. The firm-bank-quarter level variables include outstanding loan in INR million, the indicator variable *PCA*, and the indicator variable *Default* as defined in Section 4.2.

Bank - Quarter summary statistics						
Variable	**obs**	**mean**	**median**	**1st %ile**	**99th %ile**	**std dev**
NPA (in billion Rupees)	544	245.91	130.98	3.54	1,877.65	331.69
PCA score	580	0.06	-0.38	-0.96	2.85	6.67
NNPA %	580	3.88	4.68	0.33	16.02	3.67
CET1	553	11.33	10.75	0.09	27.88	5.95
ROA	580	-0.41	0.24	-7.63	1.96	6.99
CRAR	558	13.84	13.38	6.22	29.20	3.86
Leverage	113	6.72	5.82	3.01	18.9	3.07
PCA	580	0.22	0	0	1	0.41
Badfirmshare	580	0.15	0.14	0.08	0	0.40
Firm - Bank - Quarter summary statistics						
Variable	**obs**	**mean**	**median**	**1st %ile**	**99th %ile**	**std dev**
O/S loan (in million Rupees)	608,500	1850	210	26,700	0.5	240,000
PCA	558,146	0.22	0	0	1	0.42
Default	558,146	0.03	0	0	1	0.17

Table 3: Reversal in Borrower Runs - OLS

The table shows the impact of PCA regulation on strategic default using the OLS methodology. The data are organized at a bank-firm-quarter level for the sample period of 2018 (2017) to 2021 in Columns 1 and 2 (3 and 4). The dependent variable is *Default*, which takes a value of one for the bank-firm-quarters in which the firm defaults on loan repayments to the bank, zero otherwise. The indicator variable PCA is a bank-quarter level variable that takes a value of one for all quarters after the bank is placed under PCA, zero otherwise. The variable $Badfirmshare$ is the one quarter lagged value of the ratio between the bank's outstanding loan owed by firms that were involved in restructuring and the bank's total outstanding loan. In Columns 3 and 4, the variables *Pre6, Pre5, Pre4, Pre2, and Pre1* take value of one for 6, 5, 4, 2, and 1 quarters before the bank's admission to PCA, respectively, and zero otherwise. We include the control variables - (i) exposure of bank to the borrower, (ii) natural logarithm of total asset of the bank, (iii) deposit to total asset ratio of the bank, and (iv) cash to total asset ratio of the bank - in the even numbered columns. We also include firm × quarter and bank fixed effects in all columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default			
	(1)	(2)	(3)	(4)
Badfirmshare	0.010***	0.006*	0.014***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Post PCA × Badfirmshare	-0.052***	-0.050***	-0.066***	-0.066***
	(0.010)	(0.010)	(0.011)	(0.011)
Post PCA	0.002	0.002	0.013***	0.016***
	(0.003)	(0.002)	(0.003)	(0.003)
Pre6 × Badfirmshare			0.044	0.031
			(0.051)	(0.054)
Pre5 × Badfirmshare			0.085	0.073
			(0.053)	(0.055)
Pre4 × Badfirmshare			-0.031	-0.029
			(0.048)	(0.048)
Pre2 × Badfirmshare			-0.024	-0.021
			(0.048)	(0.050)
Pre1 × Badfirmshare			0.032	0.036
			(0.027)	(0.027)
Control variables	No	Yes	No	Yes
Firm × Quarter F.E.	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	Yes	Yes
Observations	407,320	392,787	483,705	467,575
R-squared	0.359	0.361	0.358	0.361

Table 4: Reversal in Borrower Runs - Robust RD

This table reports the robust RD results for the difference in default between the bank-firm-quarters which marginally breach the PCA threshold versus the bank-firm-quarters marginally below the threshold. The coefficients are estimated using the data driven local polynomial based robust inference procedure developed in Calonico et al. (2014). The data are organized at the bank-firm-quarter level for the period 2018-2021. The variable *Default* is an indicator variable set to one if the firm defaults on loan repayments to a bank in a year-quarter, zero otherwise. Column 1 reports the estimates for the conventional RD approach, which used the standard Gaussian distribution. Column 2 provides the bias-corrected RD estimates, whereas column 3 provides robust bias-corrected RD estimates. Standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default		
Method:	Conventional	Bias-corrected	Robust
	(1)	(2)	(3)
RD estimate	-0.029***	-0.034***	-0.034***
	(0.009)	(0.009)	(0.010)
Observations	33,318	33,318	33,318

Table 5: Reversal in Borrower Runs - Conventional RD

This table reports the RD inferences for the difference in default between the bank-firm-quarters which marginally breach the PCA threshold versus the bank-firm-quarters marginally below the threshold using a conventional RD approach with manually selected bandwidths. The data are organized at a bank-firm-quarter level for the period 2018-2021. The dependent variable *Default* takes a value of one for the bank-firm-quarters in which the firm defaults on loan repayments to the bank, zero otherwise. The estimates are reported using a 1st degree polynomial function of the running variable *PCAscore*, which is as defined in Section 5. The variable *Treated* is an indicator variable set to one when PCAscore is more than zero, zero otherwise. We use bandwidths of 0.1 in columns 1 and 2, 0.125 in columns 3 and 4, and 0.15 in columns 5 and 6. We include firm × quarter fixed effects in even numbered columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default					
Bandwidth	0.100		0.125		0.150	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.047***	-0.079***	-0.048***	-0.059***	-0.035***	-0.047***
	(0.007)	(0.021)	(0.005)	(0.014)	(0.004)	(0.012)
PCAscore	-0.072	0.206*	0.106***	0.222***	0.065***	0.183***
	(0.050)	(0.124)	(0.024)	(0.052)	(0.019)	(0.046)
Treated × PCAscore	1.004***	0.945***	0.675***	0.499***	0.521***	0.371***
	(0.107)	(0.332)	(0.077)	(0.173)	(0.060)	(0.126)
Firm × Quarter F.E.	No	Yes	No	Yes	No	Yes
Observations	53,118	11,965	73,651	22,702	79,688	25,844
R-squared	0.003	0.497	0.005	0.470	0.004	0.465

Table 6: Inefficient Courts and Firms in Shock

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 organized at bank-firm-quarter level for the period 2018-2021 and restricted within a bandwidth of 0.125 around *PCAscore*. The dependent variable is *Default*, which is defined in Table 3. The estimates are presented for 1st degree polynomial function of *PCAscore*. The *Firm level indicator* in column 1 is *Low court efficiency*, which is set to one if the firm is located in jurisdiction with weak legal enforcement, zero otherwise. Specifically, *Low court efficiency* takes a value of one (zero) if the firm is under the jurisdiction of a DRT court that lies in the top (bottom) tercile in terms of average days of pendency of cases across all courts. The *Firm level indicator* in column 2 is *Sales decline* which is set to one (zero) if the firm experiences a negative (positive) quarter-on-quarter growth in sales. The *Firm level indicator* in column 3 is *EBITDA decline* which is set to one (zero) if the firm experiences a negative (positive) quarter-on-quarter growth in EBITDA. The *Firm level indicator* in column 4 is *Indirect tax growth* which is set to one (zero) if the firm experiences a negative (positive) quarter-on-quarter growth in indirect taxes paid. All other variables are as defined in Table 5. We include firm × quarter fixed effects in all columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default			
Firm level measure	Low court efficiency	Sales decline	EBITDA decline	Indirect tax growth
	(1)	(2)	(3)	(4)
Treated	0.039	-0.028**	-0.032**	-0.039*
	(0.057)	(0.014)	(0.014)	(0.023)
Treated × Firm level indicator	-0.102*	-0.028	0.002	0.008
	(0.060)	(0.025)	(0.024)	(0.029)
PCAscore	-0.409	-0.015	0.083	0.090*
	(0.324)	(0.038)	(0.052)	(0.047)
Treated × PCAscore	0.358	0.486**	0.323*	0.454
	(0.840)	(0.224)	(0.187)	(0.297)
Firm level indicator × PCAscore	0.675**	0.320***	0.104	0.044
	(0.317)	(0.082)	(0.076)	(0.063)
Treated × Firm level indicator × PCAscore	0.039	-0.226	-0.158	-0.209
	(0.851)	(0.367)	(0.314)	(0.405)
Firm × Quarter F.E.	Yes	Yes	Yes	Yes
Observations	15,560	14,543	17,239	13,449
R-squared	0.463	0.472	0.478	0.486

Table 7: Timely Intervention

The table shows impact of early and late entry of banks into PCA on strategic default by borrowers. The data are organized at a bank-firm-quarter level. The sample period is 2018 to 2021. The dependent variable is *Default*, which takes a value of one for the bank-firm-quarters in which the firm defaults on loan repayments to the bank, zero otherwise. The main explanatory variables are $Marginal breach$ and $Egregious breach$. The indicator variable $Marginal(Egregious) breach$ takes a value of one if the bank's PCAscore at the time of its entry into the PCA is in the bottom 25 percentile (top 75 percentile) among all PCA violations, zero otherwise. We include control variables from Table 3 in column 2. We also include firm × quarter fixed effects in all columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default	
	(1)	(2)
Marginal breach	-0.025***	-0.015***
	(0.005)	(0.005)
Egregious breach	0.014***	0.021***
	(0.003)	(0.003)
Control variables	No	Yes
Firm × Quarter F.E.	Yes	Yes
Observations	360,500	348,234
R-squared	0.377	0.382

Table 8: Decrease in Lending by PCA Banks

This table shows the impact of PCA regulation on lending activities. In panel A (B), the data are organized at a bank-firm-quarter (district-year) level and spans the years 2018 (2016) to 2021. The dependent variable in columns 1 of panel A is *Log loan*, which is the natural logarithm of the amount of loan borrowed by the firm from the bank in the year-quarter. The dependent variable in columns 2 of panel A is *New loan*, an indicator variable that takes a value of one if the bank extends a loan to the firm in the year-quarter, zero otherwise. The explanatory variable *PCA* is as defined in Table 3. We include control variables listed in Table 3, and firm × quarter and bank fixed effects in all columns of panel A. The dependent variable in column 1 and 2 (3 and 4) of panel B is *natural logarithm of total credit* (*natural logarithm of agricultural credit*) in the district. The indicator variable *District PCA exposure* takes a value of one if the district lies above median in terms of proportion of its total outstanding loan owed to PCA banks in the previous year, zero otherwise. The indicator *Election* takes a value of one if the state which the district belongs to has an election in the year, zero otherwise. We include district and year fixed effects in all columns of panel B. The standard errors reported in the parentheses are clustered at industry (district) level and adjusted for heteroskedasticity in panel A (B). ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Firm level lending		
	Log loan	New loan
	(1)	(2)
PCA	-0.248***	-0.013***
	(0.063)	(0.003)
Control variables	Yes	Yes
Firm × Quarter F.E.	Yes	Yes
Bank F.E.	Yes	Yes
Observations	392,787	392,787
R-squared	0.342	0.353

Panel B: District level lending				
	Log total credit		Log agriculture credit	
	(1)	(2)	(3)	(4)
District PCA exposure	-0.053***	-0.051***	-0.045**	-0.038*
	(0.016)	(0.016)	(0.021)	(0.021)
Election		0.022*		0.041***
		(0.011)		(0.015)
District PCA exposure × Election		-0.016		-0.044
		(0.020)		(0.032)
District F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	2,245	2,245	2,245	2,245
R-squared	0.973	0.973	0.950	0.950

Table 9: Loan evergreening in PCA banks

The table shows the impact of PCA regime on evergreening and related party transactions (RPT). The data are organized at a firm-year level for the sample period of 2016 to 2021. The dependent variables are natural logarithm of amount of restructured loans to a firm (*Direct evergreen loan*); an indicator variable that takes a value of 1 if the firm is involved in indirect evergreening (*Indirect evergreening*); natural logarithm of total value of RPT with controlling stakeholders and managers of the firm (*Total RPT*); and natural logarithm of net RPT outflow to controlling stakeholders and managers of the firm (*Net RPT outflow*) in columns 1, 2, 3, and 4, respectively. Indirect evergreening is as defined in Kashyap et al. (2022). *PCAexposure* is an indicator variable set to one when the firm's proportion of borrowings from PCA banks lies above the median level across all firms in the previous year, zero otherwise. We also include firm and year fixed effects in all columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Direct evergreen loan	Indirect evergreening	Total RPT	Net RPT outflow
	(1)	(2)	(3)	(4)
PCA exposure	-0.327**	-0.003**	-0.035**	-0.046**
	(0.128)	(0.001)	(0.017)	(0.019)
Firm F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Observations	58,731	55,881	57,190	58,721
R-squared	0.364	0.285	0.841	0.827

Internet Appendix

A Figures and Tables

Figure A.1: The figures plots the coefficients from 100 iterations of running the RD Equation 3, with random cut-offs. The bandwidth is set at 0.1 in each iteration. The blue lines show the 95th percentile of the distribution on either side of the mean, while the red line shows our main RD coefficient with cut-off set at zero.

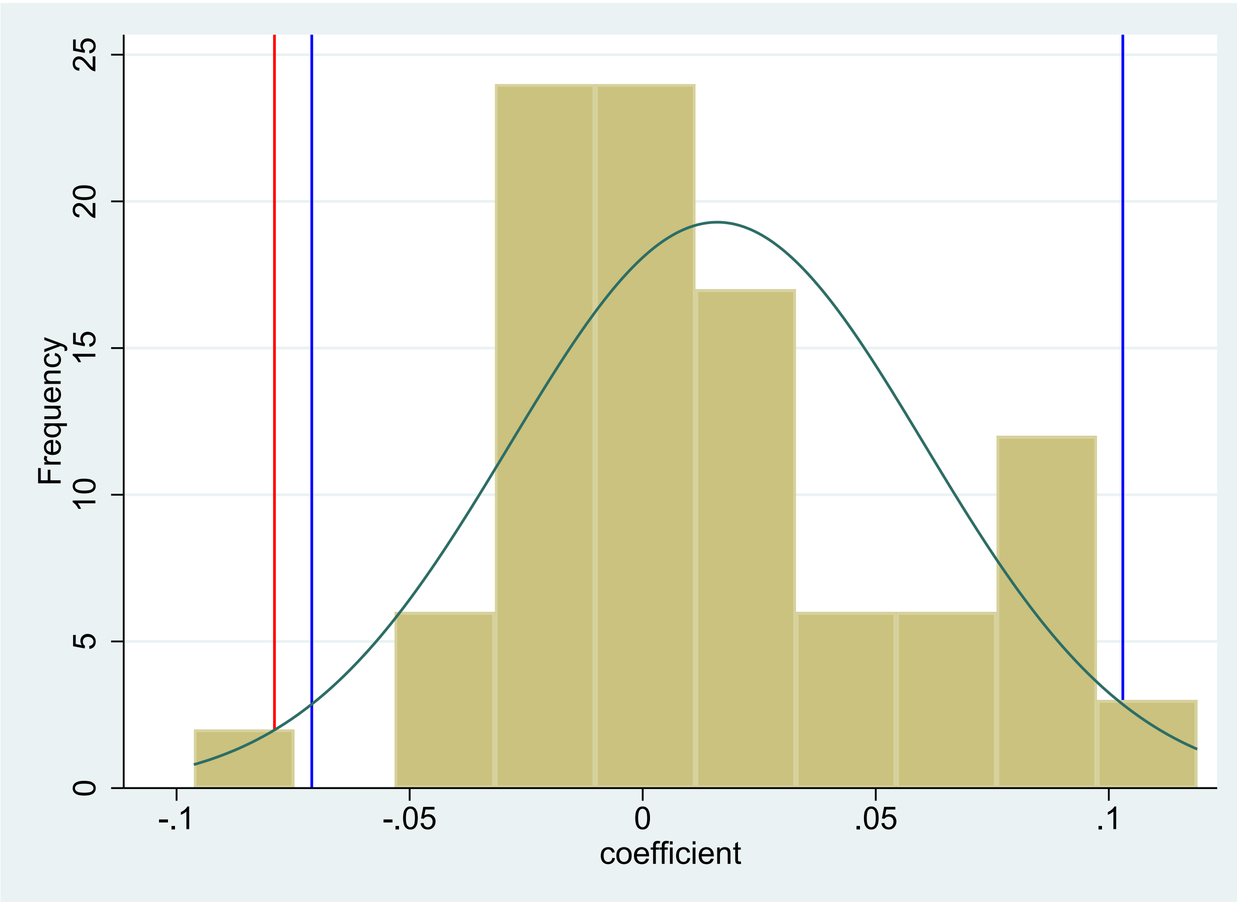
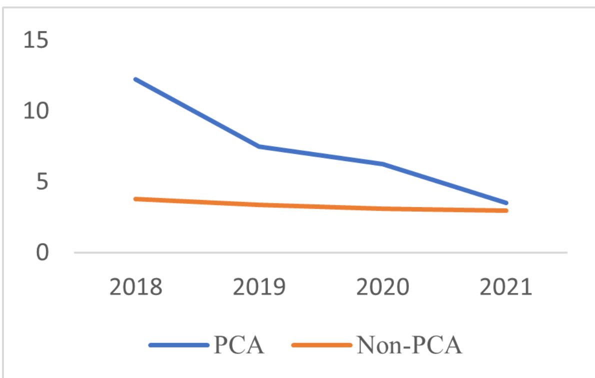
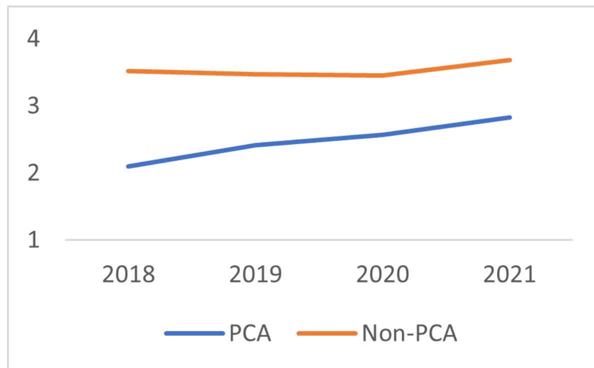


Figure A.2: The figures plot the time trend of average of bank characteristics for PCA and non-PCA banks in blue and orange lines, respectively. Panel A (B) (C) (D) (E) (F) plots the average of NNPA (NIM) (CRAR) (CET1) (OBS) (Leverage). 'NNPA' is the ratio of net NPA to the net loans and advances; 'NIM' is the net interest margin of banks calculated as the percentage of net interest income over total assets of the bank in a year; 'CRAR' is the capital adequacy ratio; 'CET1' is the ratio of Common Equity Tier I capital to risk-weighted assets (RWA) of the bank; 'OBS' is off-balance-sheet exposure expressed as percentage of total assets of the bank; and 'Leverage' is the ratio of Tier I capital to the exposure measure as defined in Basel III. All the variables are expressed in percentages.

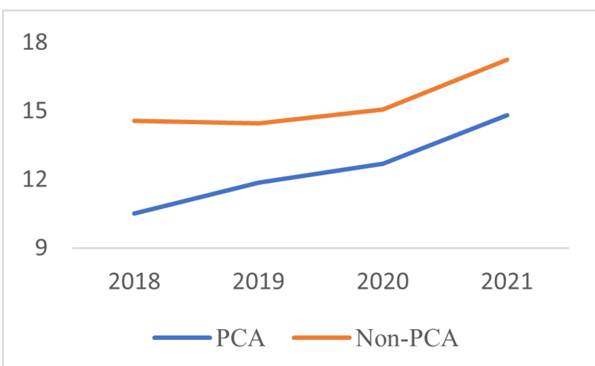
(a) Panel A: NNPA



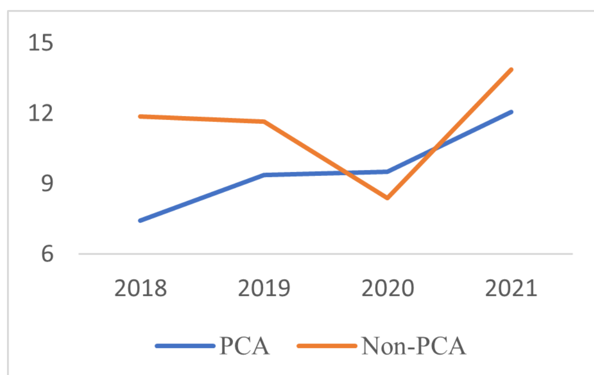
(b) Panel B: NIM



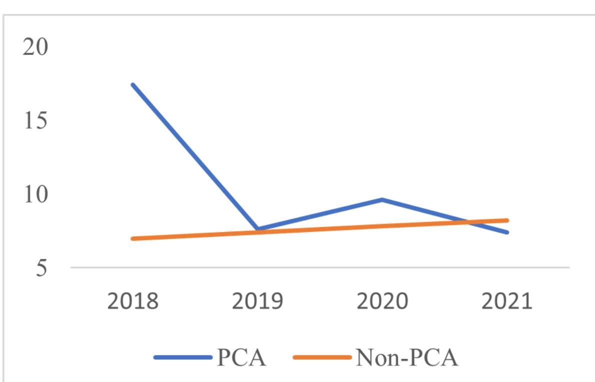
(c) Panel C: CRAR



(d) Panel D: CET1



(e) Panel E: Off balance sheet



(f) Panel F: Leverage

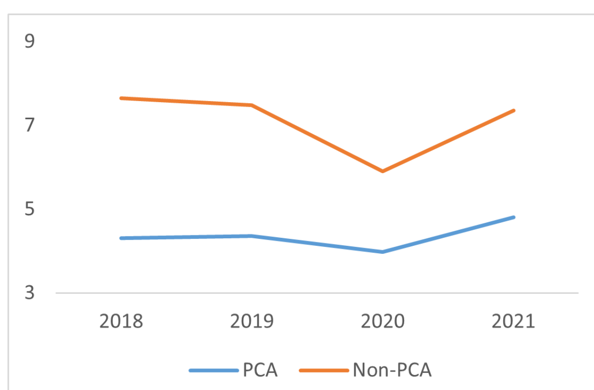


Table A.1: Reversal in Borrower Runs - Alternate measures of bank health

The table shows the impact of PCA regulation on borrower runs using the OLS methodology. The data are organized at a bank-firm-quarter level for the sample period of 2018 to 2021. The dependent variable is *Default*, which takes a value of one for the bank-firm-quarters in which the firm defaults on the bank, zero otherwise. The indicator variable PCA is a bank-quarter level variable that takes a value of one for all quarters after the bank is placed under PCA, zero otherwise.In panel A (B) the variable $Badfirmshare$ is the previous quarter's proportion of banks' outstanding loan owed to firms that are involved in restructuring of loans and have an ICR below 1 (proportion of banks' outstanding loan owed to firms that have a negative profit). We include the control variables listed in Table 3 in the even numbered columns. We also include firm × quarter and bank fixed effects in all columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default			
	Panel A: Restructuring and ICR		Panel B: Profit	
	(1)	(2)	(1)	(2)
Badfirmshare	0.017*	0.015	0.008**	0.003
	(0.009)	(0.010)	(0.004)	(0.004)
PCA × Badfirmshare	-0.051***	-0.051***	-0.017***	-0.014***
	(0.018)	(0.019)	(0.005)	(0.005)
PCA	-0.005*	-0.004*	0.001	0.000
	(0.002)	(0.002)	(0.003)	(0.003)
Control variables	No	Yes	No	Yes
Firm × Quarter F.E.	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	Yes	Yes
Observations	407,320	392,787	407,312	392,779
R-squared	0.359	0.361	0.359	0.361

Table A.2: Regression Discontinuity: Firm Performance

This table reports the robust RD results for the difference in firm characteristics between the bank-firm-quarters which marginally breach the PCA threshold versus the bank-firm-quarters which marginally miss the threshold. The coefficients are estimated using the data driven local polynomial based robust inference procedure developed in Calonico et al. (2014). The data are organized at a bank-firm-quarter level for the period 2018-2021. The dependent variable in column 1, 2, 3 and 4 are *Log Sales*, *Profit margin*, *Financial leverage*, and *Current ratio*, respectively. *Log sales* is the natural logarithm of the sales of the firm in a year-quarter. *Profit margin* is the operating profit expressed as a ratio of the total sales of the firm in a year-quarter. *Financial leverage* is the ratio of total debt to total equity of a firm in a year-quarter. *Current ratio* is the ratio of current assets to current liability of a firm in a year-quarter. *Conventional* presents the conventional RD approach estimates using a standard Gaussian distribution assumption. *Bias-corrected* provides the bias-corrected RD estimates, whereas *Robust* presents the robust bias-corrected RD estimates. Standard errors are reported in parentheses. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log Sales	Profit margin	Financial leverage	Current ratio
	(1)	(2)	(3)	(4)
Conventional	-0.138	-0.090	-0.044	1.066
	(0.098)	(0.078)	(0.188)	(1.479)
Bias-corrected	-0.134	-0.060	-0.003	1.469
	(0.098)	(0.078)	(0.188)	(1.479)
Robust	-0.134	-0.060	-0.003	1.469
	(0.120)	(0.093)	(0.223)	(1.739)
Observations	24,431	11,431	11,037	11,431

Table A.3: Second degree polynomial RD and "Donut hole" RD

This table reports the RD results for the difference in default between PCA and non-PCA bank-firm-quarters using a second degree local polynomial in panel A and tests the robustness of RD results to "donut hole" test in panel B. The data are organized at a bank-firm-quarter level for the period 2018-2021. In both panels, the dependent variable *Default* takes a value of 1 for the bank-firm-quarters in which the firm defaults on loan repayments to the bank, 0 otherwise. In panel A, the estimates are reported using a second degree local polynomial function of running variable $PCAscore$. The variable *Treated* is an indicator variable set to one when $PCAscore$ is more than zero, zero otherwise. We use bandwidth of 0.125 in all the columns of both panels. We include firm × time fixed effects in even numbered columns of panel A. In columns 1, 2, 3 and 4 of panel B, we exclude observations that are at a distance of 0.01, 0.015, 0.02, and 0.03 around the cutoff, respectively. The estimates in panel B are reported using a first degree polynomial function of running variable $PCAscore$. We include firm × quarter fixed effects in all the columns of panel B. The standard errors reported in the parentheses are clustered at industry level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively

	Default					
	Panel A		Panel B			
	(1)	(2)	(1)	(2)	(3)	(4)
Treated	-0.033***	-0.079**	-0.056***	-0.057***	-0.055***	-0.055***
	(0.010)	(0.034)	(0.014)	(0.015)	(0.015)	(0.016)
PCAscore	-0.051	0.276	0.203***	0.193***	0.192***	0.192***
	(0.115)	(0.237)	(0.053)	(0.060)	(0.066)	(0.066)
Treated × PCAscore	0.507**	0.952	0.498***	0.540***	0.527***	0.527***
	(0.234)	(0.739)	(0.167)	(0.192)	(0.196)	(0.198)
$PCAscore^2$	-1.119	0.405				
	(0.758)	(1.592)				
Treated × $PCAscore^2$	3.219*	-3.448				
	(1.884)	(5.187)				
Firm × Quarter F.E.	No	Yes	Yes	Yes	Yes	Yes
Observations	73,651	22,702	21,698	20,583	19,966	19,770
R-squared	0.005	0.470	0.473	0.470	0.471	0.471

Table A.4: Pretrends

The table tests the existence of pretrends corresponding to the lending decline at the district level and the evergreening decline at the firm level. In Panel A the data are organized at a district-year level, while in Panel B the data are organized at a firm-year level. In Panel A the dependent variables are natural logarithm of total credit and natural logarithm of agricultural credit in Columns 1 and 2, respectively. In Panel B, the dependent variables are natural logarithm of restructured loan to a firm; an indicator variable that takes a value of 1 if the firm is involved in indirect evergreening; natural logarithm of total related party transactions (RPT) with controlling stakeholders and managers of the firm; and natural logarithm of net RPT outflow to controlling stakeholders and managers of the firm in columns 1, 2, 3, and 4, respectively. The indicator variable, *PCA*, is as defined in Table 3. In Panel A (B), the *PCA exposure* is as defined in Table 8 (9). We identify the districts and firms with the *PCA exposure* with the value of one as treated districts and firms. In Panel A (B), *Pre2, Pre3,* and *Pre4* are one during 2,3, and 4 years before the firm (district) enter the treated state, zero otherwise, respectively. We also include district (firm) and year fixed effects in Panel A (B). In Panel A (B), the standard errors reported in the parentheses are clustered at district (industry) level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: District level		Panel B: Firm level			
	Log total credit	Log agricultural credit	Evergreened loan	Indirect evergreen	Total RPT	Net RPT outflow
	(1)	(2)	(1)	(2)	(3)	(4)
PCA exposure	-0.058***	-0.050**	-0.276**	-0.002**	-0.048**	-0.038**
	(0.015)	(0.021)	(0.139)	(0.001)	(0.019)	(0.017)
Pre4	-0.010	-0.027	-1.109	-0.011	0.082	0.010
	(0.031)	(0.041)	(1.278)	(0.007)	(0.159)	(0.152)
Pre3	-0.015	-0.024	0.195	-0.002	-0.001	-0.032
	(0.026)	(0.034)	(0.268)	(0.002)	(0.033)	(0.026)
Pre2	-0.025	-0.023	0.136	0.002	-0.005	-0.007
	(0.017)	(0.024)	(0.178)	(0.002)	(0.018)	(0.016)
Firm F.E.	No	No	Yes	Yes	Yes	Yes
District F.E.	Yes	Yes	No	No	No	No
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,245	2,245	58,731	58,731	58,721	57,190
R-squared	0.973	0.950	0.364	0.267	0.827	0.841

Table A.5: Improvement in Bank Health

The table shows the changes in bank parameters during the PCA regime. The data are organized at a bank-year level. The dependent variables in column 1, 2, 3, 4, 5, and 6 are CET1, CRAR, NNPA, Leverage, OBS, and NIM, respectively. OBS is the ratio of off-balance-sheet exposure to the total assets of the bank in a year. Other dependent variables are as defined in the text. The variable $Year2021$ is an indicator variable set to one if the year is 2021, and zero if it is 2018. The variable $PCAbank$ is set to one if the bank was placed under PCA in the new regime, and zero otherwise. We include Bank and Year fixed effects. The standard errors reported in the parentheses are clustered at bank level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	CET1	CRAR	NNPA	Leverage	OBS	NIM
	(1)	(2)	(3)	(4)	(5)	(6)
Year2021 × PCA bank	3.042***	1.981*	-8.661***	0.716	-0.169*	0.748**
	(0.898)	(1.120)	(1.541)	(0.472)	(0.100)	-0.322
Bank F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	62	64	64	60	56	48
R-squared	0.905	0.774	0.842	0.948	0.637	0.912

Table A.6: Reversal in Borrower Runs - controlling for AQR

The table shows the impact of PCA regulation on borrower runs using the OLS methodology. The data are organized at a bank-firm-quarter level for the sample period 2018 to 2021. The dependent variable is *Default*, which takes a value of one for the bank-firm-quarters in which the firm defaults on loan repayments to the bank, zero otherwise. The indicator variable PCA and the variable $Badfirmshare$ are as defined in Table 3. The variable *Divergence* is the divergence between the RBI estimated NPA and bank reported NPA during the AQR in the previous year. We include the control variables listed in Table 3 in column 2. We also include firm × quarter and bank fixed effects in all columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default	
	(1)	(2)
PCA × Badfirmshare	-0.051***	-0.048***
	(0.010)	(0.010)
Badfirmshare × Divergence	0.008**	0.013***
	(0.004)	(0.004)
Badfirmshare	0.009***	0.005
	(0.003)	(0.003)
PCA	0.002	0.003
	(0.003)	(0.002)
AQR control	Yes	Yes
Control variables	No	Yes
Firm × Quarter F.E.	Yes	Yes
Bank F.E.	Yes	Yes
Observations	407,320	392,787
R-squared	0.359	0.361

Table A.7: Other RBI Interventions

The table presents the results for association between loan default by borrowers and other regulatory interventions implemented by RBI in India. The data are organized at bank-firm-quarter level. The dependent variable is *Default* as defined in Table 3. In columns 1, 2, and 3 the variable *Post* denotes an indicator variable set to one for years after 2015, 2016, and 2017, respectively. The variable *Badfirmshare* is as defined in Table 3. The observation period is limited to the last year until the intervention was effective or 2017, whichever is earlier. We use the same set of control variables that were used in Table 3. We include firm × quarter and bank fixed effects in all columns. The standard errors reported in the parentheses are clustered at bank level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default		
	2015-2016 SDR scheme	2016-2017 S4A scheme	2018-2019 Feb 12 circular
	(1)	(2)	(3)
Post × Badfirmshare	-0.006	-0.005	0.006
	(0.006)	(0.006)	(0.008)
Badfirmshare	0.002	0.001	-0.007
	(0.003)	(0.005)	(0.005)
Control variables	Yes	Yes	Yes
Firm × Quarter F.E.	Yes	Yes	Yes
Bank F.E.	Yes	Yes	Yes
Observations	198,590	200,022	198,747
R-squared	0.347	0.352	0.356

Table A.8: Tests for Lax reporting of Loan Defaults by PCA Banks

The table shows the association between banks' tendency to report loan defaults and their PCA status. The data are organized at bank-quarter level for the years 2016 to 2021. The dependent variables is *Default proportion*, which is the ratio of loan amount designated as 'default' in the CIBIL database to the non performing asset of the bank in the previous year. The explanatory variable is *PCA admission* which is 1 for the years in which the bank is placed under PCA framework, 0 otherwise. The bank-year-quarter level control variables - NNPA, CET1, ROA, CCAR and Leverage - are included in the even numbered columns. We include bank and quarter fixed effects in all columns. Standard errors are clustered at bank level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default proportion	
	(1)	(2)
PCA admission	-0.006	-0.001
	(0.005)	(0.004)
Controls	No	Yes
Bank F.E.	Yes	Yes
Quarter F.E.	Yes	Yes
Observations	334	290
R-squared	0.347	0.386

Table A.9: Impact of GCB Health on Depositors and Borrowers

The table presents the differences in response of depositors and borrowers towards government controlled banks (GCBs) and non-GCBs, when banks are in trouble. The data are organized at a bank-quarter level for the period 2016-2021. The dependent variable in column 1 (2) is the natural logarithm of the total deposits (total advances) of the bank in the quarter. The variable *Low quality bank* denotes the ratio between NPA and loans and advances of the bank in the previous quarter. *GCB* is an indicator variable set to one for GCBs, and zero for non-GCBs. We use bank and quarter fixed effects in both the columns. Standard errors are clustered at the bank level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log deposits	Log advances
	(1)	(2)
Low quality bank	-0.048**	-0.021**
	(0.022)	(0.009)
GCB × Low quality bank	0.034*	-0.019**
	(0.019)	(0.009)
Bank F.E.	Yes	Yes
Quarter F.E.	Yes	Yes
Observations	773	870
R-squared	0.971	0.973

Table A.10: Reversal in Borrower Runs - OLS for GCBs

The table shows the impact of PCA regulation on borrower runs using the OLS methodology for GCBs. The data are organized at bank-firm-quarter level for a sample period of 2018 to 2021, and is restricted to GCBs. The dependent variable is *Default*, which takes a value of one for the bank-firm-quarters in which the firm defaults on the bank, zero otherwise. The indicator variable PCA takes a value of one in all years after banks go under PCA, zero otherwise. In panel A, the variable $Badfirmshare$ is the one quarter lagged value of the ratio between the bank's outstanding loan owed by firms that were involved in restructuring and the bank's total outstanding loan. In panel B, the variable $Badfirmshare$ is the previous quarter's proportion of banks' outstanding loan owed to firms that are involved in restructuring of loans and have an ICR below 1. In panel C, the variable $Badfirmshare$ is the proportion of banks' outstanding loan owed to firms that have a negative profit. We include the control variables listed in Table 3 in the even numbered columns. We also include firm × quarter and bank fixed effects in all columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default					
	Panel A: Restructuring		Panel B: Restructuring and ICR		Panel C: Profit	
	(1)	(2)	(1)	(2)	(1)	(2)
Badfirmshare	0.018***	0.013***	0.069***	0.072***	0.033***	0.027***
	(0.005)	(0.005)	(0.021)	(0.022)	(0.008)	(0.008)
PCA × Badfirmshare	-0.066***	-0.054***	-0.106***	-0.095***	-0.039***	-0.033***
	(0.013)	(0.012)	(0.027)	(0.027)	(0.008)	(0.009)
PCA	0.001	-0.000	-0.006**	-0.006**	0.006	0.004
	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)	(0.004)
Control variables	No	Yes	No	Yes	No	Yes
Firm × Quarter F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Bank F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Observations	211,301	202,958	211,301	202,958	211,301	202,958
R-squared	0.383	0.386	0.383	0.386	0.383	0.386

Table A.11: Reversal in Borrower Runs - RD for GCBs

This table reports the RD results for the difference in default between PCA and non-PCA bank-firm-quarters. The data are organized at the bank-firm-quarter level for the period 2018-2021. The sample is limited to firms that have banking relations with GCBs only in the year 2017. The dependent variable *Default* is an indicator variable set to one if the firm defaults on a loan to a bank in a year-quarter, zero otherwise. *PCAscore* is the running variable, which is defined in Section 5. Panel A reports the estimated RD coefficients using the data driven local polynomial based robust inference procedure developed in Calonico et al. (2014). Column 1 in panel A reports the estimates for the convention RD approach, which used the standard Gaussian distribution. Column 2 in panel A provides the bias-corrected RD estimates, whereas column 3 in panel A provides robust bias-corrected RD estimates. Panel B reports the RD estimates arrived at using manually selected bandwidths around the cut-off for the first degree polynomial function of the running variable. The variable *Treated* is an indicator variable set to one when PCAscore is more than zero, zero otherwise. Columns 1 and 2 (3 and 4) (5 and 6) in panel B provide the RD estimates for bandwidth of 0.1 (0.125) (0.15) around the PCA cut-off. We include firm × quarter fixed effects in the even numbered columns of panel B. The standard errors reported in the parentheses in panel B are clustered at industry level. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Robust RD			
	Default		
Method:	Conventional	Bias-corrected	Robust
	(1)	(2)	(3)
RD estimate	-0.039***	-0.053***	-0.053***
	(0.018)	(0.018)	(0.019)
Observations	8,418	8,418	8,418

Panel B: RD using manually selected bandwidths						
	Default					
Bandwidth	0.100		0.125		0.150	
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	-0.045***	-0.108***	-0.037***	-0.032	-0.025***	-0.033
	(0.011)	(0.041)	(0.008)	(0.022)	(0.007)	(0.021)
PCAscore	-0.103*	0.360	0.027	0.143	-0.008	0.065
	(0.062)	(0.240)	(0.030)	(0.091)	(0.020)	(0.081)
Treated × PCAscore	1.152***	1.421**	0.748***	0.478	0.616***	0.587**
	(0.174)	(0.586)	(0.107)	(0.303)	(0.088)	(0.271)
Firm × Quarter F.E.	No	Yes	No	Yes	No	Yes
Observations	24,730	3,196	33,739	5,918	37,025	6,997
R-squared	0.004	0.490	0.006	0.477	0.004	0.474

Table A.12: Reversal of Borrower Runs After PCA Exit

The table shows the impact of PCA regulation on strategic defaults using the OLS methodology. The data are organized at bank-firm-quarter level for a sample period of 2018 to 2021. The dependent variable is *Default*, which takes a value of one for the bank-firm-quarters in which the firm defaults on loan repayments to the bank, zero otherwise. The indicator variable, $PCAadmission$, takes a value of one when the bank is under PCA regulation, zero otherwise, while the indicator variable, $PostPCAexit$, takes a value of one after the bank exits PCA regulation, zero otherwise. The variable $Badfirmshare$ is the previous quarter's proportion of banks' outstanding loan owed to firms that are involved in restructuring of loans. We include the control variables listed in Table 3 in the even numbered columns. We also include firm × quarter and bank fixed effects in all columns. The standard errors reported in the parentheses are clustered at industry level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Default	
	(1)	(2)
Badfirmshare	0.010***	0.006*
	(0.003)	(0.003)
PCA admission × Badfirmshare	-0.047***	-0.045***
	(0.011)	(0.010)
Post PCA exit × Badfirmshare	-0.066***	-0.062***
	(0.017)	(0.017)
PCA admission	0.003	0.002
	(0.003)	(0.002)
Post PCA exit	0.002	0.002
	(0.004)	(0.004)
Control variables	No	Yes
Firm × Quarter F.E.	Yes	Yes
Bank F.E.	Yes	Yes
Observations	407,320	392,787
R-squared	0.359	0.361

Table A.13: Other Costs and Benefits: Investments

The table shows impact of PCA regime on investments. The data are organized at firm-year level for a sample period of 2016 to 2021. The dependent variables are natural logarithm of fixed asset investment (*Log gfa*), natural logarithm of addition to property, plant, and equipment (*Log PPE*), and natural logarithm of addition to plants and machinery (*Log plant*) in columns 1, 2, and 3, respectively. The variable $PCAexposure$ is an indicator variable set to one for firms which have higher than median proportion of borrowings from PCA banks in the previous year, zero otherwise. We also include firm and year fixed effects in all columns. The standard errors reported in the parentheses are clustered at bank level and adjusted for heteroskedasticity. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Log gfa	Log PPE	Log plant
	(1)	(2)	(3)
PCA exposure	-0.004	0.000	-0.047
	(0.025)	(0.025)	(0.030)
Firm F.E.	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes
Observations	94,923	94,431	73,880
R-squared	0.631	0.640	0.629