

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, large deposit losses. State-owned public sector banks (PSBs) that serve as safe havens gain windfall surpluses. We trace the credit and real-side consequences of the resource reallocation using branch-level and bank-firm matched lending data. While lending contracts and credit quality improves in run banks, lending increases and credit quality worsens at the PSBs receiving the flight-to-safety flows. The aggregate effect is negative. Thus, state protection of bank liabilities generates credible safe havens in panics but offers weaker reintermediation of surpluses. The flight to *safety* is not a flight to *quality*.

JEL Classification: F34, G23, G28, G33, K42, O53

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A bank run occurs when many depositors simultaneously withdraw their deposits. Runs can cause bank failures, and their cascading effects can threaten financial stability. Not surprisingly, preventing runs and limiting onward domino effects are key goals of bank regulations and policies ([Calomiris and Mason, 1997](#)).

We study the *resource reallocation* triggered by runs. Banks facing runs lose deposits while those perceived as safe havens receive windfall financing surpluses. For instance, in March 2023, Silicon Valley Bank, First Republic, and Signature Bank faced runs and lost deposits while big banks perceived as safe havens gained deposits ([Caglio, Dlugosz and Rezende, 2023](#)). In our setting, private banks face runs while state-owned banks that serve as safe haven destinations gain windfall surpluses of deposits. We examine the credit, productivity, and aggregate consequences of such reshuffling and characterize plausible channels that drive these outcomes.

Our analysis informs a large body of research on state-owned banks. Research led by [La Porta, López-de Silanes and Shleifer \(2002\)](#) finds that state ownership of banks, while widespread, impairs economic growth. Several studies attribute the result to the influence of politics on lending ([Sapienza, 2004](#); [Dinç, 2005](#); [Khwaja and Mian, 2005](#); [Carvalho, 2014](#)). Our study highlights a distinct and complementary channel – the *safe-haven* status conferred by state protection, through which state ownership impairs credit allocation.

In our study, deposits at state-owned banks represent safe havens for panicked depositors due to dominant government ownership, control, and statutes. While state protection generates visible, credible, and readily accessible shelters in panics, it also places the panic surpluses – and thus the direction and quality of their reintermediation – in the hands of the entities enjoying that protection. We find that this reintermediation is weak: the surpluses are lent as low-quality credit, with negative real and aggregate effects. From

the viewpoint of the safe-haven hypothesis, runs emerge as a natural experiment, generating plausibly exogenous variation in safe-haven surpluses that aids identification.

We briefly summarize the empirical evidence. When private banks face a run, it is possible that state-owned banks step in to passively fill in gaps created by the run, preserving status quo with no real effects. We do not find evidence for this view. Run banks cut credit in run geographies while the recipient state-owned banks move resources outside these geographies and make weaker loans. Using bank-firm matched lending data and structural inference methods for natural experiments proposed by [Sraer and Thesmar \(2023\)](#), we find that the aggregate effects of the reallocation are negative. Thus, runs do not just reallocate but *misallocate* resources.

We make two other observations. First, the political channel, discussed in prior research on state-owned banks, is far from irrelevant. It is the multiplier that shapes how the run-related surpluses are lent, steering them toward credit misallocation and negative aggregate effects. In addition, we note that while ownership is the channel through which the state protects bank liabilities, state protection can take other forms that can also generate similar effects, for example, “too big to fail” policies in developed markets ([Baron, Schularick and Zimmermann, 2023](#)).

The run we study occurs in Indian banks after the 2008 global financial crisis. Some private bank branches experience sudden, extreme panicked deposit outflows, resulting in a form of “silent” runs ([Baron, Verner and Xiong, 2020](#)). Two features help frame our analysis of the run. First, formal protection for private bank depositors was limited and offered little comfort to panicked depositors ([Iyer and Puri, 2012](#)). State-owned banks, known as public sector banks (PSBs) in India, serve as credible safe havens. The Indian government holds large direct stakes in PSBs, more than 70% on average. It exercises sig-

nificant control over all aspects of their functioning, such as director appointment, strategic and operational planning, hiring, pay, retention, rotation, and promotion of employees. India's 1949 Banking Regulation Act obliges the government to fulfill PSB obligations in the event of failure. Thus, it is reasonable to view PSBs as safe havens.

We identify run branches, their deposit losses, and the surpluses gained by PSBs using India's annual "Basic Statistical Returns" (BSR), a proprietary dataset that the central bank shared with us. Financial years of the banks end on March 31, so fiscal year t is the 12-month period that ends on March 31 of 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 require that the branch deposit growth rate be less than an out-of-sample prediction and that it transition to the 5th left tail of deposit growth from above in prior years. Descriptive statistics show that our filters identify extreme deposit losses. The median deposit growth for run branches flips from +25% to -25% in one year. The 99th and 1st percentiles of deposit growth are -14% and -89%, respectively.

We show that state-owned PSBs are recipients of run flows. In principle, nothing stops panicked depositors from moving deposits to higher quality *private* banks that may be safer ([Schumacher, 2000](#); [Maingi, 2026](#)). However, when the state provides the safety net, deposits at state-owned banks enjoy an imprimatur of safety not available at better-quality private banks. We find evidence for this view. Other private bank branches, even if located near run branches, do not gain from the deposit flights.

To further assess the role of PSBs as safe havens, we employ an instrumental variables approach. The idea is that the propensity to run at a private bank branch increases if there is a nearby PSB branch, which eases access to a safe haven for panicked depositors. We use pin codes (akin to US zip codes) to identify co-location, using data provided to us by

the Indian central bank. The approximately 19,000 pin codes are more granular than the 593 districts (analogous to counties) and thus credibly identify nearby branches salient for deposit runs. The co-location instrument is strong. The IV estimates show that co-located PSB branches gain deposit flows from run branches.

We next examine credit effects. We note here that unlike in the US branch data (the FDIC Summary of Deposits (SOD)), the Indian BSR dataset also reports branch-level credit data. Our first tests exploit these data to study credit effects of runs. Because the banks in our sample operate nationally, runs could have impacts outside run geographies. Thus, we construct bank-level run exposure variables using as weights resources in run geographies. Table 1 has the exact definitions. A second set of tests leverages separate bank-firm lending data from statutory filings at India’s Ministry of Corporate Affairs.

We find that run banks contract credit locally, consistent with their facing frictions in raising external finance (Kashyap and Stein, 2000). State-owned PSBs expand credit but outside run geographies. The result reflects more centralized decision making in PSBs and is inconsistent with PSBs stepping up to passively gap-fill credit reductions in run regions. We examine credit quality next. Non-performing assets decrease at run banks, consistent with disciplinary effects of runs disciplinary (Diamond and Rajan, 2001). Quality worsens at PSBs. They become visible with a lag, reflecting both natural time lags for weaknesses of incremental lending to become visible and initial central bank forbearance that turned subsequently into pressures to recognize asset quality.¹

We turn to the real effects of the credit reallocation using bank-firm lending data derived from security interest filings at India’s Ministry of Corporate Affairs (MCA). We

¹The central bank (RBI) allowed “forbearance” that could be used to delay NPA recognition, but gradually began tightening norms on asset quality recognition. See, e.g., a December 2024 interview by the then RBI governor (<https://tinyurl.com/4zjnnc3k>) or Chari, Jain and Kulkarni (2019).

find that post-run credit expands at state-owned lenders. It is of weaker quality. Recipient firms are more likely to have future interest coverage ratios below 1.0 and lower sales and capital growth. We conduct two tests to further assess real effects. The dispersion of productivity, a key indicator of allocative inefficiency ([Hsieh and Klenow, 2009](#); [Gopinath et al., 2017](#)), increases in industries gaining run surpluses. Additional tests show that the results likely reflect a political channel at work. We also use the [Sraer and Thesmar \(2023\)](#) approach to assess outcomes relative to a no-run counterfactual. The estimates show that aggregate productivity declines by about 18%.

We conduct additional tests to expand the analysis. We assess statistical robustness through placebo, power, and Oster bounds tests and an alternative KLEMS-weighted productivity measure. We consider a natural experiment that generates variation in co-location. In 2005, banks were allowed to open branches in select geographies based on per-capita bank branch density ([Young, 2017](#)). Using a regression discontinuity design based on branch density as the running variable, we show that colocated branches have more flighty deposits. We consider variation within the state-owned PSBs. Weaker state-owned banks with greater Marginal Expected Shortfall (MES) chase deposits and expand lending, consistent with their exploiting the safety “put” from state ownership. Collectively, the results show that government ownership makes state-owned banks credible safe havens but also results in weaker reintermediation of run surpluses.

We proceed as follows. Section [1](#) discusses the related literature. Section [2](#) describes institutional details and the data. Section [3](#) and Section [4](#) examine run-related deposit and credit flows, respectively. Section [5](#) analyzes firm-level outcomes and aggregate effects, and Section [6](#) discusses robustness of the evidence. Section [7](#) concludes.

1 Related Literature

The literature on runs is vast. Run theories focus on mechanisms such as self-fulfilling beliefs that generate runs. Empirical research characterizes the occurrence and outcomes of runs.² We contribute to this literature by focusing on the resource reconfiguration due to runs, and in particular, the distortions generated by the “safe-haven put” from state protection of bank liabilities.

Building on a theme developed in [Shleifer \(1998\)](#) about state ownership of enterprises, [La Porta, López-de Silanes and Shleifer \(2002\)](#) find that state ownership of banks is inefficient, although in principle, it can have developmental benefits by funding projects that the private sector is unable to fund. Subsequent research ([Sapienza, 2004](#); [Dinç, 2005](#); [Khwaja and Mian, 2005](#); [Carvalho, 2014](#)) attributes inefficiency to political capture of state-owned banks. We develop complementary evidence by highlighting a safe haven channel, which depositors value in a crisis but that can worsen resource allocation after a crisis. We do not absolve the political channel for misallocation; we show that it manifests itself in ways that rely on and exploit the funding surpluses generated by runs.

Resource misallocation is the subject of a thriving literature in economics. [Hsieh and Klenow \(2009\)](#) show that reallocating resources from underperforming firms to more productive firms enhances economic growth. A natural question is why misallocation exists in the first place. Implicated are poor property rights, financial frictions, trade and com-

²See, e.g., [Diamond and Dybvig \(1983\)](#); [Chari and Jagannathan \(1988\)](#); [Calomiris and Kahn \(1991\)](#); [Diamond and Rajan \(2001\)](#) for theory. [Bernanke \(1983\)](#); [Saunders and Wilson \(1996\)](#); [Calomiris and Mason \(1997\)](#); [Schumacher \(2000\)](#); [Iyer and Puri \(2012\)](#); [Acharya and Mora \(2015\)](#); [Monnet, Riva and Ungaro \(2023\)](#); [Blickle, Brunnermeier and Luck \(2024\)](#); [Maingi \(2026\)](#) offer empirical evidence. Research on the 2023 Silicon Valley Bank run includes [Benmelech, Yang and Zator \(2023\)](#); [Caglio, Dlugosz and Rezende \(2023\)](#); [Jiang et al. \(2024\)](#).

petition, and government regulations.³ We join this literature by highlighting an alternate channel, the implicit protection of liabilities offered by the state.

We also add to the research on international banking systems without a safety net, e.g., Argentina in the 1990s ([Schumacher, 2000](#)). This research observes that runs could be disciplinary in the aggregate if they move funds from weak to strong banks. We observe virtually no migration of this nature, suggesting that state-owned banks – and more generally, state protection – confers unique safe haven status valued by panicked depositors. The weak reintermediation offered to safe haven surpluses is consistent with the archival evidence in [Baron, Schularick and Zimmermann \(2023\)](#) on “too big to fail” private banks ([Penas and Unal, 2004](#); [Iyer et al., 2019](#)). We also add to recent work on “silent” banking panics that are panic events without realized bank failure ([Baron, Verner and Xiong, 2020](#)). We have a variety of this type of run and show that it has negative effects.

While our focus has been on bank runs, our study is also relevant to banking research beyond runs. [Di Maggio and Kermani \(2017\)](#), [Mian, Sufi and Verner \(2019\)](#), and [Blickle \(2022\)](#) discuss how credit supply causes temporary booms followed by a bust through housing and household demand channels. Our study shows similar cyclical-ity, but driven by windfall surpluses at state-owned banks. [Paravisini \(2008\)](#) notes using Argentinian data that banks expand lending when they gain unexpected surpluses, suggesting that they are ex-ante constrained. See also [Gilje, Loutskina and Strahan \(2016\)](#) on surpluses from shale booms. External financing constraints matter in our study too. Private banks depleted of resources cut back lending while state-owned banks gaining

³See [Restuccia and Rogerson \(2017\)](#) for a discussion and [Coulomb, Henriët and Reitzmann \(2025\)](#); [Chari et al. \(2021\)](#); [Adamopoulos and Restuccia \(2014\)](#); [Midrigan and Xu \(2014\)](#); [Buera, Kaboski and Shin \(2011\)](#); [Bau and Matray \(2023\)](#); [Catherine et al. \(2022\)](#) for related research. State ownership of productive assets can also matter through firm entry and growth ([Banerjee and Duflo, 2005](#); [Sapienza, 2004](#); [Dollar and Wei, 2007](#); [Song, Storesletten and Zilibotti, 2011](#); [Geng and Pan, 2024](#)).

surpluses expand lending. [Cortes and Strahan \(2017\)](#) show banks face aggregate resource constraints that forces reallocation across branching networks when faced with shocks. We see similar reallocation in the state-owned banks in our sample, with political considerations emerging as a factor shaping the reallocation.

2 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 (SBI), 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 we analyze occurs after the 2008 global financial crisis (GFC). The collapse of reputed financial institutions triggered worldwide panic. India was no exception. The panic led depositors to move funds from private to public sector banks. The aggregates in Figure 1 show this effect. Stark differences between the two types of banks emerge as the GFC took root with the Bear Stearns collapse in March 2008.⁴

2.1 State Support for PSBs

Indian PSBs enjoy safe haven status for several reasons. From a legal standpoint, 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 has an active managerial role in

⁴While 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.

all aspects of PSB operations. It holds dominant stakes in the PSBs, typically 70-80%, and has maintained its stakes through capital injections from time to time. Between 2008-09 and 2016-17, roughly our sample period, capital infusions amounted to about INR 1.2 trillion (\$17 billion) into the banking system.⁵ All these factors, coupled with the lack of depositor access to sovereign paper – available only for banks and large institutions – and the very limited deposit insurance programs – make PSBs credible safe havens.⁶

2.2 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 with March 31 as financial year-ends. We use two geographical markers. One is a district, which is roughly comparable to a US county and available as part of the BSR dataset, while the second is pin code, analogous to U.S. zip codes, for which we obtain data compiled by the central bank. Both markers are useful, as we discuss next.

Pin codes, which are more granular than districts, reflect geographical proximity, familiarity with local service providers, and ease of transportation and travel. In our opinion, these features make pin codes more relevant for panicked depositors looking to move funds. Districts are far larger, typically spanning areas of 2,000 square miles.⁷ 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

⁵See the 2017 Comptroller and Auditor Report at <https://cag.gov.in/en/audit-report/details/31779>.

⁶Deposit insurance was limited to INR 0.1 million (about \$2,000 at the 2008 exchange rate) and was not effective in mitigating runs (Iyer and Puri, 2012). Private banks lobbied to increase limits to restore parity with PSBs in provision of safe deposits (LiveMint, 2011). On February 4, 2020, a decade after the 2008 run, the limit was raised to INR 0.5 million (about \$7,000 at the early 2020 exchange rate of about INR 70=1USD)

⁷The country spans about 1.27 million square miles so its 593 districts cover an average of 2,140 square miles. With 593 districts, the typical end to end distance is 40-50 miles with poor transport connectivity. The territorial density is far greater at the pin code level, with 19,000 pin codes in our sample period.

level, making it relevant for controls for local economic conditions. We use the districts demarcated by the 2001 Indian Census, which is relevant for our sample period.

Bank-level variables are either the sum of individual branch-level data from the BSR dataset 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. We also use a loan-level dataset compiled by the Ministry of Corporate Affairs that identifies firm-bank relationships using security interest filings Table 1 details the variables used in our analysis and Table 2 provides relevant summary statistics.

3 The Run

3.1 Deposit Losses

Empirically, we identify run branches as ones that have unexpectedly large losses in fiscal 2009. We use three criteria for this purpose. First, we require that the branch deposit growth is less than its out of sample predicted value based on regression estimates on data prior to 2006, one year before the run. The regressors are branch size, credit to deposit ratio, age, and rural district and PSB identifiers. The second criterion is that its fiscal 2009 deposit growth rate is below the 5th percentile of the distribution of branch growth rates in the pre-run year (fiscal 2008). Finally, we specify that the branch is in the left 5th percentile of deposit growth rates in fiscal 2009 but not in 2008.

Figure 2 depicts a heat map in which lighter shades correspond to low deposit growth. The light shades are more visible for private banks (Panel (a)) than for PSBs (Panel (b)). Figure 3 displays descriptive statistics from the BSR data for the 6.6% of branches classified as having a run. We see that runs are more likely for new private banks, weaker ones

with greater MES ([Acharya et al., 2017](#)), young branches in urban areas or regions with more PSB presence, which we exploit in the instrumental variables specifications.

Figure 4 reports estimates of an event-study specification to assess deposit losses

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

where the $Y_{jbd,t}$ 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 $\mathbb{1}_{\tau}$ and $\mathbb{1}_{Run_j}$ are fiscal year and run indicators, respectively. The pre-2009 estimates of η_{τ} are insignificant, indicating parallel trends. The run-year coefficient η_{2009} is negative and significant both statistically and economically, whether we have district-time (panel a) or pin code-time (panel (b)) fixed effects.⁸

Co-location Instrument: Private bank branches co-located near a PSB branch should be more vulnerable to runs as it is simpler for depositors to move money if safe-haven PSBs are nearby, particularly in metro areas where depositors are more aware of and sensitive to global events like the GFC. Furthermore, the deposits in metro areas are larger than those in rural branches, making (the lack of) deposit insurance more salient. Based on these considerations, we instrument for runs using a co-location variable switches on if a branch (a) belongs to a private sector bank; (b) is located in a metropolitan area; and (c) has a PSB branch in the same pin code.⁹ The IV strategy trades off greater precision and

⁸In unreported results, we find that branches in the left tail of fiscal 2005 (as placebo) show no extreme deposit losses in 2009. The results are also robust in models that use the pre-period data to control for parallel trends ([Alencar, 2016](#); [Drechsler, Savov and Schnabl, 2021](#)). See Internet Appendix Tables A.1 and A.2.

⁹The instrument is likely conservative because branches in different pin codes are sometimes adjacent (e.g., pin codes 400021 and 400001 in Mumbai). The IV specification remains valid as the instrument relies on the correlation between the instrument and what it is instrumenting for. Further detail on local banking

economic motivation for identification against a smaller sample.

Figure 5 shows the aggregate deposits (normalized to 1 in March 2007) for co-located and other private bank branches. Co-location does not matter before the run but a stark divergence emerges between co-located and other private branches after the run. Bank-level aggregates presented earlier in Figure 1 tell a similar story.

The first and second stage equations of the IV specification for deposit losses are

$$\mathbb{1}_{\text{Branch run } jbd} = \alpha_b + \gamma_d + \beta \times \mathbb{1}_{\text{Coloc. PSB } j} + \epsilon_{jbd} \quad (2)$$

$$Y_{jbd} = \alpha_b + \gamma_d + \beta \times \widehat{\mathbb{1}_{\text{Branch run } j}} + \epsilon_{jbd} \quad (3)$$

Table 3 reports the results. Columns (1) and (2) report the first-stage estimates of equation 2 with district or pin code fixed effects, respectively. Co-location predicts runs. The F -statistics of 31.46 and 24.73 are above the Angrist and Kolesár (2024) thresholds for instrument strength. Additional IV diagnostics are reported in the Internet Appendix Table A.3.¹⁰ The second stage IV estimates of equation (3) in columns (3)-(4) are significant. The point estimates indicate the virtually complete erosion of deposits in run branches.¹¹ Regression results in Internet Appendix Table A.5 are also of interest. Co-location explains deposit declines in 2008–2009 but not in the placebo years between 2001–2008, when there are no runs for it to predict.

markets could increase power but is not available to us.

¹⁰The Kleibergen-Paap rk LM and Wald tests as well as Anderson-Rubin F and Stock-Wright LM test statistics robust to weak identification are significant at the 1% level. The more stringent and smaller-sample size within-urban-pincode fixed effects in Internet Appendix Table A.4 gives similar estimates of deposit losses with F -statistic of 13.38, indicating insensitivity of the IV estimate to locational definitions.

¹¹We note that branch-level results do not reflect bank-level variation as we include bank fixed effects throughout. The comparison is thus within a bank, specifically between co-located branches and others. See, e.g., Drechsler, Savov and Schnabl (2017) for a similar design based on HHIs. The number of observations equals the sample used in computing the coefficients and standard errors after including fixed effects. Note that the coefficients reflect the difference-in-difference estimates. The 99th and 1st percentiles of realized deposit growth are -14% and -89%, respectively.

3.2 Deposit Gains at Safe Haven PSBs

Do run-flows from private banks accrue to PSBs? We first present reduced-form evidence that this is the case. Consider the variable $\text{Pvt. Dep. Loss}_{\text{RUN PIN } j p}$, the greater of zero or the negative of the deposit growth rate in pin code p with runs. Its interaction with a PSB indicator should reflect deposit gains accruing to PSBs. Thus, we estimate

$$Y_{jbp} = \alpha_b + \kappa_p + \eta \times \text{Pvt. Dep. Loss}_{\text{RUN PIN } j p} \times \text{PSB}_b + \epsilon_{jbp} \quad (4)$$

where Y_{jbp} is the run year deposit growth of branch j of bank b in pin code p , α_b and κ_p are bank and pin code fixed-effects, respectively, and $\text{Pvt. Dep. Loss}_{\text{RUN PIN } j p}$ denotes run deposit losses. Robust standard errors are (conservatively) clustered at the district level. Columns (2) and (3) of Table 4 show that the coefficient η (for convenience, we report 100* η) for the interaction term is significant. Thus, deposit losses accrue to PSBs.

Co-location Instrument: Columns (4)-(5) present instrumental variables estimates using $\text{Pvt. Dep. Loss}_{\text{COLOC PIN}}$ as an instrument for runs (with interactions for the column (4) model). The second stage IV estimates of the interactions between PSB and run flows are positive and significant, indicating that the PSBs are beneficiaries of run flows.¹²

Private Banks Are Not Safety Nets: Our next tests exploit the institutional structure of Indian markets to assess the role of state ownership. We consider *old* private banks. As [Mishra, Prabhala and Rajan \(2022\)](#) point out, nationalization programs that created

¹²The negative coefficients for $\text{Pvt. Dep. Loss}_{\text{RUN PIN}}$ indicate the losses to private banks in run pin codes are absorbed when including pin code effects. We could include *district* fixed effects. We found that doing so has little effect. For example, the coefficients in rows (2) and (3) of column (4) remain significant and change from -0.325 to -0.421 and +0.505 to +0.531, respectively.

Indian PSBs left in place some private banks, which are as old as PSBs and as familiar to depositors. Do these old banks act as recipients for run flows? Does familiarity breed faith and safe haven status? Alternatively, does state ownership matter?

We consider two tests. Panel A in Table 5 considers deposit losses at old and new private banks. The two are statistically indistinguishable. In Panel B, we include a colocation indicator for the presence of an old private bank in the vicinity of a new private bank to assess whether the old bank branch acts as a surrogate for PSBs. Columns 1–2 show that old private bank co-location is insignificant and does not predict deposit losses in runs (columns 3–4). The IV estimates using both co-location variables as instruments (columns 5–6) are similar to the ones in Table 3. Collectively, the results suggest that state ownership of PSBs is important in making them safe havens for panic flows.

4 Credit

A bank facing runs is depleted of its deposit resources. If there are constraints in accessing external financing (Kashyap, Stein and Wilcox, 1993; Kashyap and Stein, 2000; Cortes and Strahan, 2017), run banks should cut credit. Following Diamond and Rajan (2001), credit quality should improve. The more interesting question is perhaps the disposition of surpluses by the state-owned PSBs. For these banks, the run generates windfall surpluses, generating an interesting natural experiment with plausibly exogenous variation in safe-haven surpluses that helps identify credit effects due to the safe-haven status.

If PSBs simply step in to fill in gaps due to the run under a benevolent “social hand” hypothesis, runs should be neutral with little credit reallocation or onward economic consequences. Alternatively, PSBs could redirect credit, potentially in distortionary ways following La Porta, López-de Silanes and Shleifer (2002) (or (Cole, 2009a) in the Indian

context). We turn to these issues next.

Credit Quantity: The banks in our sample have national franchises, so the effects of run surpluses likely spread across bank networks. We propose two bank-level aggregates to model outflows (for run banks) and inflows (for recipient PSBs).

$$\text{Pvt. Dep. Pct. COLOC PIN }_b = \sum_{j \in b} \frac{\text{Deposit}_j}{\text{Deposit}_b} \times \mathbb{1}_{\text{Coloc. PSB } j} \quad (5)$$

$$\begin{aligned} \text{PSB Dep. Pct. COLOC PIN }_b &= \sum_p \sum_{j \in bp} \frac{\text{Deposit}_j}{\text{Deposit}_{bp}} \times \text{Pvt. Dep. Loss COLOC PIN }_{jp} \\ &\quad \times \text{PSB Sh}_{bp} \end{aligned} \quad (6)$$

where b denotes a bank, $\text{Pvt. Dep. Loss COLOC PIN }_{jp}$ is (as before) the negative of the deposit flows at co-located private sector bank branches, $\mathbb{1}_{\text{Coloc. PSB } j}$ is the branch-level co-location instrument, and PSB Sh_{bp} is the PSB deposit share of bank b in geography p . These variables essentially weight deposits based on run exposure. The variable PSB Sh_{bp} accounts for the presence of multiple PSBs in a region that could share run flows.

To assess the outside-run geography effects for private banks, we estimate

$$Y_{jbd} = \alpha_d + \gamma \times \mathbb{1}_{\text{Coloc. PSB } j} + \beta \times \text{Pvt. Dep. Pct. COLOC PIN }_b + \epsilon_{jbd} \quad (7)$$

$$Y_{jbd} = \alpha_d + \theta_b + \gamma \times \mathbb{1}_{\text{Coloc. PSB } j} + \epsilon_{jbd} \quad (8)$$

For PSBs, the analogous specification is

$$Y_{jbd} = \theta_b + \gamma \times \text{Pvt. Dep. Loss COLOC PIN }_d + \epsilon_{jbd} \quad (9)$$

$$Y_{jbd} = \alpha_d + \gamma \times \text{PSB Dep. Pct. COLOC PIN }_b + \epsilon_{jbd} \quad (10)$$

where, Y_{jbd} denotes credit growth in branch j of bank b in district d in the run year and the run exposure variables are as defined in equations (5) and (6). District and bank fixed effects, α_d and θ_b , respectively, control for local geography and bank-specific effects. Robust standard errors are clustered at the district level. Table 6 reports the estimates.

For private banks, the within-region coefficient for $\mathbb{1}_{Coloc. PSB}$ is -22 percentage points (pp) for a one-SD increase in the run exposure. The estimate with bank fixed effects is similar, indicating that the differences are within bank. The outside run region variable Pvt. Dep. Pct.COLOC PIN is insignificant. Credit cutbacks for run banks are largely local.

Columns (3) and (4) in Table 6 turn to credit allocations by PSBs. In contrast to private banks, the PSB credit quantity effects are *not* local. PSBs instead disperse credit beyond run regions, consistent with more centralized decision-making in these banks. The asymmetry in credit reallocations between private banks and PSBs is not consistent with benevolent PSBs stepping in to fill in private lending gaps created by the run.

Credit Quality: We first generate two bank-level credit quality measures as follows.

$$\text{Pvt. Cred. Pct.COLOC PIN } b = \sum_{j \in b} \frac{\text{Credit}_j}{\text{Credit}_b} \times \mathbb{1}_{Coloc. PSB j} \quad (11)$$

$$\text{PSB Cred. Pct.COLOC PIN } b = \sum_{j \in b} \frac{\text{Credit}_j}{\text{Credit}_b} \times \text{Pvt. Dep. Loss}_{COLOC PIN jp} \quad (12)$$

where b denotes a bank, $\mathbb{1}_{Coloc. PSB j}$ is a co-location indicator, Pvt. Dep. Loss_{COLOC PIN jp} is the negative of the deposit flows at co-located private bank branches. These weights use the pre-crisis year credit (recognizing that NPAs originate from credit extended) and are standardized (z-scored) for easy interpretation.

The specifications for credit quality follow

$$Y_{jbp} = \alpha_p + \beta \times \text{Pvt. Cred. Pct. COLOC PIN } b + \epsilon_{jbp} \quad (13)$$

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

for branch j of bank b in pin code p in 2008–2009 and the exposure variables are as defined in equations (11) and (12). Empirically, Y_{jbp} denotes the change in non-performing assets (NPAs). Indian banks define NPAs as loans that are substandard (delinquent for between 90 days and one year), doubtful (no repayments for more than one year), or outright losses. We consider two post periods, 2009–2011 and 2012–2016 for reasons that we discuss shortly. We control for credit growth and scale the NPA change by the beginning of period assets, e.g., the 2009–2011 changes are relative to credit in 2009, to account for the private bank-PSB differences in credit growth due to the run-related reallocation. Pin code fixed effects α_p control for local economic conditions. Standard errors are robust and clustered at the geography level.

Table 7 reports the NPA results. For private banks, NPAs decrease in the first three years and stabilize thereafter. For PSBs, NPAs *increase* after three years. The deferred emergence reflects initial regulatory forbearance and subsequent tightening of asset quality recognition.¹³ The credit problems at the PSBs became so serious that the central bank instituted a formal asset quality review program in 2015 and the government instituted a complete makeover of the domestic bankruptcy code in 2016.¹⁴

Summarizing, we report two major findings. One, PSBs gaining windfall surpluses

¹³Under forbearance, banks could classify stressed loans as “restructured” rather than non-performing, attracting far lower capital provisioning, so restructured assets masked the deterioration and exceeded half of all stressed assets through 2015 (Chari, Jain and Kulkarni, 2019, 2020). The 2015 Asset Quality Review withdrew this latitude and forced reclassification, producing the spike in recognized NPAs. We cannot separate deliberate evergreening from the natural progression of weak loans, but both imply the lagged recognition we observe.

¹⁴See the Insolvency Board Website <https://ibbi.gov.in/en/legal-framework/act>.

did not use them to restore status quo in run regions. Two, the surpluses were channeled into credit of weak quality. We now turn to real effects of the reallocation.

5 Real Economic Effects

To assess real effects, we obtain bank-firm paired lending data from security interest filings with India’s Ministry of Corporate Affairs. We estimate the following specification for firms f borrowing from banks b :

$$Y_{fb} = \omega_f + \beta \times \text{Public Sector Bank}_b + \eta \times X_{fb} + \epsilon_{fb} \quad (15)$$

We assess both the existence of a borrowing relationship and the amount borrowed, so the dependent variable Y_{fb} is whether there is a borrowing or the total loan amount for a firm-bank pair between fiscal 2009 and 2011. X_{fb} denotes pre-run firm-bank controls measured over the three fiscal years prior to 2009. Following [Chen and Roth \(2023\)](#), we also estimate a Poisson model. Firm fixed effects serve as demand controls ([Khwaja and Mian, 2008](#); [Jimenez et al., 2020](#)). Robust standard errors are clustered at the bank level.¹⁵

Panel A in Table 8 reports the estimates of equation (15). The extensive margin results in columns (1)–(2) show that firms are more likely to receive credit from PSBs. Columns (3)–(4) show that firms borrow more from PSBs. The point estimate is INR 547 million (\$10 million) (INR 930 million (\$18 million)) when we add firm fixed effects).

Panel B reports firm-level regressions to examine allocation quality.

$$Y_f = \alpha_{i(f)} + \beta \times \text{Firm PSB Exposure}_f + \gamma \times \text{Firm PSB Exposure}_f \times \text{Top}_f + \epsilon_f \quad (16)$$

¹⁵We 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.

for a firm f in industry i . The dependent variables are whether the firm borrows or the amount borrowed. The key independent variables are *Firm PSB Exposure*, a firm-level measure of exposure to public sector banks based on loan-weighted pre-run borrowing from PSBs, and its interaction with an indicator Top_f for whether the firm's 2008 productivity of capital (estimated using CMIE Prowess data) is above median.

The results in the first row of Table 8, Panel B show that pre-run PSB relationships matter. Firms borrowing from PSBs before the run are more likely to borrow and obtain more credit after the run. The results in row (3) show that the *less* productive firms are likely to get more credit including in the preferred [Chen and Roth \(2023\)](#) Poisson regression that combines the extensive and intensive margins.

The evidence on weakening PSB credit quality is consistent with the earlier evidence in Section 4 that was based on branch-level data. The bank-firm data also show that while PSBs expand credit, the tilt is towards weaker firms in the post-run period. What are the aggregate effects of this reallocation? We turn to this issue next.

5.1 Aggregation

We use the [Sraer and Thesmar \(2023\)](#) approach to assess the aggregate impact of the resource reallocation due to the runs. In their framework, aggregate effects are driven by three moments of log-MRPK (marginal productivity of capital), namely, the variance of log-MRPK, the mean of log-MRPK, and the covariance of log-MRPK and sales

- $\Delta\Delta\sigma^2(s)$, 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 .

As in [Sraer and Thesmar \(2023\)](#), we estimate log-MRPK as the natural log of the ratio of sales to gross fixed assets. We obtain both inputs from the CMIE Prowess database. The pre- and post-run productivity are 3-year averages before and after the run. We consider industries at the 2-digit NIC industry level, resulting in a sample of 57 industries. The difference-in-difference specification is:

$$\begin{aligned} M_{ind,t} = & \alpha_s + \beta_M \times \text{Industry exposure}_s \times Post_t \\ & + \gamma \times \text{Industry exposure}_s + \eta \times Post_t + \epsilon_{ind,t} \end{aligned} \quad (17)$$

where s is the industry in period t and industry exposure is the loan-weighted firm-level exposures to PSBs. We include industry fixed effects and cluster standard errors at the industry level. Internet Appendix Figure [A.1](#) shows that the distribution of log-MRPK is approximately normal, as required for the approach. 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 $\theta = 0.83$. ϕ_s is the pre-period share of sales of industry s and κ_s is its pre-run period share of capital.

It is useful to begin the analysis by examining productivity dispersion, a simple by-product of our analysis that captures capital misallocation ([Gopinath et al., 2017](#)). Column (2) in Table [9](#) shows that the productivity dispersion, the variance of log-MRPK, increases in industries with high exposure to PSBs. The results are significant at the 10% level.¹⁶

¹⁶The significance level improves in regressions that weight MRPK by industry productivity, as we discuss later in robustness tests. We note the numerous approximations inherent to the aggregation exercise,

The three estimates required for estimating the aggregate effects 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 $\Delta\Delta\sigma_{MRPK,py}(s) = 0.244 \times \text{Industry exposure}_s$. The change in total factor productivity (TFP) is sizeable:

$$\begin{aligned} \Delta \log(TFP) &\approx \underbrace{-\frac{\alpha}{2} \left(1 + \frac{\alpha\theta}{1-\theta}\right) \sum_{s=1}^S \kappa_S \widehat{\Delta\Delta\sigma^2}(s)}_{-17.68\%} \\ &\quad \underbrace{-\frac{\alpha}{2} \left(1 + \frac{\alpha\theta}{1-\theta}\right) \sum_{s=1}^S (\phi_S - \kappa_S) \left(\widehat{\Delta\Delta\mu}(s) + \Delta\Delta\sigma_{MRPK,py}(s) + \frac{1}{2} \frac{\alpha\theta}{1-\theta} \widehat{\Delta\Delta\sigma^2}(s) \right)}_{-0.09\%} \\ &\approx -17.8\% \end{aligned} \tag{18}$$

The effect on aggregate output can be calculated using the following equation:

$$\Delta \log(Y) \approx -\frac{\alpha(1+\epsilon)}{1-\alpha} \sum_{s=1}^S \phi_S \left(\widehat{\Delta\Delta\mu}(s) + \frac{1}{2} \frac{\alpha\theta}{1-\theta} \widehat{\Delta\Delta\sigma^2}(s) + \Delta\Delta\sigma_{MRPK,py}(s) \right) \approx -23.6\% \tag{19}$$

where ϵ is the Frisch elasticity. Using $\epsilon = 0.2$, we estimate a negative effect of about 23.6% due to the credit reallocation triggered by the deposit reconfiguration in runs.

We note that the significant productivity declines we find are consistent with a large buildup of non-performing assets (NPAs) in PSBs after 2008. [Mohan and Ray \(2021\)](#) show that PSB NPAs peaked at 14.6% gross (8.0% net) of assets, about three times the private bank ratios, becoming visible under increasing central bank pressures to recognize asset quality.

such as the flows out of private banks into PSBs, their aggregation at the bank level, and the relatively small number of industries.

6 Robustness

This section contains several tests that clarify the economics and robustness of the results. Given the large number of tables and figures, it is not feasible to include all of them in the text. The vast majority of the detailed tables are in the Internet Appendix.

KLEMS weighted productivity We recompute productivity dispersion using a weighted version of the MRPK measure where the weights are KLEMS total factor productivity estimates computed by industry and year by RBI, India’s central bank.¹⁷ The estimates are at the industry level for 27 industry groups. Productivity is output minus inputs including capital K , labor L , energy E , materials M , and services S , weighted and aggregated to reflect the quantity and quality of inputs. With these industry KLEMS weights, the firm-level productivity measure is $MRPK_{iskt} = KSH_{go_k} \times \frac{Sales_{iskt}}{NetFixedAssets_{iskt}}$ for firm i in 3-digit NIC industry s within KLEMS sector k at time t . The scaling applies KLEMS industry weight KSH_{go_k} and scales sales by net rather than gross fixed assets to reflect and match RBI’s use of a net, depreciated capital stock in KLEMS. The results are in Internet Appendix Table A.6. Run exposure is positively and significantly related to productivity dispersion at the 1% level, thus sharpening the findings reported earlier in Section 5.

Aggregation Using Capital Wedge In Internet Appendix Table A.7, we consider an alternative aggregation approach suggested by Blattner, Farinha and Rebelo (2019). Three forces shape ex-post productivity and its dispersion. First, productivity is lower at run-exposed PSBs. Second, firms with greater (lower) pre-period productivity have greater (lower) post-run productivity changes. Finally, we find more discipline at run banks and

¹⁷<https://www.rbi.org.in/ScriptsPublicationReportDetails.aspx?UrlPage=&ID=855>

less productive allocations at the PSBs receiving surpluses. The capital wedge estimates suggest a 16% decline in productivity.

Statistical Tests We consider a leave-one-out (LOO) analysis for the productivity dispersion regression (17). We re-estimate the specification after dropping one industry at a time. Internet Appendix Figure A.2 plots the resulting estimates of β_M . The bars around the estimate are error bands at the (conservatively wide) 10% level. The relatively flat line indicates that our results are not driven by a specific industry.

We next conduct a placebo test by generating a random industry exposure variable uniformly distributed in $[0,1]$. We re-estimate equation (17) 100 times. Internet Appendix Figure A.3 Panel (a) plots the simulated coefficients. We note two points. First, none of the placebo coefficients (shown as the solid red line to the right) are close to the point estimate of 1.305 reported in Table 9. Only 8 out of 100 coefficients are significant at the 5% level. In Panel (b), we also considered a shuffled bootstrap that mimics the original distribution. 10 of the 100 coefficients are significant in this implementation.

We compute the Oster (2019) bounds for the estimates of the coefficient β_M in equation (17). The test attempts to estimate the size of a hypothetical unobservable that, if observed and included, would drive the true estimated coefficient to zero. Inputs for the test include the strength of the unobservables relative to the included variables and the maximum R^2 when the unobservables are included. Internet Appendix Table A.8 reports the results. Under the assumption of proportional selection ($\delta = 1$) with conservatively set $R_{\max} = 1$ as a natural upper bound, the bias-adjusted coefficients β^* slightly increase relative to the controlled OLS estimates (column 2).¹⁸

¹⁸An alternative calibration sets the bound $R_{\max} = R_1 + (R_1 - R_0)$, where R_1 and R_0 are the R^2 from the regression with and without controls. The change in R^2 is lower (relative to the maximum of 1), so

We next consider power computations. For the sample of $N = 57$ industries used in estimating equation (17), the sample estimate of the key coefficient $\hat{\beta}_M = 1.305$ with standard error of 0.74 and $t \approx 1.76$. We consider the effects of a hypothetical larger sample size, say $N_{\text{new}} = 182$. Under standard cluster asymptotic theory, holding the underlying variance per cluster constant, $t_{\text{new}} \approx t_{\text{old}} \sqrt{\frac{N_{\text{new}}}{N_{\text{old}}}} = 1.76 \times \sqrt{\frac{182}{57}} \approx 3.15$. A formal power calculation (using STATA command “power oneslope”) gives estimated power at the 5% significance level ≈ 0.41 . Thus, if the true effect equals the magnitude implied by our current estimate, a design with 57 industries would reject $H_0 : \beta = 0$ at the 5% level only about 41% of the time while it increases to 0.88 if we had 182 industries. In other words, under the same effect size and variance structure, a design based on all 182 industries would deliver a t -statistic of ≈ 3.15 and power of roughly 88% at the 5% level.

Political Channel The literature on state-owned banks attributes their negative effect on growth to the influence of politics on lending. Does politics impact how these banks allocate windfall surpluses in the crisis? ¹⁹

In India, the effect of politics on lending has historically been in the form of small-ticket loans to farmers (Cole, 2009b). Funding surpluses are not critical for these programs. The central bank could enforce such lending through “administrative” quotas and has done so. However, funding matters in large-scale infrastructure projects, which became a key voter concern in the 2000’s (Patel and Bhattacharya, 2010). Roads, power, ports, and to a lesser extent, telecom (a “luxury” at the time) became political priorities.

this choice diminishes the role of the unobservables. Setting $R_{\text{max}} = 1$ to 1 seemed like a more conservative choice. The corresponding implied value of δ required for $\beta^* = 0$ is approximately 7.2–7.3 across specifications (column 3).

¹⁹A press article by Bandopadhyay (2022) has an informative discussion on the plausible forces that drive credit allocations by PSBs. They include politics but also culture, fraud, weak creditor rights, slow courts, and delays in insolvency resolution, many reinforcing or being reinforced by the others.

Banks do not traditionally fund such projects as they are long-term, risky, and typically not commercially viable.²⁰ Moreover, infrastructure loans from state-owned banks did not count towards government indebtedness. Finally, these loans are long-term, which makes quality problems easier to mask (Patel and Bhattacharya, 2010). Thus, political misdirection of run surpluses is likely to be visible in infrastructure lending.²¹

Internet Appendix Table A.9 examines this issue, holding constant the specification (17) but bringing in an additional post-crisis interaction PSB exposure term for infrastructure firms. The interaction term for infrastructure is 2.851 and significant at the 1% level. To better understand the estimates, consider the dispersion for infrastructure (non-infrastructure) sectors, which equal 1.854 (1.288) and 2.151 (1.017) before and after the run, respectively. The difference in difference equals 0.568. The triple-interaction coefficient is large because the two sets of industries move in opposite directions. Dispersion increases in infrastructure (+0.297) but falls in non-infrastructure (−0.271).

The results reflect two opposing forces. The negative $Post \times Infra$ coefficient (−1.781) reflects a broad infrastructure push that lifts firms and reduces the within-sector dispersion. The positive triple interaction shows credit within high-exposure infrastructure firms went to lower-productivity firms, which widened dispersion and increased misallocation. These effects appear in the variance of log-MRPK rather than in its mean or its covariance with value added (columns 3 to 6). This result is consistent with the run reshuffling capital across firms, or misallocation rather than a level shift in productiv-

²⁰In fact, the state could impose revenue models that made the projects even more risky and unviable. For example, power producers faced mandates to charge lower rates to weaker sections or favored political constituents. In addition, they faced “distribution losses” from illegitimate diversion and difficulties in collecting dues for power supplied even from state governments that backstopped bills. The problem worsened to such an extent that the sector had to undergo debt restructuring in November 2015 (<https://powermin.gov.in/en/content/uday>)

²¹Banks may feel pressures to prop up local business facing gaps due to branch runs. However, the Section 4 evidence suggests that PSBs expand lending beyond run geographies.

ity.²² Internet Appendix Figure A.4 presents a simple aggregate statistic that speaks to this point. We compute it from the RBI KLEMS data on sector productivity. The figure shows that infrastructure capital productivity peaks in 2007 and then declines, ending 2016 slightly below its 1981 level, even as the sector’s real capital stock rises nine-fold.

Cash: With long histories of existence and dominant state ownership, PSBs are the ultimate safety nets in India. It is possible that panicked depositors in Indian banks engaged in cash hoarding as an alternative to shifting deposits to state-owned PSBs. District or pincode level cash data are not available to us. However, the “All India Debt and Investment Surveys” (AIDIS) conducted by India’s National Statistical Office about once a decade at the request of India’s central bank has some survey data on cash. The AIDIS survey has a question about household financial assets. Cash holdings are reported under the header “financial assets other than shares and debentures,” where item 11 records “cash in hand.” We classify districts as “high-cash districts” if the average cash holdings of their survey respondents are in the top tercile (quintile or medians give similar results).²³ We report estimates for high- and low-cash districts. The coefficients for runs are similar between these sets of districts. Please see Internet Appendix Table A.10.

Natural Experiment: 2005 Branch Deregulation We provide robustness evidence based on a 2005 deregulation of branch licensing norms by India’s central bank, the Reserve Bank of India (RBI). On September 8, 2005, the RBI allowed entry into underbanked

²²The regression-implied dispersion for infrastructure and non-infrastructure equal $(0.057 + 2.851) \times 0.823 + (-1.781) = 0.612$ and $0.057 \times 0.776 = 0.0442$. The gap is close to the difference in difference estimate.

²³We compute the household-level share of cash to the total financial assets and non-equity financial assets (excluding shares and debentures). We then aggregate this measure to the district-state level using sampling survey weights. While our baseline is based on the 2003 AIDIS prior to the run, the results based on the 2013 AIDIS gives similar results.

“banking deserts,” which we defined based on the population served per branch. Private banks entered underbanked areas (Young, 2017; Cramer, 2025). The 3-year run up between 2006 and 2008 occurs before the run year. It also generates a reasonable window for realized entry prior to the run, a fortuitous convergence of circumstances for this test.

We use a regression discontinuity design in which the population per branch is the running treatment variable. The first stage dependent variable is the pre-run PSB branch share in a district between 2006 and 2008, which generates the instrument for the subsequent deposit growth. The specifications are

$$\begin{aligned} \text{PSB share}_{bd} &= \delta_s + \beta * \text{Banked}_d + \gamma * \text{Banked}_d * f(T_d) \\ &+ \phi * (1 - \text{Banked}_d) * f(T_d) + \kappa X_d + \eta_d \end{aligned} \quad (20)$$

$$\text{Deposit Growth}_{jdst} = \alpha_{bt} + \delta_{st} + \beta \times \widehat{\text{PSB share}}_d + \eta \times X_{jdst} + \nu_{jdst} \quad (21)$$

where PSB share_{bd} denotes PSB share in district d , 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). The RD uses a triangular kernel with 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 post-period is from 2009-2011. We include 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.

Panel (a) of Figure 6 shows a discontinuous increase in the number of private sector bank branches at the RD threshold in under-banked districts, which is not seen in PSBs (Panel (b)). Panel (c) shows a discontinuous decrease in PSB deposit shares, consistent with deposit migration 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.²⁴ The run period results are in Table 10. Column (1) has the first-stage estimates of equation (20). The F -statistic is 220, indicating that the instrument is strong. 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.²⁵

Weaker PSBs This test exploits the fact that state-owned banks in India are listed on the stock market, with trading in shares not owned by the government. Following Acharya et al. (2017), weaker PSBs are the ones with greater marginal expected shortfall “MES.”²⁶ Do the vulnerable PSBs with greater MES, who gain more from the umbrella of state ownership, attract more panic flows?

Figure 7 displays some results. The figure on the left shows that flow losses are greater at weaker *private* banks with greater MES. Table 11 provides estimates of Equation (10), replacing the bank-level exposure variable with MES. Columns (1) and (3) show that for private banks, growth is lower for the weaker (high MES) banks. Columns (2) and (4) show that this relation reverses for PSBs. The weaker PSBs lend more and have greater

²⁴For evidence on covariate balance, see the Internet Appendix Table A.11, Panel (a) and McCrary plots in Internet Appendix Figure A.5. See the Internet Appendix Table A.11, Panel (b) and Internet Appendix Table A.12 for additional evidence and the relative insensitivity to the empirical choices for implementing the RD.

²⁵Placebo results for the pre-crisis periods in the Internet Appendix Table A.13 show no such effects or pre-trends. The run period flights are special.

²⁶MES is measured in our implementation 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. See Internet Appendix Table A.14 for a list of private banks and PSBs for which we can compute MES.

future non-performing assets, especially for non-agricultural loans over which they have more discretion, a relationship that reverses for private banks. These results are less granular, being at the bank-level as is the MES metric.

We obtain additional data to speak to the deposit-acquisitive behavior of the vulnerable PSBs. See Panel B of Table 11. 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)) but the relation reverses for non-retail deposits that come from more sophisticated investors who are more sensitive 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.²⁷ Moreover, several PSBs have required ex-post capital injec-

²⁷Preliminary results from the Covid-19 period are supportive of this channel. Private banks received 55% of incremental deposits in the pre-Covid periods but only 30% after.

tions, indicating that depositor perceptions about state support were not unfounded.²⁸

7 Conclusion

We study a significant bank run episode in India in which some branches of private sector banks face sudden and large losses in deposits that migrate to state-owned public sector banks (PSBs). We characterize the deposit losses at run banks and the gains at the PSBs that receive the panic flows as windfall surpluses. We assess the resulting credit effects and estimate the aggregate consequences of the resource reallocation triggered by the run.

We find that runs have effects beyond the local geographies in which they occur. Banks facing runs cut lending and their credit discipline improves. State-owned banks that receive the surplus funds expand credit for their borrowers but the credit quality is weak as reflected in the increases in non-performing assets, particularly when under asset quality recognition pressures from the central bank. The aggregate reallocation effect is negative. Productivity growth is impaired by about 18%.

An important thread in our study is that the economic consequences of runs go beyond bank instability. Runs reconfigure resources away from run banks to safe havens. The effects of the reallocation depend on the nature of the reintermediation of the panic flows. In our study, the *quality* of reintermediation offered by state-owned PSBs is weak and drives negative aggregate effects. A related mechanism arises when banks specialize. For instance, banks such as SVB often specialize in geographies, sectors, or products such as venture debt or capital call lines. If so, banks often hold hard-to-transmit “soft” information. Runs that reshuffle and reallocate resources across banks preserve capital

²⁸In February 2009, there were capital injections in 3 state-owned banks: UCO Bank, Central Bank of India and Vijaya Bank. The 2010-2011 budget included additional capital infusion in five state-owned banks: IDBI Bank, Central Bank, Bank of Maharashtra, UCO Bank and Union Bank. The injections recapitalized the worst-performing banks, which were among the highest MES banks in our sample.

and are thus capital-neutral but still have aggregate effects due to the displacement and possible loss of the soft information and relationships developed through specialization.

Our results suggest that while depositors see government support (correctly) as a valuable source of financial stability during a crisis, its provision is not free of costs. While government support ensures safety, there is no assurance of quality. Thus, a flight to *safety* is not necessarily a flight to *quality*. 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 across banks. 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 1: 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.

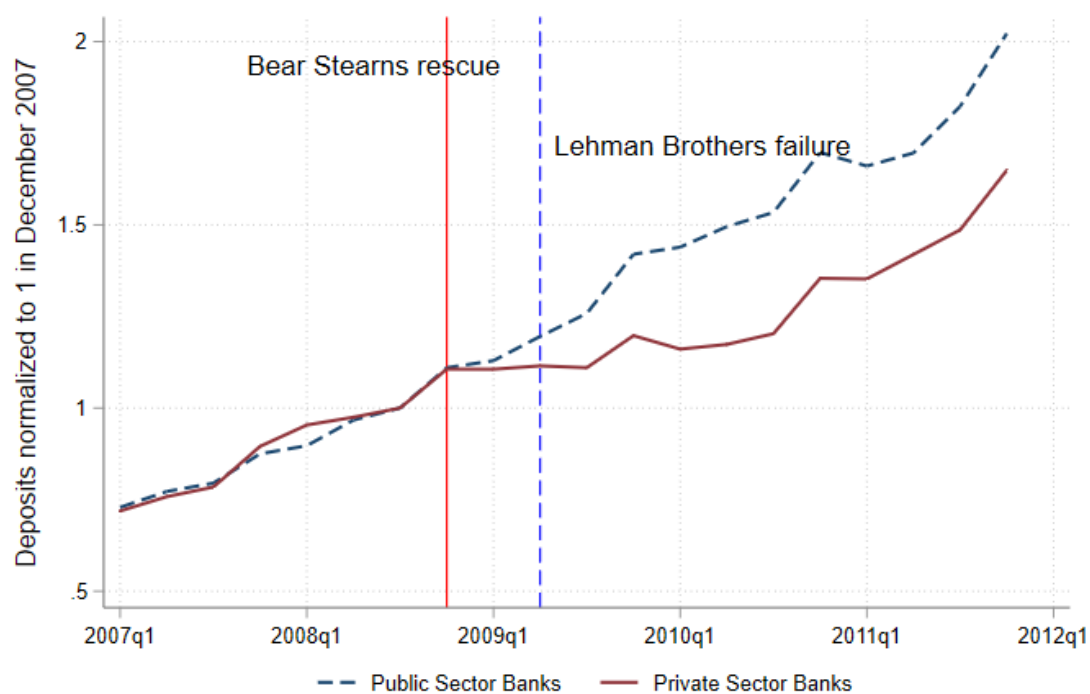
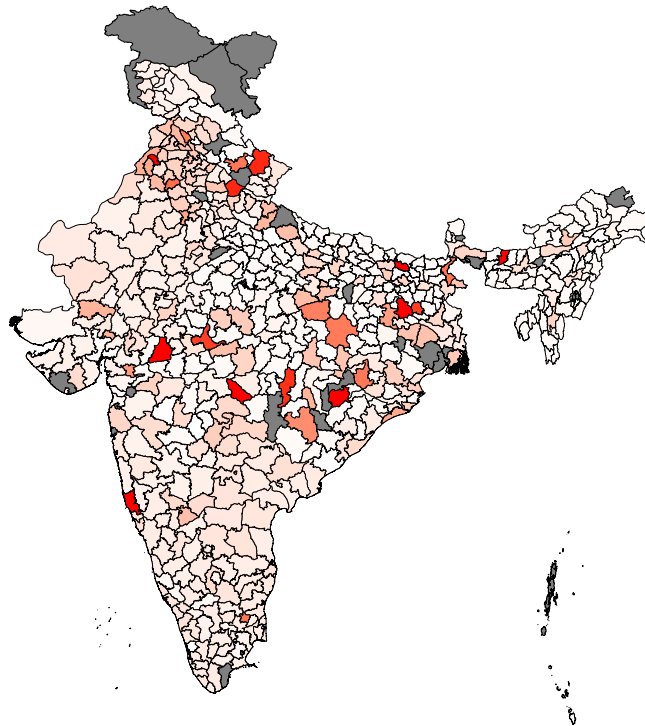


Figure 2: Heat Map

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. Panels (a) and (b) correspond to the private and public bank deposit growth, respectively. Districts with no available data are shaded in gray.

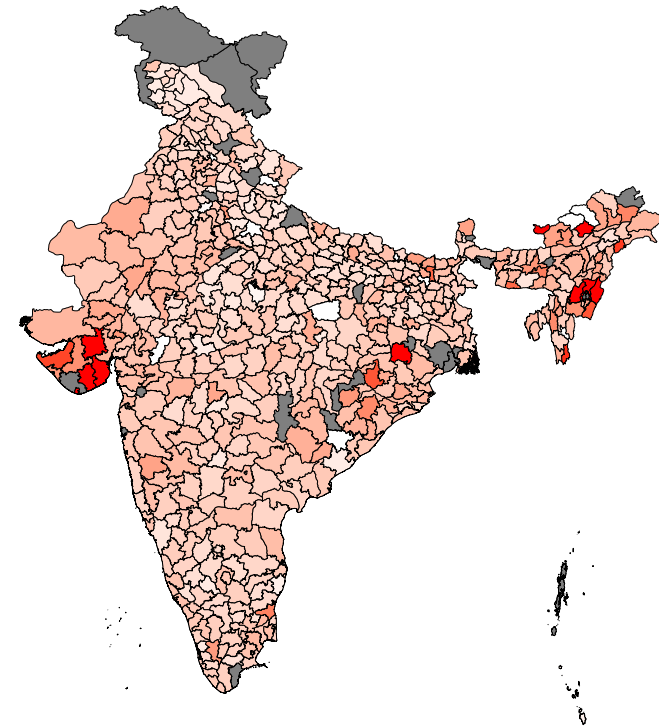
(a) Private Sector Banks



Deposit Growth Rate %

0 100 200 300

(b) Public Sector Banks



Deposit Growth Rate %

25 50 75

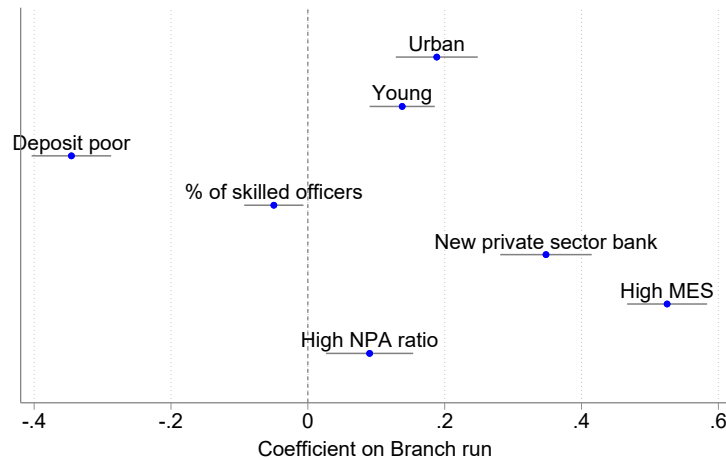
Figure 3: Characteristics of Branches With Runs

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 examined using the specification:

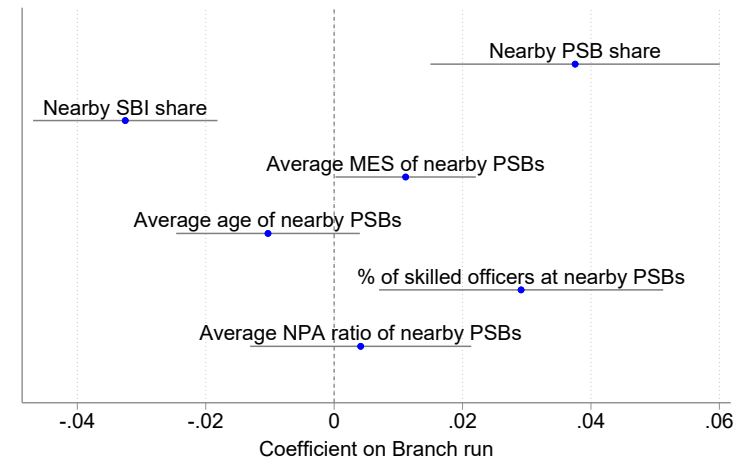
$$\text{Branch run}_j = \alpha + \beta \times \text{Char}_j + \epsilon_j$$

Branch run is an indicator variable as defined in Table 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, an indicator for the branch with non-performing asset (NPA) ratio above 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, the share of nearby PSBs and finally, the average NPA ratio of nearby PSBs. The coefficients 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.

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(a) Characteristics of branches with runs



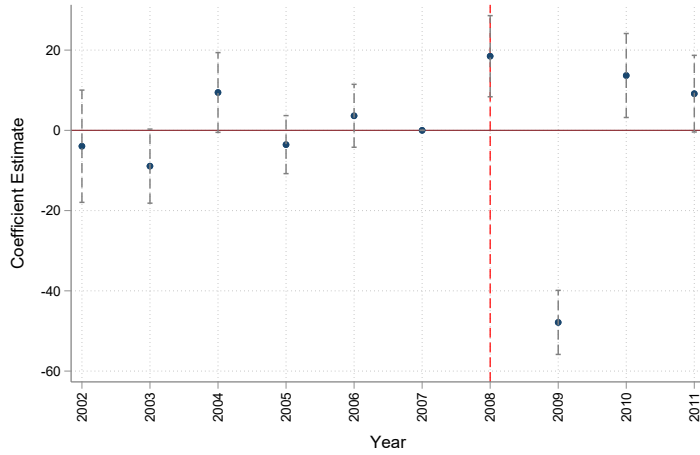
(b) Characteristics of nearby PSB branches

Figure 4: Event Study Plots

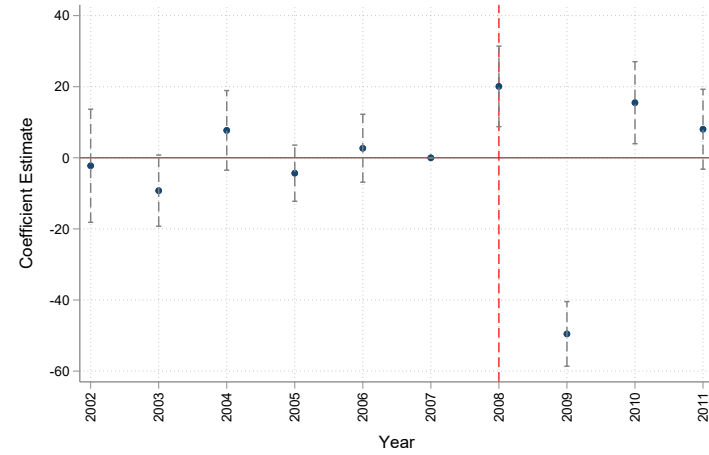
This figure shows the coefficients (η_τ) from an event study regression:

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

where the dependent variable, Y_{jbdpt} is the annual growth in deposit for branch j belonging to bank b in district d in pin code p for time-period t (where t ranges from 2002 to 2011). α_j , γ_{bt} and θ_{dt} are branch, bank-time, and pin code-time period fixed effects respectively in panel A. In Panel B, θ_{dt} is replaced with district-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 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 pin code FE

Figure 5: Deposits at Co-located Branches

This figure shows the annual deposits for private sector bank branches co-located from 2004 to 2012, where year is the fiscal year ending on March 31. Co-located branch takes a value of 1 for $\mathbb{1}_{\text{COLOC. PSB}}$, as defined in Table 1, and 0 otherwise. Deposits are aggregated to the national annual level and shown as the solid red line for co-located branches and as the dashed blue line for remaining private sector bank branches. Deposits are normalized to 1 as of March 2007 for each category. The solid vertical line is shown for March 2008.

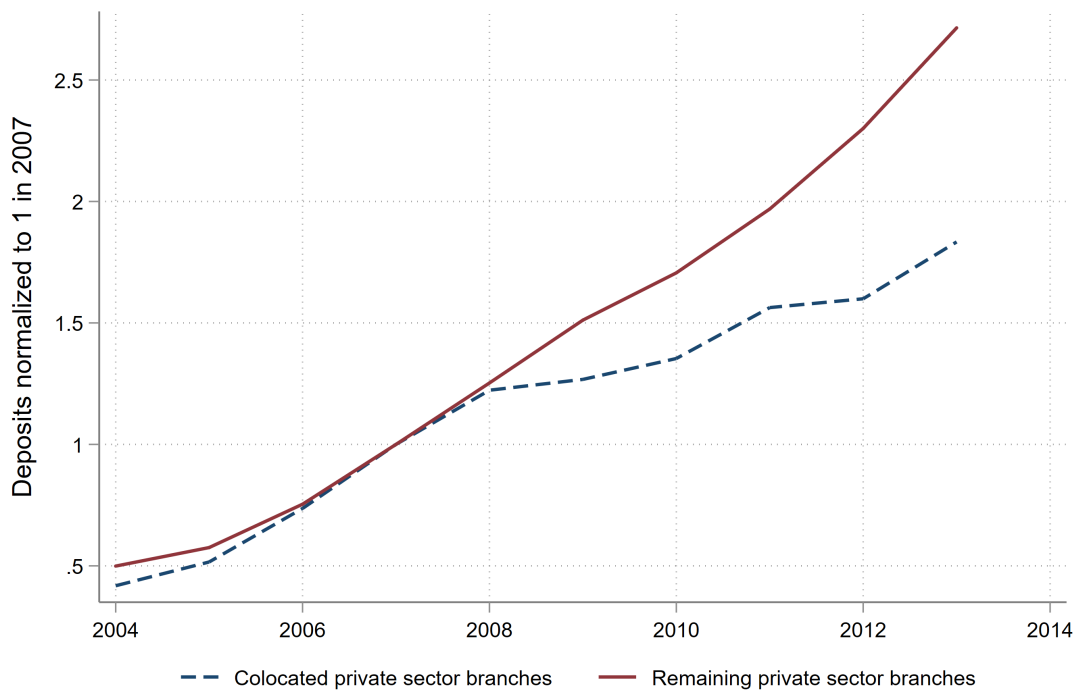
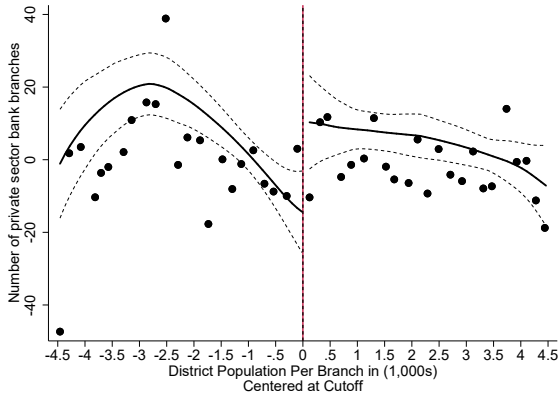
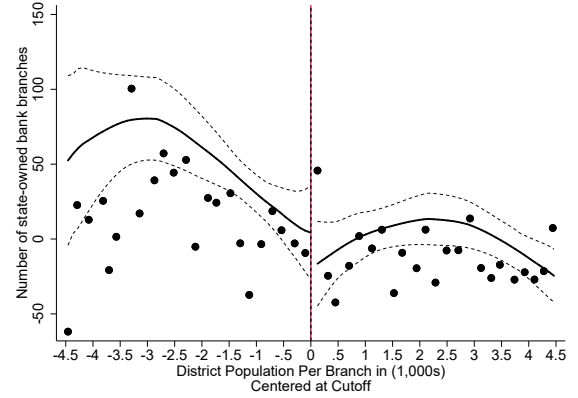


Figure 6: Regression Discontinuity: Share of State-Owned Bank Branches

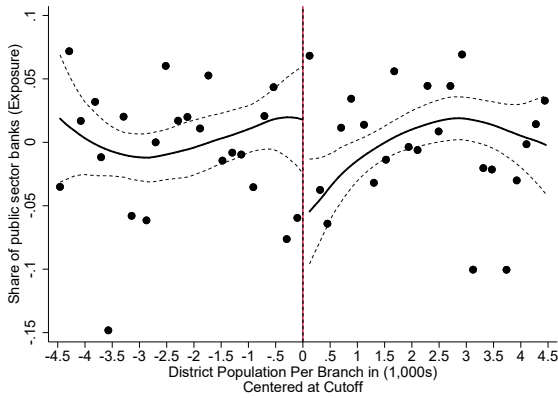
The table reports regression discontinuity (RD) plots for the number of private sector bank branches in 2006–08 (panel a), number of state-owned bank branches in 2006–08 (panel b), deposit share of state-owned banks in 2006–08 (panel c), and deposit share of state-owned banks in 2001–03 (panel d) at 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

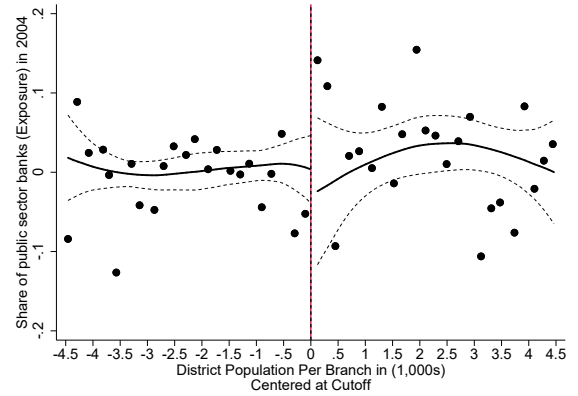


(b) State-owned bank branches in 2006–08



(c)

Deposit share of state-owned banks in 2006–08



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

Figure 7: 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 1.

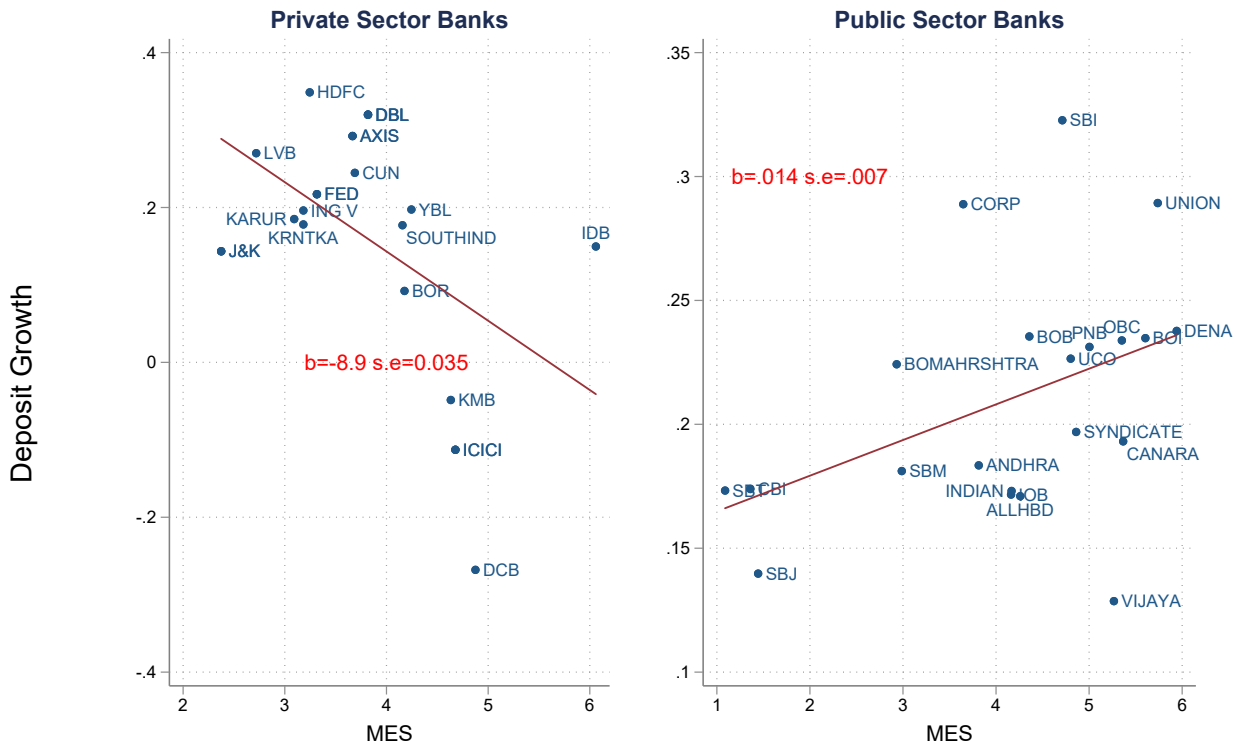


Table 1: Key Variable Definitions

Variable	Definition & Source †
(1) Year	Fiscal year t is the 12-month period ending on March 31 of calendar year t .
(2) $\mathbb{1}_{\text{Branch run}}$	Branch-level indicator that equals 1 for (a) private sector bank branches if all conditions below are satisfied and 0 for all other branches. (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.
(3) $\mathbb{1}_{\text{Coloc. PSB}}$	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 pin code and 0 otherwise.
(4) Pvt. Dep. $\text{LOSS}_{\text{RUN PIN}}$	Pin code-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.
(5) Pvt. Dep. $\text{LOSS}_{\text{COLOC PIN}}$	Pin code-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.
(6) 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).
(7) PSB Dep. $\text{Pct.}_{\text{COLOC PIN}}$	Public bank-level variable that is the deposit weighted average of the pin code 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).
(7) 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).
(8) PSB Cred. $\text{Pct.}_{\text{COLOC PIN}}$	Public bank-level variable that is the credit weighted average of the pin code exposure Pvt. Dep. $\text{LOSS}_{\text{COLOC PIN}}$ with credit as of March 31 st , 2009. The measure is standardized (z-scored).
(9) Firm PSB 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.
(10) Industry Exposure	Industry exposure is the loan-weighted Firm PSB Exposure, with the loan weights calculated using loans for 2006–2008.
(11) 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.
(12) $\mathbb{1}_{\text{Coloc. Old. Pvt.}}$	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 pin code and 0 otherwise.

Table 2: Descriptive Statistics

This table presents summary statistics. Panel A reports statistics for the exposure measures described in Table 1. Pvt. Dep. Pct.COLOC PIN and PSB Dep. Pct.COLOC PIN are shown before z-score standardization. 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 fiscal 2009. $\Delta \text{NPA}_{2009-2011}$ ($\Delta \text{NPA}_{2012-2016}$) 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 of bank-firm (firm) borrowings in the MCA data for the pre- and post-run periods. $\mathbb{1}_{\text{Loan}}$ is an indicator for a loan between a bank-firm pair. Loan amount is in INR million. Marginal productivity of capital (MRPK) is 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 for the pre-period and post-periods. Pre(post)-period refers to the 3 years from 2006 to 2008 (2009 to 2011).

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. LOSSRUN PIN	10,015	0.59	4.71
Pvt. Dep. LOSSCOLOC PIN	10,015	0.36	4.30
Pvt. Dep. Pct.COLOC PIN	19	0	1
PSB Dep. Pct.COLOC PIN	20	0	1
Pvt. Cred. Pct.COLOC PIN	19	0	1
PSB Cred. Pct.COLOC PIN	20	0	1
Firm PSB 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		25,438		5,273	
$\Delta \text{NPA}_{2009-2011}$ (in %)	1.23	5.00	1.42	4.93	0.35	5.23
Obs. (Branches)	30,648		25,375		5,368	
$\Delta \text{NPA}_{2012-2016}$ (in %)	6.38	12.73	6.99	13.04	3.51	10.68
Obs. (Branches)	30,396		25,112		5,284	

Panel C: Loan-level Variables

	All		Public		Private	
	Mean	SD	Mean	SD	Mean	SD
$\mathbb{1}_{\text{Loan}}$	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
$\mathbb{1}_{Loan}$	0.50	0.50	0.00	1.00	1.00
Loan amount (in INR million)	1356	9006	0.00	.55	305
Obs. (Firms)	12,873				

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 3: 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 fiscal 2009 (the financial year ending on March 31, 2009). 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 1. Fixed effects included are as indicated. Columns (1)-(2) show the first-stage using the instrument for branch run, and columns (3)-(4) show the instrumented variable estimates. Standard errors are clustered at the branch level.

Dependent variable:	(1)	(2)	(3)	(4)
	Branch Run		Deposit growth	
$\mathbb{1}_{\text{Branch run}}$			-105.309*** (29.687)	-108.728*** (35.851)
$\mathbb{1}_{\text{Coloc. PSB}}$	0.055*** (0.010)	0.049*** (0.010)		
R-squared	0.178	0.269	0.009	0.010
No. of Obs.	30,784	25,501	30,784	25,501
F-statistic	31.46	24.73		
Bank FE	Y	Y	Y	Y
District FE	Y	Y	Y	Y
Pincode FE	N	Y	N	Y
Type	First Stage	First Stage	IV	IV

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

Table 4: Safe-Haven Flights of Deposits to PSBs

The table shows the deposit growth of PSB branches in the run district. Observations are at the branch level. The dependent variable is the annual growth rate of deposits for fiscal 2009 (the financial year ending on March 31, 2009). Pvt. Dep. Loss_{RUN PIN} and Pvt. Dep. Loss_{COLOC PIN} (instrument) are pin code-level measures defined in Table 1. PSB is an indicator variable for public sector banks. Column 1 is the first stage of the instrumental variables estimate and confirms that run losses are related to co-location. Columns (2)-(3) and (4)-(5) show reduced form and IV estimates, respectively, of run bank losses (row (3)) and flows accruing to PSBs (row (4)). District, pin code 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 _{RUN PIN}	Deposit growth			
Pvt. Dep. Loss _{COLOC PIN}	0.733*** (0.0798)				
Pvt. Dep. Loss _{RUN PIN}		-0.280*** (0.0555)		-0.325*** (0.0838)	
PSB $\times$ Pvt. Dep. Loss _{RUN PIN}		0.413*** (0.0634)	0.375*** (0.0661)	0.505*** (0.100)	0.494*** (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				
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 5: Private Banks Are Not Safety Nets

This table presents two sets of results to test whether old private sector banks serve as safety nets. The dependent variable is deposit growth in fiscal 2009, the financial year ending on March 31, 2009. $\mathbb{1}_{\text{Coloc. PSB}}$ and $\mathbb{1}_{\text{Coloc. Old. Pvt.}}$ are as defined in Table 1. The sample for Panel A comprises all private sector bank branches and that for Panel B includes all bank branches. In the instrumental variables specification in Panel B, the first stage estimates are in columns (1)-(2), reduced form estimates are in columns (3)-(4), and the 2SLS IV estimates are in 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*** (1.802)	-58.468*** (2.512)	-64.209*** (2.322)	-64.932*** (4.377)	-54.692*** (2.492)	-58.907*** (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: Instrumental variable model for co-location with old private bank						
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Branch Run		Deposit growth			
$\mathbb{1}_{\text{Coloc. Old. Pvt.}}$	0.008 (0.016)	0.003 (0.017)	4.032 (2.769)	2.508 (2.944)		
$\mathbb{1}_{\text{Coloc. PSB}}$	0.052*** (0.012)	0.048*** (0.012)	-7.290*** (2.184)	-6.261*** (2.308)		
$\mathbb{1}_{\text{Branch run}}$					-101.346*** (28.902)	-107.444*** (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
Pin code 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 6: Credit Effects of Runs

This table shows credit growth of branches as a function of exposure to runs. The unit of observation is a branch. The dependent variable is the annual growth rate of total credit for fiscal 2009, the financial year ending on March 31, 2009. The remaining variables are defined in Table 1. Columns (1)-(2) report estimates for private banks while columns (3)-(4) report estimates for state-owned public sector banks. Fixed effects are included as indicated.

	(1)	(2)	(3)	(4)
Dependent variable:	Credit growth			
Sample:	Private Sector Banks		Public Sector Banks	
$\mathbb{1}_{\text{Coloc. PSB}}$	-22.052** (9.365)	-21.863** (9.046)		
Pvt. Dep. Pct.COLOC PIN	0.005 (3.105)			
Pvt. Dep. Loss _{COLOC PIN}			0.030 (0.044)	
PSB Dep. Pct.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 7: NPA Effects In and Beyond Run Geographies

This table reports regression results to explain non-performing assets (NPAs) associated with runs. The unit of observation is a branch. For columns (1) and (2), the dependent variable is the change in non-performing assets from 2009 to 2011 scaled by credit in 2009. Columns (3) and (4) report similar results for the change in non-performing assets from 2012 to 2016 scaled by 2012 credit. A year refers to the financial year ending on March 31. Pvt. Cred. Pct.COLOC PIN and PSB Cred. Pct.COLOC PIN are the bank-level exposure measures as defined in table 1. Both measures are standardized (z-scored). Standard errors are clustered at the pin code level.

	(1)	(2)	(3)	(4)
Dependent variable:	$\Delta \text{NPA}_{2009-2011}$		$\Delta \text{NPA}_{2012-2016}$	
Sample:	Private	Public	Private	Public
Pvt. Cred. Pct.COLOC PIN	-0.601*** (0.132)		-0.168 (0.280)	
PSB Cred. Pct.COLOC PIN		0.037 (0.035)		0.913*** (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 8: Loan-Level and Firm-level Outcomes

This table reports the extensive and intensive margins of lending around the bank run using firm-bank borrowing data from filings at the Ministry of Corporate Affairs in India, with the analysis focusing on post-period lending outcomes as a function of pre-period exposure. The dependent variable for the extensive margin specification (columns (1)-(2)) is whether a loan exists for a bank-firm pair. In the intensive margin specification in columns (3)-(4), the dependent variable is the total loan amount in INR million for a bank-firm pair conditional on a loan being made. Columns (5)-(6) report the combined extensive plus intensive margin results using a Poisson regression. In Panel A, PSB is an indicator for a public sector bank lender. The pre(post)-period denote the three years prior to (after) 2009. All columns include pre-period variables as control variables. Observations are a balanced panel at the bank-firm level for the pre- and post-period in the extensive or extensive plus intensive specifications in columns (1)-(2) and (5)-(6) and for only bank-firm pairs with a post-period loan in columns (3)-(4). Even numbered columns include firm fixed effects. The firm-level specification in Panel B models quantity and quality effects in the post-period. The dependent variables are as in Panel A, but for the post period only. Firm PSB exposure is as defined in Table 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, and the specifications include industry fixed effects. 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)			
PSB	0.017*** (0.005)	0.017*** (0.005)	547.277** (242.402)	929.954** (362.439)	1.540*** (0.475)	1.512*** (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 PSB Exposure	0.347*** (0.014)	0.365*** (0.021)	1965.382*** (541.246)	2615.190** (1031.352)	1.592*** (0.146)	1.890*** (0.197)
Top		0.170*** (0.015)		-981.922** (432.743)		0.147 (0.235)
Top × Firm PSB Exposure		-0.073*** (0.025)		-1022.016 (1159.230)		-0.581** (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	52 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 9: Industry-level Outcomes

This table shows the industry-level estimates that are relevant for computing aggregate productivity effects of the run. Observations are at the industry level for the pre- and post-periods, 2006-2008 and 2009-2011, respectively. Industry exposure is defined in Table 1. Marginal productivity of capital (MRPK) equals total sales divided by 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 10: Regression Discontinuity Results

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 between fiscal 2009 and 2011, the financial year ending on March 31 of the relevant year. The running variable used for the discontinuity is whether the population per branch minus its national average is less than zero, a sharp cutoff used by the central bank in the changed branching policy in 2005. The first- and second-stage results are shown in columns (1) and (2). Both specifications include state-year and bank-year fixed effects and covariates that include the percentage of skilled officers, the credit-to-deposit ratio in 2008, and their interactions with time trends. The observations are weighted with fiscal 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 Indian 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 11: 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, which is greater for weaker banks. The dependent variable in Panel A is the annual deposit growth for columns (1)-(2), credit growth for columns (3)-(4), and agricultural and non-agricultural non-performing assets (NPA) growth for columns (5)-(8), which are recorded at the branch level. Data are for three years after the run in the 2009 fiscal year, where year denotes the financial 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. 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. We estimate results separately for private banks and PSBs, 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*** (0.487)	0.182** (0.077)	-2.112** (0.826)	0.363*** (0.134)	8.064 (15.042)	-28.252*** (7.405)	7.702*** (2.581)	2.746** (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

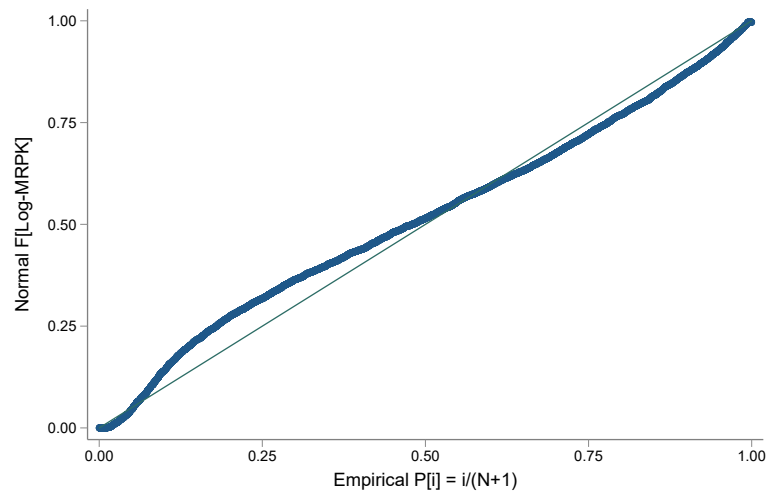
Panel B: Deposit Rates				
	(1)	(2)	(3)	(4)
Dependent variable:	Change in Deposit Rates (in BPS)			
Sample:	Private		Public	
Type:	Retail	Non-retail	Retail	Non-retail
MES	1.157 (0.765)	-0.713 (2.085)	-6.392*** (0.186)	2.483*** (0.657)
R-squared	0.752	0.370	0.539	0.060
No. of Obs.	9929	9651	40857	36736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

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

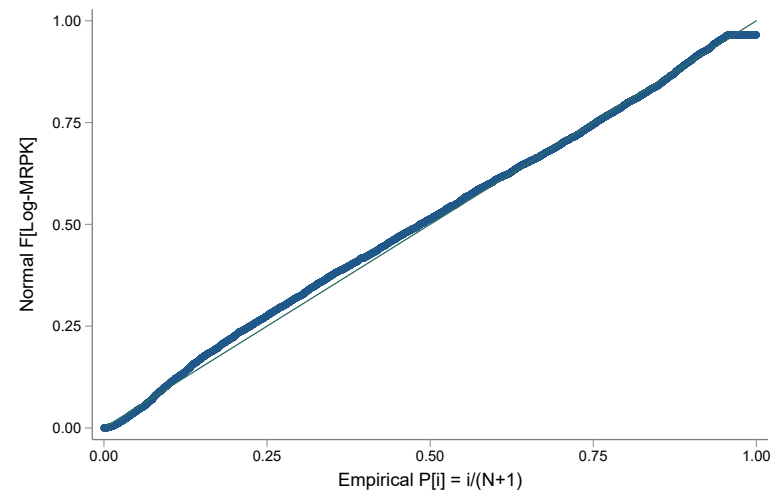
Internet Appendix

Figure A.1: Log-Normality of MRPKs in the Data

The figure shows normal probability plots for manufacturing and non-manufacturing firms for the distribution of log-MRPK. MRPK is computed as the ratio of sales to gross fixed assets. Panel (a) shows the figure for the sample of manufacturing firms and panel (b) is for the sample of non-manufacturing firms.



(a) Manufacturing firms



(b) Non-manufacturing firms

Figure A.2: Leave-One-Out Robustness Across Industries

This figure shows leave-one-out (LOO) estimates of the coefficient on $\text{Post} \times \text{Industry Exposure}$ from the industry-level difference-in-differences specification in Table 9 in the main draft. The regression assesses the impact of the run on resource reallocation through changes in productivity dispersion, measured as the cross-sectional variance of log-MRPK at the industry level, with average MRPK calculated separately for pre-period (2006-2008) and post-period (2009-2011). Industry exposure is the pre-determined, loan-weighted Firm PSB Exposure. Each point in Figure A.2 corresponds to the estimated coefficient obtained by excluding one industry at a time from the sample. Confidence intervals at the 10% level are shown.

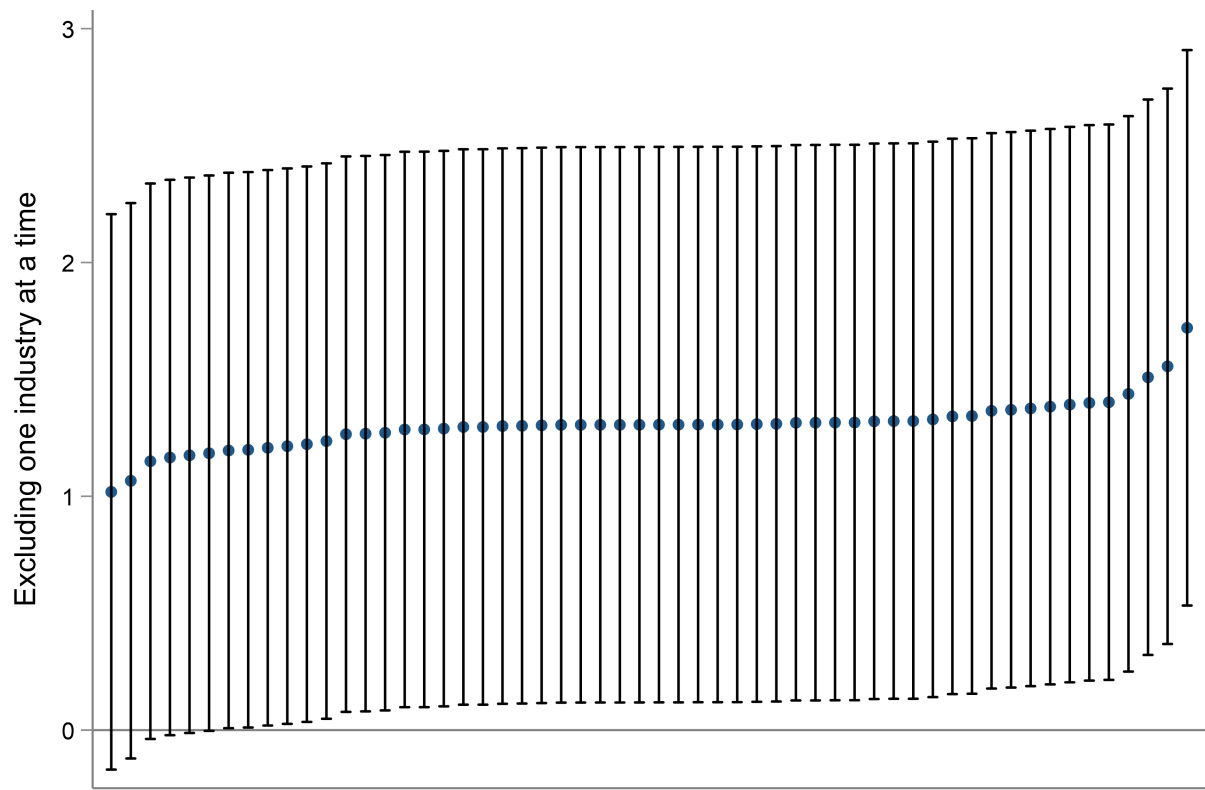
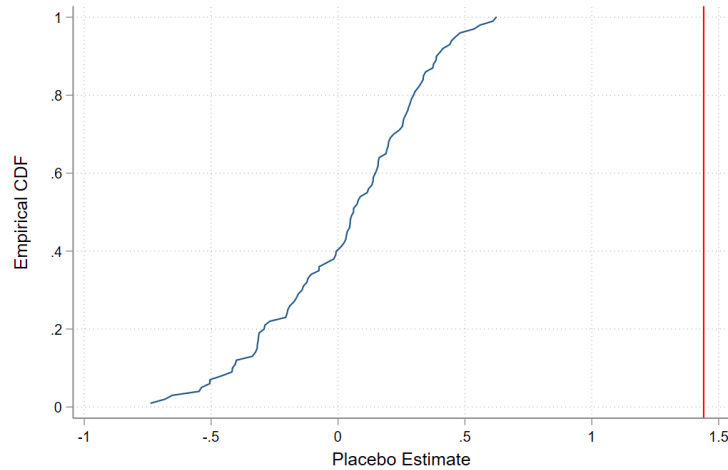
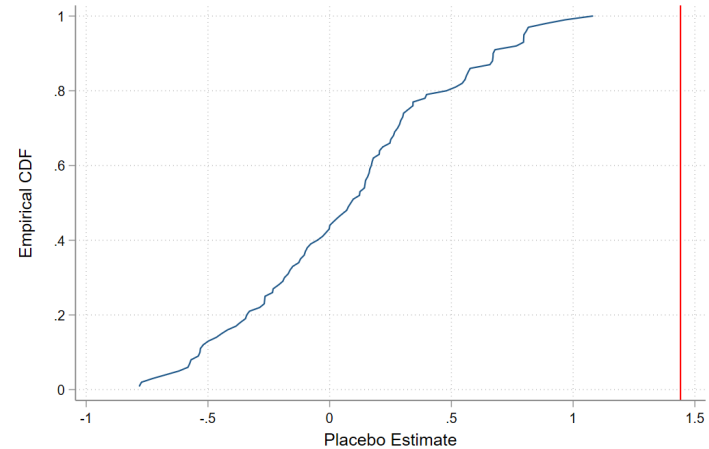


Figure A.3: Placebo Test Using Randomized Industry Exposure

This figure shows the empirical CDF of placebo estimates for the coefficient on $\text{Post} \times \text{Industry Exposure}$ from the industry-level difference-in-differences specification in Table 9 in the main draft. The underlying regression assesses the impact of the run on resource reallocation through changes in productivity dispersion, measured as the cross-sectional variance of log-MRPK at the industry level, with average MRPK calculated separately for pre-period (2006-2008) and post-period (2009-2011). In panel (a), the industry exposure variable is randomly assigned values drawn from a uniform distribution on $[0, 1]$ to match the industry exposure (which also varies between 0 and 1) in each iteration. In panel (b), the industry exposure variable is randomly reassigned across industries by resampling from the empirical distribution of the observed exposure (i.e., a shuffled bootstrap) in each iteration. The regression is re-estimated 100 times following Equation 17, replacing the original exposure measure with these placebo exposures. The vertical red line denotes the baseline estimate of 1.305 reported in Table 9.



(a) Uniform draw



(b) Shuffled bootstrap

Descriptive Statistics for Aggregate Infrastructure Capital Productivity As a descriptive precursor to the within-industry result in Table A.9, Figure A.4 plots capital productivity in infrastructure using the RBI KLEMS database. Heavy infrastructure investment did not raise productivity. Infrastructure capital productivity is flat through the 1980s and 1990s, rises into the mid-2000s, and peaks in 2007 before falling steadily, ending 2016 slightly below its 1981 level even as the sector's real capital stock rose nine-fold over the same period. The decline is broad-based, with five of the six sectors falling between 18 and 49 percent from their 2007 peak. We measure capital productivity as real value added per unit of real capital, Y/K , the aggregate counterpart of the firm-level MRPK (sales to capital) that underlies our main results. The statistic requires no assumption about factor shares and is not a production-function residual. It is descriptive and distinct from the KLEMS-weighted firm-level dispersion in Table A.6, which uses KLEMS productivity only as weights.

Figure A.4: Infrastructure Capital Productivity and the Capital Stock

Capital productivity and the real capital stock for the six infrastructure sectors (mining and quarrying, basic metals, electricity/gas/water, construction, transport and storage, and post and telecommunication), computed from the RBI KLEMS database. Panel (a) plots capital productivity, measured as the average product of capital Y/K , where Y is real value added and K is the real capital stock; panel (b) plots the real capital stock. Both series are aggregated across the six sectors and indexed to 1981 = 100. The dashed vertical line marks 2008. Capital productivity peaks at 125 in 2007 and falls to 94 by 2016, while the capital stock rises to 905. The decline is broad-based: from their 2007 peak to 2016, capital productivity falls by 49% in mining and quarrying, 44% in basic metals, 34% in construction, 30% in post and telecommunication, and 18% in electricity, gas and water; only transport and storage rises, by 6%. India, 1981–2016.

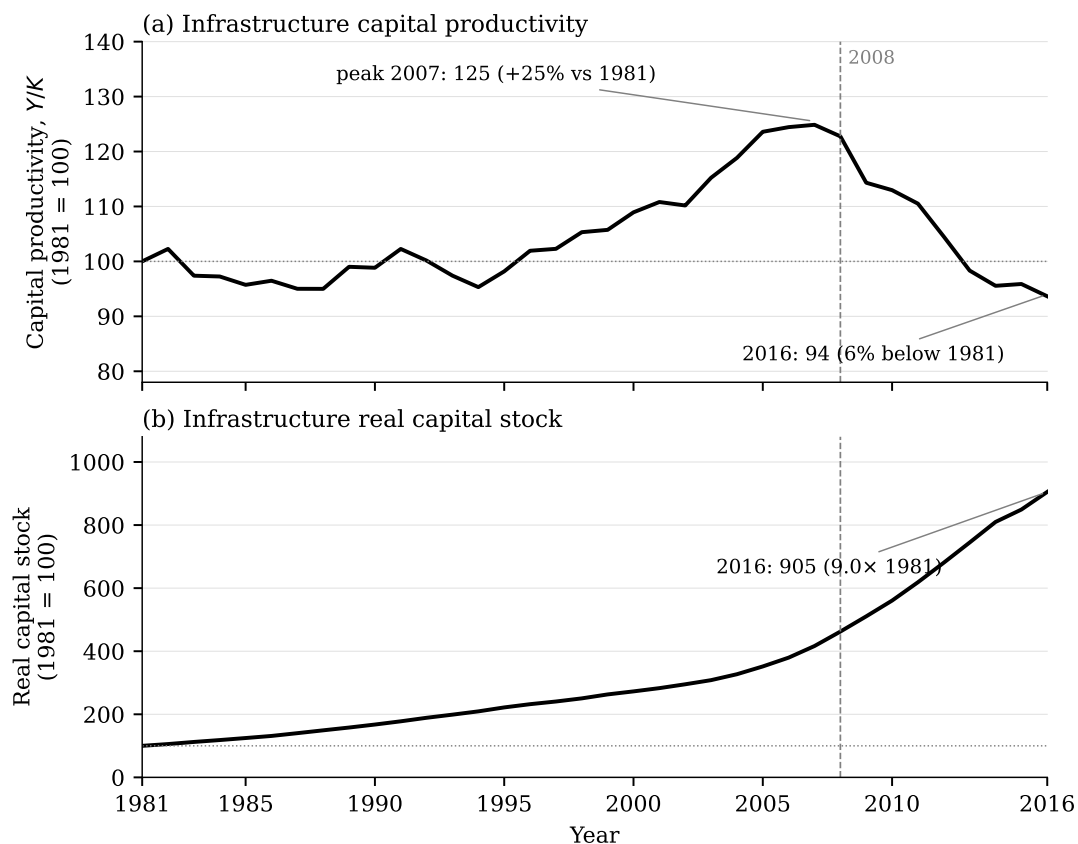
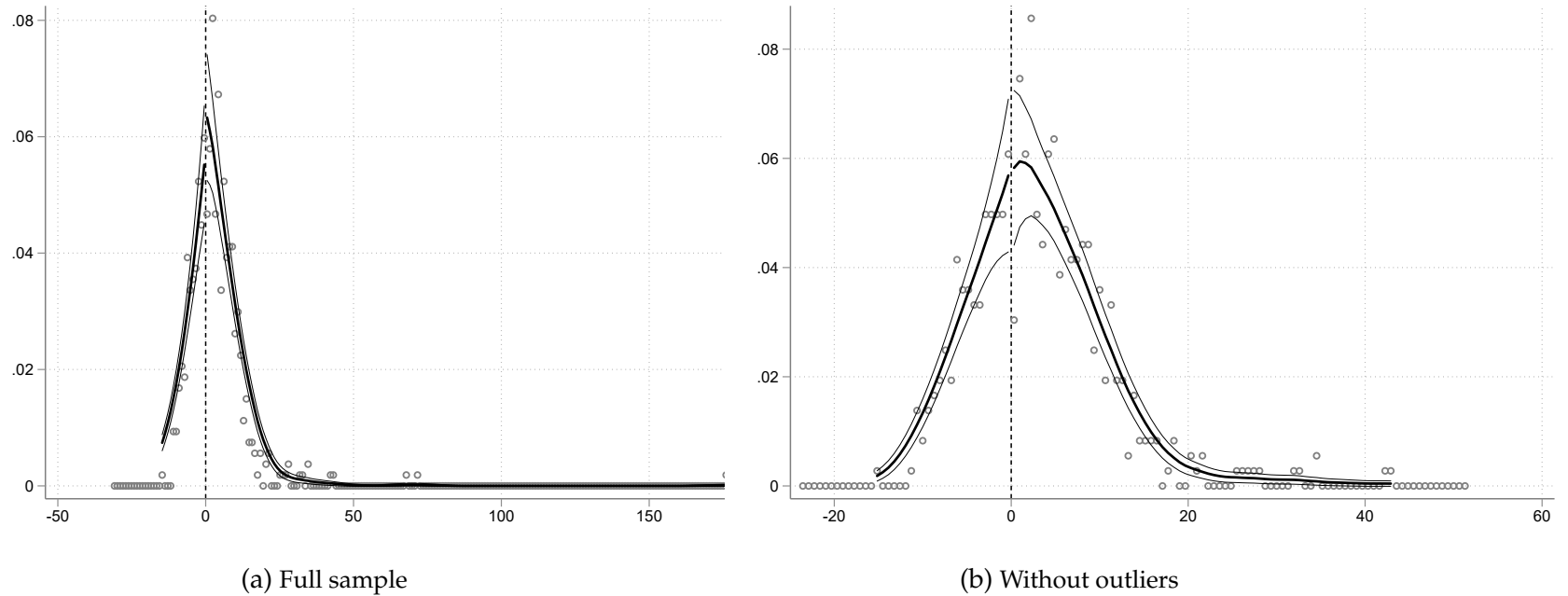


Figure A.5: Regression Discontinuity: McCrary Test

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 50. Branch-level data is from the Reserve Bank of India. Population data used to construct the running variable is from the 2001 Census.



Tables A.1 and A.2: Alternative and Placebo Specifications For Run Losses

We report two sets of results that are useful in showing the robustness of our run definitions.

In Table A.1, we estimate a model in which the post-period is the focus of the primary analysis and the pre-period is used to control for parallel trends, on the lines of Alencar (2016) and Drechsler, Savov and Schnabl (2021). We analyze deposit growth in the post-run period using the following specification:

$$Y_{jbd} = \alpha_b + \gamma_d + \beta \times \mathbb{1}_{\text{Branch run } j} + \epsilon_{jbd}, \quad (22)$$

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_d are bank and geography fixed-effects respectively.²⁹

Table A.1 reports the estimates of equation (22). The coefficient of interest, β which estimates deposit growth for run branches relative to other branches of the *same* bank, are negative and significant. Note that the number of observations differ across columns in Table 3 (and in subsequent tables) because singletons, i.e., observations that appear only once within a fixed effect category, are not reported.

In Table A.2, we show that the extreme deposit losses for run branches observed in the run years are atypical, as they are not exhibited in several years before the run.

Both sets of results follow next.³⁰

²⁹In unreported results, we find similar results using pre-period data as controls.

³⁰In more unreported results, we show that there is no difference in deposit growth between run and non-run branches in fiscal 2005, 2006, and 2007. Moreover, branches in the left tail of fiscal 2005 (as placebo) show no extreme deposit losses in 2009. These results are available for the interested reader.

Table A.1: 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 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*** (1.572)	-60.070*** (1.744)			-105.309*** (29.687)	-108.728*** (35.851)
$\mathbb{1}_{\text{Coloc. PSB}}$			0.055*** (0.010)	0.049*** (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 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 column 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 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 (4.937)	-5.746 (3.793)	9.724** (4.044)	-3.295 (3.437)	2.638 (3.875)	-0.111 (3.212)	17.050*** (3.018)	-54.637*** (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: Instrumental Variable Diagnostics and First Stage Results

This table reports first-stage results and identification diagnostics for the instrumental variable specification in Table 3 in the manuscript. The endogenous variable is $\mathbb{1}_{\text{Branch run}}$, instrumented using $\mathbb{1}_{\text{Coloc. PSB}}$. The specifications include bank-by-year, pincode, and district fixed effects. Standard errors are clustered at the pincode level. The reported Kleibergen–Paap rk LM statistic tests for underidentification, Kleibergen–Paap rk Wald F-statistic assesses weak identification. Stock–Yogo critical values at the 10% critical value are reported for reference. Anderson–Rubin and Stock–Wright tests provide inference robust to weak instruments.

Panel A: First Stage	
Dependent variable:	$\mathbb{1}_{\text{Branch run}}$
$\mathbb{1}_{\text{Coloc. PSB}}$	0.049*** (0.0099)
Observations	25,501
Panel B: Identification and Weak-IV Tests	
Kleibergen–Paap rk LM (Underidentification) p-value	23.18 0.000
Kleibergen–Paap rk Wald F (Weak ID) Stock–Yogo 10% critical value	24.73 16.38
Panel C: Weak-Instrument Robust Inference	
Anderson–Rubin F p-value	8.02 0.0047
Stock–Wright LM S p-value	7.93 0.0049

Table A.4: Deposit Growth at Branches With Runs Within Urban Pincodes

This table reports estimates of the regression in Table 3 in the manuscript with additional fixed effects. The dependent variable is the annual growth rate of deposits for fiscal 2009 (the financial year ending on March 31, 2009). 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 1 in the manuscript. Fixed effects included are as indicated, including $\text{pincode} \times \text{urban}$ fixed effect where urban is a branch-level indicator for whether the branch operates in an urban area. Columns (1)-(2) show the first-stage using the instrument for branch run, and columns (3)-(4) show the instrumented variable estimates. Standard errors are clustered at the pincode level.

	(1)	(2)	(3)	(4)
Dependent variable:	Branch Run		Deposit growth	
$\mathbb{1}_{\text{Branch run}}$			-111.291** (48.383)	-110.168** (52.088)
$\mathbb{1}_{\text{Coloc. PSB}}$	0.040*** (0.011)	0.040*** (0.011)		
R-squared	0.195	0.256	0.010	0.013
No. of Obs.	15296	14664	15296	14664
F-statistic	13.59	13.38		
Bank FE	Y	Y	Y	Y
District FE	Y	Y	Y	Y
Pincode-Urban FE	N	Y	N	Y
Type	First Stage	First Stage	IV	IV

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

Table A.5: Reduced Form: Co-location and Deposit Growth, Run Year and Placebo Years

This table reports reduced-form estimates for annual deposit growth in fiscal years between 2002–2009. The dependent variable in each column is the annual deposit growth rate. The regressor is branch co-location, $\mathbb{1}_{\text{Coloc. PSB}}$, rather than the run indicator, so each coefficient is the reduced-form effect of co-location and not the effect of a run. 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 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 (2.203)	1.490 (1.932)	-2.755 (2.241)	-0.518 (2.146)	2.756 (1.995)	1.506 (1.897)	-2.031 (1.678)	-5.365*** (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.6: Industry-level Outcomes: KLEMS-Adjusted MRPK

This table shows the industry-level estimates that are relevant for computing aggregate productivity effects of the run. Observations are at the industry level for the pre- and post-periods, 2006-2008 and 2009-2011, respectively. Industry exposure is defined in Table 1. The dependent variables are moments of log marginal revenue product of capital (MRPK), where MRPK is constructed as a ratio of firm-level sales to net fixed assets, weighted using industry-level productivity from the RBI's KLEMS database. This differs from the baseline log-MRPK in Table 9, which scales sales by gross fixed assets, and matches RBI's use of a net, depreciated capital stock in KLEMS. Columns (1)-(2) report the cross-sectional variance of log-MRPK in an industry year, columns (3)-(4) report the cross-sectional mean of log-MRPK, and columns (5)-(6) report 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. This table replicates Table 9 in Section 5.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Var(log-MRPK)		Mean(log-MRPK)		Cov(log-MRPK, log VA)	
Post * Industry exposure	2.270*** (0.702)	2.270*** (0.699)	-0.178 (0.171)	-0.178 (0.170)	0.416 (0.292)	0.416 (0.291)
Industry exposure	-1.143 (1.563)		-0.987 (0.972)		-0.075 (0.814)	
R-squared	0.029	0.924	0.061	0.981	0.039	0.919
No. of Obs.	124	124	124	124	124	124
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 A.7: Reallocation Evidence Based on Capital Wedge

As an alternative approach to estimate aggregate effects, we consider the results from a second approach. As the computations are different, we discuss the approach before showing the results.

If capital is efficiently allocated, its productivity MRPK (sales to assets) across enterprises should be equal. Thus, reallocation that increase the variation in capital productivity increase inefficiencies. We examine the evidence for the bank run event and estimate the gains from better capital allocation.

Table A.7 below examines the MRPK for firms in a specification analogous to equation 16. The MRPK in the pre- and post-periods is the average output-to-capital ratio in 2006–2008 and 2009–2011 respectively. The specification allows the elasticity to depend on the ex-ante differences in capital wedge, which reflects the degree of financial constraints faced by a firm. See, for instance, the example in [Hsieh and Klenow \(2009\)](#). As before, we proxy for the pre-run period capital wedge by the 2008 MRPK. Top denotes whether a firm’s MRPK is above median.

Column (1) in Table A.7 shows that exposed PSBs see an overall decline in MRPK. On examining heterogeneity by MRPK, the triple interaction term in Column (2) shows that high MRPK firms that were exposed public sector banks in the pre-period experienced an *increase* in MRPK. The result that high (low) MRPK firms have greater (lower) post-changes in MRPK is consistent with the one on increased dispersion of capital productivity increases. The cutback by private sector banks (as indicated by the coefficient on the uninteracted Pre-Run PSB Exposure) and the related improvement in discipline as well as the increase by public sector banks in less productive ways combines to lower allocative efficiency.

[Blattner, Farinha and Rebelo \(2019\)](#) shows how the above estimates can be used to estimate aggregate effects. Under the assumption that the changes in technical efficiency and in entry and exit are negligible, the changes in allocative efficiency are the channel for aggregate effects. These assumptions appear to be stark but are not unreasonable. In unreported results, we find no effect of runs on firm entry and exit. [Blattner, Farinha and Rebelo \(2019\)](#) finds that the contribution of the technical efficiency term to aggregate productivity is negligible for Portugal and France. Column 2, table A.7 indicates a similar pattern in our data. Under this assumption, we estimate an 16% decline in aggregate

productivity due to the run. We interpret it as a robustness check on the baseline estimates based on [Sraer and Thesmar \(2023\)](#) and view the similarity of the results as a source of comfort and robustness in understanding the aggregate effects of the run.

The relevant table [A.7](#) follows below.

Table A.7: Aggregate Effects Using The Capital Wedge Approach

This table shows the impact on firm-level borrowing on MRPK growth. Post-period (pre-period) is the 3-year fiscal period between 1st April 2009 to March 31st 2011 (April 2006 to March 2008). Firm PSB exposure is as defined in Table 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. Observations are for firms that borrow in the post-period. Standard errors are clustered at the industry-level.

	(1)	(2)
Dependent variable:	MRPK growth	
Pre-Run PSB Exposure	-0.093*** (0.031)	-0.126*** (0.042)
Top		0.072 (0.050)
Top × Pre-Run PSB Exposure		0.103* (0.060)
R-squared	0.026	0.033
No. of Obs.	5414	5414
Industry FE	Y	Y
Type	OLS	OLS
Standard errors in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$		

Table A.8: Oster Bounds

This table reports Oster bounds for the effect of $\text{Post} \times \text{Industry Exposure}$ from the industry-level difference-in-differences specification in Table 9. The regression assesses the impact of the run on resource reallocation through changes in productivity dispersion, measured as the cross-sectional variance of log-MRPK at the industry level, with average MRPK calculated separately for pre-period (2006-2008) and post-period (2009-2011). Industry exposure is defined in Table 1. Column (1) presents the baseline estimates with corresponding R^2 . Column (2) reports the bias-adjusted coefficient β^* under the assumption of proportional selection ($\delta = 1$) with conservatively set $R_{\max} = 1$ as a natural upper bound, while column (3) reports the corresponding implied value of δ required to drive the effect to zero ($\beta^* = 0$). 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. This table computes Oster bounds for the specification in Equation 17, with and without controls (Tobin's Q).

Variable	(1) Controlled Bias-Adjusted Effect [R^2]	(2) Coefficient (β^*)	(3) $\tilde{\delta}$ for $\beta = 0$ $R_{\max}=1$
Post $\times$ Industry Exposure (Excluding control)	1.305439 [0.866396]	1.345058	7.177721
Post $\times$ Industry Exposure (Including control)	1.305439 [0.866396]	1.354521	7.317245
Period FE	Y	Y	Y
Industry FE	Y	Y	Y

Table A.9: Productivity Dispersion in Infrastructure

This table reports industry-level difference-in-differences estimates that allow the run effect to differ for infrastructure sectors. The dependent variables are the cross-sectional variance (columns 1–2), the mean (columns 3–4), and the covariance with log value added (columns 5–6) of log-MRPK, with average MRPK computed for the pre-period (2006–2008) and post-period (2009–2011). *Infra sector* is an indicator for infrastructure industries and industry exposure is defined in Table 1. *Post* is a dummy variable for the 2009–2011 period. Even-numbered columns include 3-digit industry fixed effects; all columns include period fixed effects. 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 * Infra sector	2.851*** (0.705)	2.851*** (0.696)	-0.039 (0.461)	-0.039 (0.456)	-0.450 (0.761)	-0.450 (0.752)
Post * Industry exposure	0.057 (0.539)	0.057 (0.532)	-0.072 (0.447)	-0.072 (0.441)	0.637 (0.524)	0.637 (0.517)
Post * Infra sector	-1.781*** (0.565)	-1.781*** (0.557)	-0.121 (0.371)	-0.121 (0.366)	0.526 (0.616)	0.526 (0.608)
Industry exposure * Infra sector	-3.327* (1.673)		-1.150 (1.507)		0.960 (1.352)	
Industry exposure	0.820 (1.050)		-0.110 (1.051)		-0.837 (1.066)	
Infra sector	3.265** (1.356)		0.748 (1.102)		-0.568 (1.039)	
R-squared	0.249	0.947	0.098	0.983	0.084	0.923
No. of Obs.	124	124	124	124	124	124
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 A.10: Cash Balances

The table shows the deposit growth of PSB branches in run districts. Observations are at the branch level. The dependent variable is the annual growth rate of deposits for fiscal 2009 (the financial year ending on March 31, 2009). The sample is split based on districts' cash-holding propensity, measured using data from the 2003 AIDIS, where high-cash districts are defined as those districts in which the average cash holdings of all survey respondents fall in the top tercile. Districts Columns (1)-(2) present estimates for high-cash districts, while columns (3)-(4) present estimates for low-cash districts. District, pin code and bank fixed effects are included as shown. Standard errors are clustered at the district level.

	(1)	(2)	(3)	(4)
Dependent variable:	Deposit growth			
Sample:	High Cash District		Low Cash District	
Branch run	-57.763*** (7.445)	-55.670*** (9.225)	-58.360*** (1.613)	-59.904*** (1.781)
R-squared	0.162	0.342	0.121	0.264
No. of Obs.	5299	3784	25485	21561
F-statistic				
Bank FE	Y	Y	Y	Y
District FE	Y	Y	Y	Y
Pincode FE	N	Y	N	Y
Type	OLS	OLS	OLS	OLS

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

Table A.11: 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							
Dependent variable: Ln (Wages)	(1)	(2)	(3) Fraction rural population (in %)	(4) Fraction female (in %)	(5) Fraction high- school (in %)	(6) Unemp. rate (in %)	(7) Deposit share of public sector branches in 2001–03
Banked	0.0915 (0.174)	0.0481 (0.0509)	-5.335 (8.009)	0.00834 (0.0106)	0.0242 (0.0159)	0.0531 (0.0327)	0.0844 (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				
Dependent variable:	(1) Number of private sector bank branches	(2) Number of PSB bank branches	(3) Fraction of PSB bank branches	(4) Deposit share of PSB bank branches
Banked	-27.76** (10.97)	20.84 (13.19)	0.118** (0.0578)	0.0971** (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.12: 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* (0.0574)	0.100* (0.0497)	0.104** (0.0491)	0.0782* (0.0434)	0.0726** (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.13: 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 (80.82)	97.26 (70.91)	22.35 (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.14: 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	4.26	Axis Bank	3.67
Andhra Bank	3.81	Bank of Rajasthan	4.18
Bank of Baroda	4.36	City Union Bank	3.69
Bank of India	5.60	Development Credit Bank	4.88
Bank of Maharashtra	2.93	Dhanalakshmi Bank	3.82
Canara Bank	5.37	Federal Bank	3.32
Central Bank of India	1.36	HDFC Bank	3.25
Corporation Bank	3.65	ICICI Bank	4.68
Dena Bank	5.94	IndusInd Bank	6.06
Indian Bank	4.17	ING Vysya Bank	3.18
Indian Overseas Bank	4.16	Jammu & Kashmir Bank	2.37
Oriental Bank of Commerce	5.35	Karnataka Bank	3.18
Punjab National Bank	5.00	Karur Vysya Bank	3.09
State Bank of Bikaner and Jaipur	1.44	Kotak Mahindra Bank	4.63
State Bank of India	4.71	Lakshmi Vilas Bank	2.72
State Bank of Mysore	2.99	South Indian Bank	4.16
State Bank of Travancore	1.09	Yes Bank	4.25
Syndicate Bank	4.86		
UCO Bank	4.80		
Union Bank of India	5.74		
Vijaya Bank	5.27		