Regulatory Credit Supply Shocks, Reallocation, and Real Economic Outcomes *

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Abstract

We study how regulatory interventions targeting weak banks affect credit allocation and real economic outcomes. Using staggered bank-level exposure to regulatory restrictions and the universe of collateralized corporate loans matched with firm-level financial data, we find that affected banks reduce lending disproportionately to high-risk firms, which subsequently experience persistent declines in sales and investment and are largely unable to substitute toward non-bank financing. In contrast, low-risk firms in exposed industries receive relatively more credit and expand investment and employment. The results are robust to controlling for firm-quarter fixed effects, which help isolate supply-side effects, employing recent advances in DiD estimators with heterogeneous treatment effects, and using an instrumental variables approach that relies on bank regulatory thresholds to predict PCA entry. We further document a decline in output prices in PCA-exposed industries. The price reduction is smaller for low-risk firms, indicating heterogeneous competitive adjustments. These patterns align with the "zombie-congestion mechanism", whereby continued lending to weak firms depresses prices and weakens competitive discipline. Overall, our findings show that regulatory enforcement restricting credit to high-risk firms improves competitive discipline in output markets and is accompanied by modest gains in productivity.

Keywords: Banking Regulation; Bank Clean-Ups; Bank Enforcement Actions; Creative Destruction; Zombie; Aggregate Productivity.

JEL Codes: E58, G21, G23, G28.

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1 Introduction

Undercapitalized banks often continue lending to risky, non-performing firms in order to avoid recognizing losses and incurring higher provisioning requirements. Such behavior leads to persistent credit misallocation, diverting resources away from healthier and more productive firms. Prolonged zombie lending in post-crisis environments is well documented (Caballero et al., 2008; Peek and Rosengren, 2005). However, there is limited causal evidence on which policy interventions are effective in curbing risky lending, and even less evidence on whether such reductions in lending translate into improvements in aggregate economic performance (Acharya et al., 2018; Kulkarni et al., 2019). This paper examines whether regulatory enforcement actions by central banks can mitigate risky lending and improve broader economic outcomes.

We study an early detection and intervention policy, the Prompt Corrective Action (PCA) framework, implemented by the Reserve Bank of India as a regulatory enforcement mechanism aimed at restoring bank health. Under the PCA framework, banks that breach specified thresholds across five accounting and operational indicators are subject to mandatory and, in some cases, discretionary supervisory actions, including restrictions on dividend distributions and branch expansion, heightened provisioning requirements for non-performing assets (NPAs), and constraints on risky lending. During our study period, PCA-admitted banks accounted for nearly 15.6% of total bank lending, implying that the policy affected a substantial share of financial intermediation. Our analysis examines how these regulatory constraints on financially weak banks influenced the supply of credit to firms and whether firms more exposed to the resulting credit supply shocks experienced changes in real economic outcomes. We further assess whether banking-sector reforms facilitated a broader reallocation of credit in the real economy, shifting resources away from high-risk firms toward healthier and more productive ones, and whether such reallocation translated into improvements in aggregate economic outcomes.

We use the universe of collateralized loans from the Ministry of Corporate Affairs (MCA),

Government of India, combined with firm-level financial information of non-financial firms from the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE) over the period 2013–2019. To estimate the effects of PCA, we employ a staggered difference-in-differences (DiD) design that exploits variation in the timing of banks' entry into PCA across quarters.

We find a decline in overall lending by PCA banks following the intervention, with a significant portion of this reduction attributable to decreased lending to high-risk firms (whose Interest Coverage Ratio (ICR) is less than 2). This reduction in lending to high-risk firms is driven by both intensive margin (decreased lending to borrowers who had a substantial prior relationship with the bank) and extensive margin (decreased lending to borrowers who did not have a prior relationship with the bank). These results hold at the creditor level and at the firm-creditor level, where we control for possible demand channels that can influence lending outcomes, thus isolating the supply channel (following Khwaja and Mian, 2008).

Next, we find little evidence that high-risk treated firms, those with prior relationships with PCA banks, are able to substitute lost bank credit with borrowing from non-banks or shadow banks. While low-risk firms with prior exposure to PCA banks exhibit a relatively more favorable credit response, the aggregate effect for low-risk firms is statistically insignificant. High-risk treated firms experience a significant decline in real outcomes, including sales, capital work-in-progress, and net investment in buildings. Consistent with the reallocation of credit from high-risk to low-risk firms, we also observe a reallocation of productive resources across firms. Low-risk firms, particularly in PCA-exposed industries, experience differential increases in net fixed assets, including capital work-in-progress, plant, land, and buildings, as well as higher wage bills, a proxy for employment.

High-risk firms with substantial prior relationships with lenders closely align with the concept of "zombie" firms: insolvent businesses that survive solely through continuous extensions of bank credit. Although our definition of high-risk firms is a somewhat more lenient interpretation of the traditional zombie firm definition, the finding that PCA curtailed lending

even to firms less risky than typical zombies underscores the power of the PCA intervention. Still, we construct a zombie measure closer to the papers in the literature to examine the impact on zombie lending. We classify firms as zombies using two alternative definitions. First, following Chopra et al., 2020, we define zombie firms as those with an interest coverage ratio (ICR) below one after excluding related-party transactions from interest expenses. Second, we define zombies as firms with an ICR below one that also maintain a substantial prior lending relationship with the bank. Using both definitions, we find a statistically significant reduction in zombie lending by PCA banks.

We further find a negative effect on prices in PCA-exposed industries, but the magnitude of the decline is smaller for low-risk firms. Our results align with (Caballero et al. (2008)), who document that zombie firms can congest industries by artificially depressing prices and weakening competitive forces. We show that a regulatory policy such as PCA, by restricting bank credit to high-risk firms, contributes to price adjustments and ultimately promotes greater competitive discipline in the output market.

We employ multiple strategies to address potential endogeneity issues arising from the non-random entry of banks into the PCA. First, we test for parallel trends across PCA and non-PCA lenders using the dynamic two-way fixed effects estimation. Given recent literature highlighting potential issues with the two-way fixed effects estimator (as discussed by Roth et al. (2023)), we also apply the recent estimators addressing these issues (Callaway and Sant'Anna (2021), De Chaisemartin and d'Haultfoeuille (2024), and Sun and Abraham (2021)). We show that PCA and non-PCA lenders have similar trends in lending before PCA, as shown by the pre-treatment coefficients, which are statistically indistinguishable from zero, but have a significant negative effect on lending for high-risk firms in the post-period.

Second, PCA-admitted banks are classified into three tiers based on the severity of threshold breaches, with higher tiers subject to more stringent restrictions and closer supervisory oversight. In our baseline analysis, we define banks admitted to tier-2 and tier-3 as the treatment group, reflecting the greater intensity and enforcement of regulatory intervention in

these categories, while all other banks serve as the control group. Because this control group may comprise a mix of relatively healthy and unhealthy banks, we re-estimate our specifications using a more comparable set of controls. Specifically, we restrict the control group to tier-1 PCA banks, which are subject to relatively mild supervisory actions. The estimated effects of admission into tier-2 and tier-3 remain robust under this alternative specification.

Third, although PCA was intended to be triggered based strictly on threshold breaches, not all unhealthy banks were placed under PCA. We address endogeneity concerns stemming from the selective enforcement of the regime, where some unhealthy banks were subject to PCA while others were not. We create an instrument variable based on the deviation of balance sheet indicators from the thresholds. Each bank was assigned a score based on the deviation score. A positive score indicates a breach of thresholds, and a negative score indicates a healthy bank. We construct a binary variable that takes the value 1 in the first instance of the score turning positive, and takes the value 0 otherwise. We then estimate specifications using this binary variable as an instrumental variable for banks' actual PCA entry. Our results on the negative impact of PCA on high-risk lending, especially to firms with a prior relation, are robust using the IV estimator.

Fourth, while the intent of PCA is primarily corrective, it can also act as a deterrence and incentivise bank management and shareholders to contain risks so they do not end up in PCA in the first place (Acharya (2018)). This implies that banks in control groups might also reduce high-risk lending. Indeed, we also show that non-PCA banks reduced high-risk lending and increased low-risk lending in exposed industries. This suggests a spillover of treatment, which can indicate bias. However, this bias would only make our baseline estimates on the reduction in high-risk credit the lower bound.

Our paper contributes to several strands of the literature. First, we speak to the literature on policies aimed at curtailing risky lending (Acharya et al., 2018; Chopra et al., 2020; Cortés et al., 2020; Kulkarni et al., 2019). While much of this literature focuses on bank clean-up measures such as stress tests and Asset Quality Reviews (AQR), relatively few studies

examine policies centered on early detection and intervention, of which the Prompt Corrective Action (PCA) framework is a prominent example (Aggarwal and Jacques, 1998; Jones and King, 1995; Kashyap et al., 2021).[1] Prior evidence shows that the Federal Deposit Insurance Corporation Improvement Act (FDICIA) in the United States improved bank capitalization and reduced credit risk (Aggarwal and Jacques, 1998; Jones and King, 1995). In related work, Kashyap et al., 2021 examine the 2018 PCA episode in India and document that PCA mitigated strategic defaults by firms in response to deteriorating bank health. We extend this literature by investigating the effects of PCA, an early detection and intervention mechanism, on bank lending, firm-level credit substitution, and real economic outcomes.

Our findings on the reduction in lending to high-risk and zombie firms under PCA are particularly notable when contrasted with the effects of other policy interventions aimed at addressing zombie lending. For instance, Chopra et al., 2020 evaluate the impact of the 2015 Asset Quality Review (AQR) on non-performing asset recognition and zombie lending, and document an increase in zombie lending among exposed banks, which they attribute to the absence of post-AQR recapitalization. Similarly, Kulkarni et al. (2019) find no effect of the introduction of the bankruptcy code on zombie lending. While they document a decline in zombie lending following the February 2012 circular, which required lenders to recognize borrower delinquency at the first instance of non-repayment, this effect does not extend to undercapitalized public sector banks. More broadly, prior to PCA, Reserve Bank of India policies were largely ineffective in improving the balance sheets of undercapitalized public sector banks (PSBs). In contrast, PCA, albeit not explicitly designed to target zombie firms, primarily affected PSBs and successfully curtailed high-risk lending while generating minimal disruption to lending to low-risk firms.

[1]Early detection policies are regulatory frameworks designed to identify and intervene in financially weak institutions at an early stage, before insolvency or large-scale asset impairment occurs, typically through pre-defined supervisory thresholds and mandatory corrective actions. Early detection of bank undercapitalization is important for two reasons. First, undercapitalized banks must offer substantially higher returns to induce equity infusions than better-capitalized banks, exacerbating profitability constraints (Myers (1977)). Second, although government recapitalization is often assumed to occur promptly to mitigate real and systemic risks, in practice fiscal constraints may delay recapitalization (Acharya (2018)).

Second, we contribute to the literature documenting the real effects of credit constraints (Acharya et al., 2015; Campello et al., 2010; Chodorow-Reich, 2014; Ivashina and Scharfstein, 2010).[2] With the exception of Acharya et al. (2015), which examines the European sovereign debt crisis beginning in 2009, much of this literature focuses on credit contractions in the aftermath of the GFC. We depart from these studies by examining the real effects of an early detection and intervention banking reform that curtailed credit supply at a subset of banks, and assessing how such policy-induced credit contractions affect firm-level and aggregate economic outcomes.

Third, in examining real outcomes, we contribute to the literature on zombie congestion, creative destruction, and the misallocation of productive resources (Caballero et al., 2008; Peek and Rosengren, 2005). Our findings on the reallocation of resources from high-risk to low-risk firms are consistent with Caballero et al., 2008, who show that non-zombie firms operating in zombie-exposed industries exhibit lower capital and labor. Following the implementation of PCA, we find that low-risk firms in PCA-exposed industries experience increases in capital and labor. Taken together, these results suggest that banking-sector reforms can facilitate a reallocation of productive resources in the real economy by alleviating zombie congestion.

Fourth, we also contribute to the literature on banking enforcement actions. Financial regulators, across the world, issue enforcement actions against financial institutions that violate regulations or engage in risky practices (An et al., 2024; Delis and Staikouras, 2011; Delis et al., 2017; Kleymenova and Tomy, 2022). PCA is one such enforcement tool. Studies document that enforcement actions improve risk management, internal governance, lending practices, and credit access for minority borrowers.[3] We contribute by showing that such

[2]Campello et al., 2010 show that firms perceived by their CEOs as credit constrained in the aftermath of the Global Financial Crisis (GFC) reduced investment and experienced a rise in stalled projects. Ivashina and Scharfstein, 2010 document a decline in bank lending for real expenditures following the GFC. Chodorow-Reich, 2014 finds that firms with pre-crisis relationships with weaker lenders were less likely to obtain credit after the Lehman collapse, paid higher interest rates when they did borrow, and reduced employment more sharply than firms connected to healthier lenders.

[3]See: An et al., 2024; Balakrishnan and Roychowdhury, 2021; Bertomeu and Cheynel, 2023; Chircop and Novotny-Farkas, 2016; Corona, 2019; Costello et al., 2019; Delis et al., 2017; Ertan et al., 2017; Granja, 2018;

enforcement actions can also help reallocate credit and resources to more productive uses.

Lastly, we contribute to the strand of literature on the rise of shadow banking with tighter banking regulation. Irani et al., 2020 and Lee et al., 2024 examine the impact of tighter capital requirements of banks on shadow banks, channelized through credit substitution by affected firms. In contrast, we find that firms directly connected to PCA banks are not able to substitute with non-bank credit.

The rest of the paper is organized as follows. Section 2 explains the details of PCA and the institutional background, section 3 describes the data, section 4 discusses our empirical strategy and results, section 5 presents the robustness checks, and section 6 concludes.

2 Institutional Background

The case for structured early intervention in the banking system emerged from the savings and loan crises (S&L) in the United States during the mid-1980s. Low levels of bank capitalization led to significant government bailouts in the form of blanket deposit insurance. Taxpayer money was being used to protect the banking system from further damage due to lax regulatory discipline. What emerged from this crisis was the need to adopt a "structured early intervention and resolution" (SEIR) approach leading to the passing of the Federal Deposit Insurance Corporation (FDIC) Improvement Act (FDICIA) in 1991. First, FDICIA contained a provision for the early closure of institutions that were critically undercapitalized. This early closure policy saved the Federal Deposit Fund and by extension the government from lots of losses coming from bailing out failed banks. The second provision of FDICIA, is prompt corrective action (PCA) that involves early intervention in problem banks by regulators. FDICIA legislated mandatory intervention, rather than regulatory discretion, in under-capitalized institutions to save banks from becoming insolvent. Failures declined precipitously in the years following the passage of FDICIA (Aggarwal and Jacques (1998)).

The Reserve Bank of India's (RBI) Prompt Corrective Action (PCA) framework was in-

Granja and Leuz, 2024; Mahieux et al., 2023; Wheeler, 2019

troduced in December 2002 as a structured early intervention mechanism. It was viewed as an "ICU for sick banks". The PCA framework was later reviewed, incorporating recommendations from the Working Group of the Financial Stability and Development Council(FSDC) on Resolution Regimes for Financial Institutions in India. RBI issued the Revised PCA Framework on April 13, 2017.

As per the PCA, the RBI is supposed to initiate structured actions and interventions as banks hit trigger points for certain preset criteria. The older version of PCA (until 2017) had trigger points in terms of CRAR (Capital to Risk Weighted Asset Ratio), Net Non-Performing Assets as a % of Net Advances (NNPA), and Return on Assets (ROA). For each of these criteria, there are breach thresholds that indicate the seriousness of the breach. For example, banks were classified under risk threshold-1 if CRAR was less than 9% but greater than or equal to 6%, under risk threshold-2 if CRAR was less than 6% but greater than or equal to 3%, and under risk threshold-3 if CRAR was less than 3%. The new framework introduced in 2017 improved over the older one on many dimensions. First, recognizing the importance of the common equity capital of a bank in its loss absorption capacity, it introduced the CET-1 ratio in addition to the pre-existing CRAR ratio in measuring banks' capital adequacy. Second, it introduced the leverage ratio (capital by total assets) as an additional criterion.

There is a set of structured and discretionary actions listed by RBI that must be implemented by banks that have triggered the PCA. The actions increase in stringency as the risk threshold progresses. For example, threshold 1 actions include restrictions on dividend distribution, and threshold 2 actions include everything in threshold 1 with an additional restriction on branch expansion. Unlike the pre-2017 framework that emphasized mandatory actions, the revised framework in 2017 increased the scope of discretionary actions. The central bank's mandatory actions post-2017 were limited to restrictions on dividend distribution and remittance of profits, requiring promoters to bring more capital, restrictions on branch expansion and management compensation, and requirements on higher capital pro-

visioning. [4] The banks going into PCA, parameter definitions and the frameworks are in Table 1 Table 2, Table 3 and the restrictions are in Table 4.

The policy had little success in the initial days, primarily because bank balance sheets did not reflect true bank health and painted a better picture than the actual situation. Further, RBI introduced regulatory forbearance after the GFC in 2008, relaxing provisioning requirements on restructured loans. Undercapitalized banks had the incentive to mask a defaulted loan as a restructured one to avoid costly capital provisioning (Chari et al. (2021), Mannil et al. (2024)). Regulatory forbearance was slowly withdrawn in 2013 in a phased manner. Realizing issues in bank balance sheets, a new intervention called the Asset Quality Review (AQR) was set up where appointed auditors evaluated the balance sheets of scheduled commercial banks and checked for the accounting treatment of large loans especially those that were restructured in the regulatory forbearance period (Chopra et al. (2020)). The auditors independently estimated the gross NPAs and banks were required to report all divergence wherever (a) the additional provisioning requirement as per the AQR exercise exceeded 15% of the bank's net profits or (b) additional gross NPAs (GNPA) identified by the auditors exceeded 15% of the incremental gross NPAs for the year. Annual audits were also supposed to be conducted in the subsequent years according to AQR guidelines.

Prior to the AQR, governance and disclosure of banks did not follow a clear standard, making PCA that was an intervention based on bank balance sheets, ineffectual. With AQR in place, balance sheets started showing the true picture and becoming more reliable.

3 Data

Our data comes from three sources. We have web-scraped the universe of loan-level data of collateralized corporate loans from the website of the Ministry of Corporate Affairs(MCA),

[4] Discretionary actions post-2017 were wide-ranging. They included, for example, special supervisory actions like Special Supervisory Monitoring Meetings (SSMMs) at quarterly or other identified frequencies, capital-related actions like restriction on investment in subsidiaries/associates, and credit risk-related actions like strengthening of loan review mechanism.

Government of India (GOI). This data represents the universe of collateralized loans, as every company is required to register the loan charge with the Registrar of Companies (ROC) within a specified period (typically 30 days) after the loan's creation, by submitting designated forms to the ROC. Once the charge is registered with the ROC, the details get uploaded to the Index of Charges maintained by the MCA. The web-scraped MCA data also includes the Corporate Identification Number (CIN), a unique code given to a firm, the date of creation of the loan, the date of modification of the loan if any, the date of satisfaction if the loan has been paid back, name of the Creditor, address of loan disbursal, and the amount of the loan. We do not have information about the terms of the loan like interest rate or tenure. The MCA data has both bank and non-bank creditors. Lenders from MCA, which have not matched to Prowessdx's financial firms super set have been excluded. Table A1 shows that, on average, low-risk firms have 2.62 lenders and high-risk firms have 2.52 lenders. The higher number of average lenders for high-risk compared to low-risk firms is observed for PCA banks and non-banks, but not for non-PCA banks. Table 5 shows that PCA-banks' lending comprises almost 15.6% of the total bank lending in our study period, which indicates that a large proportion of the lending was affected by the policy.

Second, we use data on company financial information from Prowess, published by the Centre for Monitoring Indian Economy(CMIE). Prowess covers both publicly listed and unlisted firms from a variety of industries including manufacturing, services, utilities, and finance. About one-third of the firms in Prowess are publicly listed firms. It contains the universe of publicly listed firms. The companies in Prowess account for more than 70% of India's industrial output, 75% of corporate taxes, and more than 95% of excise taxes collected by the Government of India (Chari et al. (2021)). For analysis, we retain companies with loans between FY2013 and FY 2019. Using the CINs, we merge the MCA loan data with the Prowess database. Our final dataset comprises 14,928 companies. Table 6 reveals some interesting patterns of low-risk and high-risk firms. High-risk and low-risk firms have very similar annual investments in net fixed assets and their components. Yet, annual sales

of high-risk firms is considerably lower(almost half) than those of low-risk firms. This points towards lower capital productivity of high-risk firms.

To compute bank ratios that are relevant for PCA entry, we utilize bank financial information from the Database for Indian Economy (DBIE), publicly available and published by the Reserve Bank of India. We have data for 127 scheduled commercial banks across 4 categories, namely, public sector banks, private banks, foreign banks, and local area banks. We are able to calculate the five ratios relevant for PCA-trigger, namely, CRAR, CET1, NPA, Leverage, and ROA.

4 Empirical Strategy and Results

Our identification strategy relies on the assumption that the treatment and control groups have similar trends before the intervention for which we provide supporting evidence through event studies. The intervention is triggered by the first instance of breach of specific thresholds based on capital adequacy, performance, and asset quality. To the best of our knowledge, there are no other policies that differentially affect our treated and control groups. This makes our identification clean. We conduct robustness checks by altering our control group and find the results to be qualitatively unchanged. We also use Callaway and Sant'Anna (2021) methodology to corroborate our findings.

4.1 Lending Outcomes

4.1.1 Creditor Level

We analyse the impact of the intervention using a staggered difference-in-difference approach which compares outcomes before and after the treatment for treated and the control creditors. First, we organize the data at the bank quarter level and estimate the following two-way fixed effects specification.

$$Y_{ct} = \alpha_c + \gamma_t + \sigma PCA_{ct} + \epsilon_{ct} \tag{1}$$

where the outcome variable Y_{ct} is the amount of credit issued by creditor c in time t. α_c and γ_t are bank and time fixed effects respectively. PCA_{ct} takes value 1 after a bank enters PCA, and 0 otherwise. For our baseline analysis, we consider the breach of threshold 2 and threshold 3 as effective treatment because the policy enforcement was weak for the threshold 1 breach. There were mild structured actions defined for threshold 1 that did not disturb the operations of the bank. Henceforth, unless mentioned otherwise treatment means thresholds 2 and 3. We cluster standard errors at the creditor level to allow for serial correlations within the creditor across time.

The RBI monitors the credit risk of PCA banks which is exacerbated by high-risk lending. Next, we test for lending outcomes across low-risk and high-risk firms. For defining low-risk and high-risk firms, we use a cutoff based on the interest coverage ratio (ICR) obtained from the Prowess database.[5] ICR serves as a measure of the adequacy of a company's profits to meet its interest payments or the comfort with which a company can service its debt. We consider a firm high-risk if its average ICR between 2013 and 2015 is less than 2, and low-risk otherwise. This method is regularly used in the literature to define the safety of firms (McGowan et al. (2017), Banerjee and Hofmann (2018)). We estimate Equation 1 where Y_{ct} is now lending to high-risk and low-risk firms.

Next, we further disaggregate the outcome variable based on whether the firm had a prior relationship with the lender. We define the prior relation between a creditor and the firm based on the number of loans taken by the firm before PCA. If the firm had taken more than one loan between 2013 and the PCA, we define the firm to have a prior relationship with the bank, and no prior relationship otherwise. We estimate Equation 1 again, where Y_{ct} is now lending to high-risk borrowers with prior relationships, high-risk borrowers without prior relationships, low-risk borrowers with prior relationships, and low-risk borrowers without prior relationships.

Results are presented in Table 7. We see a reduction in overall lending by treated banks

[5]We now consider firms that have ICR information in Prowess.

both in terms of the amount loaned out and the number of loans made (column 1 in panels A and B). On disaggregation, we see that high-risk firms experience a reduction in loan amount and number of loans, while low-risk firms see a reduction in new loans with the effect on aggregate amount being statistically insignificant (columns 2 and 3 in panels A and B). There is no statistically significant differential impact of high-risk firms that have a prior relationship with the PCA banks and those that do not (columns 4 to 7, panels A and B).

To test for parallel trends between the treated and untreated banks in the outcome variables, we estimate the following specification

$$Y_{ct} = \alpha_c + \gamma_t + \sum_{r \neq -1} \beta_r 1[D_c = 1] \times 1[t = r] + \epsilon_{ct} \tag{2}$$

where $1[D_b = 1]$ is an indicator variable that takes the value 1 if bank b is treated, and 0 otherwise. $1[t = r]$ is an indicator variable that takes the value 1 if the quarter refers to a particular quarter r. r represents periods (quarters) relative to treatment. Negative values represent pre-treatment periods and positive numbers represent post-treatment periods. We consider 6 quarters before treatment and 6 quarters after treatment. Figure 1 shows dynamic TWFE event-studies for select outcomes. All pre-treatment coefficients are statistically indistinguishable from zero, indicating the absence of pre-trends.

Since the two-way fixed effects estimator could be biased with time-varying treatment groups, we also estimate the recent estimators proposed by Callaway and Sant'Anna, 2021; De Chaisemartin and d'Haultfoeuille, 2024; Sun and Abraham, 2021.[6] In each of the sub-figures in Figure 1, pre-treatment coefficients are insignificant and have 95% confidence intervals coinciding with 0. Thus, we have no grounds to reject our parallel trends hypothesis, implying that lending in PCA banks and non-PCA creditors had similar patterns before treatment.

[6]In line with Roth et al. (2023) and his note on interpreting event study designs of different DID approaches, we have estimated Callaway and Sant'Anna, 2021 with **long2** option, making it perfectly comparable with our dynamic two-way fixed effects specification Equation 2.

4.1.2 Firm-Creditor Level Analysis

Credit reduction could come from demand shocks or supply shocks. Given the rather uneventful macroeconomic conditions in the period 2014 to 2019, credit demand shocks are not likely. Nonetheless, we follow Khwaja and Mian (2008) in spirit to isolate the bank lending channel and to rule out demand shocks. We collapse the loan origination data from the MCA at the firm-creditor level. We estimate

$$Y_{cft} = \alpha_{cf} + \gamma_t + \sigma PCA_{ct} + \epsilon_{cft} \tag{3}$$

where Y_{cft} here refers to credit disbursed or the number of loans issued by bank c to firm f in time t. We control for the time-invariant heterogeneity in the firm-creditor relationship (α_{cf}) which is known to have an impact on lending patterns (Bolton et al., 2016, Agarwal and Hauswald, 2010). We cluster standard errors at the firm-lender level. Next, we estimate the following two regressions:

$$Y_{cft} = \alpha_{cf} + \gamma_t + \sigma PCA_{ct} + \delta HighRisk_f + \beta PCA_{ct} \times HighRisk_f + \epsilon_{cft} \tag{4}$$

$$\begin{aligned} Amount_{cft} = \alpha_{cf} + \gamma_t + \sigma PCA_{ct} + \delta HighRisk_f + \\ \beta PCA_{ct} \times HighRisk_f + \mu Prior_{cf} + \nu HighRisk_f \times Prior_{cf} + \\ \xi PCA_{ct} \times Prior_{cf} + \kappa PCA_{ct} \times Prior_{cf} \times HighRisk + \epsilon_{cft} \end{aligned} \tag{5}$$

Next, in line with Chopra et al. (2020), we control for creditor-level time-invariant heterogeneity and time-variant firm-level differences in the form of creditor fixed effects and firm-quarter fixed and effects respectively and estimate Equation 3, Equation 4 and Equation 5.

Table 8 presents the results. In line with our creditor-level results, the overall treatment effect is negative (column 1, panels A and B). The coefficient of interaction between PCA_{ct}

and $HighRisk_f$ $\hat{\beta}$ is negative and significant, indicating a larger fall in credit, both amount and accounts, to high-risk firms (columns 2 and 5). $\hat{\kappa}$, the coefficient for the triple interaction is also negative (and significant for the total amount outcomes), indicating that high-risk firms having a prior relationship with PCA banks are experiencing a stronger reduction in credit as compared to high-risk firms having no prior relationship. [7]

4.1.3 Additional Endogeneity Checks

Though we have ruled out the presence of pre-trends through our dynamic two-way fixed effects estimations and Callaway and Sant'Anna, 2021, comparing unhealthy banks to the whole set of healthy and unhealthy lenders can be challenging. Further, our result on reduction in overall and high-risk lending could be picking up the effect of Asset Quality Review (AQR) which severely affected weakly capitalized banks with poor asset quality. We can mitigate these concerns by comparing unhealthy banks with unhealthy banks that had stronger PCA intervention. We estimate Equation 3, Equation 4, and Equation 5 using tier-1 PCA as the control group. Having weak banks as the control group would help up establish that the lending reduction is coming only from the PCA intervention. Table 9 presents the results. The coefficient on $PCA_{ct} \times HighRisk_f$ is negative and significant, supporting our baseline results.

The Reserve Bank of India has limited authority over government-owned banks ("Urjit R Patel: Banking regulatory powers should be ownership neutral bis.org" (2018)), which form a large portion of aggregate lending in India. Given this, there have been concerns about the effective enforcement of the policy itself in that, some banks which cross PCA thresholds have not been admitted to PCA. Until now, we used the list of banks that went into PCA as the treatment group, but it is possible that some equally bad banks didn't. This could create endogeneity concerns. To support our baseline results, we use an instrumental variables approach where the probability of a bank entering PCA is used as an instrument

[7]Note that in our baseline specification i.e. Panel A of Table 8, $Prior_{cf}$, $HighRisk_f$ and $HighRisk_f \times Prior_{cf}$ are not estimated because they get absorbed by the firm-creditor fixed effect α_{cf}.

for the actual treatment.

The instrument is constructed in the following way. We create a measure of PCA threshold violation similar to Kashyap et al. (2021). We have 3 criteria from the 2002 mandate and 5 criteria after the revised framework. For each of these criteria, we create a measure of deviation normalized by the mandated threshold value using bank balance sheet data from DBIE. For example, in the case of net NPA where the cutoff for threshold-2 is 9%, the measure of deviation for a bank will be $(Net_NPA_{ct} - 9)/9$. We do the same for CRAR, CET-1, ROA, and Leverage ratio. A positive normalized value implies a violation of the particular threshold. Since the breach of any one of the criteria results in the trigger of penalties, we take the maximum of these deviations to create a score. If the bank's score takes a positive value then the instrument turns from 0 to 1 in periods $t + r$, where r $\geq$ 1, and 0 otherwise. For example, if Allahabad Bank's score is positive based on March 31, 2017 financial information, then it is treated in financial year 2018 and 2019 in our study. We run instrument variable regressions for all the firm-lender Equation 3, Equation 4 and Equation 5, where the instrument is created from the method explained above. Since the quarterly balance sheet data from RBI (DBIE) is available only for scheduled commercial banks, our IV is estimated only for a sample of firms borrowing from banks.

Results of the instrument variable regressions are very similar to our baseline results (Table 10). The first stage is strong with Kleibergen-Paap rk Wald F statistic above 10. The coefficient of the double interaction between PCA_{ct} and $HighRisk_f$ is negative for the amount and accounts (but not significant for accounts) at the firm-lender level. The triple interaction coefficient is negative and significant for the amount. This gives us assurance about the validity of our baseline results.

4.1.4 Discussion

The results on lending reduction to high-risk firms with a prior relationship are striking because they indicate a reduction in zombie lending by PCA banks. Zombies are insolvent

firms kept afloat solely through repeated extensions of bank credit (Kulkarni et al. (2019)). Literature suggests a variety of ways to identify zombies. Caballero et al. (2008) classify firms as zombies only based on whether they receive subsidized credit, abstracting from productivity or profitability. Incidentally, a widely accepted method defines zombies as firms with low interest coverage ratios (Banerjee and Hofmann (2018); McGowan et al. (2017)) which is exactly how we have defined our safety measure. Our intersection of high-risk and prior relation succinctly fits the definition of zombie lending. Absence of interest rate information for each loan in our datasets might add some skepticism because we cannot address the subsidized credit aspect of zombie lending, but RBI forbids banks from lending below the benchmark Base rate which is determined by the ("Reserve Bank of India — rbi.org.in" (2010)).This result is important because it contrasts papers studying other RBI policies. (Chopra et al. (2020)) document that zombie lending actually increased following AQR. Kulkarni et al. (2019) document the reduction in lending to zombies post Feb 12 circular on NPA declaration to be the weakest for under-capitalized public sector banks. Up until now, RBI policies have been unsuccessful in improving the balance sheets of under-capitalized public sector banks (PSBs). PCA, which mostly affected PSBs was successful in reducing zombie lending, without much collateral damage to low-risk lending.

4.1.5 Firm Level Credit Outcomes

A reduction in credit supply from a set of banks could manifest in reduced funding for affected firms, or it could lead to credit substitution using other lines of credit. We now examine if exposed firms experience a change in lending from other lender types, such as non-PCA lenders comprising banks and non-banks.

To examine this, we need to define PCA exposure at the firm level. We define firm-level exposure through firms' prior relationships with the treated creditor. We follow Chodorow-Reich (2014),Acharya et al. (2015) positing that creditor-borrower relationships are sticky. More simply, firms having a prior relationship with treated banks will be more affected than

firms that do not have a lending relationship with a treated bank. We consider a firm to be treated if it has had at least two loans from a bank in the quarter before the bank went into PCA (takes the value 1), and not treated otherwise (takes the value 0). For example, if Firm A has had at least 2 loans from Bank B in the quarter before Bank B went into PCA, and Bank B went into PCA in May 2017, then Firm A is considered treated from May 2017. If there are firms with loans from multiple banks, the firm is considered treated from the quarter when the earlier bank gets into PCA. For example, suppose Firm A has at least two loans each from Bank B and Bank C. If Bank B went into PCA in May 2017 and Bank C in November 2017, we would consider Firm A to be treated from calendar quarter 2 of 2017. We estimate the following specification at the firm-quarter level.

$$Y_{ft} = \alpha_f + \gamma_t + \delta LowRisk_f + \sigma FirmTreatment_{ft} + \beta FirmTreatment_{ft} \times LowRisk_f + \epsilon_{ft} \quad (6)$$

where Y_{ft} represents lending from different types of creditors. α_f are firm fixed effects and γ_t are quarter fixed effects. We will have high-risk firms as the base category for all the specifications hereon. We define the low-risk dummy as $LowRisk = 1 - HighRisk$. Standard errors are clustered at the firm level.

Results presented in panel A of Table 11 indicate a statistically significant decline in credit to firms having a higher exposure to PCA banks through prior relation with these banks (column 1). The decline is largely driven by PCA banks, non-PCA lenders, particularly non-PCA banks. Lending effects from other categories are statistically indistinguishable from zero (columns 5 and 6). The coefficient of interaction of firm treatment and the low-risk dummy is positive, implying that the reduction in credit is much larger for high-risk firms compared to low-risk firms having a prior relation with PCA banks.[8]

Next, we define an industry-level exposure measure to PCA. A 3-digit level industry

[8]Firms may also be seeking funds elsewhere other than the formal financing system. We examine this by estimating the impact on Related Party Transactions (RPT). Results show that there are no changes in related party receipts. These results are not reported in the paper but will be available upon request. However, the results on RPT should be viewed with caution because Prowessdx data on RPT is particularly sparse.

(based on the National Industrial Classification (NIC)) is considered exposed if an industry has more than the median share of exposed firms (takes the value 1), and considered untreated otherwise (takes the value 0). An exposed industry is treated when the first firm in the industry is treated through the treatment explained earlier, and not treated otherwise. We estimate

$$Y_{ft} = \alpha_f + \gamma_t + \delta LowRisk_f + \sigma IndustryTreatment_{ft} + \beta IndustryTreatment_{ft} \times LowRisk_f + \epsilon_{ft} \quad (7)$$

From Panel B of Table 11, it is evident that PCA banks are reducing credit to high-risk firms in exposed industries even if the individual firm doesn't have a prior relationship with PCA banks (columns 1 and 2). Moreover, high-risk firms are unable to obtain more credit from non-banks, particularly NBFCs (columns 5 and 6). This contrasts Irani et al., 2020 and Lee et al., 2024 who document a rise of the shadow banking sector post the tightening of banking regulation due to the global financial crises (GFC) in 2008, in the form of BASEL III guidelines. The coefficient on the interaction of industry treatment and low-risk is positive, indicating that low-risk firms in an exposed industry are getting a credit boost from PCA and non-PCA lenders (columns 2 and 3). Broadly, there is a reallocation of credit from high-risk to low-risk firms. In light of this reallocation, it is essential to examine the real outcomes for firms affected by PCA and, more significantly, for industries exposed to PCA.

4.2 Real Outcomes

4.2.1 Firm-Level

Next, we document the impact of the treatment on firm-level real outcomes. We use a specification similar to Equation 6, but at the annual level rather than the quarter level because firm-level real variables are better reported by Prowess at the annual level. The firm treatment variable is defined at the year level. We use year-fixed effects instead of quarter-

fixed effects and log transform the outcomes variables. Standard errors are clustered at the firm level.

The results from the estimation are presented in Panel A of Table 12. We see a 18% decline in sales of high-risk treated firms (column 1), a 10% decline in net fixed assets [9] (column 2), a 31% decline in capital work-in-progress (column 3), a 15% decline in the net value of plant and machinery (column 4), and about a 12% decline in salaries (column 5) and the net value of both land (column 6) and buildings (column 7). For plants, salaries, land and buildings, the coefficient of interaction $\hat{\beta}$ is positive and significant, and higher than the effect for high-risk firms, showing that there is a positive impact of the treatment on low-risk firms in these categories.

Using Equation 9, we now document the impact of PCA on firms belonging to an exposed industry. Panel B of Table 12 presents the results. We see that an high-risk firm belonging to a high-exposure industry experiences a decline in sales and various categories of capital. The coefficient of interaction here $\hat{\beta}$ is positive and significant and almost always $\geq$ the magnitude of the base category coefficient, which shows that low-risk firms in an exposed industry experience a differential increase in real outcomes. These results speak to the creative destruction literature (Caballero et al. (2008)) that refers to the adverse effects of zombie firms' congestion in an industry on the real outcomes of non-zombie firms in the industry. This happens because of excessive credit supply to high-risk firms before PCA which choked the credit supply to low-risk firms. As seen in Table 11, low-risk firms in PCA-exposed industries are receiving more credit (which is coming from the credit denied to high-risk firms) post-treatment, and are hence able to increase productive investment and sales. PCA has successfully reduced the congestion in exposed industries and allowed a reallocation of productive resources from high-risk to low-risk firms. While these results

[9] Net fixed assets is the net value of the fixed assets of a company after adjusting for additions/(deductions) to gross fixed assets and the cumulative depreciation on gross fixed assets. It is derived as the sum of net intangible assets, net land and buildings, net plant & machinery, computers and electrical installations, net transport & communication equipment and infrastructure, net furniture, social amenities, and other fixed assets, and net lease adjustment reserves. Arrears of depreciation and provisions for impairment are deducted from the above.

are consistent with prior studies that find a reduction in capital expenditure of zombie firms after regulatory forbearance was withdrawn (Chari et al., 2021) and after the February 12th circular (Kulkarni et al., 2019), to the best of our knowledge, ours is the first study to document a reallocation of productive resources from high-risk to low-risk firms after a bank clean up.[10]

4.2.2 Industry Level

Next, we examine if credit and resource reallocation to low-risk firms in treated industries improved productivity in these industries. We construct three measures of productivity. The first measure is aggregate labour productivity, defined by the ratio of aggregate net sales at the industry level to aggregate labour costs aggregated at the industry level. The second is capital productivity defined by the ratio of net sales to net fixed assets at the industry level. The third measure is total factor productivity (TFP) based on Ackerberg et al. (2015).[11]. We assume a Translog production function and estimate TFP at the firm level. We then take simple mean of the exponents of these firm-level productivity measures at the industry level. [12] We estimate the following equation:

$$Y_{it} = \alpha_i + \gamma_t + \beta IndustryTreatment_{it} + \epsilon_{it} \tag{8}$$

where Y_{it} refers to productivity. α_i are industry fixed effects, and γ_t are year fixed effects. Standard errors are clustered at the 3-digit NIC 2008 level. We also estimate a variant of this equation by adding industry-specific time trends. Table 13 shows that industry-level measures of productivity are rising. Column 1 shows a rise in labour productivity, but the results are weaker in column 2 after adding industry time trends. Columns 3 and 4 are

[10]Chopra et al., 2020 also document a fall in investments of firms that had high exposure to AQR, but they do not examine outcomes separately for Zombie firms.

[11]Ackerberg et al. (2015) extend the productivity estimation literature by improving the identification concerns in Olley and Pakes (1996) and Levinsohn and Petrin (2003)

[12]In line with Bartelsman et al. (2013), while aggregating firm-level real outcomes at the industry level, we also take weighted aggregates, where weights come from the share of sales of a firm in its industry **??**

positive but statistically indistinguishable from 0. Columns 5 and 6 show a positive impact on average TFP. Thus, the results from Panel B in Table 12 feed into the aggregate industry outcomes. Higher credit and capital investment in low-risk firms post-treatment resulted in higher productivity in exposed industries.

We also examine the impact of PCA on firm–product prices in treated industries. The Prowess database provides detailed product-level information for each firm, including the quantity sold and the value of sales for each reported product. We use these variables to construct firm–product-level prices. We estimate the following specification:

$$P_{pft} = \lambda_p + \alpha_f + \gamma_t + \delta LowRisk_f + \sigma IndustryTreatment_{ft} + \beta IndustryTreatment_{ft} \times LowRisk_f + \epsilon_{pft} \quad (9)$$

where P_{pft} refers to the firm-product level prices and. λ_p are product fixed effects, α_f are firm fixed effects and γ_t are year fixed effects. Standard errors are clustered at the firm level. Table 14 reports the results. We find that the overall effect of industry treatment is negative, but the magnitude of the decline is smaller for low-risk firms. Our results align with (Caballero et al. (2008)), who document that zombie firms can congest industries by artificially depressing prices and weakening competitive forces. We show that a regulatory policy such as PCA, by restricting bank credit to high-risk firms, contributes to price adjustments and ultimately promotes greater competitive discipline in the market.

4.3 Bank Behaviour

While the intent of PCA is primarily remedial, it can also act as a deterrence and incentivize bank management and shareholders to contain risks so they do not end up in PCA in the first place. (Acharya (2018)). We mentioned in the beginning of section 4 that we consider only risk thresholds 2 and 3 as treatment because restrictions on threshold 1 banks were mild and did not pertain to operations. To test whether PCA deters banks from lending to

risky borrowers, we estimate Equation 3, Equation 4 & Equation 5 using only threshold-1 banks as the treatment group, and excluding threshold 2 and 3 banks from the sample. Any reduction in lending from threshold-1 banks can be attributed to their fear of moving beyond thresholds 2 or 3 where they will be subject to more restrictions. The results are presented in **??**. We see a significant reduction in lending post-PCA, particularly towards high-risk firms and high-risk firms with a prior relation. This gives credence to the deterrence channel. [13]

We test for the bank-level balance sheet variables on capital, asset quality and profitability, to check if these measures improve for treated banks post-PCA. Our outcomes of interest are CRAR, RWA, Net NPAs, Restructured assets and ROA.

$$Y_{ct} = \alpha_c + \gamma_t + \beta PCA_{ct} + \epsilon_{ct} \tag{10}$$

Where Y_{ct} stands for a balance sheet outcome of bank b in quarter t. α_c represents bank fixed effects, and γ_t is quarter fixed effects. $Treatment_{ct}$ takes the value 1 in the calendar quarter when the bank gets treated and thereon, and is 0 otherwise. We have excluded foreign bank groups and local area banks from our sample, leaving only public and private sector banks. All our variables pertain only to domestic operations. Table 16 presents the results. There is a reduction in total (Panel A column 2) and tier one capital (Panel A column 4) with an increase in provisioning for NPAs (Panel B column 4). Writing off NPAs due to the provisioning has led to a reduction in NPAs. A strong decline in risk-weighted assets of the treated banks implies a reduction in risk in the bank's balance sheet. There is no change in share capital (Panel A column 6) of treated banks which indicates that capital going into higher provisions is not being replenished. There is an increase in profit margin (Panel C column 3), profit before (Panel C column 4), and after-tax (Panel C column 5). The results point towards a clean-up in the bank balance sheets.

[13] Notably, the magnitude of reduction in high-risk lending for threshold 1 banks is lower than threshold 2 and 3 seen in Table 7.

5 Robustness Checks

There exist a variety of definitions for zombies. We follow Chopra et al., 2020 by calculating the interest coverage ratio after excluding related party transactions. We define one zombie as a firm with the average interest cover (excluding RPT) between 2013-2015 to be less than 1 (Zombie1). Our second measure is $Zombie1 \times Prior$. In Table A2 we see that the coefficient of double interaction for both amount and number of loans is negative and significant, showing a reduction in zombie lending and corroborating our results in Table 8.

We have estimated the impact on the number of loans using linear regressions in all our creditor-level regressions. However since the number of loans is a count variable, we show robustness to our results using Poisson regressions for all specifications where the number of loans is an outcome.[14]

Next, we estimate our creditor and firm-creditor level regressions at the year level instead of the quarter level. We estimate Equation 1 and Equation 3 at the year level. If a bank is treated in May 2017, we consider it to be treated in the financial year 2017-2018 and onwards. Table A3 shows the results (columns (1), (2), (5), and 6). The overall reduction in lending for PCA banks is consistent with our baseline results at the quarter level. We also consider treatment only after the revised PCA framework and allow treatment to start from the financial year 2017-2018. Columns (3), (4), (7) and (8) present the results. We see the same pattern of reduction in overall lending across all columns.

6 Conclusion

Most bank clean-up measures like the Asset Quality Review or the Feb 12, 2018 circular revolve around the declaration of bad assets. They have the consequence of higher provisioning requirements leading to capital depletion. These unintentional negative consequences alter bank incentives, precluding them from taking the high road in the spirit of the clean-up

[14]These results are not presented in the paper but are available upon request.

(Chopra et al., 2020). This is where Prompt Corrective Action is different because it is a structured early intervention and resolution mechanism. It doesn't alter bank balance sheets, it only monitors them and helps reduce risk. While we do not undermine the importance of other clean-up measures because they were instrumental in revealing the true health of the bank, they couldn't eliminate the perverse incentives of undercapitalized banks to give more risky loans. PCA on the other hand was able to reduce lending to high-risk firms without much collateral damage to low-risk firms. Low-risk firms were able to substitute their marginal reduction in credit from PCA banks through increased credit from non-PCA banks. The credit reallocation from high-risk to low-risk firms in exposed industries translates to real outcomes too. Post PCA, low-risk firms in exposed industries increase their net fixed assets and salaries. This further translates to higher aggregate industrial productivity.

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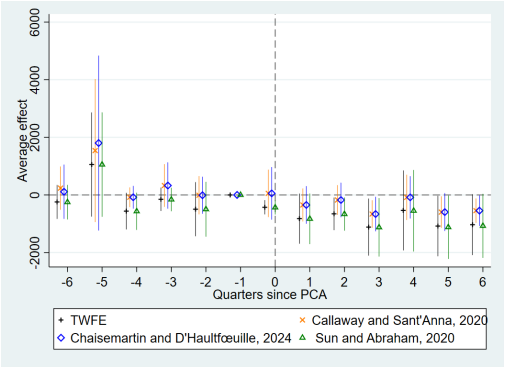
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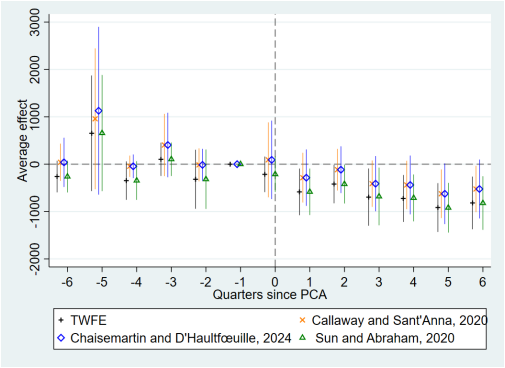
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Figure 1: Creditor Level Event-studies using Dynamic TWFE

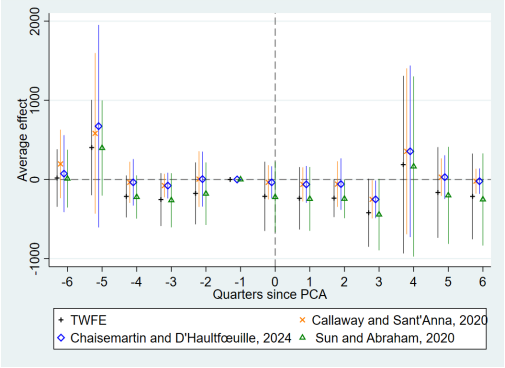
(a) Overall Amount



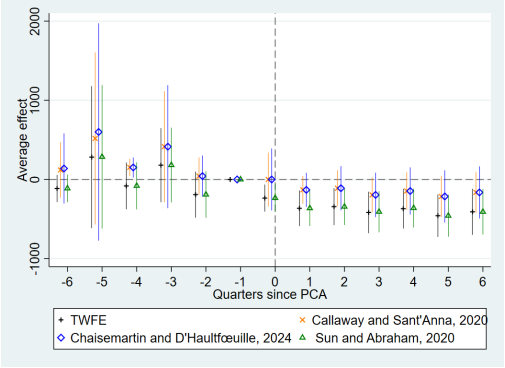
(b) High-Risk Amount



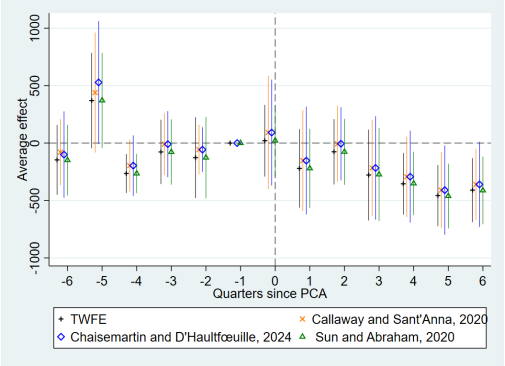
(c) Low-Risk Amount



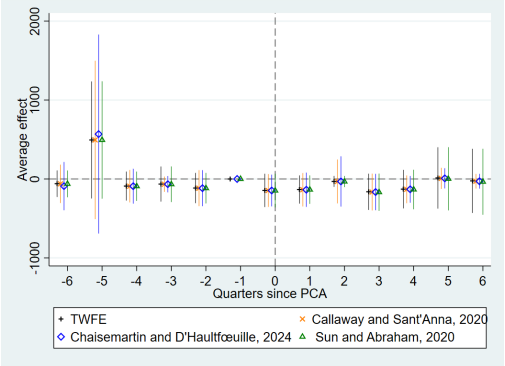
(d) High-Risk Prior Amount



(e) High-Risk No-Prior Amount



(f) Low-Risk Prior Amount



(g) Low-Risk No-Prior Amount

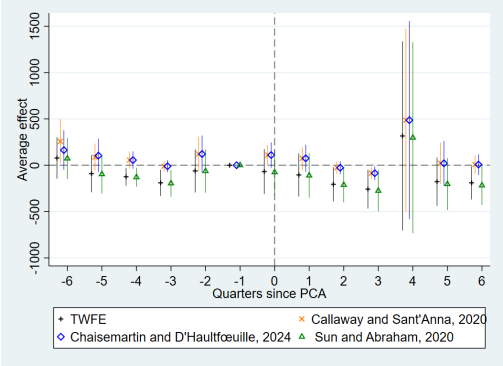
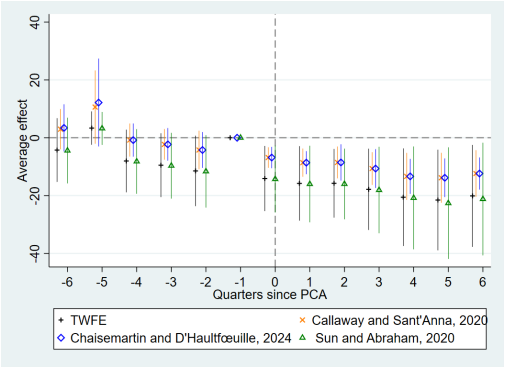
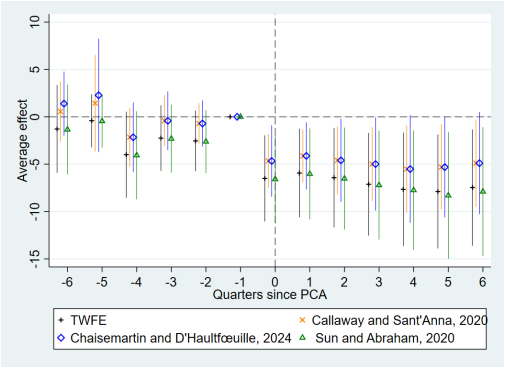


Figure 2: Creditor Level Event-studies using Dynamic TWFE

(a) Overall Accounts

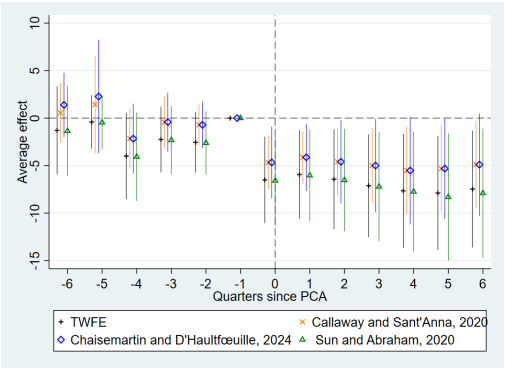


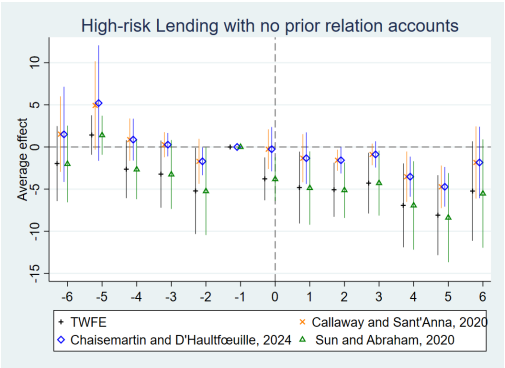
(b) High-Risk Accounts



(c) High-Risk Prior Accounts

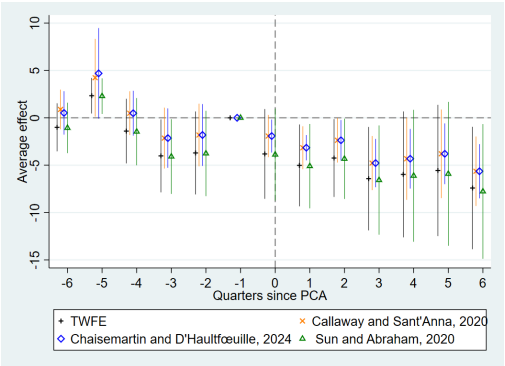
(d) High-Risk No-Prior Accounts

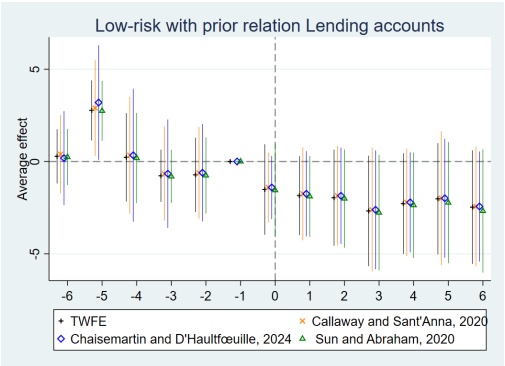




(e) Low-Risk Accounts

(f) Low-Risk Prior Accounts





(g) Low-Risk No-Prior Accounts

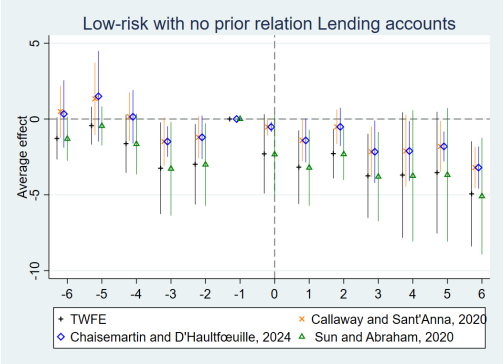


Table 1: List of Banks in PCA

Bank	Date of Entry	Threshold
Indian Overseas Bank	Oct 2015	II
Dhanlaxmi Bank	Nov 2015	II
IDBI Bank	May 2017	III
UCO Bank	May 2017	II
Central Bank of India	June 2017	II
Bank of Maharashtra	June 2017	II
Oriental Bank of Commerce	Oct 2017	I
United Bank of India	Dec 2017	II
Corporation Bank	Dec 2017	I
Bank of India	Dec 2017	I
Allahabad Bank	Jan 2018	I
Dena Bank	May 2018	II

Table 2: Parameter Definitions

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 non-performing assets (non-performing assets 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 3: Thresholds of Revised PCA

Year	**Tier Level**	**CRAR**	**CET1**	**NNPA**[15]	**Leverage**[16]	**ROA**
March 31, 2017	I	<10.25%	<6.75%	$\geq$ 6%	$\leq$ 4%	Negative for 2 years
	II	<7.75%	<5.125%	$\geq$ 9%	<3.5%	Negative for 3 years
	III	<6.25%	<3.625%	$\geq$ 12%	<3.5%	Negative for 4 years
March 31, 2018	I	<10.875%	<7.375%	$\geq$ 6%	$\leq$ 4%	Negative for 2 years
	II	<8.375%	<5.75%	$\geq$ 9%	<3.5%	Negative for 3 years
	III	<6.875%	<4.25%	$\geq$ 12%	<3.5%	Negative for 4 years
March 31, 2019	I	<11.5%	<8%	$\geq$ 6%	$\leq$ 4%	Negative for 2 years
	II	<9%	<6.375%	$\geq$ 9%	<3.5%	Negative of 3 years
	III	<8%	<4.875%	$\geq$ 12%	<3.5%	Negative for 4 years

Table 4: Mandatory and Discretionary Actions of Revised PCA

Specifications	**Risk Threshold I**	**Risk Threshold II**	**Risk Threshold III**
Mandatory Actions	• Restriction on dividend distribution/remittance of profits. • Promoters/owners/parent in the case of foreign banks to bring in capital.	• In addition to mandatory actions of Threshold 1, • Restriction on branch expansion; domestic and/or overseas. • Higher provisions as part of the coverage regime.	• In addition to mandatory actions of Threshold 1, • Restriction on branch expansion; domestic and/or overseas. • Restriction on management compensation and directors' fees, as applicable.
Discretionary Actions	• Special Supervisory Interactions • Strategy related • Governance related • Capital related • Credit risk related • Market risk related • HR related • Profitability related • Operations related • Any other		

Table 5: Lending Share by Banks and non-Banks

Type	Lending Share	
	Q4 FY2015	Q4 FY 2019
Banks	38.32%	37.65%
PCA Banks	*15.6%*	*3.13%*
Non-PCA Bank	*84.40%*	*96.87%*
Non-banks	61.68%	62.35%

Note: Data are sourced from the Ministry of Corporate Affairs(MCA).

Table 6: Summary Statistics across Firm Types

Firm-Type	Low-Risk Firm			High-Risk Firm		
	Mean	Median	N	Mean	Median	N
Net Sales	7667.99	1020.5	30,780	3991.96	447.1	46,227
Net Fixed Assets	3166.36	167.4	30,780	3009.845	123.2	46,227
Capital WIP	733.7	0	30,780	676.7	0	46,227
Net Plant	1845.85	33.7	30,780	1713.67	21.9	46,227
Salaries	458.8938	61.5	30,780	211.2649	21.6	46,227
Net Land	226.8651	6.7	30,780	295.2515	3.3	46,227
Net Building	385.1356	24.8	30,780	357.6835	12.5	46,227

Table 7: Impact of PCA on Lending Outcomes using Creditor Data

Panel A: Two-Way Fixed Effects (Amount)							
	Overall	High-Risk	Low-Risk	High-Risk		Low-Risk	
				Prior	No-Prior	Prior	No-Prior
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PCA	-846.5**	-619.0***	-213.0	-214.7	-246.1**	-7.920	-131.7
	(390.4)	(226.8)	(192.3)	(169.6)	(99.42)	(119.1)	(85.22)
Observations	8,320	7,640	5,920	3,540	7,440	2,780	5,760
R-squared	0.839	0.818	0.778	0.694	0.744	0.677	0.667
Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B :Two-Way Fixed Effects (Accounts)							
	Overall	High-Risk	Low-Risk	High-Risk		Low-Risk	
				Prior	No-Prior	Prior	No-Prior
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
PCA	-16.94***	-11.66***	-5.277**	-4.958**	-5.092***	-0.512	-3.387***
	(5.688)	(3.672)	(2.191)	(2.412)	(1.418)	(1.347)	(1.089)
Observations	8,320	7,640	5,920	3,540	7,440	2,780	5,760
R-squared	0.938	0.898	0.933	0.783	0.808	0.851	0.799
Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes the impact of PCA on creditor-quarter level outcomes disaggregated by safety (which is defined using interest coverage ratio) and prior relationship (which is defined using the number of loans before PCA). Standard errors are clustered at the creditor level. The data on amount and accounts are sourced from the Ministry of Corporate Affairs (MCA). The data on safety are from CMIE's ProwessDx. Years between financial years 2012-2013 and 2018-2019. The amounts are in crores of Rupees and all variables are winsorized at 2%.

Table 8: Impact of PCA on Lending Outcomes using Firm-Creditor Data

Panel A						
	Amount			Number of Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
PCA × High-Risk × Prior			-3.941*			-0.0106
			(2.395)			(0.0100)
PCA × Prior			-4.330**			-0.102***
			(2.169)			(0.00896)
PCA × High-Risk		-1.341**	-0.406		-0.00480	-0.00169
		(0.634)	(0.434)		(0.00406)	(0.00385)
PCA	-2.006***	-1.051*	-0.0835	-0.0517***	-0.0483***	-0.0255***
	(0.327)	(0.583)	(0.395)	(0.00249)	(0.00390)	(0.00372)
Observations	858,792	858,792	858,792	858,792	858,792	858,792
R-squared	0.135	0.135	0.135	0.202	0.202	0.203
Firm-Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B						
	Amount			Number of Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
PCA × High-Risk × Prior			-8.011**			0.0131
			(3.164)			(0.0199)
PCA × Prior			-2.712			-0.118***
			(3.533)			(0.0218)
High-Risk × Prior			5.185***			-0.0284**
			(1.238)			(0.0122)
Prior			6.740***			0.156***
			(1.914)			(0.0178)
PCA × High-Risk		-2.015	0.484		-0.00266	-0.00391
		(1.421)	(1.247)		(0.00557)	(0.00848)
PCA	-1.226	0.134	0.651	-0.0472***	-0.0454***	-0.0158*
	(1.148)	(1.380)	(1.272)	(0.00630)	(0.00723)	(0.00874)
Observations	702,648	702,648	702,648	702,648	702,648	702,648
R-squared	0.250	0.250	0.253	0.297	0.297	0.305
Firm-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes the impact of PCA on firm-creditor-quarter level outcomes. In Panel A standard errors are clustered at the firm-creditor level and in Panel B at the creditor level. The data on amounts and accounts are sourced from MCA. The data on safety are from CMIE's ProwessDx. The periods covered are from the financial year 2012-2013 to 2018-2019. All amounts are in crores of Rupees and all variables are winsorized at 2%.

Table 9: Impact of PCA on Credit outcomes at Firm-Creditor level using Tier-1 control

	Amount			Number of Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
PCA × High-Risk × Prior			-3.913			-0.0105
			(2.400)			(0.0100)
PCA × Prior			-4.313**			-0.102***
			(2.174)			(0.00896)
PCA × High-Risk		-1.330**	-0.403		-0.00477	-0.00168
		(0.635)	(0.434)		(0.00406)	(0.00385)
PCA	-0.225	0.725	1.706***	0.00226	0.00567	0.0287***
	(0.466)	(0.688)	(0.518)	(0.00313)	(0.00436)	(0.00415)
Observations	115,656	115,656	115,656	115,656	115,656	115,656
R-squared	0.067	0.067	0.068	0.057	0.057	0.061
Firm-Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. Standard errors are clustered at the firm-creditor level. The data on amount and accounts are sourced from MCA. The data on safety are from ProwessDx. Periods covered are from financial year 2012-2013 to 2018-2019. All amounts are in crores of Rupees and all variables are winsorized at 2%.

Table 10: Instrument Variable Regression at Firm-Creditor level data

	Amount			Number of Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
PCA × High-Risk × Prior			-1.353			-0.0175
			(2.920)			(0.0194)
PCA × Prior			-14.06***			-0.216***
			(2.610)			(0.0165)
PCA × High-Risk		-1.863**	-1.492*		-0.00445	0.000502
		(0.894)	(0.819)		(0.00592)	(0.00536)
PCA	-3.615***	-2.337***	0.668	-0.0866***	-0.0836***	-0.0375***
	(0.414)	(0.793)	(0.738)	(0.00476)	(0.00640)	(0.00599)
Observations	607,191	607,191	607,191	607,191	607,191	607,191
F-stat	11743.19	1961.59	1031.14	11743.19	1961.59	1031.14
Firm-Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes an instrument variable regression following 2SLS at the firm-creditor-quarter level. Standard errors are clustered at the firm-creditor level. Data on bank financials is from DBIE. The data on amount and accounts are sourced from MCA. Periods covered are from financial year 2013-2014 to 2018-2019. The amounts are in crores of Rupees and all variables are winsorized at 2%.

Table 11: Impact of PCA on Credit Substitution using Firm-Level Data

Panel A	Total	PCA-Bank	Non-PCA	Non-PCA Bank	Non-Bank	NBFC
	(1)	(2)	(3)	(4)	(5)	(6)
Firm Treatment	-41.58***	-18.88***	-22.70***	-17.38***	-5.323	-0.121
	(9.580)	(3.135)	(7.422)	(6.405)	(3.642)	(0.159)
Firm Treatment × Low-Risk	27.66**	9.408**	18.25**	12.36*	5.891	0.0551
	(11.36)	(4.402)	(8.585)	(7.025)	(4.607)	(0.255)
Observations	335,184	335,184	335,184	335,184	335,184	335,184
R-squared	0.249	0.120	0.241	0.162	0.219	0.090
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B	Total	PCA-Bank	Non-PCA	Non-PCA Bank	Non-Bank	NBFC
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Treatment	-1.454	-0.816***	-0.639	-1.696**	1.058	0.0443
	(1.183)	(0.232)	(1.122)	(0.700)	(0.846)	(0.0513)
Industry Treatment × Low-Risk	5.075***	1.144***	3.931***	3.045***	0.886	0.0475
	(1.241)	(0.271)	(1.151)	(0.649)	(0.907)	(0.0524)
Observations	335,184	335,184	335,184	335,184	335,184	335,184
R-squared	0.249	0.117	0.240	0.162	0.219	0.090
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes the impact of PCA on firm-level credit substitution. The data is at the firm-quarter level. Standard errors are clustered at the firm-level. The data on credit is sourced from MCA and the data on safety are from ProwessDx. Periods covered are from financial year 2012-2013 to 2018-2019. The Amounts are in crores of Rupees and all variables are winsorized at 2%.

Table 12: Impact of PCA on Real Outcomes

Panel A	l(Net Sales)	l(Net Fixed Assets)	l(Cap- WIP)	l(Net Plant)	l(Salaries)	l(Net Land)	l(Net Building)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Firm Treatment	-0.179***	-0.101**	-0.312***	-0.151***	-0.122***	-0.115**	-0.132***
	(0.0538)	(0.0462)	(0.105)	(0.0573)	(0.0427)	(0.0585)	(0.0449)
Firm Treatment × Low-Risk	0.137	0.212***	0.333	0.201**	0.119*	0.207*	0.213***
	(0.0948)	(0.0715)	(0.257)	(0.0884)	(0.0630)	(0.106)	(0.0806)
Observations	70,972	72,860	31,715	58,189	70,535	48,595	53,640
R-squared	0.908	0.927	0.782	0.946	0.938	0.933	0.946
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B	l(Net Sales)	l(Net Fixed Assets)	l(Cap- WIP)	l(Net Plant)	l(Salaries)	l(Net Land)	l(Net Building)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Industry Treatment	-0.0671***	-0.118***	-0.223***	-0.0697***	-0.0717***	-0.0723***	-0.0678***
	(0.0163)	(0.0174)	(0.0426)	(0.0181)	(0.0124)	(0.0172)	(0.0147)
Industry Treatment × Low-Risk	0.0498***	0.143***	0.356***	0.138***	0.0878***	0.118***	0.130***
	(0.0190)	(0.0212)	(0.0502)	(0.0213)	(0.0152)	(0.0235)	(0.0188)
Observations	70,772	72,625	31,566	57,991	70,346	48,418	53,462
R-squared	0.909	0.928	0.783	0.946	0.938	0.934	0.946
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes the impact of PCA on firm-level real outcomes. The data is at the firm-year level. Standard errors are clustered at the firm-level. The periods covered are from the financial year 2012-2013 to 2018-2019. All data are sourced from ProwessDx. We have taken natural logs of all variables.

Table 13: Impact of PCA on Industrial Productivity

	Labour Productivity $\frac{Y}{L}$		Capital Productivity $\frac{Y}{K}$		Total Factor Productivity Ackerberg et al. (2015)	
	(1)	(2)	(3)	(4)	(5)	(6)
Industry Treatment	2.389**	0.806	0.787	0.322	4.305	7.628*
	(1.034)	(0.906)	(0.550)	(0.748)	(3.806)	(3.993)
Observations	1,118	1,118	1,127	1,127	1,310	1,310
R-squared	0.954	0.987	0.862	0.907	0.798	0.874
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry*Year Trend	No	Yes	No	Yes	No	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes the impact of PCA on aggregate industrial productivity. The data is at the industry-year level. Standard errors are clustered at NIC-3 digit level. Periods covered are from the financial year 2012-2013 to 2018-2019.All data are sourced from ProwessDx.

Table 14: Impact of PCA on Firm-Product Prices

	(1) log(price)	(2) log(price)	(3) log(price)	(4) log(price)	(5) log(price)	(6) log(price)	(7) log(price)	(8) log(price)
Industry Treatment	-0.0609**	-0.0909***	-0.138***	-0.128***	-0.0466*	-0.0758***	-0.0347	-0.0649**
	(0.0266)	(0.0289)	(0.0337)	(0.0355)	(0.0261)	(0.0284)	(0.0253)	(0.0275)
Industry Treatment × Low Risk		0.0694**		-0.0260		0.0674**		0.0694**
		(0.0319)		(0.0329)		(0.0316)		(0.0312)
Firm FE	Yes	Yes	No	No	Yes	Yes	No	No
Product FE	No	No	Yes	Yes	Yes	Yes	No	No
Firm-Product	No	No	No	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	298083	298083	293308	293308	293141	293141	282967	282967
R-squared	0.669	0.669	0.329	0.329	0.702	0.702	0.730	0.730

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes impact of PCA on Firm-Product Prices. The data is at the industry-year level. Standard errors are clustered at firm-level. Periods covered are from financial year 2012-2013 to 2018-2019. All data are sourced from ProwessDx.

Table 15: Impact of PCA on Lending Outcomes at Firm-Creditor Level Data and Tier-1 Banks as Treatment

	Overall	High-Risk	Low-Risk	High-Risk		Low-Risk	
				Prior	No-Prior	Prior	No-Prior
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tier-1 PCA	-874.7***	-495.3***	-359.2***	-473.3*	108.4	-212.1	-81.38
	(244.8)	(170.5)	(92.08)	(257.2)	(89.73)	(148.3)	(68.87)
Observations	8,320	7,640	5,920	3,540	7,440	2,780	5,760
R-squared	0.839	0.818	0.778	0.694	0.744	0.677	0.667
Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes the impact of PCA on lending outcomes of tier-1 banks only. The data is at the creditor-quarter level. Standard errors are clustered at the creditor level. Periods covered are from financial year 2012-2013 to 2018-2019. Amount are in crores of Rupees. Data on safety is sourced from ProwessDx and data on lending are from MCA.

Table 16: Impact of PCA on Bank Financials

Panel A : Bank Capital						
VARIABLES	CRAR	l(total capital)	Tier-1 Capital Ratio	l(Tier-1 Capital)	l(Risk Weighted Assets)	l(Share Capital)
	(1)	(2)	(3)	(4)	(5)	(6)
PCA	-0.929**	-0.550***	-0.538	-0.523***	-0.456***	0.208
	(0.429)	(0.0560)	(0.334)	(0.0564)	(0.0462)	(0.168)
Observations	1,134	1,134	1,134	1,134	1,134	1,151
R-squared	0.976	0.988	0.976	0.987	0.991	0.906
Bank FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Panel B : Bank Asset Quality						
VARIABLES	Net NPA to Net Advances	l(Net NPA)	l(Net Advances)	Prov Coverage Ratio	l(Restructured Advances)	Restructured Advances Ratio
	(1)	(2)	(3)	(4)	(5)	(6)
PCA	3.625**	-0.410*	-0.471***	7.987*	-0.372	-1.650
	(1.405)	(0.211)	(0.0462)	(4.340)	(0.230)	(0.999)
Observations	1,151	1,129	1,151	1,144	1,097	1,141
R-squared	0.792	0.961	0.989	0.591	0.918	0.778
Bank FE	YES	YES	YES	YES	YES	YES
Quarter FE	YES	YES	YES	YES	YES	YES
Panel C : Bank Performance Indicators						
VARIABLES	Leverage Ratio	ROA	l(Profit Margin)	l(PBT)	l(Net PAT)	
	(1)	(2)	(3)	(4)	(5)	
PCA	-0.0107***	-0.584**	1.270***	0.740***	0.836***	
	(0.00251)	(0.264)	(0.111)	(0.124)	(0.133)	
Observations	1,134	1,149	905	895	905	
R-squared	0.974	0.745	0.687	0.912	0.901	
Bank FE	YES	YES	YES	YES	YES	
Quarter FE	YES	YES	YES	YES	YES	

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. This table describes the impact of PCA on balance sheet outcomes of banks. The data is at the bank-quarter level Standard errors are clustered at the bank-quarter level. Periods covered are from financial year 2012-2013 to 2018-2019. Data are sourced from DBIE.

Appendix

Table A1: Average Number of Creditors by Firm and Creditor Types

	Firm-type			
Creditor Type	Low-Risk	High-Risk	Difference	t-stat
PCA Bank	0.27	0.39	-0.12	9.82
Non PCA Bank	1.79	1.41	0.38	-12.52
Non Bank	0.56	0.72	-0.16	7.28
All	2.62	2.52	10	-2.16

Notes: This table gives average number of creditors by type for safe versus unsafe firms. Safety of firms is defined on the basis of their interest coverage ratio in the baseline years FY2013 to FY2015. If the ICR is less than 2, a firm is considered unsafe.

Table A2: Impact of PCA on Zombie Firms

	Amount		Number of Loans	
	(1)	(2)	(3)	(4)
PCA	-2.439***	-2.586***	-0.0530***	-0.0514***
	(0.354)	(0.327)	(0.00251)	(0.00236)
PCA × Zombie1	-2.782***		-0.0134***	
	(0.657)		(0.00441)	
PCA × Zombie2		-7.440***		-0.0960***
		(1.857)		(0.00875)
Observations	967,920	967,920	967,920	967,920
R-squared	0.175	0.175	0.214	0.214
Firm-Creditor FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. The table is at the firm-creditor level, between the years 2012-2013 and 2018-2019. Standard errors are clustered at the firm-lender level. Variables are winsorized with 2% cuts on both sides. Zombie1 are firms with ICR < 1 (excluding related party transactions). Zombie2 stands for Zombie1 × Prior relationship dummy.

Table A3: Yearly Outcomes

	Amount		Number of Loans	
	(1)	(2)	(3)	(4)
PCA	-2,439**	-6.978***	-51.33***	-0.182***
	(1,201)	(1.090)	(17.56)	(0.00847)
Observations	2,496	250,481	2,496	250,481
R-squared	0.788	0.329	0.860	0.375
Creditor FE	Yes		Yes	
Firm-Creditor FE		Yes		Yes
Year FE	Yes	Yes	Yes	Yes

Notes: Standard errors are enclosed in the parentheses. *** p<0.01, ** p<0.05, * p<0.1. Cols 1-4 are at the creditor level with standard errors clustered at the creditor level. Cols 5-8 are at the firm-creditor level with standard errors clustered at the firm-creditor level. Periods cover financial years 2012-2013 and 2018-2019. Variables are winsorized with 2% cuts on both sides.

Table A4: Impact on Interest Rates

	Interest Rate		
	(1)	(2)	(3)
PCA	-1.264***	-1.211***	-0.616
	(0.214)	(0.339)	(0.553)
PCA × High-Risk		-0.0820	-0.758
		(0.424)	(0.659)
PCA × Prior			-0.700
			(0.663)
PCA × High-Risk × Prior			0.843
			(0.843)
Observations	16,868	16,868	16,868
R-squared	0.782	0.782	0.782
Firm-Creditor FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Notes: Data source: MCA.
Data is at the loan level. Quarter FE controls for the quarter of loan disbursal.

Table A5: OLS Corresponding to IV

	Amount			Number of Loans		
	(1)	(2)	(3)	(4)	(5)	(6)
PCA × High-Risk × Prior			-1.475			-0.00184
			(2.270)			(0.00836)
PCA × Prior			-6.454***			-0.108***
			(2.064)			(0.00733)
PCA × High-Risk		-0.422	-0.0464		-0.00132	-0.000265
		(0.607)	(0.418)		(0.00394)	(0.00394)
PCA	-1.775***	-1.474***	-0.0362	-0.0449***	-0.0439***	-0.0200***
	(0.291)	(0.549)	(0.366)	(0.00292)	(0.00409)	(0.00408)
Observations	607,191	607,191	607,191	607,191	607,191	607,191
R-squared	0.073	0.073	0.073	0.227	0.227	0.227
Firm-Creditor FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes

Table A6: Old PCA Matrix

Criterias	Trigger Points	Structured Actions	Discretionary Actions
CRAR	CRAR less than 9%, but equal or more than 6%	Submission and implementation of capital restoration plan Restriction on expansion of risk-weighted assets No new lines of business No access to costly deposits and CDs Reduce/skip dividend payments	RBI orders recapitalization No increase in subsidiaries' stake Reduce exposure to sensitive sectors (capital market, real estate, non-SLR) Restrictions on borrowings from inter-bank market Revision of credit/investment strategy
	CRAR less than 6%, but equal or more than 3%	All structured actions from previous zone RBI discusses corrective plan with bank's Board RBI orders recapitalization No increase in subsidiaries' stake Credit/investment strategy revision	New management/Board Business restructuring consultants Change of promoters/ownership Merge bank if recapitalization fails
	CRAR less than 3%	All structured actions from earlier zone RBI observes the bank more closely RBI/Govt. will merge, amalgamate, liquidate, or impose moratorium if CRAR doesn't improve in 1 year	Same as Above
Net NPAs	Net NPAs over 10% but less than 15%	Special drive to reduce NPAs Review loan policy Upgrade credit appraisal skills Strengthen loan follow-up and review mechanisms Follow up on suit filed/decreed debts Strengthen credit-risk management policies Reduce loan concentration	No new lines of business Reduce/skip dividend payments No increase in subsidiaries' stake
	Net NPAs 15% and above	All structured actions from earlier zone RBI discusses corrective plan with bank's Board No new lines of business Reduce/skip dividend payments No increase in subsidiaries' stake	Same as Above
ROA	ROA less than 0.25%	No access to costly deposits and CDs Increase fee-based income Contain administrative expenses Special drive to reduce NPAs No new lines of business Reduce/skip dividend payments Restrictions on borrowings from inter-bank market	No capital expenditure (except technological upgrades/emergent replacements) No expansion of staff/filling vacancies