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DEPOSIT AND CREDIT REALLOCATION IN A BANKING PANIC: THE ROLE OF STATE-OWNED BANKS

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ABSTRACT

We study a bank run in India in which private bank branches experience sudden and considerable loss of deposits, which migrate to state-owned public sector banks (PSBs) that serve as safe havens. We trace the consequences of the deposit reallocation using bank branch-level balance sheet and firm-bank lending data. The flight to safety is not a flight to quality. Lending shrinks and credit quality improves in run banks, but worsens in PSBs receiving the flight-to-safety flows. The reallocation of resources is not efficient in the aggregate.

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A bank run occurs when many depositors suddenly withdraw their deposits in a short period of time. As runs can cause bank failures and trigger domino effects across banks that threaten financial stability, a major focus of bank regulations and policies is to avoid runs (Calomiris and Mason, 1997; Saunders and Wilson, 1996). Moreover, if runs do occur, policies have included aggressive measures to stop them and ensure financial stability. For example, the 2023 runs at Silicon Valley Bank (Acharya et al., 2023) were met with an unprecedented policy response that guaranteed all deposits, even above the $250,000 insurance threshold.

Although stability has appropriately been a key focus of research and policy on bank runs, we study a different issue, viz., the *resource reallocation* resulting from runs. As motivation, consider the March 2023 failure of three major banks – Silicon Valley Bank, First Republic Bank, and Signature Bank – due to depositor runs. The result was a flight to safety of deposits from regional banks to larger banks perceived as safe havens (Caglio, Dlugosz and Rezende, 2023). The central question in our study is the onward consequences of such a deposit migration – for banks, bank borrowers, and the real economy.

We develop insights on these run consequences from a 2008-2009 bank run episode in India during the 2008 global financial crisis. Private banks experienced runs and related deposit flights, which migrated to state-owned public sector banks (PSBs) that served as safe havens. We characterize the consequences for the banks experiencing runs and the PSBs receiving run-related flows, the ensuing credit reallocation, and the efficiency of the reallocation in the real economy. using proprietary bank branch data as well as bank-firm lending data from statutory filings.

A key lesson that emerges from our analysis is that the resource reconfiguration towards the PSBs from the run private banks is not necessarily neutral. The credit reallocationis not necessarily a one-for-one gap-filling exercise by the recipients of run flows. We find that lending discipline improves at the run banks but credit quality worsens at the PSBs receiving run surpluses. Estimates based on the technique recently proposed by Sraer and Thesmar (2023) indicate that the aggregate effects are negative as productivity growth is impaired. In other words, the run does not just reallocate – but *misallocates* resources so a flight to *safety* need not be a flight to *quality*. The nature and the quality of the reintermediation of the windfall surpluses matter.

The run we study occurs after the 2008 global financial crisis when some branches of private banks in India experience a sudden and rather extreme loss of deposits. State-owned "public sector" banks (PSBs), the safe-haven destination for the run outflows, see a surge in deposits. A proprietary branch-level dataset, the annual "Basic Statistical Returns" (BSR), which India's central bank shared with us, lets us identify run branches, the related deposit flows, the PSBs gaining flows, and the credit quantity and quality. A second dataset on bank-firm relationships, which we obtain from statutory filings, lets us analyze lending after runs.

Two features help frame our analysis. One, the formal protection for Indian bank depositors is limited and offers little comfort to panicked depositors (Iyer and Puri, 2012). A second feature is the presence of state-owned public sector banks (PSBs) in India, which serve as credible safe havens. The Indian government holds large direct stakes in PSBs—70% on average. In addition, the state exercises significant control over all aspects of PSBs, including director appointment, strategic and operational planning, as well as hiring, pay, retention, rotation, and promotion of employees at all levels. Finally, India's 1949 Banking Regulation Act obliges the government to fulfill the obligations of PSBs in the event of bank failure. This clause adds comfort to the perceived safety of PSBs. Thus, depositors fleeing private banks could regard PSBs as safe repositories for their funds.

We find that runs occur in our setting at the bank-branch level, a variety of "silent" runs (Baron, Verner and Xiong, 2020), which we can identify using branch-level data. The BSR data are as of March-end so fiscal year t is the 12-month period ending on March 31 of the calendar year t. We define a bank branch as having a run if it experiences extreme deposit flight in fiscal 2009, which brackets the 2008 Global Financial Crisis (GFC). Empirically, we use three criteria, viz., the branch deposit growth rate is (1) less than out-of-sample predicted growth rates, (2) is below the 5th percentile of growth rates in 2007 and 2008, and (3) transitions from being above the 5% left tail cutoff in 2008 to below this cutoff in 2009.

Simple descriptive statistics show that our filters identify extreme deposit losses in fiscal year 2009. The median growth in deposits for run branches flips from +25% to -25% in one year while the 99th and 1st percentiles of deposit losses are -14% and -89%, respectively. We show that the run deposit losses flow to PSB branches in the same geography. We also consider an interesting sample of private bank branches that don't have runs but are in the run geographies. These branches do not show deposit gains, indicating that PSBs have a unique role as safe havens.

We estimate an instrumental variable specification that identifies run propensity. We hypothesize that private bank branches with a nearby PSB are more likely to face runs, the intuition being that the presence of proximate PSB branches eases access to safe havens for depositors. Deposit flows in co-located branches serve as an instrument for run-related flows. We use pin codes (akin to US zip codes) to identify co-location, using a dataset provided to us by the Indian central bank. The approximately 19,000 pin codes are far more granular than the 593 districts (which are like counties), and thus credibly identify nearby branches salient for panicked depositors. The co-location instrument is strong. The IV estimates indicate that runs erode branch deposits while co-located PSBs gain deposit flows.

We find that runs impact both credit quantity and quality and in asymmetric ways across run banks and PSBs. The most direct impact is on the run branches. We find that they contract credit, consistent with frictions in raising external finance (Kashyap and Stein, 1995, 2000), it is difficult to seamlessly replace funds that branches lose to runs. Because the banks in our sample operate nationally, runs in select geographies can have repercussions outside the run regions. To assess these effects, we compute the a bank-level run exposure variable that aggregates the deposits using as weights deposits in branches subject to run. For state-owned PSBs, this bank-level exposure variable aggregates the deposits in the geographies subject to runs.

For private banks facing runs, credit shrinks significantly both within and outside run regions. Conversely, we see credit growth at state-owned PSBs that have receive run flows. Our specifications account for areas with multiple PSB branches that could split run flows. Interestingly, and in contrast to private bank branches, PSBs appear to grow credit beyond the run geographies, consistent with more centralized decision-making in these state-owned entities. The asymmetry between local cutbacks at run branches and the dispersion of credit by PSBs across their networks is one indicator that PSBs do not passively gap-fill credit reductions suffered by borrowers of run branches.

We also find asymmetry in the changes in credit quality. Non-performing assets (NPAs) diminish at the run banks. These results are consistent with models in which runs discipline banks (Calomiris and Kahn, 1991; Diamond and Rajan, 2001). In contrast, NPAs increase at PSBs that receive run surpluses. We note that PSB NPA increases are significant with 3-year lag, a pattern not seen in private banks. This pattern could reflect the natural time lag taken for credit issues to become visible, particularly for fresh credits fueled by the deposit surge. Part of the pattern also reflects deferred NPA recognition by PSBs using latitude granted them by the Indian central bank.[1]

The credit quality results can also be viewed as outcomes of a natural experiment in which banks gain sudden surpluses and misallocate them (Lamont, 1997). Here, we have both resource expansion and contraction based on the nature of bank ownership. For corporations, Jensen (1986) attributes misallocation of surplus cash to insufficient managerial ownership. Here, an agency problem comes from the converse problem of *excessive* ownership by the state. State ownership provides stable funding surpluses to PSBs but this imprimatur also shelters PSBs from market discipline that can constrain misallocation.

We turn to firm-level tests next. We use a database maintained by India's Ministry of Corporate Affairs (MCA) on bank-firm relationships drawn from security interest filings (Chopra, Subramanian and Tantri, 2021). We match the MCA data with firm accounting data in the CMIE Prowess database. We find that at the firm-bank level, firms exposed to run banks (through their lending relationship) are more likely to exit these relationships. Credit to these run-exposed borrowers decreases. Conversely, credit increases for firms banking with state-owned banks that benefit more from the run surpluses. Firms in the latter group get more credit but of weaker quality. They are more likely to have future interest coverage ratios below 1.0 – indicating impaired credit quality – and witness lower sales and capital growth.

We then examine the aggregate consequences of the run. Following Hsieh and Klenow

[1] In the post-crisis regime, the central bank gave considerable "forbearance" latitude to banks that was used to delay NPA recognition. See, e.g., a December 2024 interview by the then-governor of India's central bank https://www.ndtvprofit.com/economy-finance/raghuram-rajan-blames-upa-corruption-for-bank-npas-lauds-modi-governments-write-offs

(2009), the dispersion of marginal productivity of capital indicates deterioration in allocative efficiency. We find that productivity dispersion increases in industries more exposed to runs. Using the approach suggested by Sraer and Thesmar (2023), we assess outcomes relative to a no-run counterfactual. The estimates show that aggregate productivity declines by about 17%. The results appear reflect within-sector effects rather than credit reallocation across industries.

We next consider a natural experiment that complements our earlier co-location instrumental variables strategy. In 2005, India's central bank liberalized branch licensing rules based on per-capita bank branch density (Young, 2017; Cramer, 2020). This policy creates an interesting regression discontinuity design based on the licensing cutoff in which branch density is the running variable that generates varying exposures to PSBs. The idea here is that a new private bank branch with less longstanding, loyal depositors is likely to have more flighty deposits when there is a nearby PSB. We find results consistent with this hypothesis.

We consider another heterogeneity test based on the variation within the state-owned PSBs. As weaker state-owned banks, benefit more from the implicit put due to state ownership, we conjecture that these banks are more likely to attract flows. Acharya et al. (2017) suggest a measure of a bank's weakness, the Marginal Expected Shortfall (MES).[2] We find that weak PSBs with greater MES are more likely to expand lending in response to runs, and their loans have poorer ex-post performance. Additional data and anecdotal evidence are supportive. We obtain data on deposit rates and report that weaker PSBs offer higher rates. Press reports (Business Line, 2008) indicate that deposit-chasing by weaker PSBs became so rampant that the central government had to step in to curb it. These re-

[2] MES is measured in our implementation as the negative of the average returns of a stock given that the market return is below its 5$^{\text{th}}$- percentile during the period 1$^{\text{st}}$ January 2007 to 31$^{\text{st}}$ December 2007.

sults, coupled with the absence of run deposit migration to other private banks, suggest that state ownership makes banks credible as safe havens but also results in weaker reintermediation of run surpluses from within-sector misallocation, with negative economic consequences.

We proceed as follows. Section I describes the institutional details and the data. Section II examines deposit and credit growth triggered by the runs. Section III analyzes firm-level outcomes and aggregate effects. Sections IV and V provide additional evidence from the exogenous entry of banks and the variation *within* PSBs. Section VI discusses the related literature. Section VII concludes.

I Institutional Details and Data

India has two major types of banks: private banks and state-owned or public sector banks (PSBs). Among the PSBs, the State Bank of India, formed in 1806, is the oldest. The other PSBs, formed through two nationalization waves in 1969 and 1980, are also old, with an average age of about 80 years. Both PSBs and private banks are licensed to operate across the country. The PSBs have a combined 70% market share of banking assets, while a 28% share is with private banks, primarily the "new private banks" formed after India's 1991 liberalization (Mishra, Prabhala and Rajan, 2022).

The run episode we analyze occurs around the 2008 global financial crisis (GFC). The collapse of reputed financial institutions such as Lehman Brothers and Bear Stearns triggered worldwide panic. India was no exception. The shock led depositors to move from private to public sector banks. Figure I, constructed at the bank level using publicly available data, shows that stark differences emerged as the GFC took root with the Bear Stearns collapse in March 2008.[3]

I.A State Support for PSBs

India's 1949 Banking Regulation Act states that all obligations of PSBs will be fulfilled by the Indian government in case of failure. The government is an active shareholder, involved in all important aspects of PSB operations. On the financial side, the government supports PSBs through capital injections from time to time through budgetary appropriations. For example, it infused about INR 31 billion (approximately $0.5 billion) in 2009 (World Bank, 2009). These features make PSBs credible safety nets for depositors.

India's Deposit Insurance and Credit Guarantee Corporation (DICGC) insures bank deposits. The 2008 coverage (INR 0.1 million or about $2000) per depositor per bank was meager and depositors face delays in processing deposit insurance claims. Not surprisingly, the insurance program has not mitigated the propensity to run (Iyer and Puri, 2012).[4] Moreover, PSBs were perhaps the only accessible safe havens for depositors as Indian sovereign paper was available only for banks and other large institutions.

I.B Data

Branch-level data on deposits and credit come from the "Basic Statistical Returns" (BSR) dataset maintained by India's central bank, the Reserve Bank of India (RBI). The BSR data are annual as of March 31, the financial year-end for banks. We use two geographical markers. One is a district, which is roughly comparable to a US county and available as

[3]While not critical for our analysis, panic seems to drive the run in our sample as Indian banks had little exposure to U.S. mortgages that were at the root of the 2008 crisis (Acharya and Richardson, 2008). Note that the figure is at the bank level and not for individual branches that faced deposit flights.

[4]Private banks blamed state support as being responsible for the 2008 runs and lobbied for an increase in deposit insurance for greater parity in the provision of safe deposits. (LiveMint, 2011). On February 4, 2020, a decade after the run episode we analyze, the deposit insurance coverage was increased to INR 500,000.

part of the BSR dataset. The other marker is pin code, which was obtained from a dataset compiled by the central bank. We retain branches for which the pincode information is available for the baseline analysis. We discuss the distinctions further to motivate the appropriate geographical unit to use in the analysis.

In our sample period, there are 593 districts and over 10,015 pin codes. Pincodes are more granular, reflecting geographical proximity, familiarity with local service providers, and ease of transportation and travel. In our view, this level of granularity is relevant for panicked depositors looking for a different bank branch. Districts are larger economically integrated regions, typically spanning large areas of 2,000 square miles. In India, districts are the units of governance, with "collectors" appointed to run all administrative matters on behalf of elected politicians. Economic data are also compiled at the district level. Thus, local economic conditions or spillovers are better assessed or controlled for at the district level. We use the districts demarcated by the Indian Census in 2001, which are relevant for the time period covered by our sample.[5]

We obtain aggregate bank-level variables as either the sum of individual branch-level data or from annual audited financial statements in the Prowess DX database compiled by the Center for Monitoring the Indian Economy (CMIE). We use this data for financial variables in the firm-level analyses. Please see Appendix Table A.1 for more details on variables used in our analysis. A third database is a loan-level dataset compiled by the Ministry of Corporate Affairs, which identifies firm-bank relationships using security interest filings (Chopra, Subramanian and Tantri, 2021) like UCC filings in the U.S. analyzed by Gopal and Schnabl (2022). Table I provides summary statistics for the variables used in our analysis.

[5]The typical district spans an area of 2000 square miles (or end to end distances of 40-50 miles) often with poor connectivity.

II The Deposit Run

We define a bank branch as having a run if it satisfies three criteria.

Criterion 1 requires that the branch deposit growth rate is less than its out-of-sample predicted value, which we estimate using a regression. The data are from pre-2006, one year prior to the run. The explanatory variables are the size (lagged log credit), the branch age, a dummy variable for whether the branch is in a rural district, the lagged credit-to-deposit ratio and a dummy variable for whether the bank is state-owned.

Criterion 2 attempts to identify whether the deposit growth is in the extreme left tail. We require that the fiscal 2009 branch deposit growth rate is below the 5$^{\text{th}}$ percentile of the distribution of branch growth rates in the pre-run year (fiscal 2008).

Criterion 3: We require that a branch is not in the left tail of deposit growth rates g in 2008 but has a left tail event in 2009, i.e., $g_{2008} > p_5$ but $g_{2009} < p_5$ where p_5 as the 5$^{\text{th}}$ percentile of the deposit growth rate for private banks in 2008, one year before the run.

In our sample, about 0.7% of all branches face runs. Figure II shows a heat map in which lighter shades (whites) correspond to more run-prone regions. For private banks (Panel (b)), more regions have low deposit growth relative to PSBs (Panel (c)).[6]

II.A Event Study Evidence on Deposits

We estimate an event-study regression

$$Y_{jbdt} = \alpha_j + \theta_{dt} + \gamma_{bt} + \sum_{\tau} \eta_\tau \times \mathbb{1}_\tau \times \mathbb{1}_{(Run_j)} + \epsilon_{jt}, \tag{1}$$

[6]The Internet Appendix gives more color on the run branches. Figure A.1 shows the fiscal 2009 tail events relative to a 2008 placebo. Figure A.2 shows that run branches are significant contributors to deposit-raising activities and are located in regions with a greater presence of PSB branches. At the bank level, the run banks are weaker as per the marginal expected shortfall (MES) criterion (Acharya et al., 2017).

where the dependent variable Y_{jbdt} is the annual deposit growth for branch j of bank b in district d for fiscal year t, α_j, θ_{dt}, and γ_{bt} are branch, district-time, and bank-time fixed effects respectively, and $\mathbb{1}_\tau = 1$ if the fiscal year is τ (ranging from 2002 to 2011).[7]

If the run and non-run branches have similar (parallel) trends before the run year, we should find that the coefficients η_τ are close to zero in the pre-run period. Figure IV shows that this is the case whether we use bank-time fixed effects or not. Figure IV also shows a sharp decline in deposits for the branches we identify as having a run in fiscal 2009. The two specifications are with district-time fixed effects (panel a) and the more stringent pincode-time fixed effects (panel b). The coefficients normalize after the sharp 2009 drop.

II.B The Run: Deposit Losses

We analyze deposit growth in the post-run period using the following specification:

$$Y_{jbd} = \alpha_b + \gamma_d + \beta \times \mathbb{1}_{\text{Branch run } j} + \epsilon_{jbd}, \tag{2}$$

where Y_{jbd} is the annual deposit growth rate for a given branch j of a bank b in district d for fiscal year 2008-2009. The variable $\mathbb{1}_{\text{Branch run } j}$ is an indicator for whether a branch j has a run. α_b and γ_{dt} are bank and geography fixed-effects respectively.[8] Robust standard errors are clustered at the branch level; clustering at district level gives similar results. .

Table II reports the estimates of equation (2). Note that the coefficient of interest β estimates the deposit growth for run branches relative to other branches of the *same* bank. The estimates of β are negative and significant, indicating that our run definitions ap-

[7]We get similar results with pincode-time fixed effects rather than district time fixed effects (θ_{dt})

[8]The specification is akin to that used in Alencar (2016) and Drechsler, Savov and Schnabl (2021), in which the post-period is the focus of the primary analysis and the pre-period is used to control for parallel trends. In unreported results, we find that specifications with pre-period data as controls yield similar results.

pear to identify run branches even after including a rich of fixed effects, and in a sample that also includes PSBs. Column (2) in Table II reports similar negative and significant estimates when we include more granular pincode fixed effects.[9] Placebo tests reported in the Internet Appendix Table A.2 show that the run results are not typical of non-run years.[10]

We turn to an instrumental variables (IV) estimator next. We instrument for branch run with an indicator variable that is non-zero if a branch (a) belongs to a private sector bank; (b) is located in a metropolitan area; and (c) has a state-owned bank in the same pincode. This co-location variable ($\mathbb{1}_{\text{Coloc. PSB}}$) is based on two observations. First, our baseline hypothesis is that the presence of state-owned bank branches makes private sector branch deposits more flighty. Second, depositors in metropolitan areas are more likely to be aware of events such as the GFC and entertain the possibility of its salience to their financial conditions. Further, deposit accounts are larger in metros compared to rural branches, making government guarantees salient. In the aggregate, PSB deposit growth outpaced that of private banks more prominently in metros (Figure III). Appendix Table A.3 shows that even at the branch-level, co-location is strongly associated with a decline in deposits in 2008–2009, but not in earlier placebo years between 2001–2008 (Appendix Table A.4).

The first stage equation instrument for the branch run is:

$$\mathbb{1}_{\text{Branch run } jbd} = \alpha_b + \gamma_d + \beta \times \mathbb{1}_{\text{Coloc. PSB } j} + \epsilon_{jbd}, \tag{3}$$

[9] Number of observations differ across columns in Table II (and in subsequent tables) because singletons, i.e., observations that appear only once within a fixed effect category, are not reported.

[10] We show that there is no difference in deposit growth between run and non-run branches in fiscal 2005, 2006, and 2007. Branches in the left tail of fiscal 2005 (as placebo) show no extreme deposit losses in 2009.

The second stage is:

$$Y_{jbd} = \alpha_b + \gamma_d + \beta \times \widehat{\mathbb{1}_{\text{Branch run}}}_j + \epsilon_{jbd}, \tag{4}$$

Columns 3 and 4 in Table II, with district and pincode fixed effects, respectively, show that the branch-level instrument is a strong predictor of branch run. F-statistics are well above the standard thresholds (Angrist and Kolesár, 2024). The second stage IV estimates in columns 5–6 are significant and indicate a virtually full erosion of the deposits of run branches.[11]

Private Banks Are Not Safety Nets We present evidence that PSBs play a unique role as safety nets. For this test, we exploit the within-variation in private banks. As Mishra, Prabhala and Rajan (2022) point out, virtually all Indian PSBs were formed through nationalization programs, but these programs left in place some private banks. These banks are as old as PSBs and familiar to depositors given their continued operations for decades. We compare whether these old private sector banks act as recipients for run flows.

Table A.5 shows that this is not the case. Panel A shows that deposit losses at the old and new banks are statistically indistinguishable. In Panel B, we define an alternate co-location variable: an indicator for whether a metro *new* private sector branch in a pin code is co-located with an *old* private sector branch. The first stage now includes the baseline co-location with a metro PSB ($\mathbb{1}_{\text{Coloc. PSB}}$) and the new co-location with an old private sector branch. Columns 1–2 show that the new co-location variable is not correlated with the branch run variable. Furthermore, the new co-location variable does not predict deposit

[11] The IV results show the relevance of focusing on metro branches. The 2SLS IV produces a local average treatment effect (LATE). With the underlying heterogeneity across branches, the estimates captures the impact of the co-located branches.

losses (columns 3–4). Finally, the 2SLS IV estimates remain unchanged when we include both the co-location variables as instruments (columns 5–6). The results point to a unique role for PSBs as safe havens.

II.C Deposit Flights to PSBs

To assess deposit flights to PSBs, we construct variable Pvt. Dep. $\text{Loss}_{\text{RUN PIN}}$, the greater of 0 or the negative of the deposit growth of the run branches in pincode p. The greater its value, the greater the deposit flight in pincode p. We estimate the following specification for 2008-2009, the run year.

$$Y_{jbp} = \alpha_b + \kappa_p + \eta \times \text{Pvt. Dep. Loss}_{\text{RUN PIN }jp} \times PSB_b + \epsilon_{jbp} \tag{5}$$

The key outcome variable Y_{jbp} is the deposit growth rate for branch j of a bank b in pincode p in 2008-2009, while α_b and κ_p are bank and pincode fixed-effects, respectively.

The coefficient of interest in Equation (5) is η. We report $\eta * 100$, the impact on the outcome variable, say deposit growth, due to a 1 percent decline in the deposit growth of private sector branches with runs in the district. Standard errors are robust and (conservatively) clustered at the district level.

Table III reports the results. In column (2–3), the sample includes all branches and the specification has bank fixed effects. Thus, the coefficient η compares a branch in a pincode with high exposure to runs with another branch of the *same* bank with low exposure. The negative and significant estimate of η shows that branches in pin codes with greater run exposure lose deposits. The interaction term of pin code exposure and its interaction with a PSB dummy variable is positive and significant, so the inflows are driven by a deposit flight to PSBs. On the other hand, the negative coefficient for Pvt. Dep. $\text{Loss}_{\text{RUN PIN}}$

shows that private bank branches suffer net deposit losses.[12]

We also instrument for the exposure variable, Pvt. Dep. $\text{Loss}_{\text{RUN PIN}}$ and define Pvt. Dep. $\text{Loss}_{\text{COLOC PIN}}$ as the greater of 0 or negative of deposit growth at branches with $\mathbb{1}_{\text{Coloc. PSB}}$ equal to 1. Columns 3 and 4 in Table III indicate that the relevance condition holds, with the first stage F-statistics well above the threshold. The 2SLS IV estimates in columns 5 and 6 confirm the negative and statistically significant effect on deposit growth at private sector bank branches. The interaction term indicates positive deposit growth at public sector bank branches. Results are robust to excluding the run private sector bank branches and comparing within public and private banks (Table A.6).

II.D Credit Quantity

Runs at a branch deplete its resources. If the bank does not have frictionless access to external funds (e.g., Kashyap, Stein and Wilcox (1993); Kashyap and Stein (2000)), local deposit losses can translate into credit losses, both locally and bank-wide, given that banks operate nationally. Conversely, for PSBs, windfall inflows can translate into extra lending. To estimate these effects, we develop the following metrics of exposure to runs, one for private banks and another for PSBs.

$$\text{Pvt. Dep. Pct.}_{\text{COLOC PIN } b} = \sum_{j \in b} \frac{\text{Deposit}_j}{\text{Deposit}_b} \times \mathbb{1}_{\text{Coloc. PSB } j} \tag{6}$$

$$\text{PSB Dep. Pct.}_{\text{COLOC PIN } b} = \sum_{j \in b} \frac{Deposit_j}{\text{Deposit}_b} \times \text{Pvt. Dep. Loss}_{\text{COLOC PIN } jp} \times \text{PSB Share}_b \tag{7}$$

where b denotes a bank, Pvt. Dep. $\text{Loss}_{\text{COLOC PIN } jp}$ is (as before) the negative of the deposit flows at these co-located private sector bank branches, and $\mathbb{1}_{\text{Coloc. PSB } j}$ is the branch-

[12] Appendix Table A.6 reports the specification for PSB branches (column 1) alone and confirms the overall positive deposit flows.

level co-location instrument, PSB Share$_b$ is the share of PSB deposits of bank b.

In equations (6) and 7), weights are based on fiscal 2008 (pre-crisis) deposits and the measure is standardized (z-scored) for easy interpretation. The two exposure variables have symmetric interpretations. Because one type of entity faces outflows while the other finds itself with surpluses, the exposure captures outflows (inflows) for the private (public sector) bank indexed by b. In addition, since the deposit outflows are shared by public sector banks in a pincode, we include PSB Share measuring the share of deposits of that PSB relative to remaining PSBs as of 2008.

The specifications to assess run effects outside the run geographies follow. For private sector banks, they are:

$$Y_{jbd} = \alpha_d + \gamma \times \mathbb{1}_{\text{Coloc. PSB } j} + \beta \times \text{Pvt. Dep. Pct.}_{\text{COLOC PIN } b} + \epsilon_{jbd} \tag{8}$$

$$Y_{jbd} = \alpha_d + \theta_b + \gamma \times \mathbb{1}_{\text{Coloc. PSB } j} + \epsilon_{jbd} \tag{9}$$

For PSBs, the specifications are:

$$Y_{jbd} = \theta_b + \gamma \times \text{Pvt. Dep. Loss}_{\text{COLOC PIN } d} + \epsilon_{jbd} \tag{10}$$

$$Y_{jbd} = \alpha_d + \gamma \times \text{PSB Dep. Pct.}_{\text{COLOC PIN } b} + \epsilon_{jbd} \tag{11}$$

where, Y_{jbd} denotes credit growth in branch j of bank b in district d in 2008–2009, the crisis year and interactions as in equation (1) and the exposure variables are as defined in equations (6) and (7). We include district fixed effects α_d as strong controls for local heterogeneity. θ_b is the bank fixed effect, allowing us to compare across branches within the same bank. Standard errors are robust and clustered at the district level.

Table IV reports the estimates. In column (1), we see that the coefficient for $\mathbb{1}_{Coloc.\ PSB}$

is negative and significant. Thus, branches facing runs contract credit with a direct effect of -22.1 pp for a one-SD increase in the run exposure. For robustness, column (2) includes bank-year fixed effects, which absorb the (bank level) private bank exposure variable. The own effect is of similar magnitude. Columns (3) and (4) report analogous specifications for PSBs. We see significant credit growth for PSBs bank-wide (column 4) with minimal effects in run geographies (column 3), respectively.[13]

II.E Credit: Quality

India's central bank, RBI, provided us with data on markers for non-performing assets (NPAs) at the branch level. Impaired loans are marked as substandard, doubtful, or loss.[14] We analyze the relation between loan quality and run inflows or exposures.

We define two variables, $\text{Pvt. Cred. Pct.}_{\text{COLOC PIN}}$ and $\text{PSB Cred. Pct.}_{\text{COLOC PIN}}$:

$$\text{Pvt. Cred. Pct.}_{\text{COLOC PIN}\ b} = \sum_{j \in b} \frac{\text{Credit}_j}{\text{Credit}_b} \times \mathbb{1}_{\text{Coloc. PSB}\ j} \tag{12}$$

$$\text{PSB Cred. Pct.}_{\text{COLOC PIN}\ b} = \sum_{j \in b} \frac{Credit_j}{\text{Credit}_b} \times \text{Pvt. Dep. Loss}_{\text{COLOC PIN}\ jp} \tag{13}$$

where b denotes a bank, $\mathbb{1}_{\text{Coloc. PSB}\ j}$ is the branch-level co-location instrument, $\text{Pvt. Dep. Loss}_{\text{COLOC PIN}\ jp}$ is (as before) the negative of the deposit flows at these co-located private sector bank branches. The weights are based on fiscal 2008 (pre-crisis) credit, and the measure is standardized (z-scored) for easy interpretation.

[13] In unreported results, we considered alternate "leave-one-out" measures to examine within-bank spillovers. These results confirm that run banks cut credit locally, while PSB credit growth does not show similar variation across branches. These specifications do not help capture flows from private banks to PSBs, which is our main focus; they have been also subject to criticism following Angrist (2014).

[14] In our sample period, substandard loans are delinquent for between 90 days and two years. Doubtful loans have no repayments for more than two years. Loss loans are loans that are written off.

The specifications to assess effect on NPA are as follows:

$$Y_{jbp} = \alpha_p + \beta \times \text{Pvt. Cred. Pct.}_{\text{COLOC PIN } b} + \epsilon_{jbp} \quad (14)$$

$$Y_{jbd} = \alpha_p + \gamma \times \text{PSB Cred. Pct.}_{\text{COLOC PIN } b} + \epsilon_{jbp} \quad (15)$$

for branch j of bank b in pincode p in 2008–2009, the crisis year and interactions as in equation (1) and the exposure variables are as defined in equations (12) and (13). Y_{jbd} denotes the change in NPA three years after the crisis, 2009-2011, relative to credit in 2009. Similarly, we also examine NPA growth over a longer horizon, 2012–2016 relative to credit in 2012. Both regressions also include credit growth over the period 2009–2011 and 2012–2016. We include geography fixed effects α_p to control for local heterogeneity. Economic conditions are best proxied by district fixed effects (we get similar results with pincodes). Standard errors are robust and clustered at the geography level.

Table V reports the estimates. Briefly, we find that NPAs shrink at the private sector banks experiencing runs within three years following the run episode. For the PSBs, the initial three year period reveals little change in NPAs. In the subsequent period, there is a significant increase in NPAs (column 4). We discuss the likely economics of this time pattern next, as it reflects concerns that led to a regime shift in bank supervision and bankruptcy laws in India.

Deferred NPA recognition is consistent with other research (Chopra, Subramanian and Tantri, 2021) and reflects two issues. One is the time taken for loans to become non-performing. This factor may be salient for the new loans made in the post-GFC period although we do not see similar significance for private bank NPAs. The other issue is disclosure. The central bank allowed banks discretion in classifying loans as non-performing under "forbearance" policies, which let PSBs defer NPA recognition (footnote 1). These norms were tightened over time and culminated in an asset quality review program. The problem was serious enough that the country had do-over of the entire bankruptcy code in 2016.[15]

In sum, we find both credit quantity and credit quality effects associated with the run. Private banks facing runs contract credit and improve loan quality. PSBs that served as safe havens for the run inflows have worsening credit quality. We next turn to the aggregate effects of this resource reallocation by exploiting data on bank-firm linkages.

III Aggregate Effects

We turn to a firm-level analysis next. The tests contrast the credit impacts for firms exposed to banks facing runs with those for firms with PSB relationships. We then assess the aggregate effect across firms from the resource reallocation due to the run. The data on firm-bank relationships come from security interest filings with the Ministry of Corporate Affairs (MCA), which we combine with financial data from the CMIE Prowess database.[16]

III.A Changes in Credit Relationships

We estimate the following specification for firms f borrowing from bank b:

$$Y_{fb} = \omega_f + \beta \times \text{Public Sector Bank}_b + \eta \times X_{fb} + \epsilon_{fb} \tag{16}$$

We have mixed data with both zeros and non-zero dependent variables, and follow-

[15] See the Insolvency Board Website https://ibbi.gov.in//en/legal-framework/act

[16] We exclude industries with the 2-digit National Industrial Classification code (NIC) codes between 01-03, 45 or 47, and 69-75, corresponding to agricultural, wholesale and retail trade or repair of motor vehicles and motorcycles, and professional, scientific and technical activities, respectively.

ing Chen and Roth (2023), our specification is a Poisson regression but we briefly comment on the two margins that we also estimate separately. For the extensive margin test, the dependent variable is an indicator for whether a firm borrows from a bank. For intensive margin tests, the dependent variable is the aggregated loan amount for a firm-bank pair between fiscal 2009–2011. Of interest to us is the variable "Public Sector Bank," which is an indicator for whether a firm borrows from a public sector bank. We include pre-period loan using data from the 3 years prior to the crisis. This variable is either whether the firm borrows from a bank or the amount borrowed. We balance the bank-firm panel by filling in zeroes when no relationship exists in the post-period (pre-period) but a relationship exists in the pre-period (post-period). The combined extensive and intensive margin specification is a Poisson regression (following Chen and Roth (2023)). We cluster robust standard errors at the bank level.

Table VI reports the results. Columns (1) and (2) of Panel A show the extensive margin results, that is whether a firm borrowing borrowed from a public sector bank post-crisis, controlling for ex-ante borrowing in the pre-period. In column (1), we find that a firm is 1.7% more likely to borrow from a public sector bank. Controlling for firm level demand using firm fixed effects in the spirit of the Khwaja and Mian (2008) design that compares the same firm borrowing from different banks, we see a similar effect. The similarity of the results with and without firm fixed effect indicate that demand-side factors do not drive firm borrowing from PSBs (Jimenez et al., 2020).

In column (3) of Table VI, we examine the impact on loan amounts conditional on borrowing. The estimates suggest that firms borrow more from public sector banks; the point estimate is INR 547 million (about $10 million at the 2008 exchange rate of US$1=INR 50). Including firm fixed effects in column (4) shows that borrowings increase by INR 930 million (US$ 18 million) when the same firm borrow from a PSB relative to a private sector bank. In the combined extensive-intensive Poisson specification of Chen and Roth (2023), credit access is greater for firms borrowing from public sector banks.

III.B Firm-Level Outcomes

To assess firm-level outcomes, we estimate:

$$\Delta Y_f = \alpha_{i(f)} + \beta \times \text{Firm exposure}_f + \gamma \times \text{Firm exposure}_f \times \text{Top}_f + \epsilon_f \tag{17}$$

for a firm f in industry i. The dependent variables includes an indicator for whether a firm is a borrower as well as the total loan amount from 2009-2011. Firm exposure is whether a firm borrows from a public sector bank pre-run between 2006–2008. We analyze the heterogeneity in the results by interacting the exposure variables with an indicator TOP_f denoting whether the 2008 productivity of capital is above median. All regressions include industry fixed effect, which are 3-digit NIC codes provided by CMIE Prowess. Standard errors are clustered at the industry level.

Table VI, Panel B presents the results. In the first column (row (1)), we find that the estimate of β is negative for the extensive margin. Thus, credit contracts for borrowers who rely on public banks. The results in column (2), row 1, shows that the aggregate credit for firms with PSB exposure expands. More interestingly, the results in row 3 demonstrate a credit contraction at the *more* productive firms. The results are similar when we condition on the firms that borrowed: credit expands for firms linked to public sector banks and there is a contraction at the more productive firms but the results are not significant. In the preferred Poisson regression specification in columns 5–6 that allows us to examine both the extensive and intensive margins, credit increases at exposed firms, but less so for the productive firms.

III.C Aggregate Industry-level Effects

Our previous results suggest that the resource reallocation from the runs has negative effects driven by PSB credit allocations to weaker firms. In this section, we attempt to assess the aggregate effects of these reallocations at the industry level. We examine this issue using the methods recently developed by Sraer and Thesmar (2023). In their framework, the aggregate effect depends on three moments of log-MRPK (marginal productivity of capital): the variance of log-MRPK, the mean of log-MRPK, and the covariance of log-MRPK and sales. We estimate these as:

- $\Delta\Delta\sigma^2(s)$, the difference-in-differences estimate of the effect of an event on the variance of log-MRPK in a given industry s, or the change in MRPK variance for firms in the industry s relative to those in unaffected (or less affected) industries.
- $\Delta\Delta\mu(s)$ is the difference-in-differences estimate of the effect of the event on the mean log-MRPK in industry s.
- $\Delta\Delta\sigma_{MRPK,py}(s)$ is the difference-in-differences estimate of the effect of the event on the covariance between log output and log sales in the industry s.

Empirically, we proceed as follows. We have 100 unique industries identified by their 3-digit NICs, thus giving 200 before-after observations. As in Sraer and Thesmar (2023), the output-to-capital ratio, log-MRPK, at the firm level is the log of the ratio of sales to the gross book value of total assets, averaged over the pre- and post-periods, 2006–2008 and

2009-2011, respectively, in our case.

$$M_{ind,t} = \alpha_s + \beta_M \times \text{Industry exposure}_s \times Post_t$$
$$+\gamma \times \text{Industry exposure}_s \times Post_t + \eta \times Post_t + \epsilon_{ind,t} \tag{18}$$

where s is the industry in period t. All specifications include industry-fixed effects, and standard errors are clustered at the industry level.

Table VII presents the estimates of equation (18). In column (2), we find that industries with high exposure to PSBs see an increase in the variance of log-MRPK, i.e., the dispersion in productivity, the usual indicator of inefficient capital allocation. The results are significant at the 10% level. We will shortly consider its economic effects in an industry-level aggregation to assess the counterfactual productivity.[17] Because we omit industry-fixed effects in column (1), we can compare exposed and unexposed industries in the pre-period. The insignificant coefficient for the exposure term without interactions shows that the differences are not significant. Columns (3), (4), (5), and (6) show that the pre-period differences in other moments are not significant.

We estimate all three specifications required for the aggregation exercise. [18] For the approach to be well-specified, the distribution of log-MRPK should be normally distributed, which we verify in the Internet Appendix Figure A.3. Using the calibration parameters in David and Venkateswaran (2019) and Sraer and Thesmar (2023), we set the capital share in production to 0.33, the price elasticity of demand to 6.0 corresponding to

[17]We note that the significance level is likely conservative due to the approximations needed, e.g., to estimate flows out of private banks into PSBs, aggregate them to the bank level, the relatively small number of industries. Moreover, the economic effects of the dispersion are better reflected in their impact on aggregate TFP, which we turn to next.

[18]The estimates are $\Delta\Delta\sigma^2(s) = 1.305 \times \text{Industry exposure}_s$, $\Delta\Delta\mu(s) = -0.032 \times \text{Industry exposure}_s$, and $\Delta\Delta\sigma_{MRPK,py}(s) = 0.244 \times \text{Industry exposure}_s$.

$\theta = 0.83$. ϕ_s is the pre-period share of sales of industry s and κ_s is its pre-run period share of capital.

The aggregation to obtain the overall change in total factor productivity (TFP) is:

$$\Delta \log(TFP) \approx \underbrace{-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1}^{S}\kappa_S \widehat{\Delta\Delta\sigma^2}(s)}_{\text{-17.68\%}}$$
$$\underbrace{-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1}^{S}(\phi_S-\kappa_S)\left(\widehat{\Delta\Delta\mu(s)}+\Delta\Delta\sigma_{\widehat{MRPK,py}}(s)+\frac{1}{2}\frac{\alpha\theta}{1-\theta}\widehat{\Delta\Delta\sigma^2}(s)\right)}_{\text{-0.09\%}}$$
$$\approx -17.8\% \tag{19}$$

The sizeable effects noted in this section is consistent with the significant evidence on non-performing assets at PSBs. The effect on aggregate output can be calculated using the following equation:

$$\Delta\log(Y) \approx -\frac{\alpha(1+\epsilon)}{1-\alpha}\sum_{s=1}^{S}\phi_S\left(\widehat{\Delta\Delta\mu(s)}+\frac{1}{2}\frac{\alpha\theta}{1-\theta}\widehat{\Delta\Delta\sigma^2}(s)+\Delta\Delta\sigma_{\widehat{MRPK,py}}(s)\right) \approx -23.6\% \tag{20}$$

where ϵ is the Frisch elasticity. Using $\epsilon = 0.2$, we estimate a negative effect of about 23.6% due to bank runs and credit reallocation from private to public banks.

IV Natural Experiment: 2005 Branch Licensing Rules

Does the presence of PSBs in a district make private banks more vulnerable to runs? We present evidence from a regression discontinuity design (RD).

In India, the branch licensing policies are set by RBI, India's central bank. On September 8, 2005, the central bank moved to quantitative formulas for branch licensing. Entry was allowed in underbanked districts, which were defined as ones in which the population per branch exceeded the national average. Following the reform, private sector banks were incentivized to enter – and did enter – underbanked areas while state-owned public sector banks did not, perhaps because of their legacy presence.

Thus, the 2005 branching rules generate exogenous variation in private branch exposure to PSBs in ways that vary across districts. See Young (2017) and recently, Cramer (2020) and Khanna and Mukherjee (2020). The hypothesis is that if newer branches have less established depositor relationships and loyalty, their deposits are likely to be more flighty. We can test this hypothesis through a discontinuity design with the population per branch as the running treatment variable subject to a threshold discontinuity.

We thus estimate

$$\begin{aligned} \text{PSB share}_b &= \delta_s + \beta * \text{Banked}_d + \gamma * \text{Banked}_d * f(T_d) \\ &+ \phi * (1 - \text{Banked}_d) * f(T_d) + \kappa X_d + \eta_d \end{aligned} \tag{21}$$

where PSB share_b denotes the deposit share of state-owned banks, T_d denotes the running treatment variable, the population per branch minus its national average, Banked is an indicator for whether $T_d < 0$, i.e., the district is not underbanked. δ_s denotes state fixed effects while X_d denotes linear and squared terms (Gelman and Imbens, 2019). We estimate the regression for fiscal 2006-2008. This is prior to the run and also has a window after the 2005 policy change to allow for realized entry by private banks. As suggested in Imbens and Kalyanaraman (2012), the RD estimation uses a triangular kernel. We use a 4.5 persons per thousand bandwidth, but results are robust to other choices suggested in the literature (e.g., Calonico, Cattaneo and Titiunik (2014); Young (2017)). The regressions are weighted by the 2001 population estimates used to define underbanked thresholds.

The fitted value of the dependent variable estimates the exposure of private sector banks to PSBs in a district accounting for the threshold discontinuity generated by the 2005 policy change. Analyzing runs is then straightforward using an IV specification.

$$\text{Deposit Growth}_{jdst} = \alpha_{bt} + \delta_{st} + \beta \times \widehat{\text{PSB share}}_d + \eta \times X_{jdst} + \nu_{jdst} \tag{22}$$

The specification includes state-year and bank-year fixed effects and also covariates X_{jdst}, viz., an indicator for whether a branch is deposit poor (below median deposits in 2008), the percentage of skilled officers, and the credit to deposit ratio in 2008 and their interactions with time trends. We weight the regressions with 2007 deposits and cluster standard errors at the district level.

We turn to the main results. In Figure V, Panel (a), we find that there is a discontinuous increase in the number of private sector bank branches at the RD threshold in under-banked districts. Panel (b) confirms that this does not occur at state-owned banks, as discussed above. Panel (c) depicts the results for deposit shares around the RD threshold: state-owned banks see a discontinuous decrease in deposit shares, reflecting the expansion of private bank shares around the threshold after the 2005 rule change. The discontinuity is economically equivalent to about 28 private sector branches and 9.71 pp in terms of deposit share.[19]

The run period results are in Table VIII. In column (1), we display the estimates of the first-stage equation (21). The F-statistic is 220, indicating that the instrument is strong.

[19] For evidence on covariate balance, see the Internet Appendix Table A.7 and McCrary plots in Figure A.4 and Internet Appendixes Table A.7, Panel (b) and Table A.8 for additional evidence and the relative insensitivity to the empirical choices for implementing the RD.

The second stage regression estimates are in Column (2). Private banks in districts with greater exposure to state-owned banks are more likely to witness runs.[20]

V Heterogeneity Within PSBs

Following Acharya et al. (2017), we classify banks based on "MES," or marginal expected shortfall. Weaker banks that have greater leverage or are more exposed to aggregate risk have greater MES. One advantage of the Indian bank setting is while the government holds majority stakes in PSBs, the outside shareholdings are traded in the market, so we can compute the MES for PSBs and all major private banks. See the Internet Appendix Table A.10 for a list of private banks and PSBs for which we can compute MES.

We ask whether the more vulnerable banks, the high MES banks, attract panic flows. The intuition for the test is that the more vulnerable banks benefit more from the protection conferred by state ownership and thus have greater marginal benefit from taking in the panic flows. Figure VI depicts the evidence on deposit flows. The more vulnerable – weaker – private banks show lower deposit growth. In contrast, weaker state-owned banks had *greater* deposit growth. Table IX provides estimates of Equation (11), replacing the bank-level exposure variable with the bank vulnerability. Columns (1) and (3) show that for private banks, MES is negatively related to deposit and credit growth. Thus, vulnerable private banks are *less* likely to attract deposit flows. In contrast, columns (2) and (4) show that for PSBs, the relation reverses, with greater growth for the more vulnerable PSBs. High-MES PSBs also have greater non-performing assets in non-agricultural loans, over which the banks have more discretion but the relationship is reversed for private banks.

[20]Placebo results for the pre-crisis periods in the Internet Appendix Table A.9 show no such effects or pre-trends. The run period flights are special.

We obtain additional data to speak to the deposit-acquisitive behavior of the more vulnerable PSBs. See Panel B of Table IX. The branch-level BSR data give average deposit rates in different categories, viz., deposits paying less than 5%, and in 1% increments for 5 to 15%, and finally, a bucket for deposits above 15%. The weighted average is based on the two end-points and the multiple mid-points. Private bank deposit rates do not vary with MES (columns 1 and 2). Retail deposit rates are negatively related to MES for PSBs (column (3)). However, the relationship reverses for non-retail deposits. The depositors in this segment are more sophisticated and thus, exhibit more sensitivity to bank strength and state ownership. The more vulnerable PSBs appear to understand this feature in setting deposit rates.

While we cannot say much more formally given what data are available, we also collected anecdotal evidence on the deposit-acquisition strategies of the vulnerable state-owned banks. The increase in deposit rates by these banks during the crisis to chase deposit outflows from private sector banks became so rampant that the Indian Finance Ministry had to step in to curb the behavior (Business Line, 2008). In sum, the more vulnerable PSBs exploit the safety net provided by the government guarantee in crises when the government ownership umbrella becomes more valuable for both the banks and more salient for depositors. These results add texture to our baseline point that access to government support eases funding access for state-owned PSBs, especially in crises, making stabilization more difficult.[21] Ex-post events reveal that the safety-net perceptions of depositors concerning the state's implicit guarantee were not irrational.[22]

[21]Preliminary results from the Covid-19 period are supportive of this channel. Private sector banks, which received 55% of incremental deposits in the pre-Covid periods, saw their share shrink to 30% in the Covid period. We are developing and pursuing this analysis in future work.

[22]In February 2009, the government announced capital injections in 3 state-owned banks: UCO Bank, Central Bank of India and Vijaya Bank. As part of the 2010-2011 budget, the government announced additional capital infusion in five state-owned banks: IDBI Bank, Central Bank, Bank of Maharashtra, UCO

VI Related Literature

Given the economic importance of (avoiding) bank runs, the literature on runs is vast.[23] We add to this literature by analyzing the resource reconfiguration triggered by runs from run banks to safe havens. Our study shows how the aggregate effects of runs require consideration of not only the banks subject to runs but also those gaining run surpluses, and the two-pronged nature of the safety nets provided by state-owned banks.

The nature and consequences of the state ownership of banks have been debated in the economics literature. Shleifer and Vishny (1994) point out that the developmental and market imperfection-correcting role of state-owned banks is impaired by the possibility of political capture. See also Banerjee (1997); Banerjee, Cole and Duflo (2005); Qian and Yeung (2015); Barth, Caprio and Levine (2001); Cole (2009); Dinç (2005); Shleifer (1998). We develop a related point. When state-owned banks exist alongside private banks, as in our setting, the shelter provided by state ownership, which confers protection to state-owned banks, can distort resource flows and impair credit allocation.

The broader issue of resource misallocation is the subject of a thriving literature in economics. Hsieh and Klenow (2009) show that underperforming firms exist. Reallocating resources from them to more productive firms enhances economic growth. A natural question is why misallocation exists in the first place. Implicated are poor property rights,

Bank and Union Bank. These injections were based on capital needs, so they effectively recapitalized the worse-performing banks. These banks are among the highest MES banks in our sample.

[23]Theoretical models of runs include Diamond and Dybvig (1983); Chari and Jagannathan (1988); Calomiris and Kahn (1991); Diamond and Rajan (2001). For empirical evidence characterizing runs, see e.g., Bernanke (1983); Saunders and Wilson (1996); Calomiris and Mason (1997); Iyer and Puri (2012); Acharya and Mora (2015); Blickle, Brunnermeier and Luck (2022); Schumacher (1998); Monnet, Riva and Ungaro (2023), and more recently, in the wake of the 2023 failure of Silicon Valley Bank, Benmelech, Yang and Zator (2023); Caglio, Dlugosz and Rezende (2023); Jiang et al. (2023).

financial frictions, trade and competition, and government regulations.[24]

State ownership of productive assets can contribute to resource misallocation, and policies to subsidize and protect state-owned firms (possibly due to political considerations) impact the better ones in the same businesses. [25] We join this literature by highlighting an alternate channel, the distortion created by the implicit protection of deposits for state-owned banks that is not available to private banks. In developed economies, such protection is associated with size, as especially large banks are "too big to fail" (Penas and Unal, 2004; Iyer et al., 2019). We do not rely on size but identify implicit protection through state ownership and control of banks and the related banking law.

Our evidence on resource reallocation adds to three streams of research. One is about banking systems without a safety net, e.g., Argentina in the 1990s (Schumacher, 1998). Here, runs move funds from weak to strong private banks with greater credit discipline, although see Baron, Schuralick and Zimmerman (2023) for a different viewpoint. We show that outcomes worsen when state-owned banks are safety nets. We also add to recent work on "silent" banking panics without accompanying bank failure (Baron, Verner and Xiong, 2020). Our study features exactly this type of run. We analyze the resulting resource reallocation and show its effects on both the banks experiencing runs and the banks receiving run flows. We find that even silent runs do have negative effects, supporting the conservative stance towards runs taken by central banks.

Finally, runs and the resulting resource flights are a key issue confronting U.S. policymakers in the wake of the runs on Silicon Valley Bank and other institutions in March

[24]See Restuccia and Rogerson (2017) for a discussion. Related work includes Adamopoulos and Restuccia (2014); Midrigan and Xu (2014); Buera, Kaboski and Shin (2011); Bau and Matray (Forthcoming); Pavcnik (2002); Trefler (2004); Hopenhayn and Rogerson (1993); Guner, Ventura and Xu (2008).

[25]See Dollar and Wei (2007); Song, Storesletten and Zilibotti (2011); Brandt, Tombe and Zhu (2013) and Hsieh and Klenow (2009) for state ownership of firms, and Banerjee and Duflo (2005); Hsieh and Klenow (2009); Geng and Pan (2022); Sapienza (2004) and Dinç (2005) on the effects on private firms.

2023 (Acharya et al. (2023), Jiang et al. (2023), Caglio, Dlugosz and Rezende (2023)). Our study highlights some issues in assessing and responding to these runs. The flight to safety is not necessarily a flight to quality. Its aggregate effect depends not only on the banks facing deposit deficits or even failing but also on those gaining deposits, and the quality and direction of the reintermediation they offer for the windfall surpluses.

VII Conclusion

We study a significant bank run episode in India in which private sector bank branches face sudden and large losses in deposits that migrate to safe public sector banks (PSBs) owned by the state. A key feature of our analysis is that we observe outcomes for both the bank branches that face runs and the ones that gain from the flight-to-safety flows. Using data on bank-firm relationships, we also assess the onward impact on bank borrowers and estimate the aggregate impact of the run.

We find that runs propagate beyond the local geographies in which they occur. Banks facing runs cut lending and their credit discipline improves. Credit expands but quality worsens at the state-owned PSBs receiving windfall run surpluses. At the firm level, credit contracts for borrowers with relationships with run banks. While credit expands for firms borrowing from the run beneficiaries, these firms perform worse ex-post. The aggregate reallocation effect is negative, with productivity growth impaired by about 5%.

An important thread in our study is that while the banks facing runs and their clientele have been the principal focus of research and policy on bank runs, what also matters is how the flight-to-safety flows are reintermediated back to the real economy. In our study, reintermediation occurs through state-owned bank branches, the weaker ones. They seem to bear greater responsibility for the negative aggregate effects of the run. A policy implication is that while government support is (correctly) seen as a source of financial stability during a crisis, its provision is not free of costs. In the instance we study, the support that lends stability also shelters banks from discipline in the funding market, leading to lax credit allocation.

In our specific setting, the variation in the ownership structure between state-owned and private banks results in a clear marker of differential government support. It seems interesting for further empirical inquiry to test the plausible hypothesis that our conclusions carry over to other settings with differential access to government support, such as for too-big-to-fail or too-systemic-to-fail banks vis-a-vis other banks, and for government-sponsored enterprises vis-a-vis private financial institutions.

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Figure I: Time Trends in Deposits of Private and State-Owned Public Sector Banks in India

This figure shows the quarterly deposits for private and state-owned public sector banks from 2007 to 2012, where year is the fiscal year ending on March 31. Deposits are normalized to 1 as of December 2007 (i.e., quarter 3 of fiscal 2008). The solid vertical line represents the date of the Bear Stearns rescue in March 2008. The dashed vertical line dates the bankruptcy of Lehman Brothers in September 2008. Data for quarterly deposits are from the publicly available “Database on Indian Economy" provided by the Reserve Bank of India.

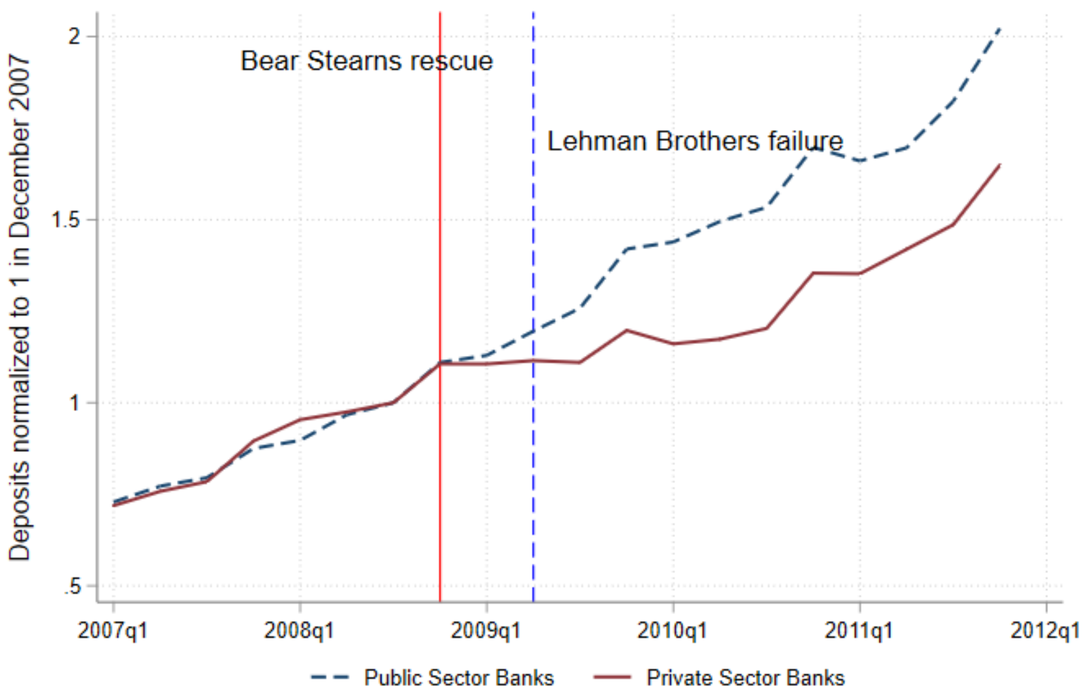


Figure II: Heat Map

This figure shows the heat map for the deposit growth of private and public sector banks at the district level for 2009, where year refers to the fiscal year ending on March 31. Panel (a), (b), and (c) correspond to the overall, private, and public bank deposit growth, respectively. Districts with no available data are shaded in gray.

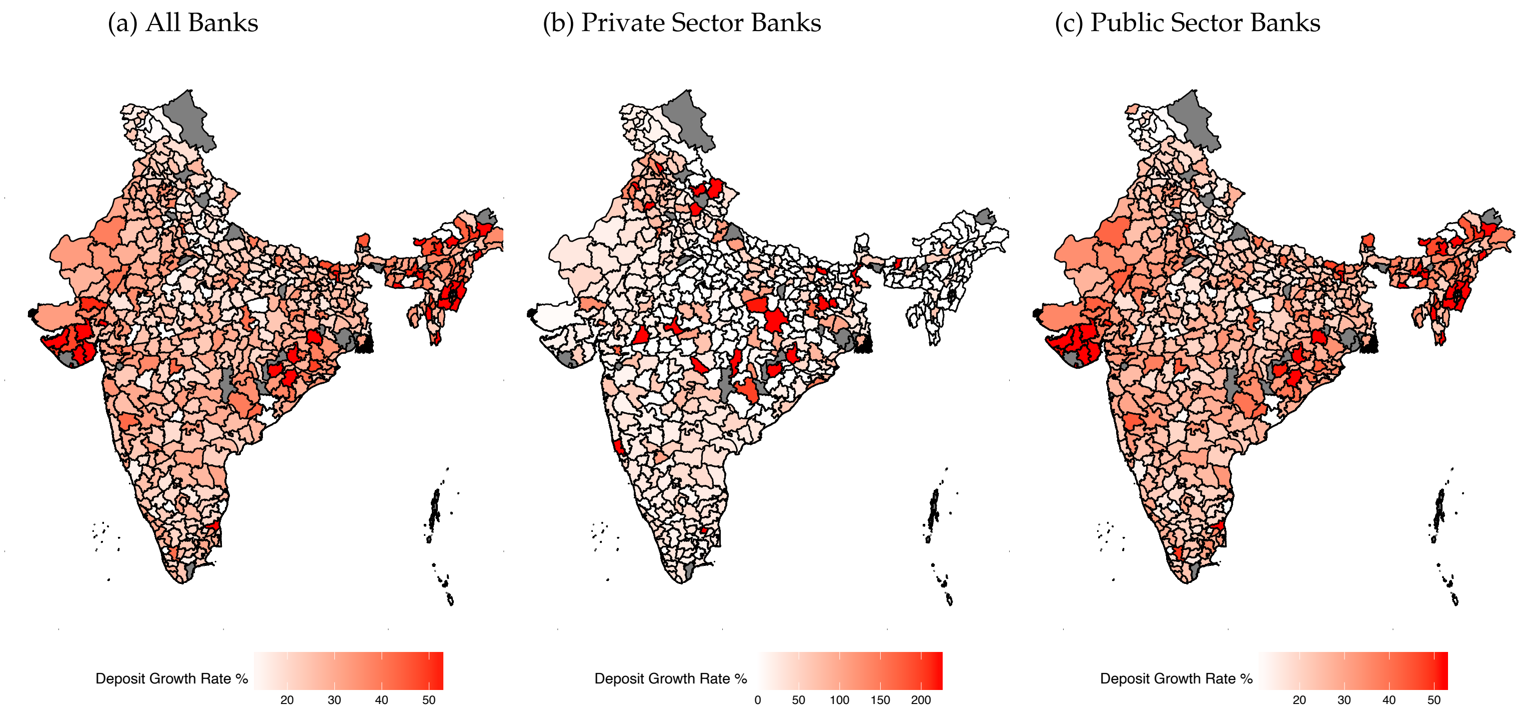
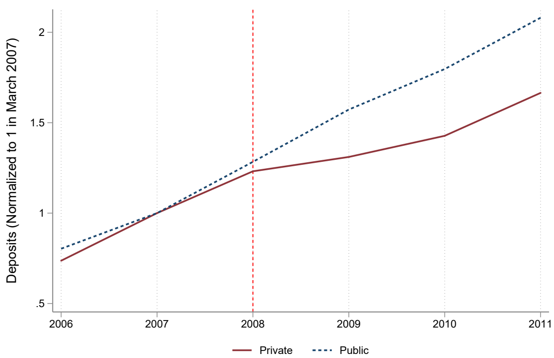
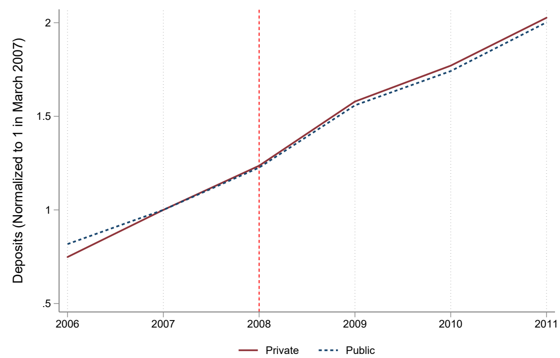


Figure III: Deposits by region: Metro, urban, semi-urban and rural

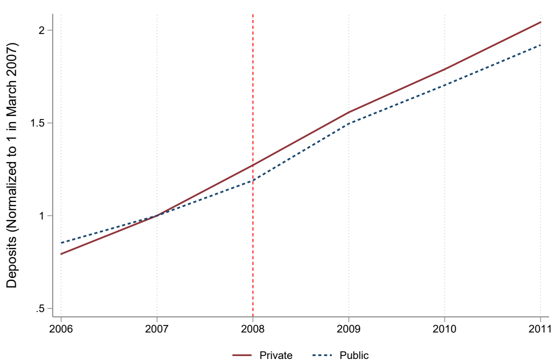
This figure shows the annual deposits (normalized to deposits in 2007) separately for public and private sector banks in metro, urban, semi-urban and rural branches aggregated to the national level for the years 2006 to 2011. Year refers to the fiscal year ending March 31.



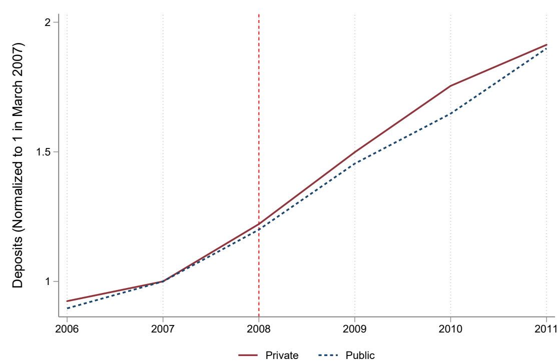
(a) **Metro**



(b) **Urban**



(c) **Semi-urban**



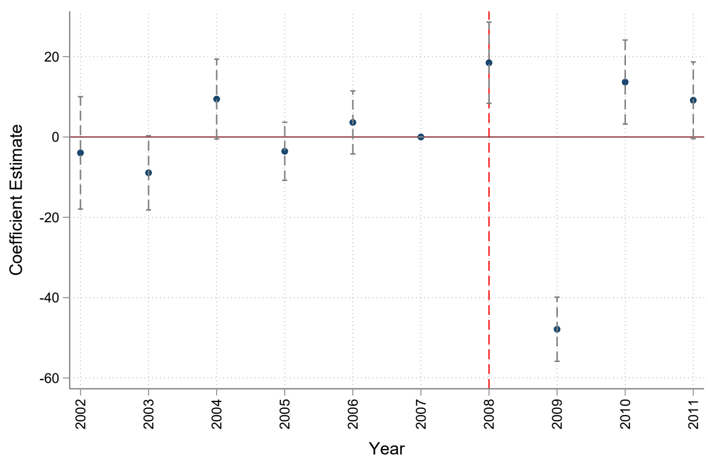
(d) **Rural**

Figure IV: Event Study Plots

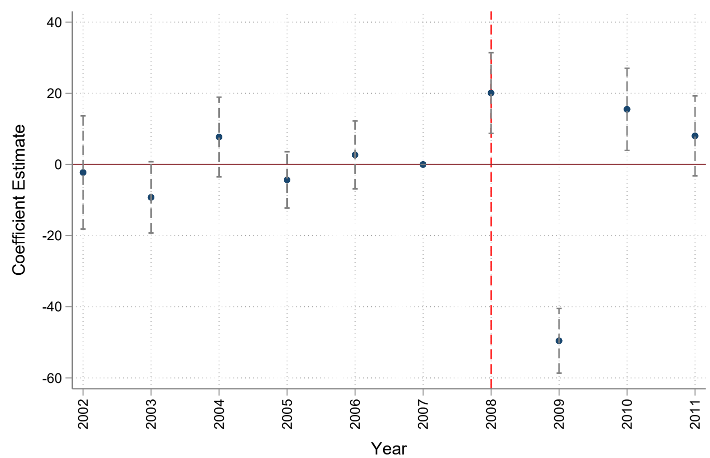
This figure shows the coefficients (η_τ) from an event study regression:

$$Y_{jbdpt} = \alpha_j + \theta_{dt} + \gamma_{bt} + \sum_{\tau} \eta_\tau \times \mathbb{1}_\tau \times \mathbb{1}_{\text{Branch run}} + \epsilon_{jbdpt}$$

where the dependent variable, Y_{jbdpt} is the annual growth in deposit for branch j belonging to bank b in district d in pincode p for time-period t (where t ranges from 2002 to 2011). α_j, γ_{bt} and θ_{dt} are branch, bank-time, and pincode-time period fixed effects respectively in panel A. In Panel B, θ_{dt} is replaced with pincode-time fixed effect. $\mathbb{1}_\tau = 1$ if the year is τ, with τ ranging from 2002 to 2011. The branch run variable, $\mathbb{1}_{\text{Branch run}}$, is as defined in Table A.1. Year refers to the fiscal year from April 1st to March 31st. Standard errors are clustered at the branch level. The figure plots the η_τ coefficients. Dashed grey lines depict the 5% confidence intervals.



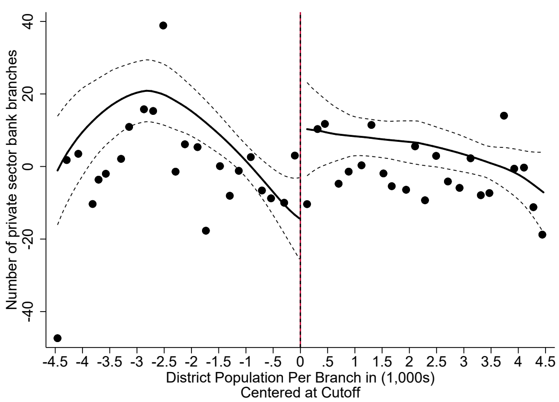
(a) With district FE



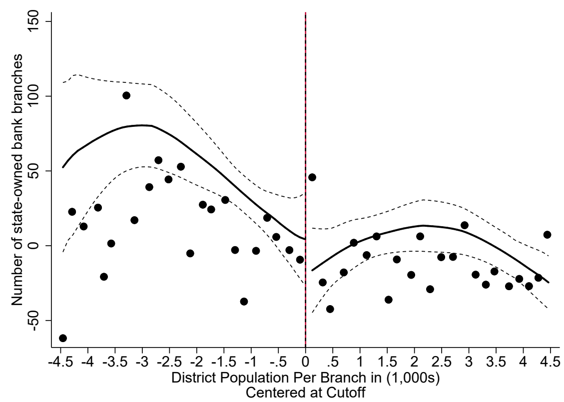
(b) With pincode FE

Figure V: Regression Discontinuity: Share of State-Owned Bank Branches

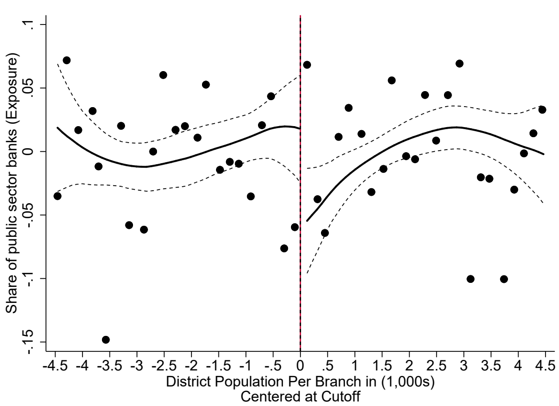
The table reports regression discontinuity (RD) plots for the number of private sector bank branches in 2006–08 (panel a), number of state-owned bank branches in 2006–08 (panel b), deposit share of state-owned banks in 2006–08 (panel c), and deposit share of state-owned banks in 2001–03 (panel d) at the district-level. Year refers to the fiscal year from April 1st to March 31st. The running variable on the horizontal axis is the national average population per branch subtracted from the district average population per branch. It is centered at zero and scaled to thousands of persons per district. Points to the right (left) of 0 are under-banked (banked) districts. Each point represents the average value of the outcome in 0.2 percentage point run variable bins. The solid line plots predicted values, with separate quadratic trends with triangular kernels estimated on either of 0. Bandwidth of (-4.5,4.5) is used. State-fixed effects have been partialled out. The dashed lines show 95 percent confidence intervals. Robust standard errors are shown. Population data used to construct the running variable is from the 2001 Census.



(a) Private sector bank branches in 2006–08

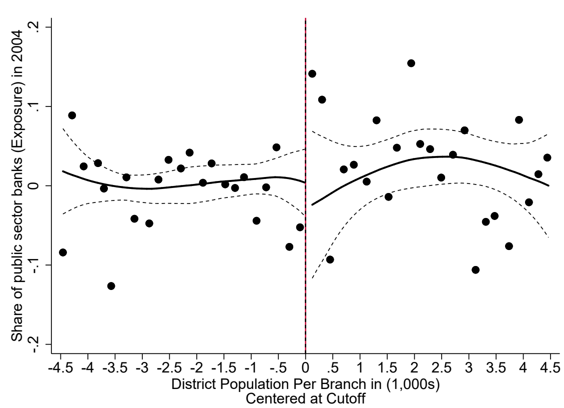


(b) State-owned bank branches in 2006–08



(c)

Deposit share of state-owned banks in 2006–08



(d) Deposit share of state-owned banks in 2001–03

Figure VI: Deposit Growth and Bank Vulnerability

This figure plots the deposit growth in fiscal 2009 against MES for private and state-owned banks where the fiscal year is the year ending on March 31. MES is defined as the negative of the average returns of a stock given that the market return is below its 5th- percentile during the period 1st January 2007 to 31st December 2007. Stock market data required to compute MES are from the National Stock Exchange and the Bombay Stock Exchange. MES is defined in Table A.1.

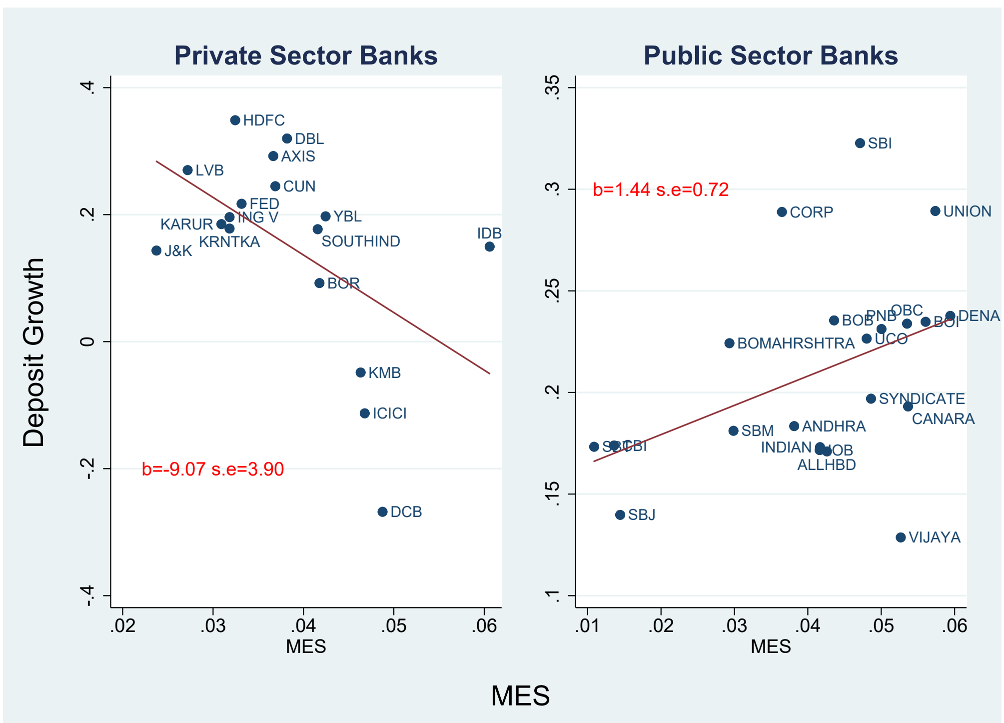


Table I: Descriptive Statistics

This table presents the summary statistics for all variables in our analysis. Panel A shows the summary statistics for the exposure measures described in Table A.1. Pvt. Dep. Pct.$_{\text{COLOC PIN}}$ and PSB Dep. Pct.$_{\text{COLOC PIN}}$ are shown before standardization (z-scoring). Panels B, C, D, and E show the summary statistics for variables at the branch, loan, firm, and industry level, respectively. Deposit and credit growth are for the fisal year between 2008–2009. Δ NPA$_{2009-2011}$ (Δ NPA$_{2012-2016}$) is the change in non-performing assets for 2009–2011 (2012–2016) relative to credit in 2009 in pp. Observations in Panel C (Panel D) are from a balanced panel at the bank-firm (firm) level for the pre- and post-period. $\mathbb{1}_{Loan}$ is an indicator for whether a loan exists between a bank-firm pair. Loan amount is in INR million. Marginal productivity of capital (MRPK) is calculated as total sales to gross fixed assets. Panel E shows the summary statistics for three moments of the log-MRPK distribution at the 3-digit industry: the cross-sectional variance of log-MRPK in an industry period, the cross-sectional mean of log-MRPK, and the correlation of log-MRPK and log VA (log sales), with average MRPK calculated for the pre-period and post-periods. Pre-period refers to 2006–2008 and post-period to 2009–2011. Year denotes the financial year from April 1$^{\text{st}}$ to March 31$^{\text{st}}$.

Panel A: Exposure measures

	Obs	Mean	SD
$\mathbb{1}_{\text{Branch run}}$	30,806	0.01	0.11
$\mathbb{1}_{\text{Coloc. PSB}}$	30,806	0.05	0.21
Pvt. Dep. Loss$_{\text{RUN PIN}}$	10,015	0.59	4.71
Pvt. Dep. Loss$_{\text{COLOC PIN}}$	10,015	0.36	4.30
Pvt. Dep. Pct.$_{\text{COLOC PIN}}$	19	0.297	0.429
PSB Dep. Pct.$_{\text{COLOC PIN}}$	20	52.740	29.474
PSB Dep. Pct.$_{\text{COLOC PIN}}$	20	52.740	29.474
Firm Exposure	8,272	0.799	0.239
Industry Exposure	57	0.672	0.434

Panel B: Branch-level Variables

	All		Public		Private	
	Mean	SD	Mean	SD	Mean	SD
Deposit growth 2008–2009 (in %)	30.96	38.84	29.58	36.62	37.48	47.45
Credit growth 2008–2009 (in %)	33.72	71.67	30.13	64.28	50.75	97.71
Obs. (Branch)	30,806		58,203		5,273	
Δ NPA$_{2009-2011}$ (in %)	1.23	5.00	1.42	4.93	0.35	5.23
Δ NPA$_{2012-2016}$ (in %)	6.38	12.73	6.99	13.04	3.51	10.68
Obs. (Branches)	30,648		25,375		5,368	

Panel C: Loan-level Variables

	All		Public		Private	
	Mean	SD	Mean	SD	Mean	SD
$\mathbb{1}_{Loan}$	0.02	0.14	0.03	0.18	0.01	0.11
Loan amount (in INR million)	27	930	54	1366	11	504
Obs. (Loans)	636,918		240,996		395,922	

Panel D: Firm-Level Variables

	Mean	SD	p25	p50	p75
$\mathbb{1}_{Loan}$	0.57	0.49	0.00	1.00	1.00
Loan amount (in INR million)	1699	10,483	0.00	23	450
Obs. (Firms)			12,668		

Panel E: Industry-Level Moments of Log-MRPK Distribution

	Mean	SD	p25	p50	p75
Pre-period Var(log-MRPK)	2.39	1.28	1.60	1.96	2.88
Pre-period Mean(log-MRPK)	0.59	0.51	0.28	0.61	0.92
Pre-period Cov(log-MRPK, log VA)	0.56	0.21	0.51	0.58	0.70
Post-period Var(log-MRPK)	2.19	1.25	1.37	1.89	2.75
Post-period Mean(log-MRPK)	0.67	0.52	0.29	0.70	1.01
Post-period Cov(log-MRPK, log VA	0.52	0.20	0.41	0.52	0.66
Obs. (Industry)			57		

Table II: Deposit Growth at Branches With Runs

This table reports estimates of a regression in which the dependent variable is the annual growth rate of deposits for 2008–2009. Year refers to the fiscal year from April 1st to March 31st. Observations are at the branch level. The branch run variable, $\mathbb{1}_{\text{Branch run}}$, and the branch-level instrument, $\mathbb{1}_{\text{COLOC. PSB}}$, are defined in Table A.1. Fixed effects included are as indicated. Columns 1–2 show the OLS estimates, columns 3–4 show the first-stage using the instrument for branch run, and columns 5–6 show the instrumented variables 2SLS IV estimates. Standard errors are clustered at the branch level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Deposit growth		Branch Run		Deposit growth	
$\mathbb{1}_{\text{Branch run}}$	-58.453***	-60.070***			-105.309***	-108.728***
	(1.572)	(1.744)			(29.687)	(35.851)
$\mathbb{1}_{\text{Coloc. PSB}}$			0.055***	0.049***		
			(0.010)	(0.010)		
R-squared	0.125	0.274	0.178	0.269	0.009	0.010
No. of Obs.	30784	25501	30784	25501	30784	25501
F-statistic			31.46	24.73		
Bank FE	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Pincode FE	N	Y	N	Y	N	Y
Type	OLS	OLS	First Stage	First Stage	IV	IV

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table III: Deposit Flights In Local Geography

The table shows the impact on deposit growth of runs on branches in the same district. Observations are at the branch level. The dependent variable in all columns is the annual growth rate of deposits for 2008–2009, where year is fiscal year ending March 31st. Pvt. Dep. Loss$_{\text{RUN PIN}}$ and Pvt. Dep. Loss$_{\text{COLOC PIN}}$ (instrument) are pincode-level measures defined in Table A.1. Public is an indicator variable for public sector banks. Column 1 shows the first stage for Pincode Exposure instrumented with Pincode Exposure Propensity. Columns 2–3 and 4–5 show the OLS and the instrumented variable 2SLS IV regression, respectively. District, pincode and bank fixed effects are included as shown. Standard errors are clustered at the district level.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	Pvt. Dep. Loss$_{\text{RUN PIN}}$	Deposit growth			
Pvt. Dep. Loss$_{\text{COLOC PIN}}$	0.733***				
	(0.0798)				
Pvt. Dep. Loss$_{\text{RUN PIN}}$		-0.280***		-0.325***	
		(0.0555)		(0.0838)	
Public $\times$ Pvt. Dep. Loss$_{\text{RUN PIN}}$		0.413***	0.375***	0.505***	0.494***
		(0.0634)	(0.0661)	(0.100)	(0.107)
R-squared	0.459	0.0698	0.255	0.00370	0.00352
No. of Obs.	30806	30806	25501	30806	25501
F-statistic	84.43			33.22	64.54
Bank FE	Y	Y	Y	Y	Y
District FE	N	N	Y	N	Y
Pincode FE	N	N	Y	N	Y
Type	First Stage	OLS	OLS	IV	IV

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IV: Credit Effects In and Beyond Run Geographies

This table shows the impact on credit growth of branches with different exposure to runs. Observations are at the branch level. The dependent variable is the annual growth rate of total credit for 2008–2009. Year refers to the fiscal year from April 1st to March 31st. Remaining variables are defined in Table A.1. Only private sector bank branches are included in columns 1-2 and public sector bank branches in columns 3–4. Fixed effects are included as indicated. Standard errors are clustered at the pincode level.

	(1)	(2)	(3)	(4)
Dependent variable:	Credit growth			
Sample:	Private Sector Banks		Public Sector Banks	
$\mathbb{1}_{\text{Coloc. PSB}}$	-22.052**	-21.863**		
	(9.365)	(9.046)		
Pvt. Dep. Pct.$_{\text{COLOC PIN}}$	0.005			
	(3.105)			
Pvt. Dep. Loss$_{\text{COLOC PIN}}$			0.030	
			(0.044)	
PSB Dep. Pct.$_{\text{COLOC PIN}}$				1.573***
				(0.325)
R-squared	0.129	0.175	0.019	0.059
No. of Obs.	5307	5307	25438	25409
Bank FE	N	Y	Y	N
District FE	Y	Y	N	Y

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table V: NPA Effects In and Beyond Run Geographies: Long difference

This table shows the relation between runs and loan performance. Observations are at the branch level. The dependent variable is the change in non-performing assets from 2009–2011 relative to credit in 2009 (columns 1–2) and the change in non-performing assets from 2012–2016 relative to credit in 2012 (columns 3–4). Credit growth between 2009 and 2011 (columns 1–2) and between 2012 and 2016 (columns 3–4) is included as controls. Year refers to the financial year ending on March 31. Pvt. Cred. $\text{Pct.}_{\text{COLOC PIN}}$ and PSB Cred. $\text{Pct.}_{\text{COLOC PIN}}$ are the bank-level exposure measures as defined in table A.1. Both measures are standardized (z-scored). Standard errors are clustered at the pincode level.

	(1)	(2)	(3)	(4)
Dependent variable:	Δ $\text{NPA}_{2009-2011}$		Δ $\text{NPA}_{2012-2016}$	
Sample:	Private	Public	Private	Public
Pvt. Cred. $\text{Pct.}_{\text{COLOC PIN}}$	-0.601***		-0.168	
	(0.132)		(0.280)	
PSB Cred. $\text{Pct.}_{\text{COLOC PIN}}$		0.037		0.913***
		(0.035)		(0.100)
R-squared	0.186	0.185	0.253	0.257
No. of Obs.	25259	25259	25146	25146
Pincode FE	Y	Y	Y	Y

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table VI: Loan-Level and Firm-level Outcomes

This table shows the impact on loan-level and firm-level borrowing in Panel A and B, respectively. Post-period (pre-period) is the 3-year fiscal period between 1st April 2009 to March 31st 2011 (April 2006 to March 2008). The extensive margin dependent variable in columns 1–2 is whether a loan exists for a bank-firm pair in the post-period. The intensive margin dependent variable in columns 3–4 is the total loan amount in INR million for a bank-firm pair in the post-period, conditional on a loan being made. The dependent variable in columns 3–4 combines the intensive/extensive margin and is the total loan amount between a bank-firm pair (including 0). All columns in Panel A include the respective pre-period variables as control variables. Public Sector Bank is an indicator at the bank-firm pair in Panel A. Even numbered columns include firm fixed effect. Observations are a balanced panel at the bank-firm level for the pre- and post-period in columns 1–2 and 5–6, and for only bank-firm pairs where there is a loan in the post-period in columns 3–4 in Panel B. In panel B, the dependent variable at the extensive margin is whether a loan was extended in the post-period (columns 1–2), at the intensive margin is the total loan amount in INR million to a firm conditional on a loan being made (columns 3–4), and at the combined intensive/extensive margin is the total loan amount at the firm level (including 0s). Firm exposure is as defined in Table A.1. Top is an indicator equal to 1 if the average MRPK (calculated as total sales to gross fixed assets) in the pre-period is above median. All columns include industry fixed effects in Panel B. Observations are a balanced panel at the firm-level for the pre- and post-period in columns 1–2 and 5–6, and for only firms that borrow in the post-period in columns 3–4 in Panel B. In both panels OLS estimation is used in columns 1–4 and Poisson regression in columns 5–6. Standard errors are clustered at the bank-level in Panel A and at the industry-level in Panel B.

Panel A: Loan-level

	(1)	(2)	(3)	(4)	(5)	(6)
	Extensive		Intensive		Extensive+Intensive	
Dependent variable:	$\mathbb{1}_{Loan}$		Amount (in INR million)			
Public Sector Bank	0.017***	0.017***	547.277**	929.954**	1.540***	1.512***
	(0.005)	(0.005)	(242.402)	(362.439)	(0.475)	(0.443)
R-squared	0.078	0.108	0.040	0.296		
No. of Obs.	636918	636918	13256	9368	636918	479372
Firm FE	N	Y	N	Y	Y	Y
Type	OLS	OLS	OLS	OLS	Poisson	Poisson

Panel B: Firm-level

	(1)	(2)	(3)	(4)	(5)	(6)
	Extensive		Intensive		Extensive+Intensive	
Dependent variable:	$\mathbb{1}_{Loan}$		Amount (in INR million)			
Firm Exposure	0.347***	0.365***	1965.382***	2615.190**	1.592***	1.890***
	(0.014)	(0.021)	(541.246)	(1031.352)	(0.146)	(0.197)
Top		0.170***		-981.922**		0.147
		(0.015)		(432.743)		(0.235)
Top × Firm Exposure		-0.073***		-1022.016		-0.581**
		(0.025)		(1159.230)		(0.286)
R-squared	0.106	0.130	0.033	0.038		
No. of Obs.	8272	8272	2962	2962	8272	8272
Industry FE	Y	Y	Y	Y	Y	Y
Type	OLS	OLS	OLS	OLS	Poisson	Poisson

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table VII: Industry-level Outcomes

This table shows the estimates at the industry-level used to calculated the impact on aggregate productivity. Observations are at the industry level for the pre- and post-periods, 2006-2008 and 2009-2011, respectively. Industry exposure is defined in Table A.1. Marginal productivity of capital (MRPK) is calculated as total sales to gross fixed assets. The dependent variable is one of the three moments of the log-MRPK distribution: the cross-sectional variance of log-MRPK in an industry year (columns 1–2), the cross-sectional mean of log-MRPK (columns 3–4), and in columns 5–6, the correlation of log-MRPK and log VA (log sales), with average MRPK calculated for the pre-period and post-periods. Post is a dummy variable for the 2009-2011 period. Time and 3-digit industry fixed effects are included as shown. Standard errors are clustered at the industry level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Var(log-MRPK)		Mean(log-MRPK)		Cov(log-MRPK, log VA)	
Post * Industry exposure	1.305*	1.305*	-0.032	-0.032	0.244	0.244
	(0.741)	(0.737)	(0.160)	(0.159)	(0.161)	(0.160)
Industry exposure	-0.105		0.715		-0.068	
	(1.134)		(0.583)		(0.187)	
R-squared	0.036	0.866	0.041	0.974	0.063	0.831
No. of Obs.	114	114	114	114	114	114
Industry FE	N	Y	N	Y	N	Y
Period FE	Y	Y	Y	Y	Y	Y

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table VIII: Evidence From Regression Discontinuity Design

This table shows the estimates for deposit growth of private bank branches using a regression discontinuity design. The dependent variable is the annual growth rate of deposits for 2009–2011. Year refers to the financial year from April 1st to March 31st. We instrument the public sector bank (PSB) deposit share with whether a district is banked, that is, whether the population per branch minus its national average is less than zero, a running variable based on a new branching policy by the central bank' using a sharp cutoff based on branching density. The first- and second-stage results are shown in columns 1 and 2. Both specifications include state-year and bank-year fixed effects and the following covariates: the percentage of skilled officers, the credit-to-deposit ratio in 2008, and their interactions with time trends. Observations are weighted with 2007 deposits. Standard errors are clustered at the district level. Branch data is from the Reserve Bank of India. Population data to construct the running variable are from the 2001 Census.

	(1)	(2)
Dependent variable:	Deposit growth	
Sample:	Private sector bank branches	
	First stage	Second stage
Banked	0.0387***	
	(0.00305)	
Exposure to state-owned banks		-58.11**
		(22.74)
F-stat	220	
R-squared	0.816	0.187
No. of Obs.	12098	12098
State-Year FE	Y	Y
Bank-Year FE	Y	Y
Controls	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table IX: Heterogeneity Within Private and State-Owned Banks: Bank Vulnerability

This table shows the heterogeneity in the credit outcomes related to bank runs when banks are sorted by MES, a weakness measure.. The dependent variable in Panel A is the annual deposit growth (columns 1–2), credit growth (columns 3–4), and agricultural and non-agricultural non-performing assets (NPA) growth (columns 5–8) at the branch level for 2009–2011. Year refers to the fiscal year from April 1^{st} to March 31^{st}. MES is defined as the negative of the average returns of a stock given that the market return is below its 5^{th}- percentile during the period 1^{st} January 2007 to 31^{st} December 2007. The dependent variable in Panel B is the change in the weighted average deposit rate in basis points (BPS) for retail (columns 1 and 3) and non-retail (columns 2 and 4) depositors. Public and private sector bank branches are examined separately, as indicated in both panels. All columns include district-year fixed effects. Standard errors are clustered at the branch level.

Panel A: Deposit, Credit, and Non-performing Asset Growth

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Deposit growth		Credit growth		NPA growth			
Sample:	Private	Public	Private	Public	Private		Public	
Type:					Agri.	Non-Agri.	Agri.	Non-Agri.
MES	-2.367***	0.182**	-2.112**	0.363***	8.064	-28.252***	7.702***	2.746**
	(0.487)	(0.077)	(0.826)	(0.134)	(15.042)	(7.405)	(2.581)	(1.348)
R-squared	0.099	0.049	0.078	0.037	0.235	0.116	0.108	0.028
No. of Obs.	18924	103966	18924	103966	2001	6900	17536	52589
District-Year FE	Y	Y	Y	Y	Y	Y	Y	Y

Panel B: Deposit Rates

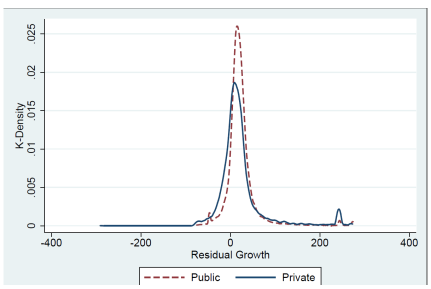
	(1)	(2)	(3)	(4)
Dependent variable:	Change in Deposit Rates (in BPS)			
Sample:	Private		Public	
Type:	Retail	Non-retail	Retail	Non-retail
MES	1.157	-0.713	-6.392***	2.483***
	(0.765)	(2.085)	(0.186)	(0.657)
R-squared	0.752	0.370	0.539	0.060
No. of Obs.	9929	9651	40857	36736
District-Year FE	Y	Y	Y	Y

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Internet Appendix

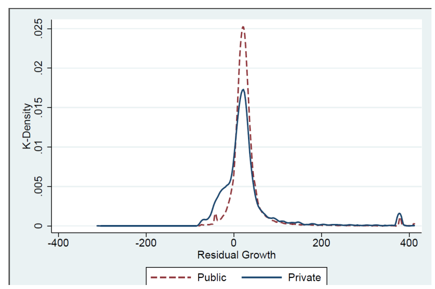
Figure A.1: Distribution of ΔDeposit Growth Rates

Panels (a) and (b) show the excess deposit growth in the year 2008 and year 2009. Year refers to the fiscal year from April 1st to March 31st. Residual deposit growth is the difference between the actual deposit growth rate and the predicted growth on an out-of-sample basis using a regression of deposit growth on size (lagged credit), age, whether rural, lagged credit to deposit ratio and whether public for the years between 2002 and 2006. Panels (c) and (d) show the distribution of the change in growth rates of deposits. Panel (c) shows the difference in growth rates for the year 2007 and year 2008 (Δ of growth rates). Panel (d) shows the difference in growth rates for the year 2008 and year 2009. Panel (e) and (f) show the distribution of deposit growth rates for years 2008 and 2009 for public sector banks and private sector banks and restrict to branches with deposit growth rates below zero.



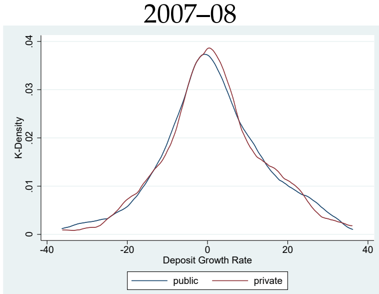
(a)

2007–08



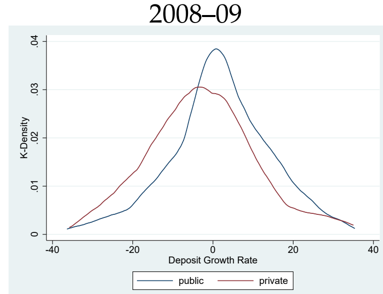
(b)

2008–09



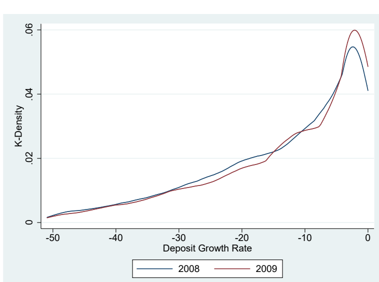
(c)

2007–08



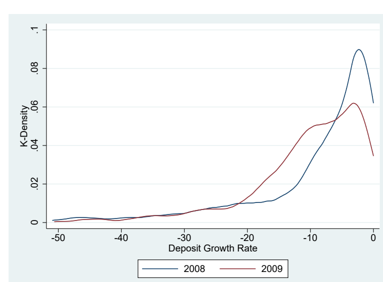
(d)

2008–09



(e)

2007–08



(f)

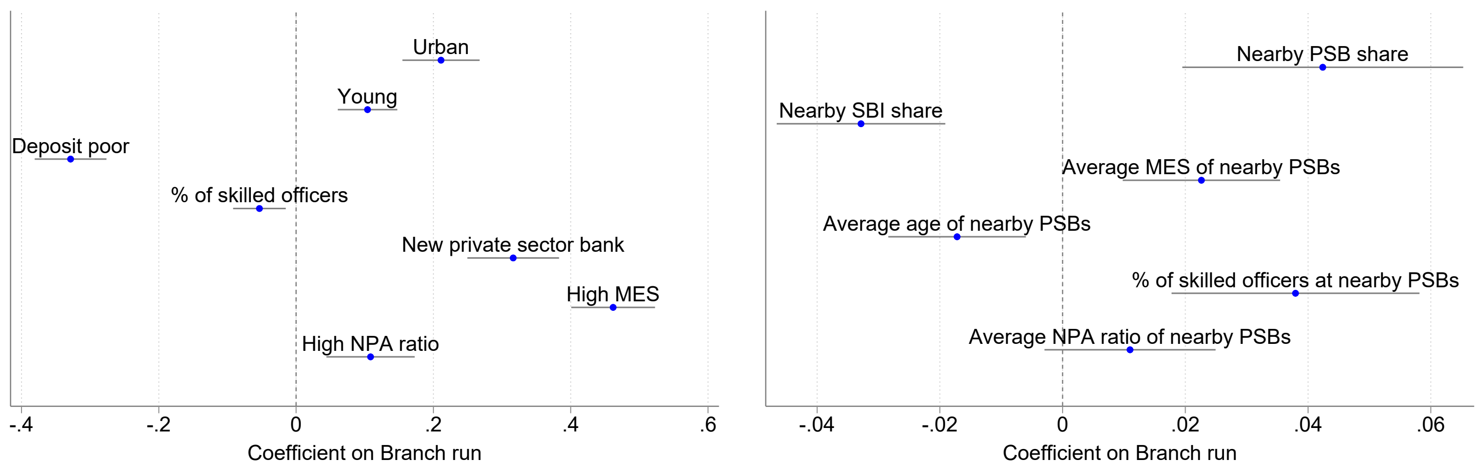
2008–09

Figure A.2: Characteristics of Branches With Runs

The figure shows the characteristics of branches with runs and the characteristics of the public sector bank branches in these districts. The correlates of the branch run variable and branch and district characteristics are examines using the specification:

$$\text{Branch run}_j = \alpha + \beta \times \text{Char}_j + \epsilon_j$$

Branch run is an indicator variable as defined in Table A.1. Char_j are branch-level and district-level characteristics. The branch-level characteristics in panel (a) are an indicator for deposits below the median deposits of all bank branches i.e. deposit poor branch, the percentage of skilled workers in the branch, an indicator for branch less than five years old i.e. Young, an indicator for the branch being in an urban area, an indicator for the branch belonging to a new private bank, indicator for branch with non-performing asset (NPA) ratio is higher than the median ratio, an indicator for the branch belonging to a bank with high marginal expected shortfall. The RHS variable in panel (b) are the district-level characteristics of the public sector bank branches in the district where the run branch is located. The district-level characteristics are the share of SBI and its associates in deposits, the average age of nearby PSBs, the average marginal expected shortfall (MES) of nearby PSBs, the percentage of skilled workers in nearby PSBs and finally, the share of nearby PSBs. The coefficient from each regression using different branch-level and district-level characteristics are shown. The dot represents the mean coefficient, and the line along the dot represents the 95 percent confidence interval.

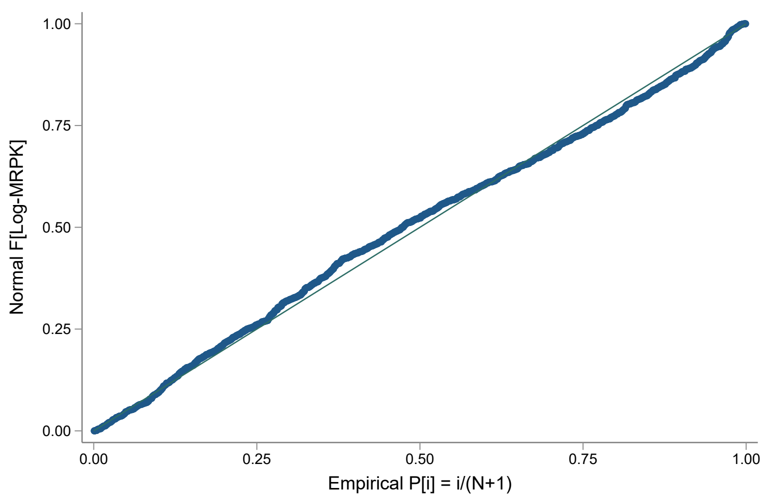


(a) **Characteristics of branches with runs**

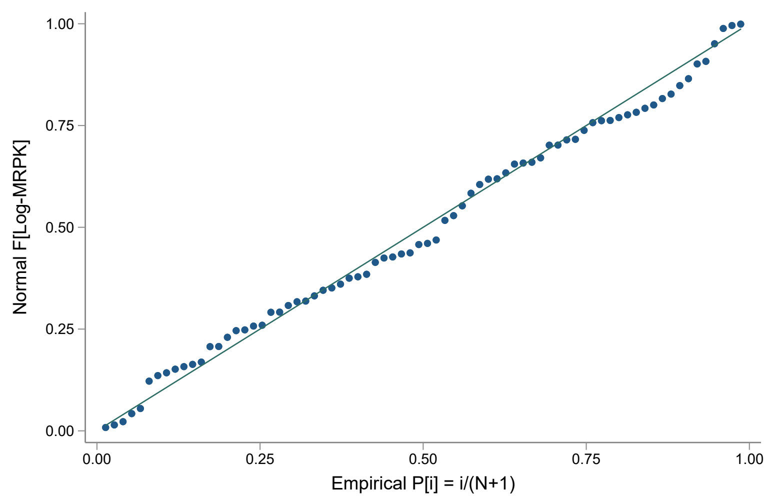
(b) **Characteristics of nearby PSB branches**

Figure A.3: Log-Normality of MRPKs in the Data

The figure shows the quantiles of log-MRPK against quantiles of normal distribution. MRPK is as of 2008 and computed as the ratio of sales to the gross book value of total assets and is then standardized (z-scored by subtracting the mean value and dividing by the standard deviation). Panel (a) shows the figure for the sample of manufacturing firms and panel (b) is for the remaining sample of non-manufacturing firms.



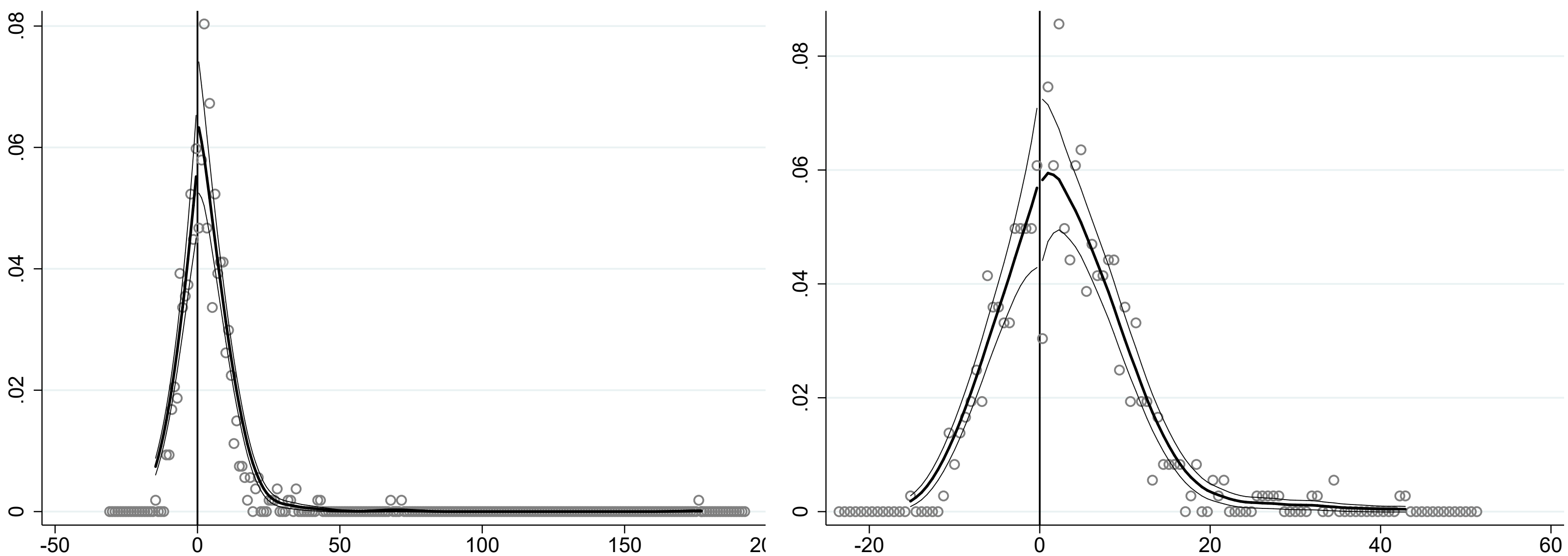
(a) Manufacturing firms



(b) Non-manufacturing firms

Figure A.4: Regression Discontinuity: McCrary Test

This figure plots the McCrary graphs. It graphs the density of the running variable. The running variable on the horizontal axis is the national average population per branch subtracted from the district average population per branch. It is centered at zero and scaled to thousands of persons per district. Points to the right (left) of 0 are under-banked (banked) districts. Panel (a) is the full sample and Panel (b) removes outliers above 60. Branch-level data is from the Reserve Bank of India. Population data used to construct the running variable is from the 2001 Census.



(a) Full sample

(b) Without outliers

Table A.1: Key Variables

Variable	Definition & Source †
(1) $\mathbb{1}_{\text{Branch run}}$	Branch-level indicator that equals 1 if (a) private sector bank branches if all conditions below are satisfied and 0 for all other branches. Year is the 12-month financial year ending on March 31^{st}. (i) Deposit growth is less than predicted based on a regression of annual deposit growth on size (lagged credit), age, whether rural, lagged credit to deposit ratio and whether public using BSR branch data from 2002 to 2006. (ii) Deposit growth falls in 2008–2009 (post-period) is less than that in 2007–2008. (iii) The branch is in the bottom 5th percentile of deposit growth in the year 2009 but not in 2008.
(2) $\mathbb{1}_{\text{Coloc. PSB}}$	Branch-level indicator that equals 1 for a private sector branch in a metro, which has another metro public sector bank branch in the same pincode and 0 otherwise.
(3) Pvt. Dep. $\text{Loss}_{\text{RUN PIN}}$	Pincode-level variable that is the maximum of 0 and the negative total deposit growth rate from 2008 to 2009 of branches in a district with Branch Run (defined above) equal to 1.
(4) Pvt. Dep. $\text{Loss}_{\text{COLOC PIN}}$	Pincode-level variable that is the maximum of 0 and the negative deposit growth rate from 2008 to 2009 of branches in a district with $\mathbb{1}_{\text{Coloc. PSB}}$ (defined above) equal to 1.
(5) Pvt. Dep. $\text{Pct.}_{\text{COLOC PIN}}$	Private bank-level variable that is the deposit weighted average of the $\mathbb{1}_{\text{Coloc. PSB}}$ for all bank branch in the sample with the March 31^{st}, 2008 deposits as weights. The measure is standardized (z-scored).
(6) PSB Dep. $\text{Pct.}_{\text{COLOC PIN}}$	Public bank-level variable that is the deposit weighted average of the pincode exposure Pvt. Dep. $\text{Loss}_{\text{COLOC PIN}}$ for each bank branch multiplied by the share of deposits of metro public sector branch as of March 31^{st}, 2008. The measure is standardized (z-scored).
(9) Pvt. Cred. $\text{Pct.}_{\text{COLOC PIN}}$	Private bank-level variable that is the credit weighted average of $\mathbb{1}_{\text{Coloc. PSB}}$ with credit as of March 31^{st}, 2009. The measure is standardized (z-scored).
(10) PSB Cred. $\text{Pct.}_{\text{COLOC PIN}}$	Public bank-level variable that is the credit weighted average of the pincode exposure Pvt. Dep. $\text{Loss}_{\text{COLOC PIN}}$ with credit as of March 31^{st}, 2009. The measure is standardized (z-scored).
(11) Firm Exposure	Firm-level exposure measure of the loan-weighted exposure to whether a firm borrows from public sector bank, with the loan weights calculated using loans between March 2006 to March 2008.
(12) Industry Exposure	Industry exposure is the loan-weighted Firm Exposure, with the loan weights calculated using loans for 2006–2008.
(13) MES	MES (Marginal Expected Shortfall) is the negative of the average returns of a stock given that the market return is below its 5^{th}-percentile during the period 1^{st} January, 2007 to 31^{st} December, 2007.
(14) $\mathbb{1}_{\text{Coloc. Old. Pvt.}}$	Branch-level indicator that equals 1 for a private sector branch in a metro, which has another metro old private sector bank branch in the same pincode and 0 otherwise.

† Year is the 12-month financial year ending on March 31^{st}

Table A.2: Deposit Growth at Branches With Runs: Robustness Placebo Years

This table reports placebo tests for annual deposit growth in fiscal years between 2002–2009. The dependent variable in each columns is the annual deposit growth rate. Year refers to the fiscal year from April 1st to March 31st. Observations are at the branch level. Branch-level variable $\mathbb{1}_{\text{Branch run}}$ is defined in Table A.1. Fixed effects included are as indicated. Standard errors are clustered at the branch level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Desposit Growth							
	2001-2002	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009
$\mathbb{1}_{\text{Branch run}}$	1.086	-5.746	9.724**	-3.295	2.638	-0.111	17.050***	-54.637***
	(4.937)	(3.793)	(4.044)	(3.437)	(3.875)	(3.212)	(3.018)	(1.541)
R-squared	0.279	0.249	0.278	0.267	0.291	0.259	0.269	0.278
No. of Obs.	17812	18313	18970	19582	20635	21343	22833	25501
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Reduced Form for Deposit Growth at Branches With Runs

This table reports estimates of a regression in which the dependent variable is the annual growth rate of deposits for 2008–2009. Year refers to the fiscal year from April 1st to March 31st. Observations are at the branch level. Branch-level variables $\mathbb{1}_{\text{Coloc. PSB}}$ is as defined in Table A.1. Fixed effects included are as indicated. Standard errors are clustered at the branch level.

	(1)	(2)
Dependent variable:	Deposit growth	
$\mathbb{1}_{\text{Coloc. PSB}}$	-5.828***	-5.365***
	(1.777)	(1.895)
R-squared	0.104	0.253
No. of Obs.	30784	25501
Bank FE	Y	Y
District FE	Y	Y
Pincode FE	N	Y
Type	RF	RF

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.4: Deposit Growth at Branches With Runs (co-location instrument): Robustness Placebo Years

This table reports placebo tests for annual deposit growth in fiscal years between 2002–2009. The dependent variable in each columns is the annual deposit growth rate. Year refers to the fiscal year from April 1st to March 31st. Observations are at the branch level. Branch-level variable $\mathbb{1}_{\text{Coloc. PSB}}$ is defined in Table A.1. Fixed effects included are as indicated. Standard errors are clustered at the branch level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent variable:	Deposit Growth							
	2001-2002	2002-2003	2003-2004	2004-2005	2005-2006	2006-2007	2007-2008	2008-2009
$\mathbb{1}_{\text{Coloc. PSB}}$	-2.336	1.490	-2.755	-0.518	2.756	1.506	-2.031	-5.365***
	(2.203)	(1.932)	(2.241)	(2.146)	(1.995)	(1.897)	(1.678)	(1.895)
R-squared	0.279	0.249	0.278	0.267	0.291	0.259	0.267	0.253
No. of Obs.	17812	18313	18970	19582	20635	21343	22833	25501
Bank FE	Y	Y	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y	Y	Y
Pincode FE	Y	Y	Y	Y	Y	Y	Y	Y

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Alternate Hypothesis: Private Banks As Safety Nets

This table examines an alternate hypothesis based on proximity to old private sector banks. The dependent variable is deposit growth in 2008–2009, where year refers to the fiscal year ending March 31st. $\mathbb{1}_{\text{Coloc. PSB}}$ and $\mathbb{1}_{\text{Coloc. Old. Pvt.}}$ are as defined in Table A.1. In Panel A, the sample is restricted to all private sector bank branches and includes all branches in the analysis in Panel B. In Panel B, columns refer to the first stage (columns 1–2), reduced form (columns 3–4), and the 2SLS IV (columns 5–6). Fixed effects included are as indicated. Standard errors are clustered at the branch level.

Panel A: Within-private bank variation

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Deposit growth					
Sample:	Private Sector Banks					
	All		New private		Old private	
$\mathbb{1}_{\text{Branch run}}$	-56.984***	-58.468***	-64.209***	-64.932***	-54.692***	-58.907***
	(1.802)	(2.512)	(2.322)	(4.377)	(2.492)	(3.861)
R-squared	0.293	0.453	0.241	0.449	0.372	0.518
No. of Obs.	5307	3948	2877	1771	2378	1755
Bank FE	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Pincode FE	N	Y	N	Y	N	Y

Panel B: Including instrument for co-location with urban old private bank

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Branch Run		Deposit growth			
$\mathbb{1}_{\text{Coloc. Old. Pvt.}}$	0.008	0.003	4.032	2.508		
	(0.016)	(0.017)	(2.769)	(2.944)		
$\mathbb{1}_{\text{Coloc. PSB}}$	0.052***	0.048***	-7.290***	-6.261***		
	(0.012)	(0.012)	(2.184)	(2.308)		
$\mathbb{1}_{\text{Branch run}}$					-101.346***	-107.444***
					(28.902)	(35.453)
R-squared	0.178	0.269	0.104	0.253	0.011	0.011
No. of Obs.	30784	25501	30784	25501	30784	25501
F-statistic	129.0	82.25				
Bank FE	Y	Y	Y	Y	Y	Y
District FE	Y	Y	Y	Y	Y	Y
Pincode FE	N	Y	N	Y	N	Y
Type	First Stage	First Stage	RF	RF	IV	IV

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Deposit Flights In Local Geography: Examining public and private sector banks separately

The table shows the impact on deposit growth of runs on branches in the same district. Observations are at the branch level. Columns 1, 3, 5 subset to the public sector bank branches and columns 2, 4, and 6 subset to private sector bank branches excluding the run branches (that is $\mathbb{1}_{\text{Branch run}}$ equal to 1). $\mathbb{1}_{\text{Branch run}}$, The district run variable measures the propensity of bank runs among the private sector branches at the district level., Pvt. Dep. $\text{Loss}_{\text{COLOC PIN}}$ are as defined in Table A.1. The dependent variable in all columns is the annual growth rate of deposits for 2008–2009. Year refers to the fiscal year from April 1st to March 31st. Fixed effects are included as shown. Standard errors are clustered at the district level.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:			Deposit growth			
Sample:	Public	Private excl. run branches	Public	Private excl. run branches	Public	Private excl. run branches
Pvt. Dep. $\text{Loss}_{\text{RUN PIN}}$	0.134***	-0.316**			0.181***	2.163
	(0.0245)	(0.132)			(0.0345)	(3.202)
Pvt. Dep. $\text{Loss}_{\text{COLOC PIN}}$			0.135***	1.157		
			(0.0250)	(0.755)		
R-squared	0.0388	0.134	0.0385	0.130	0.00195	-0.319
No. of Obs.	25438	3895	25438	3895	25438	3895
F-statistic					89.12	1.125
Bank FE	Y	Y	Y	Y	Y	Y
District FE	N	N	N	N	Y	Y
Pincode FE	N	N	N	N	Y	Y
Type	OLS	OLS	RF	RF	IV	IV

Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: RD Results: Under-Banked Status and PSB Deposit Share

This table shows results from a regression discontinuity (RD) test using a 2005 banking reform act to generate the discontinuity. Panel A examines covariate balance with a standard RD specification. Panel B shows the RD estimates. The running variable that generates the discontinuity is the national average population per branch subtracted from the district-level average population per branch. Banked takes a value of 1 if the running variable is negative. All regressions use second-degree polynomials and triangular kernels with a bandwidth of 4.5 around the cut-off. Observations are weighted by the population in 2001. Controls include population and population squared. Standard errors are clustered at the district level. Population data to construct the running variable is from the 2001 Census.

Panel A: Covariate Balance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	Ln (Wages)	Age	Fraction rural population (in %)	Fraction female (in %)	Fraction high-school (in %)	Unemp. rate (in %)	Deposit share of public sector branches in 2001–03
Banked	0.0915	0.0481	-5.335	0.00834	0.0242	0.0531	0.0844
	(0.174)	(0.0509)	(8.009)	(0.0106)	(0.0159)	(0.0327)	(0.0505)
R squared	0.580	0.705	0.551	0.264	0.466	0.214	0.579
No. of Obs.	247	247	247	247	247	247	247
State-FE	Y	Y	Y	Y	Y	Y	Y

Panel B: Share of State-Owned Banks in 2006–08

	(1)	(2)	(3)	(4)
Dependent variable:	Number of private sector bank branches	Number of PSB bank branches	Fraction of PSB bank branches	Deposit share of PSB bank branches
Banked	-27.76**	20.84	0.118**	0.0971**
	(10.97)	(13.19)	(0.0578)	(0.0411)
R squared	0.630	0.926	0.456	0.547
No. of Obs.	265	265	265	265
State-FE	Y	Y	Y	Y

Table A.8: RD Results: Robustness

This table shows the robustness of the regression discontinuity (RD) estimates that use a 2005 banking reform act to generate the discontinuity. The dependent variable is the deposit share of state-owned banks in 2006–08 at the district level. Year refers to the fiscal year ending on March 31. Column 1 uses the Imbens and Kalyanaraman (2012) bandwidth. Column 2 uses the Calonico, Cattaneo and Titiunik (2014) bandwidth. Columns 3 and 4 use a bandwidth of (-4,+4) and (-5, +5) around the cut-off. Column 5 uses a bandwidth of (-3.5, +3.5). The running variable is the national average population per branch subtracted from the district-level average population per branch. Population data to construct the running variable from India's 2001 Census. The variable "Banked" is an indicator for whether the running variable is negative. Regressions in columns 1-4 use a second-degree polynomial and a triangular kernel with a bandwidth of 4.5 around the cut-off. Column 5 uses a local linear polynomial. All regressions include state-fixed effects and are weighted by the 2001 population. Controls include population and population squared. Standard errors are clustered at the district level.

	(1)	(2)	(3)	(4)	(5)
Dependent variable:			Deposit growth		
Bandwidth Type:	Imbens-Kalyanaraman bandwidth	Calonico, Cattaneo, and Titiunik bandwidth	Bandwidth=4	Bandwidth=5	Bandwidth=3.5, Linear polynomial
Banked	0.101*	0.100*	0.104**	0.0782*	0.0726**
	(0.0574)	(0.0497)	(0.0491)	(0.0434)	(0.0300)
R squared	0.556	0.556	0.559	0.484	0.538
No. of Obs.	220	247	229	285	207
State-FE	Y	Y	Y	Y	Y

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.9: RD Placebo

This table shows the regression discontinuity (RD) estimates for deposit growth for placebo years 2005–2006, 2006–2007, and 2007–2008. The dependent variable in all columns is the annual growth rate of deposits. Year refers to the fiscal year ending on March 31. PSB Exposure is the firm-level share of loans and advances from PSBs (state-owned public sector banks). Standard errors are clustered at the district level. Population data to construct the running variable is from the 2001 Census.

	(1)	(2)	(3)
Dependent variable:	Deposit growth		
Sample:	2005–06	2006–07	2007–08
Exposure to PSBs	53.58	97.26	22.35
	(80.82)	(70.91)	(63.78)
F-stat	17	24	30
R-squared	0.265	0.176	0.295
No. of Obs.	1990	1973	1923
State-Year FE	Y	Y	Y
Bank-Year FE	Y	Y	Y
Controls	Y	Y	Y

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.10: Banks and MES During 2007–2009

This table shows the bank vulnerability measure for the 21 state-owned banks and 17 private-sector banks in our analysis. All stock market data are from the National Stock Exchange and the Bombay Stock Exchange.

State-owned Public Sector Banks (PSBs)		Private sector banks	
Bank Name	MES	Bank Name	MES
Allahabad Bank	0.04	Axis Bank	0.04
Andhra Bank	0.04	Bank of Rajasthan	0.04
Bank of Baroda	0.04	City Union Bank	0.04
Bank of India	0.06	Development Credit Bank	0.05
Bank of Maharashtra	0.03	Dhanalakshmi Bank	0.04
Canara Bank	0.05	Federal Bank	0.03
Central Bank of India	0.01	HDFC Bank	0.03
Corporation Bank	0.04	ICICI Bank	0.05
Dena Bank	0.06	IndusInd Bank	0.06
Indian Bank	0.04	ING Vysya Bank	0.03
Indian Overseas Bank	0.04	Jammu & Kashmir Bank	0.02
Oriental Bank of Commerce	0.05	Karnataka Bank	0.03
Punjab National Bank	0.05	Karur Vysya Bank	0.03
State Bank of Bikaner and Jaipur	0.01	Kotak Mahindra Bank	0.05
State Bank of India	0.05	Lakshmi Vilas Bank	0.03
State Bank of Mysore	0.03	South Indian Bank	0.04
State Bank of Travancore	0.01	Yes Bank	0.04
Syndicate Bank	0.05		
UCO Bank	0.05		
Union Bank of India	0.06		
Vijaya Bank	0.05		