Banking Catch-22: Trading off Mark-To-Market and Default Risk in the Presence of Guaranteed Deposits

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ABSTRACT

We provide evidence that the deposit franchise of privately owned banks is driven by their deposit market concentration while state owned banks derive their franchise value from government guarantees. Using the boom period of the 2000s in India as a laboratory, when monetary policy tightened precipitously, we document that banks with stronger deposit franchises significantly increased exposure to the infrastructure sector, at the expense of investing in marked-to-market government securities. Subsequently, these banks have higher non-performing loans. This highlights an important trade-off between mark-to-market and default risk for banks, particularly in economies with incomplete asset markets and significant state guarantees for banking assets.

JEL Codes: G01,G21,G28,H1
Keywords: Deposit franchise, mark-to-market losses, state-owned banking, interest rate risk, default risk, emerging economy.

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1 Introduction

In one of the most notable developments of the Indian economy in recent history, the share of bank credit to the infrastructure sector doubled within a span of four years from 2004 to 2008[1]. In the aftermath of this credit boom, a significant fraction of infrastructure loans on bank balance sheets turned bad, resulting in a stark increase in the ratio of non-performing loans to total assets[2]. Contrary to common perception, there exists substantial cross-sectional heterogeneity in the extent of infrastructure lending undertaken by banks during this period. In this paper, we attempt to utilise this heterogeneity to offer a distinct explanation of the bank lending behaviour during this period based on deposit franchise of Indian banks and fixed costs associated with maintaining this franchise.

Deposit franchise can give banks market power over retail deposits, allowing them to borrow at rates which are low and insensitive to the monetary policy rate (Drechsler et al., 2021). However, running a deposit franchise requires fixed operating expenses on branches (e.g. salaries). Thus, while deposits may be short-term, deposit franchise makes banks' funding resemble long-term fixed-rate debt. The associated interest rate risk incentivises banks to hedge by holding long-term fixed-rate assets. But, banks still have to decide on which sectors to direct their fixed rate lending. In making this choice, banks face a Catch-22 situation: investing in government securities carries the risk of mark-to-market losses while lending to other sectors of the economy comes with the risk of default.

With this intuition in mind, we explore the relevance of deposit franchise for banks' supply of lending in the Indian context. The Indian context provides a unique setting to explore three important issues: (i) deposit franchise of state-owned banks compared to that of private sector banks, (ii) atypically high holdings of long-term government securities by many Indian banks prior to the credit boom, and also in general; and (iii) the sharp rise in lending to the infrastructure sector in the 2000s.

[1] Shah (2015) finds a 300% increase in infrastructure lending during the period, with the exact estimate depending on the definition of infrastructure used. However, the trends are largely the same

[2] After an asset quality review by the Reserve Bank of India, conservative estimates placed the ratio of non-performing loans to total assets at more than 6%, among the highest in the world

Using district-bank level panel data for India, we present four main sets of findings. We hypothesise and provide evidence for two distinct channels of deposit franchise for private and public sector banks. First, we show that public sector banks derive their franchise value from a source independent of local deposit market concentration. We find a significant negative relationship between deposit market concentration and interest expense sensitivity to Repo rate for private sector banks. Public sector banks, on the other hand, show lower interest expense sensitivity than private banks in general, and unlike the private sector banks, this measure is not linked to their deposit market concentration. We surmise that this independent source of market power for public sector banks comes from explicit legislative guarantees for deposits at these banks. On the other hand, the franchise value of private banks are found to be more closely associated with the deposit market concentration in the areas they operate.

Third, we document that with the sudden rise in government bond yields starting in 2004, there was a shift in banking sector assets away from government securities investment towards other long-term loans in order to avoid the concomitant mark-to-market losses associated with government security holdings. Between 2004 and 2008, the average ratio of long term securities to bank assets declined drastically from about 0.30 to 0.17, while the ratio of infrastructure loans to assets doubled from 0.035 to close to 0.07. Finally, exploiting differences in ex-ante exposure to government securities, we find that this shift, particularly towards infrastructure sector loans, was more pronounced for banks with higher franchise value. Correspondingly, we also find that ex-post, banks with lower sensitivity of interest expense to Repo rate have higher non-performing loans. These findings imply an important trade-off that banks face between mark-to-market risk and default risk when deciding on their optimal loan portfolio.

To rationalize these findings, we sketch a model of bank franchise value determination following Drechsler et al. (2017) and a model of optimal bank loan portfolio choice following DeYoung et al. (2015). A model of household portfolio choice with imperfect substitutability of deposits across banks can endogeneously generate bank franchise value from the deposit side. Further, if the proportion of non-switching deposits are allowed to vary across banks, this generates an independent source of franchise value for banks with a larger share of non-switching deposits. A larger share of non-switching deposits at public sector banks can be motivated as resulting from the explicit legislative guarantees available to depositors with these banks.

To explain the mechanisms underlying the switch to infrastructure loans following an increase in mark-to-market losses associated with government securities holdings, we build a multi-sector model of bank loan portfolio choice with interest rate risk. Under the assumption that returns to infrastructure lending and government security investment are positively correlated, the model can explain the shift towards infrastructure loans following an increase in the mean and variance of expected losses on holding government securities. The key requirement for the increase in infrastructure loan supply in this context is an insufficient availability of other sectors with returns which co-move sufficiently with both infrastructure and government securities.

Finally, we analyse whether this lending behaviour can be rationalised by higher demand for infrastructure loans from a subset of the banks instead of a supply side explanation. While controlling for district-time fixed effects can address variations in district level demand, it is possible that the demand for infrastructure loans was variable across the cross section of banks. For instance, a political economy theory may imply that firms demand infrastructure loans from state-owned banks. In order to test whether demand for infrastructure loans varied across banks, we estimate bank-state-year level interest rates on infrastructure loans from BSR data.[3]. We hypothesise that if demand were the main cause of this heterogeneous lending behaviour, then we should find a rise in infrastructure lending rates among the subset of banks which were central to the credit boom. However, consistent with the supply side explanation, we find that the infrastructure lending rates of banks with strong deposit franchise did not increase relative to the rates offered by banks with weak deposit franchise, despite the significant difference in lending to the sector during the period.

Related Literature: Banks 'transform' short-term deposits into long-term loans. This primary attribute of maturity transformation has received perennial interest in both Macroeconomics and Finance. A mismatch in the maturity of assets and liabilities are associated with two interrelated but distinct risks: liquidity risk and interest rate risk. Implications of liquidity risk for banks has

[3]Our data lacks the granularity to estimate the lending rates at the bank-district-year level

previously been studied, for instance, by Brunnermeier et al. (2012) and Bai et al. (2018). More closely related to our study, Li et al. (2019) relate liquidity risk to bank deposit market power and use these insights to explain heterogeneity in the extent of bank maturity mismatch undertaken by banks. On the other hand, Drechsler et al. (2021) focus on the interest rate risk hedging motive of maturity transformation. This justification for maturity mismatch contrasts with theories underlying the 'balance sheet channel' of monetary policy emphasised by Gertler and Bernanke (1989), and Bernanke et al. (1999), which follow the intuition that if banks have short term liabilities and long term fixed rate assets, then an increase in market interest rates exposes banks to losses. Drechsler et al. (2021) argue that instead of exposing banks to interest rate risk, maturity mismatch is actually a way to hedge against it. Hoffmann et al. (2019) provide empirical evidence consistent with this theory from 104 banks in 18 euro area countries. They find that banks' exposure to interest rate risk is small on aggregate, but heterogeneous in the cross-section and depends significantly on the cross-country differences in loan-rate fixation conventions for mortgages. The evidence we derive from India also seems to favor the motivation based on hedging interest rate risk rather than the one based on liquidity risk, at least for the period we consider. In this paper, we contribute to the above literature by extending the analysis of Drechsler et al. (2021) along three dimensions: First, we substantiate the findings of Drechsler et al. (2021) by providing further evidence from a prominent emerging economy banking sector. Second, we reinterpret the significance of their findings in the presence of an incomplete asset market characterised by scarce non-risky long-term fixed rate lending opportunities. And finally, we analyze a financial system where the banks differ in their source of deposit franchise, i.e. state-owned banks derive their deposit franchise from government guarantees whereas private sector banks derive theirs from deposit market concentration.

Our focus on incomplete asset markets and the consequent exposure of banks to interest rate risk or default risk also relates this study to the literature analysing the banks' risk management. Jarrow and Turnbull (2000) theoretically integrate interest rate and credit risk and Alessandri and Drehmann (2010) build upon their research by studying the interactions between interest rate risk and default risk in a framework where these risks are analysed jointly. We add to this literature by providing some empirical evidence that in an economy with incomplete asset markets, banks may need to choose between hedging against interest rate risk or default risk. If asset markets are incomplete, then banks hedging against interest rate risk may end up exposing themselves to default risk.

Our paper is also related to the substantial literature which seeks to identify how banks' liabilities may affect transmission of monetary policy to banks' credit supply. Duquerroy et al. (2020) find that banks' cost of funding is a crucial channel of the transmission of monetary policy to credit supply. Paz (2020) finds that heterogeneity in bank capitalization rates play an important role in the transmission of monetary policy to bank lending. He finds that highly-capitalized banks reduce their lending more after a monetary tightening and have a riskier portfolio. Moreover, default rates on their loans increase relatively more after a tightening in monetary policy. In another related study, Wang et al. (2020) quantify the impact of bank market power on monetary policy transmission through banks to borrowers by estimating a dynamic banking model in which monetary policy affects imperfectly competitive banks' funding costs. They find that bank market power is an important determinant of the transmission of monetary policy to borrowers, with an effect comparable to that of bank capital regulation.

Finally, our paper is related to a strand of literature which studies the relevance of state-ownership in the financial sector. Acharya et al. (2019) analyse the impact of state ownership on the liquidity risk faced by Indian banks during Great Recession. Their work, in turn, ties to a vast body of literature on the impact of state-owned banks in less financially developed countries such as La Porta et al. (2002) and Bonin et al. (2014).

Our paper is organized as follows: Section 2 outlines the models of bank franchise value determination and optimal loan portfolio choice. Section 3 provides the institutional details. Section 4 explains the data and deposit concentration measure used in our analysis. Section **??** examines the bank interest rate hedging in India. Section 6 examines potential measures of deposit franchise of banks. Section 7 explains the identification results, Section 8 provides some robustness results, and Section 9 concludes.

2 Theory: Bank Deposit Betas and Portfolio Choice

This section outlines a model of deposit beta determination and a model of bank portfolio choice which present the mechanisms that can jointly account for the empirical results to follow in subsequent sections. The models illustrate the economic mechanisms that explain four key facts in the data: (i) Lower deposit betas at public sector banks, (ii) a flatter relationship between market power and deposit betas at public sector banks, (iii) switching by banks towards infrastructure lending from government securities investment following a prolonged interest rate hiking cycle and (iv) low deposit beta banks switching towards infrastructure lending by larger amounts.

2.1 Model of Bank Deposit Beta Determination

2.1.1 Household Problem

The model follows Drechsler et al. (2017). The model is static: All decisions are made and outcomes realised in the same time period. A representative household maximizes utility over final wealth (W) and liquidity services (l):

$$u(W_0) = \left[W^{\frac{\rho-1}{\rho}} + \lambda l^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}$$

Liquidity services are derived from holding cash (M) and deposits (D):

$$l(M, D) = \left[M^{\frac{\epsilon-1}{\epsilon}} + \delta D^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}$$

Deposits are a composite good produced by a set of N banks:

$$D = \left[\frac{1}{N} \sum_{i=1}^{N} D_i^{\frac{\eta-1}{\eta}} \right]^{\frac{\eta}{\eta-1}}$$

Households can also invest in a third class of assets, "bonds", which provide no special liquidity, but return the repo rate r.

2.1.2 Banks

Banks make profits by raising deposits and investing in assets. Suppose that banks invest all their assets in "bonds". On the deposit side, banks charge depositors a spread s_i on the repo rate, charging a deposit rate $r - s_i$. Banks set the spread to maximise profits $D_i s_i$ which yields:

$$\frac{\partial D_i}{\partial s_i}\frac{s_i}{D_i} = -1$$

The banks raise the spread until the point where the marginal increase in the spread no longer improves bank profits.

2.1.3 Household's Demand for Bank Deposits

The household budget constraint is:

$$W = W_0(1+r) - Mr - Ds$$

where $s \equiv \frac{1}{N}\sum_{i=1}^{N}\frac{D_i}{D}s_i$ is the weighted-average deposit spread. In a symmetric equilibrium, household elasticity of demand for deposits of bank i is given by

$$\frac{\partial D_i}{\partial s_i}\frac{s_i}{D_i} = \frac{1}{N}\left(\frac{\partial D}{\partial s}\frac{s}{D}\right) - \eta\left(1 - \frac{1}{N}\right)$$

Households' decision to shift deposits away from bank i, in response to an increase in s_i, depends on the aggregate elasticity of bank deposits to the weighted-average deposit spread and the elasticity of substitution between different banks. Suppose that deposits $D_{i,ns}$ are non-switching. They correspond to depositors who do not switch banks in response to an increase in the deposit spread. This can be motivated as arising from a number of different sources like guaranteed deposits, high switching costs or lack of financial sophistication. The elasticity of demand for deposits for non-switching depositors is then:

$$\frac{\partial D_{i,ns}}{\partial s_i}\frac{s_i}{D_{i,ns}} = \frac{1}{N}\left(\frac{\partial D}{\partial s}\frac{s}{D}\right)$$

The demand for non-swithcing deposits depends only on the aggregate deposit elasticity.

2.1.4 Determination of the Deposit Spread

In the presence of non-switching depositors, the banks' profit maximization condition becomes:

$$\alpha_{i,ns}\left(\frac{\partial D_{i,ns}}{\partial s_i}\frac{s_i}{D_{i,ns}}\right)+(1-\alpha_{i,ns})\left(\frac{\partial D_i}{\partial s_i}\frac{s_i}{D_i}\right)=-1$$

where $\alpha_{i,ns}$ is the share of non-switching depositors in bank i. The aggregate deposit elasticity, letting $\lambda \to 0$, is:

$$-\frac{\partial D}{\partial s}\frac{s}{D}=\left[\frac{1}{1+\delta^{\epsilon}\left(\frac{r}{s}\right)^{\epsilon-1}}\right]\epsilon+\left[\frac{\delta^{\epsilon}\left(\frac{r}{s}\right)^{\epsilon-1}}{1+\delta^{\epsilon}\left(\frac{r}{s}\right)^{\epsilon-1}}\right]\rho$$

The aggregate deposit elasticity is a weighted average of the elasticity of substitution to cash and bonds. Combining the above expressions yields the following proposition for the equilibrium deposit spread.

Proposition 1: Let $\rho < 1 < \epsilon, \eta$, let $\mathcal{M}_{ns} = 1-(\eta-1)\left[\frac{1}{\alpha_{ns}+(1-\alpha_{ns})\frac{1}{N}}-1\right]$ and consider the limiting case when $\lambda \to 0$. If $\mathcal{M} < \rho$, then the deposit spread s is 0. Otherwise,

$$s=\delta^{\frac{\epsilon}{\epsilon-1}}\left(\frac{\mathcal{M}_{ns}-\rho}{\epsilon-\mathcal{M}_{ns}}\right)r$$

Implication 1: The deposit spread is increasing in deposit market concentration

Implication 2: The relationship between deposit market concentration and the deposit spread is weaker when the fraction of non-switching deposits are larger

2.2 Model of Bank Portfolio Choice

The model follows DeYoung et al. (2015). Consider B banks which differ in their level of the deposit franchise and hence their deposit betas, β_b^d. Let the spread they charge over the prevailing policy interest rate $(1-\beta_b^d)r_t \equiv p_{b,t}^d$.

Bank loans can be funded out of net internal capital W or external funds F, where external funds are assumed to be more costly than internal funds. Banks seek to maximize an objective function $P(W)$ (say profits) which is dependent on its net internal capital. We assume that $P_W \equiv$

$\frac{\partial P(W)}{\partial W} > 0$ and $P_{WW} \equiv \frac{\partial^2 P(W)}{\partial W^2} < 0$. Further, the risk-aversion term $\frac{-E[P_{WW}]}{E[P_W]} \equiv G_{b,t}$ is assumed to be constant for each bank b.

2.2.1 Timing

Banks begin period t with $W_{b,t-1}$ in net internal funds and $L_{b,t-1,i}$ in outstanding loans in sector i and net external finance $F_{b,t-1} = \sum_i (L_{b,t-1,i}) - W_{b,t-1} > 0$. Let $\delta_{b,t-1,i}$ be the proportion of outstanding loans in sector i which are illiquid.

During period t, the bank can make new loans $NL_{b,t,i}$ to each sector i, resulting in end-of-period outstanding debt of $F_{b,t} = \sum_i (\delta_{b,t-1,i} L_{t-1,i} + NL_{b,t,i}) - W_{b,t-1}$. Assuming that all external funding is subject to the banks' franchise value, the gross per dollar cost of external funding is $1 + r_t - p^d_{b,t}$, where $p^d_{b,t}$ is the spread charged by banks on their external funding.

2.2.2 Stochastic Environment

During period t, banks realize the gross per dollar return of $\tilde{R}_{b,t,i/t-1}$ on loans to sector i which originated in period $t-1$, where $\tilde{R}_{b,t,i/t-1} = 1 + r_t + p_{b,t-1,i} - \tilde{\eta}_{t,i}$. $\tilde{\eta}_{t,i}$ are the random per dollar losses on loans to sector i in period t and $p_{b,t-1,i}$ are the per dollar credit spreads charged by bank b to loans outstanding in sector i in period $t-1$. Similarly, the gross per dollar return on new loans $\tilde{R}_{b,t,i/t} = 1 + r_t + p_{b,t,i} - \tilde{\eta}_{t,i}$.

The period t losses on loans to sector i outstanding at the end of the period are assumed to be perfectly correlated across banks and time of origination. Current period losses are assumed to be joint-normally distributed: $\tilde{\boldsymbol{\eta}}_{\boldsymbol{t}} \sim N(\boldsymbol{\mu}_t, \boldsymbol{\Sigma}_{\boldsymbol{t}})$. $\boldsymbol{\mu}_{\boldsymbol{t}}$ is an N-dimensional vector of mean losses $\{\mu_{t,i}\}_{i=1}^N$ and $\boldsymbol{\Sigma}_{\boldsymbol{t}} \equiv \{\sigma_{t,ij}\}_{i=1,j=1}^N$ is the N x N dimensional variance-covariance matrix of loan losses. Hence, losses in sector i in period t are given by: $\tilde{\eta}_{t,i} \sim N(\mu_{t,i}, \sigma_{t,ii})$, where $\mu_{t,i}$ and $\sigma_{t,ii}$ are decreasing in the economic outlook of sector i at the start of period t.

2.2.3 Banks' Optimal Supply of Loans

Given the model setup above, bank b's net capital at the end of period t is:

$$\tilde{W}_{b,t} = \sum_{i=1}^{n} \left[\delta_{b,t-1,i} L_{b,t-1,i} \tilde{R}_{b,t,i/t-1} + NL_{b,t,i} \tilde{R}_{t,i/t}\right] - F_t \left(1 + r_t - p^d_{b,t}\right)$$

$$= W_{b,t-1}\left(1 + r_t - p^d_{b,t}\right) + \sum_{i=1}^{n} [\delta_{b,t-1,i} L_{b,t-1,i}\left(p_{b,t-1,i} + p^d_{b,t} - \tilde{\eta}_{t,i}\right)$$

$$+ NL_{b,t,i}\left(p_{b,t,i} + p^d_{b,t} - \tilde{\eta}_{t,i}\right)]$$

The banks choose their new loan portfolio $\{NL_{b,t,i}\}_{i=1}^{n}$ to maximize expected profits $E[P(\tilde{W}_{b,t})]$.

Taking First Order Conditions with respect to $NL_{b,t,i}$ yields:

$$0 = E\left[P_W \frac{\partial \tilde{W}_{b,t,i}}{\partial NL_{b,t,i}}\right] = E\left[P_W\left(p_{b,t,i} + p^d_{b,t} - \tilde{\eta}_{t,i}\right)\right]$$

Using that $E(xy) = E(x)E(y) + Cov(x, y)$, the expression above simplifies to:

$$0 = \left(p_{b,t,i} + p^d_{b,t} - \mu_{i,t}\right) E(P_W) - Cov(P_W, \tilde{\eta}_{t,i})$$

Using Stein's Lemma, this expression simplifies to

$$0 = \left(p_{b,t,i} + p^d_{b,t} - \mu_{i,t}\right) E(P_W) - E(P_{WW}) Cov(\tilde{W}_{b,t}, \tilde{\eta}_{t,i})$$

Now, the expression $Cov(\tilde{W}_{b,t}, \tilde{\eta}_{t,i})$ is given by

$$Cov(\tilde{W}_{b,t}, \tilde{\eta}_{t,i}) = \sum_{j=1}^{n} \left[Cov(\tilde{\eta}_{t,i}, \tilde{\eta}_{t,j})\left(\delta_{b,t-1,j} L_{b,t-1,j} + NL_{b,t,j}\right)\right]$$

Hence, the optimal choice of loan supply by bank b at time t in sector i is:

$$NL^s_{b,t,i} = -\sum_{j \neq i}\left[\frac{\sigma_{t,ij}}{\sigma_{t,ii}} \delta_{b,t-1,j} L_{b,t-1,j}\right] - \delta_{b,t-1,i} L_{b,t-1,i} - \sum_{j \neq i}\left[\frac{\sigma_{t,ij}}{\sigma_{t,ii}} NL^s_{b,t,j}\right] + \frac{1}{G_{b,t}} \frac{p_{b,t,i} + p^d_{b,t} - \mu_{t,i}}{\sigma_{t,ii}}$$

where $G_{b,t} = \frac{-E[P_{WW}]}{E[P_W]}$ is a measure of the bank b's risk aversion at time t and $\sigma_{t,ij} \equiv Cov(\tilde{\eta}_{t,i}, \tilde{\eta}_{t,j})$

2.2.4 Comparative Statics

Now, consider two sectors I and G, corresponding to infrastructure and government securities.

The loan supply to sector I can be expressed as a function of loan supply to sector G as follows:

$$NL^s_{b,t,I} = -\sum_{j \neq I} \left[\frac{\sigma_{t,Ij}}{\sigma_{t,II}} \delta_{b,t-1,j} L_{b,t-1,j} \right] - \delta_{b,t-1,I} L_{b,t-1,I} - \sum_{j \neq I} \left[\frac{\sigma_{t,Ij}}{\sigma_{t,II}} NL^s_{b,t,j} \right] + \frac{1}{G_{b,t}} \frac{p_{b,t,I} + p^d_{b,t} - \mu_{t,I}}{\sigma_{t,II}}$$

Suppose that beginning in 2004, the mean prospective losses on government security holdings as well as the uncertainty associated with this increases due to the interest rate hiking cycle of the RBI. In the context of the model, this can be represented as an increase in $\mu_{t,G}$ and $\sigma_{t,GG}$. The change in $NL_{b,t,I}$ following a change in $\mu_{t,G}$ is given by:

$$\frac{\partial NL^s_{b,t,I}}{\partial \mu_{t,G}} = -\frac{\partial NL^s_{b,t,G}}{\partial \mu_{t,G}} \sum_{j \neq I} \left[\frac{\sigma_{t,Ij}}{\sigma_{t,II}} \frac{\partial NL^s_{b,t,j}}{\partial NL^s_{b,t,G}} \right]$$

which simplifies to,

$$\frac{\partial NL^s_{b,t,I}}{\partial \mu_{t,G}} = -\frac{\partial NL^s_{b,t,G}}{\partial \mu_{t,G}} \left[\frac{\sigma_{t,IG}}{\sigma_{t,II}} - \sum_{j \neq \{I,G\}} \left[\frac{\sigma_{t,Ij}}{\sigma_{t,II}} \frac{\sigma_{t,jG}}{\sigma_{t,jj}} \right] \right]$$

Furthermore, it is known that

$$\frac{\partial NL^s_{b,t,G}}{\partial \mu_{t,G}} = -\frac{1}{G_{b,t} \sigma_{t,GG}} < 0$$

Proposition 2: Assuming that $\frac{\sigma_{IG}}{\sigma_{II}} - \sum_{j \neq \{I,G\}} \left[\frac{\sigma_{Ij}}{\sigma_{II}} \frac{\sigma_{jG}}{\sigma_{jj}} \right] > 0$, new loans to sector I are increasing in $\mu_{t,G}$ i.e.,

$$\frac{\partial NL^s_{b,t,I}}{\partial \mu_{t,G}} > 0$$

Similarly, the change in $NL_{b,t,I}$, following a change in $\sigma_{t,GG}$ is given by:

$$\frac{\partial NL^s_{b,t,I}}{\partial \sigma_{t,GG}} = -\frac{\partial NL^s_{b,t,G}}{\partial \sigma_{t,GG}} \left[\frac{\sigma_{IG}}{\sigma_{II}} - \sum_{j \neq \{I,G\}} \left[\frac{\sigma_{Ij}}{\sigma_{II}} \frac{\sigma_{jG}}{\sigma_{jj}} \right] \right]$$

Now, the response of new government lending $NL^s_{b,t,G}$ to an increase in the uncertainty associated with the losses on those loans $\sigma_{t,GG}$ has a theoretically ambiguous sign:

$$\frac{\partial NL^s_{b,t,G}}{\partial \sigma_{t,GG}} = \sum_{j \neq G} \left[\frac{\sigma_{t,Gj}}{\sigma^2_{t,GG}} \delta_{b,t-1,j} L_{b,t-1,j} \right] + \sum_{j \neq G} \left[\frac{\sigma_{t,Gj}}{\sigma^2_{t,GG}} NL^s_{b,t,j} \right] - \frac{1}{G_{b,t}} \frac{p_{b,t,I} + p^d_{b,t} - \mu_{t,I}}{\sigma^2_{t,GG}}$$

Moreover, it is known that the cross derivative of government loan supply with bank's spread on borrowings $p^d_{b,t}$ and the volatility of government loan losses $\sigma_{t,GG}$ is less than zero.

$$\frac{\partial^2 NL^s_{b,t,G}}{\partial p^d_{b,t} \partial \sigma_{t,GG}} = -\frac{1}{G_{t,b} \sigma^2_{t,GG}} < 0$$

This results in the following comparative statics for loan supply to sector I:

Proposition 3: Assuming that $\frac{\sigma_{IG}}{\sigma_{II}} - \sum_{j \neq \{I,G\}} \left[\frac{\sigma_{Ij}}{\sigma_{II}} \frac{\sigma_{jG}}{\sigma_{jj}} \right] > 0$ and $\frac{\partial NL^s_{b,t,G}}{\partial \sigma_{t,GG}} < 0$, new loans to sector I are increasing in $\sigma_{t,GG}$ and in $p^d_{b,t}$ i.e.,

$$\frac{\partial NL^s_{b,t,I}}{\partial \sigma_{t,GG}} > 0$$

$$\frac{\partial^2 NL^s_{b,t,I}}{\partial p^d_{b,t} \partial \sigma_{t,GG}} > 0$$

What does the assumption $\frac{\sigma_{IG}}{\sigma_{II}} - \sum_{j \neq \{I,G\}} \left[\frac{\sigma_{Ij}}{\sigma_{II}} \frac{\sigma_{jG}}{\sigma_{jj}} \right] > 0$ require? Suppose that $\sigma_{IG} > 0$. Then, the assumption requires either that (i) there are few other sectors whose returns co-move sufficiently positively with returns on government securities as the infrastructure sector ($\sigma_{t,jG}$'s are low) or that (ii) Returns to infrastructure lending do not co-move sufficiently positively with returns to lending towards other sectors with positive co-movement with government security returns in the economy ($\sigma_{t,Ij}$'s are low). In both cases, following an increase in mark-to-market government securities losses, banks have a risk-diversification incentive to lend more towards the infrastructure sector.

Hence, following in increase in the expectation and spread of mark-to-market losses on government securities, this model predicts that (i) banks will shift their lending away from government towards alternate similar assets like infrastructure loans and that (ii) banks with higher deposit spreads will do so by greater amounts.

3 Institutional Details

The Indian banking sector is characterised by the co-existence of government-owned state banks [known in India as public-sector banks (PSBs)] and private sector banks. Historically, the banking sector was dominated by public-sector banks, with the government having a major say in the banks' lending decisions. Economic liberalisation in the 1990s ushered in a new phase of the Indian banking sector by removing barriers to the entry of private sector banks and subsequently improving their ease of functioning through further reforms. Consequently, the dominance of the public sector banks started to recede over the next two decades and the Indian banking sector transformed from being primarily centrally governed to a system driven by market forces. In this section we highlight some of the institutional details relevant to our study.

3.1 Credit Boom, Lending to Infrastructure, and Long-term Investment

India experienced a massive boom in bank credit from 2002-2012, with the bank credit-to-GDP ratio rising from close to 20% in 2002 to almost 50% in 2012. A substantial share of the increase in bank credit during this time was accounted for by the infrastructure sector. Outstanding bank credit to the sector increased from Rs.95 billion in March 2001 to Rs.9,853 billion in March 2016 (Vishwanathan, 2016). At the height of the credit boom from 2004 to 2008, bank share of project loans related to infrastructure and construction in total assets doubled, with a corresponding fall in their share of long-term investment in total assets to almost half within the period as shown in Figures 1 and 2.

Lending to infrastructure sector is inherently different from lending to other sectors. Usually, infrastructure projects require long-term financing ranging from 10 to 25 years. With developed financial markets, a majority of such lending is financed through long term bonds by institutions with corresponding long-term liabilities. However, in an economy with underdeveloped bond markets like India, a majority of the lending to infrastructure is carried out by commercial banks. Since bank deposits are of a significantly lower maturity, lending to infrastructure exposes banks to substantial maturity mismatch, thus posing a threat to the financial sector as a whole. Moreover, infrastructure projects in India are subject to diverse risks including abrupt changes in government policies, issues related to project clearances, natural calamities etc. These factors have an important bearing on the economic viability of the project and ultimately that of the infrastructure loan. Finally, as highlighted by Vishwanathan (2016), infrastructure projects are often extremely complex and involve a large number of parties. All of these features contribute to the credit and liquidity risk associated with infrastructure loans in India.

A range of factors played a role in the sharp rise in lending to infrastructure and decline in long-term investment during this period. Prior to 1997, Development Finance Institutions were the main providers of finance to the infrastructure sector. The need for these specialised institutions arose primarily because of the inability of scheduled commercial banks to shoulder the liquidity and credit risks associated with lending to the infrastructure sector. By providing DFIs with long term subsidised finance, the government had essentially assumed the role of primary financier to infrastructure projects. With subsequent development of the financial sector and increased borrowing need of a rapidly growing infrastructure sector, the government felt the need to diversify the sources of lending. Thus, in 1997, with a view to increase competition in this sector, the government put a stop to the issuance of tax-free bonds by DFIs (Sen, 2018). Since these were the main sources of low cost funds for these institutions, this decision was key to their subsequent decline. This move was accompanied by other steps to free up the resources of scheduled commercial banks, such as the reduction in the Statutory Liquidity Ratio, which was reduced from 32% to 25% in 1997. Additionally, RBI imposed a risk weight of 2.5% on government securities and a ceiling on held to maturity securities (25% of investment and 25% of demand and time liabilities) in 2000 and 2001 respectively. The resulting increased duration risk made it less attractive for banks to keep their funds parked in these long term securities and is one potential cause of the stark substitution from long-term investment to long-term loans by banks during this period.

Investment Fluctuation Reserves: Having introduced a ceiling on held to maturity securities in 2001, RBI sought to ensure banks with significant duration risk on their balance sheets had enough reserves to weather potential treasury losses from swings in the Repo rate. In keeping with this objective, in 2002 RBI advised banks to build an investment fluctuation reserves of a minimum of 5% of investments classified in the held-for-trading and available-for-sale categories, since it reasoned that held-to-maturity securities did not pose an interest rate risk to the banks on account of not being traded. According to Sy (2007), these reserves were initially introduced as an alternative to Basel 1 requirements. However, after 2005, capital charge for market risk was introduced in accordance with the Basel norms, with the reserves gradually merged into Tier 1 capital. Since IFR provides a more direct measure of our subject of interest, i.e. bank exposure to high duration securities, as opposed to Tier 1 capital which has a broader role in guarding banks against a variety of risks, we are fortunate that IFR was replaced by capital charge only post-2004. Data show that IFR grew significantly till 2005, but then fell drastically as the Basel norms came into place.

Next, we turn our attention to a brief analysis of the characteristics of the Indian banks with different ownership structures:

Public Sector Banks: In principle, both public and private sector banks are insured by the Deposit Insurance and Credit Guarantee Corporation (DICGC). However, as of 2007, this deposit insurance coverage was limited to only Rs.100,000 (approximately $2000) per depositor. Moreover, as highlighted in Iyer and Puri (2012), the processing of deposit insurance claims is associated with significant uncertainty and delay which reduces their effectiveness. In this context, explicit government guarantees endowed to public sector banks by virtue of The Banking Regulations Act (1949), which guarantees all obligations of public sector banks in the event of their failure, assume much greater importance. Acharya et al. (2019) emphasise the relevance of these sovereign guarantees for the deposit flight from private to public sector banks in 2007-09.

We argue that sovereign guarantees endow public sector banks with strong deposit franchise and enables them to pay interest rates that are low and insensitive to the RBI Repo rate. This sovereign backing, however, is not free of cost. Public sector banks are subject to the same operational constraints and rigidities as the rest of government enterprises in India. In order to satisfy the governments financial inclusion goals, public sector banks operate a wider network of branches across urban as well as rural regions. This means that they significantly lag behind private and foreign sector banks in terms of average deposits/credit per branch (Chatterjee, 2006). Moreover, PSB employee productivity is also significantly lower as compared to private sector banks because of a difference in the employment practices across the two sets of institutions. A report by Financial Express (Financial Express, 2019) highlights this stark difference: the officer to clerk ratio for private banks was 16:1 compared to the 1.25:1 ratio for public sector banks. To the extent that banking is an increasingly specialised service, hurdles faced by government owned institutions in changing their hiring practices contribute significantly to the cost inefficiencies of the PSBs relative to PVBs. In this paper, we treat these costs as the fixed costs of sovereign guarantees.

Private Sector Banks: While sovereign guarantees are the source of the strong deposit franchise of public sector banks, private sector banks have to invest in building deposit market concentration in order to strengthen theirs. In this sense, the functioning of private sector banks corresponds directly to the setup in Drechsler et al. (2021). While the source of deposit franchise may be different for public and private sector banks, its influence on bank lending behaviour is quite similar. For both public and private sector banks, deposit franchise is associated with fixed operating costs, which make their funding resemble long-term debt and thus incentivise them to undertake maturity transformation. In the following sections, we argue that sources of deposit franchise, i.e. sovereign guarantees and deposit market concentration for PSBs and PVBs respectively, are important determinants of banks' lending to infrastructure from 2004-2008.

3.2 Consequences

While there were a myriad of internal and external reasons for the sharp rise in non-performing loans in the banking sector, infrastructure loans contributed significantly to the mess. Lahiri and Neelakatan (2021) find that four sectors, basic Metals and Metal Products, Construction, Electricity, Gas, and Water, and Mining and Quarrying, all of which are closely related to infrastructure, were responsible for nearly half of the total NPLs as of 2018. Worrying signs regarding the quality of infrastructure loans had begun appearing as early as 2008 (Chari et al., 2021). In view of the deterioration in the cash flow of overly leveraged firms due to the Great Recession, the RBI announced a ‘Special Regulatory Treatment’ for restructuring debt. While this asset quality forbearance was initially introduced as a temporary relief measure, restructuring of assets became the norm. Chari et al. (2021) find that by 2013, restructured assets constituted close to 70% (50%) of stressed assets for public (private) banks. From 2014, RBI started the process of winding down widespread asset restructuring initiating the ‘Asset Quality Review’, under which banks were forced to recognise non-performing loans in their balance sheets and the proportion of restructured assets finally began to decline. Within a couple of years of the implementation of AQR, the proportion of non-performing loans in total bank assets increased drastically from 3.4% of gross advances in March 2013 to 9.9% in March 2017.

4 Data

We use annual branch and bank level data from the Reserve Bank of India to compute our bank-level HHI measure, for our bank-district level regressions, for data on sector and maturity wise bank lending, and for our subsequent analysis on branch level non-performing loans. Data on the Repo rate is also obtained from RBI. While bank level data is publicly available, branch-level data is only collected for regulatory purposes and is proprietary. The regulatory branch-level data, also called Basic Statistical Returns (BSR) has previously been used by Das et al. (2015) and Cole (2009). This data is collected as of March 31st of every year and covers a wide range of variables, such as amounts of deposits by type (demand, savings and term), amount of credit by sector, weighted average lending rate, branch characteristics and personnel characteristics (skilled/unskilled). Data on NPLs is also from the RBI, though it is not collected as part of BSR and hence only 77% of the branches have data on NPL.

We use quarterly financial data from CMIE Prowess in order to compute the sensitivity of bank level interest expense, interest income, return on assets to changes in the RBI Repo rate, and to derive the aggregate time series for average net interest margin and return on assets. We also obtain bank level data on investment fluctuation reserves and total assets from Prowess. This is a private database covering the universe of listed companies as well as a large set of unlisted companies by compiling data from audited annual reports of companies.

4.1 Our sample of banks

We use an unbalanced panel of bank-district level deposit and credit data from 2000 to 2016 for our regression analysis. In regressions involving Repo rate, our sample begins from 2002-03 because RBI Repo rate has been used as a monetary policy instrument since then. Moreover, in regressions involving BSR data, our data is only available till 2016. Our data covers 639 districts, however some are omitted due to lack of relevant data. Districts are economically integrated areas, comparable to counties within the US. We restrict the sample to banks that have at least 30 quarterly observations between 2002 and 2016. This is a weaker inclusion criterion than the one in Drechsler et al. (2021), which included banks with a minimum of 60 quarterly observations. However, it is necessary on account of the shorter time span of our data. This yields a sample of 43 banks, with 28 public sector banks and 15 private sector banks.

5 Deposit franchise and bank assets

In this section, we evaluate the relationship between asset portfolio of banks and their deposit franchise as measured by the interest expense beta. Importantly, we test for whether banks' exposure to infrastructure loans is related to their deposit franchise. Finally, we directly test for the relationship between banks' interest expense betas and exposure to default risk by analysing their correlation with ex-post non-performing loans uncovered after an Asset Quality Review was undertaken in 2014.

5.1 Infrastructure lending

We now test the relation between a bank's deposit franchise and the extent of its exposure to the infrastructure sector over the boom period. More specifically, we analyse the relationship between interest expense beta and the share of a bank's lending to infrastructure as a proportion of its total assets. We classify infrastructure lending as the aggregate of lending to sectors closely related to infrastructure, and usually characterized by long-term fixed rate loans, namely: construction, metals, mining, and electricity, gas water sectors. The exact classification of infrastructure related sectors is vague. While transport is also usually included as a crucial sector in infrastructure, according to an RBI report dated 2005[4], lending by Indian scheduled commercial banks was primarily limited to transport operators, while project financing was extremely scarce. Since lending to transport operators is usually shorter term and at more flexible interest rates, we leave out transport from our definition of infrastructure.

In order to derive the estimate of banks' interest expense sensitivity, we run the following time series regression for each bank i:

$$\Delta \text{IntExp}_{i,t} = \alpha_i + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta \text{RepoRate}_{t-\tau} + \epsilon_{i,t} \tag{1}$$

In Figure 4a, we show the match between interest expense beta and the average increase in the share of infra lending to total lending during the period 2002 to 2016 using a binned scatter plot. We find that share of lending to infrastructure sectors is negatively related to the interest expense betas of banks.

5.2 Relevance

This finding may have important implications for the financial system and the economy as a whole on account of the higher default risk associated with infrastructure loans. It is possible that in order to hedge against interest rate risk, banks with strong deposit franchise may be influenced to undertake excessive exposure to default risk. We explicitly test for this by comparing the interest expense betas of banks to their non-performing loans (NPL). However, on account of regulatory forbearance on restructured advances during the boom period (Chari et al., 2021) which carried on until the Asset Quality Review in 2014-15, obtaining an accurate measure of non performing loans for Indian banks is a challenge. We therefore use the average of banks' NPLs over the three year time period from 2014 to 2016 as a proxy for their exposure to default risk in the boom period. Figure 4b presents the relationship between interest expense beta and ex-post NPL ratio of banks. Consistent with our prediction, banks with low interest expense beta are associated with a greater ex-post NPL ratio, indicating a potential link between the deposit franchise of banks and their exposure to default risk.

[4] RBI Report 2005

Finally, in Figure 4c we further investigate the anecdotal evidence regarding the default risk associated with lending to infrastructure sectors using a binned scatter plot of ex-post NPL ratio against the share of infrastructure lending. We find that the data indicates a positive relation between the two variables, substantiating our argument that, at least in the Indian context, infrastructure lending is associated with substantial default risk.

While still preliminary, the results point towards a greater incentive for banks with stronger deposit franchise, i.e. lower interest expense beta, to hedge against interest rate risk at the cost of having to lend to sectors with default risk, specifically the infrastructure sector. Consistent with the regular warnings by RBI (Reserve Bank of India, 2009), greater exposure to infrastructure sector during this boom period is associated with greater ex-post NPL ratios of banks.

6 Potential measures of deposit franchise

6.1 Deposit franchise and state-ownership

Results in the previous sections indicate that deposit franchise may have a significant bearing on the lending behaviour of the banks. But what determines the strength of a bank's deposit franchise? In Table 1, we provide some evidence on the importance of state ownership for the sensitivity of interest expense to Repo rates. Here, we compute the interest expense sensitivity to changes in Repo rate by regressing the change in interest expense divided by assets on contemporaneous and lagged changes in the Repo rate, with the latter now also interacted with an indicator variable for public sector banks as shown in the equation below:

$$\Delta \text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3} \left(\beta^0_{\tau,psb} + \beta^1_{\tau,psb} \times \mathbb{1}\{\text{PSB}_i\} \right) \Delta \text{RepoRate}_{t-\tau} + \epsilon_{i,t} \tag{2}$$

where $\mathbb{1}\{PSB_i\}$ is an indicator variable which takes the value 1 for public sector banks and 0 for private sector banks. We find that the interest expense beta of public sector banks is lower than that of private sector banks, with the coefficient of the interaction term being -0.094. This finding corroborates evidence in Acharya et al. (2019) that highlights the importance of government guarantees in shaping depositors' behaviour and hence bank deposit rate decisions.

6.2 Deposit franchise and deposit market power

In this sub-section, we aim to test whether deposit market concentration, as measured by a bank level HHI measure, is informative in this context. In order to compute the bank-HHI, we start by computing a district level measure of HHI. Since the primary competition is between different banks within a district and not between different branches, we collapse the bank-branch level data to the bank-district level for the calculation of the district level HHI. This district level HHI is at the district-year level and equals the sum of squared deposit market shares for all banks within a given district. To capture the funding deposit concentration of the bank, we build a measure of Bank-HHI that is equal to the weighted average of the district HHI, where the weights are determined by the fraction of deposits raised in each district where the bank operates. This variable is used in the subsequent analysis as a measure of the deposit market power of a bank.

In Figure 5a, a binned scatter shows the negative relation between interest expense beta and bank HHI. This is consistent with the Drechsler et al. (2021) perspective that the deposit market power, as measured by a higher bank-HHI, may allow banks to set deposit interest rates that are low and insensitive to changes in the monetary policy rate. To formally analyse the relationship between bank-HHI and interest sensitivity matching, we run the following regression in Table 2:

$$\Delta\text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3}\left(\beta^0_{\tau,hhi} + \beta^1_{\tau,hhi} \times \mathbb{1}\{\text{High HHI}_{2005,i}\}\right)\Delta\text{RepoRate}_{t-\tau} + \epsilon_{i,t} \tag{3}$$

where $\mathbb{1}\{High\ HHI_{2005,i}\}$ is an indicator variable which takes the value 1 for banks characterised by above median deposit market concentration in 2005 i.e. bank-HHI. We find that banks with above median HHI are characterised by a reduced sensitivity of interest expense rate to Repo rates, by a magnitude of -0.096. This finding complements that of Figure 5a in showing that deposit market concentration is positively related to banks' deposit franchise.

From the evidence so far, it appears that bank-HHI is strongly associated to the deposit franchise of banks. The heterogeneous ownership structure of the banking sector in India, with the mix of public sector banks and private sector banks commanding non-negligible market shares, enables us to further analyse whether the ownership has a significant impact on the link between bank-HHI and deposit franchise. We hypothesise that the relevance of bank-HHI for deposit franchise should be greater for private sector banks relative to public sector banks. This is because all public sector banks are endowed with explicit government guarantee. Given the significance of such a guarantee in an emerging economy with a weak financial sector, deposits with public sector banks are generally viewed as more attractive than those with private sector banks, ensuring stronger deposit franchise of public sector banks irrespective of their deposit market concentration. In Figure 5b and Figure 5c we provide the scatter plots for the relation between deposit market concentration and interest expense beta separately for public and private sector banks. We find that the negative relation only holds for the private sector banks, while the public sector banks do not show in similar trends.

In order to further substantiate these findings, we rerun Equation 3 separately for private and public sector banks. The results for this regression are also provided in Table 2. We find strong evidence for our hypothesis: private sector banks with above median bank-HHI are associated with an interest expense beta lower by 0.191 relative to that of below median HHI banks, with the relation significant at the 1% level. However, for public sector banks, bank-HHI is not significantly related to the interest expense beta, even at the 10% level. We interpret these findings as evidence of separate determinants of deposit franchise for public and private sector banks, i.e. government guarantees and deposit market power respectively.

6.3 Deposit franchise and investment fluctuation reserves

Beginning in 2002, banks were required to build Investment Fluctuation Reserves of a minimum of 5% investment in held-for-trading (HFT)and available-for-sale (AFS) securities to account for potential mark to market losses. This section documents that banks with a higher deposit franchise had ex-ante higher investment in AFS and HFT government securities. This could have been the result either of (i) a steady decline in expected mark-to-market losses in holding these securities in a period of falling interest rates before 2004 as suggested by the loan portfolio choice model in Section 2 or (ii) an interest rate hedging motive as documented in Appendix A.

In Figure 6, we show using scatter plots how the ratio of banks' investment fluctuation reserves to their total assets in 2005 relates to their lending towards infrastructure and housing sectors after 2005, i.e. sectors prominently associated with fixed- and flexible-interest rates respectively. We find that banks with higher investment fluctuation reserve ratio in 2005 were characterised by higher increase in exposure to the infrastructure sectors (Figure 6a) and lower increase in exposure to the housing sectors after 2005 (Figure 6b) relative to banks with low IFR rates. In order to analyse how IFR ratio is associated to the sensitivity of banks' interest expense rates to changes in the Repo rate, we run the following regression:

$$\Delta \text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3} \left(\beta^0_{\tau,IFR} + \beta^1_{\tau,IFR} \times \mathbb{1}\{\text{High IFR}_{2005,i}\} \right) \Delta \text{RepoRate}_{t-\tau} + \epsilon_{i,t} \tag{4}$$

where $\mathbb{1}\{High\ IFR_{2005,i}\}$ is an indicator variable which takes the value 1 for banks with above median IFR ratio in 2005 and value 0 otherwise. Since the organizational structures of public sector banks and private sector banks differs so significantly, we define median separately for each ownership category. As can be seen in Table 3, above median IFR banks are associated with lower responsiveness to the Repo rate. The elimination of significance with inclusion of time fixed effects may be due to the very small sample size we are left with when running regression separately for public- and private sector banks, but the significance of results with bank fixed effects, and robust results for the entire sample of banks leads us to believe the channel we suggest may indeed be valid.

7 Identification

We now conduct a more formal analysis of the relevance of deposit market franchise for bank lending decisions. As can be seen in Figure 1 and Figure 3, with the exogenous shocks to government bond yields and increased domestic demand, the asset portfolio of the Indian banking sector underwent significant change, with the Indian banks transitioning from largely holding government securities to private sector lending, especially to sectors characterise by long term fixed rate loans, such as infrastructure. We seek to conduct a within district comparison of the evolution of sectoral lending across banks from 1999 to 2016 to identify whether ex-ante variations in deposit franchise had a significant role to play in the lending patterns observed after 2004. By controlling for district-time fixed effects and bank-district fixed effects, we hope to be able to disentangle the supply side variations arising due to ex-ante deposit franchise of banks.

7.1 Investment Fluctuation Reserves in 2004 and Infrastructure Lending

Since the interest expense beta analysed so far is calculated at the individual bank level using a time series regression for the whole sample from 2002 to 2016[5], it does not lend itself easily to our regression analysis due to the lack of sufficient pre-2004 data to estimate beta. Moreover, we have also provided evidence that deposit market concentration as measure by bank HHI is not a suitable measure of deposit franchise for public sector banks, which make up the bulk of the financial sector in India. Hence, we use the ratio to investment fluctuation reserves to total assets of Indian banks at the end of 2004 to identify variations in deposit franchise across banks[6].

We conduct the following difference-in-differences regression analysis to identify the impact of banks' ex-ante deposit franchise on their lending post 2004:

$$\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}} = \alpha_{d,t} + \delta_{i,d} + \beta \times \mathbb{1}\{\text{High IFR ratio}_{2004,i}\} \times \mathbb{1}\{\text{Post}_{2004,t}\} + \text{X}_{2004,i} + \epsilon_{id,t} \tag{5}$$

where $\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}}$ refers to the ratio of end-of-period outstanding infrastructure loans by bank i in district d and year t relative to the ratio of end-of-period infrastructure loans by bank i in district d in year 2002. We use 2002 as the baseline year for the normalization because of two reasons: First, choosing an year before 2002 leads to the loss of a number of banks because of missing data before then, and second, Indian banks were largely opened up to private sector lending since 2002 (this can also be seen in the Figure 1), and hence 2002 is apt as the benchmark year. $\alpha_{d,t}$ refers to district-time fixed effects and $\delta_{i,d}$ refers to bank-district fixed effects, with the former being the crucial inclusion so as to control for demand side effects. IFR ratio is measured as the investment fluctuation reserves relative to the total assets for a bank. The variable $\mathbb{1}\{\text{High IFR ratio}_{2004,i}\}$ is an indicator variable which takes the value 1 if the IFR ratio of a bank at the end of 2004 is above the median IFR ratio of Indian Banks. $\mathbb{1}\{Post_{2004,t}\}$ is an indicator variable which takes the value 1 for years after 2004. Controls $\text{X}_{2004,i}$ include size of the banks, fraction of total deposits raised in

[5]Repo rate has been used as a monetary policy instrument since 2002

[6]Note that in our analysis, 2004 refers to the financial year April 2003- March 2004

metropolitan cities, and ownership category of the banks.

We show the results for these regressions in Table 4. We find that banks with above median IFR ratio in 2004 were characterised by higher lending to sectors associated with infrastructure in the boom period post 2004.

In Figure 7, we show the event study plot for our fixed effects regression analysis of infrastructure lending:

$$\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}} = \alpha_{d,t} + \delta_{i,d} + \sum_{\tau=1999}^{2016} \beta_\tau \times \mathbb{1}\{\text{IFR ratio}_{2004,i}\} \times \mathbb{1}_t + \text{X}_{2004,i} + \epsilon_{id,t} \tag{6}$$

These plots serve to show that the parallel trends assumption holds in the pre-period of our study, and to show how lending to infrastructure varied by the ex-ante IFR ratio of the banks over the time period we consider.

An alternate explanation for the observed pattern of infrastructure lending may be increased demand for infrastructure loans after 2004 from a subsection of the banks. If this were the case, we would expect a relative increase in interest rates on infrastructure loans of banks with above median IFR ratio in 2004. We test this using the regression specification:

$$\text{Infra Int Rate}_{id,t} = \alpha_{d,t} + \delta_{i,d} + \beta \times \mathbb{1}\{\text{IFR ratio}_{2004,i}\} \times \mathbb{1}\{\text{Post}_{2004,t}\} + \text{X}_{2004,i} + \epsilon_{id,t} \tag{7}$$

Contrary to the demand driven explanation, we find in Table 5 that the interest rate on outstanding infrastructure loans after 2004 did not differ significantly across banks with varying levels of IFR ratio. This evidence, along with the higher outstanding infrastructure loans by banks with above median IFR ratio in 2004, implies a supply side explanation. We argue that banks with higher duration risk in 2004, as measured by their IFR ratios, undertook substitution of assets from long term fixed rate securities to long term fixed rate loans in order to hedge against interest rate risk.

This evidence is also supported by the event study plot in Figure 8 for the regression specification:

$$\text{Infra Int Rate}_{id,t} = \alpha_{d,t} + \delta_{i,d} + \sum_{\tau=1999}^{2016} \beta_\tau \times \mathbb{1}\{\text{IFR ratio}_{2004,i}\} \times \mathbb{1}_t + \text{X}_{2004,i} + \epsilon_{id,t} \tag{8}$$

The results we provide may be especially important in the Indian context, because they imply that banks' exposure to infrastructure sectors over the boom period may have also been incentivised by pure market forces instead of being driven solely by government pressure, as is usually portrayed in media. This may have important policy implications for the future.

7.2 Interest Expense Beta and Infrastructure Lending

In order to analyse relevance of interest expense sensitivity of banks for their infrastructure lending post 2004, we ideally need to estimate bank betas using data prior to 2004. However, this is problematic in the Indian context because Repo rate became the official policy rate only after 2002. In order to deal with this problem, we employ measure of Indian policy rate developed by the Bank for International Settlements which uses 'bank rate' for years prior to 2002, and Repo rate afterwards. Bank rate is, in essence, similar to the Repo rate and refers the the minimum rate of interest at which the Central Bank may lend to the financial institutions (not necessarily short term as for the Repo rate). We compute interest expense beta for each bank following Equation 1, and use this sensitivity as a measure of the strength of deposit franchise of banks. Importantly, this measure is quite general and does not suffer from the same limitations as the Herfindahl-Hirschman Index in the presence of state ownership (as discussed in Section **??**).

We conduct the following difference-in-differences regression analysis to identify the impact of banks' ex-ante deposit franchise, as measured by their interest expense beta, on their lending post 2004:

$$\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}} = \alpha_{d,t} + \delta_{i,d} + \beta \times \mathbb{1}\{\text{High Expense Beta}_{2004,i}\} \times \mathbb{1}\{\text{Post}_{2004,t}\} + \text{X}_{2004,i} + \epsilon_{id,t} \tag{9}$$

where $\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}}$ refers to the ratio of end-of-period outstanding infrastructure loans by bank i in district d and year t relative to the ratio of end-of-period infrastructure loans by bank i in district d in year 2002. $\alpha_{d,t}$ refers to district-time fixed effects and $\delta_{i,d}$ refers to bank-district fixed effects, with the former being the crucial inclusion so as to control for demand side effects. The variable $\mathbb{1}\{\text{High Expense Beta}_{2004,i}\}$ is an indicator variable which takes the value 1 if the interest expense beta of a bank measured using bank-level data till the end of 2004 is above the median expense beta of Indian Banks. $\mathbb{1}\{Post_{2004,t}\}$ is an indicator variable which takes the value 1 for years after 2004. Controls $X_{2004,i}$ include size of the banks, fraction of total deposits raised in metropolitan cities, and ownership category of the banks.

We show the results for these regressions in Table 6. We find that banks with below median expense beta were characterised by higher lending to sectors associated with infrastructure in the boom period post 2004.

In Figure 9, we show the event study plot for our fixed effects regression analysis of infrastructure lending:

$$\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}} = \alpha_{d,t} + \delta_{i,d} + \sum_{\tau=1999}^{2016} \beta_\tau \times \mathbb{1}\{\text{High Expense Beta}_{2004,i}\} \times \mathbb{1}_t + \text{X}_{2004,i} + \epsilon_{id,t} \qquad (10)$$

These plots serve to show that the parallel trends assumption holds in the pre-period of our study, and to show how lending to infrastructure varied by the ex-ante expense beta of the banks over the time period we consider.

In order to test whether this increase in lending to infrastructure sector by a subset of banks was not simply driven by increased demand, we employ the following regression specification:

$$\text{Infra Int Rate}_{id,t} = \alpha_{d,t} + \delta_{i,d} + \beta \times \mathbb{1}\{\text{High Expense Beta}_{2004,i}\} \times \mathbb{1}\{\text{Post}_{2004,t}\} + \text{X}_{2004,i} + \epsilon_{id,t} \quad (11)$$

Contrary to the demand driven explanation, we find in Table 7 that the interest rate on outstanding infrastructure loans after 2004 did not differ significantly across banks with varying levels of interest expense beta. This evidence, along with the higher outstanding infrastructure loans by banks with below median expense beta, implies a supply side explanation. We argue that banks with stronger deposit franchise in 2004, as measured by their expense betas, undertook substitution of assets from long term fixed rate securities to long term fixed rate loans in order to hedge against interest rate risk.

The event study plot for the above regression is shown in Figure 10, and is obtained as follows:

$$\text{Infra Int Rate}_{id,t} = \alpha_{d,t} + \delta_{i,d} + \sum_{\tau=1999}^{2016} \beta_\tau \times \mathbb{1}\{\text{High Expense Beta}_{2004,i}\} \times \mathbb{1}_t + X_{2004,i} + \epsilon_{id,t} \quad (12)$$

8 Robustness

In this section, we present an alternative regression specification as robustness tests for our results in the previous section. This specification follows the one employed in Drechsler et al. (2022), and is as follows:

$$\Delta\text{Log}(\text{Infra}_{2007-2004,id}) = \alpha_d + \beta \times \mathbb{1}\{\text{High Var}_{2004,i}\} + X_{2004,i} + \epsilon_{id} \quad (13)$$

where Var refers to the variable of interest: IFR ratio or the Interest Expense Beta, and $\mathbb{1}\{\text{High Var}_{2004,i}\}$ is an indicator variable which takes the value 1 if the bank has above median value of the variable of interest. $\Delta\text{Log}(\text{Infra}_{2007-2004,id})$ refers to the increase in outstanding infrastructure loans by bank and district from 2004 to 2007, as measured in logs, $\text{Log}(\text{Infra}_{2007,id})$- $\text{Log}(\text{Infra}_{2004,id})$. α_d refers to district fixed effects and is included to control for demand side effects. Controls, symbolised by $X_{2004,i}$, include size of the banks, fraction of total deposits raised in metropolitan cities, and ownership category of the banks.

The results for IFR ratio as the explanatory variable are shown in Table 8. We find that banks with above median IFR ratio in 2004 are characterised by 22 percentage point higher growth in infrastructure loans from 2004 to 2007. Similarly, the results for interest expense beta as the explanatory variable of interest are shown in Table 9. Banks with below median interest expense beta (computed using data up till 2004) show higher growth in infrastructure loans from 2004 to 2007 by a magnitude of 18 percentage points.

9 Conclusion

This paper examines the deposit franchise of banks in India and relates it to banks' supply of loans. We first hypothesize and provide evidence for two distinct deposit franchise channels in India: the deposit franchise of private sector banks comes from private sector banks' deposit market power, whereas for state-owned banks, deposit franchise comes from the implicit government guarantees that allow them to maintain their market power.

Then, using the boom period of the 2000s in India as a laboratory, we document that banks with higher deposit franchise shifted from long-term government securities to loans particularly in the infrastructure sector. Analysing the above channels during the unique credit boom episode in India, which ended with massive non-performing loans in the banking sector, allows us to provide evidence on the link between deposit franchise of banks and their lending behaviour in the presence of not only interest rate risk, but also default risk. Our paper shows that banks face an important tradeoff in their lending decisions between mark-to-market risk and default risk in the absence of safe long-term lending avenues.

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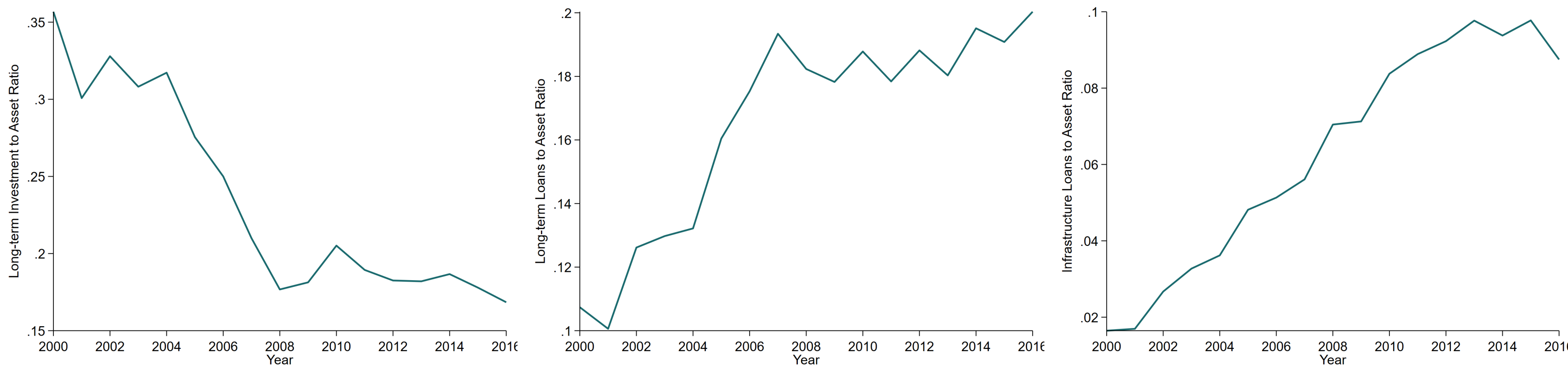
Figure 1
Time series share of long-term securities, long-term loans, and infrastructure loans in total assets

The figures below shows the time series of the share of long-term securities, long-term loans, and infrastructure loans in total assets. Panel (a) plots the time series of the average share of long-term securities in total assets from 2000 to 2020. Long-term securities refer to securities with maturity > 5 years. Panel (b) plots the time series of the average share of long-term loans in total assets. Long-term loans refer to securities with maturity > 5 years from 2000 to 2020. Panel (c) plots the time series of the average share of infrastructure loans in total assets from 2000 to 2016 (BSR data available till 2016). Infrastructure lending refers to bank loans towards construction, transport, and electricity, gas & water sectors. The data are sourced from Banking Statistical Returns (RBI) and CMIE Prowess.



(a) Long-term securities ratio **(b) Long-term loan ratio** **(c) Infrastructure loan ratio**

Figure 2
Infrastructure Lending and Long-term Investment

The figures below shows the time series of the share of long-term securities and infrastructure loans in total assets during the period of credit boom. Long-term securities refer to securities with maturity > 5 years. Infrastructure lending refers to bank loans towards construction, mining, and electricity, gas & water sectors. The data are sourced from Banking Statistical Returns (RBI) and CMIE Prowess.

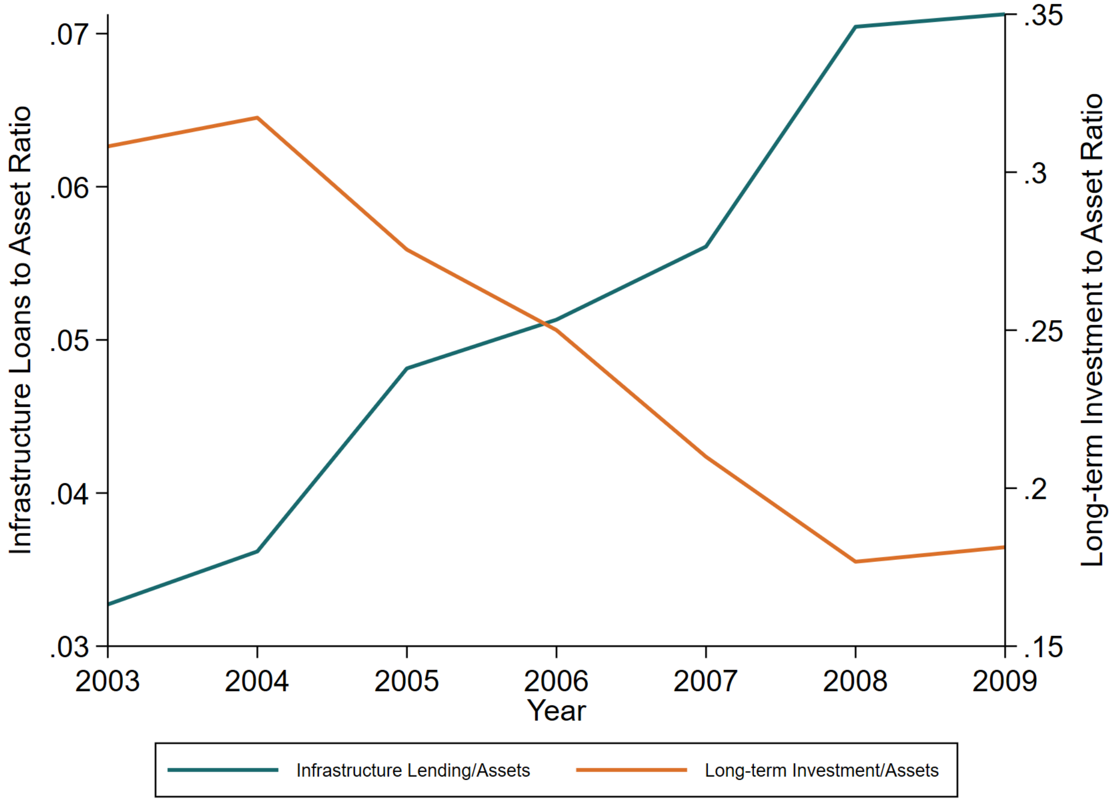


Figure 3
Monthly Bank Credit Time Series

The figure below shows the aggregate time series of non-food bank credit and investment. It shows the variation in their trends coincide with an exogenous shock to Indian government bond yields due to the first US Federal Fund Rate Hike since May 2000 and higher oil prices caused by Hurricane Ivan. The data are monthly from RBI DBIE, 2000 to 2008.

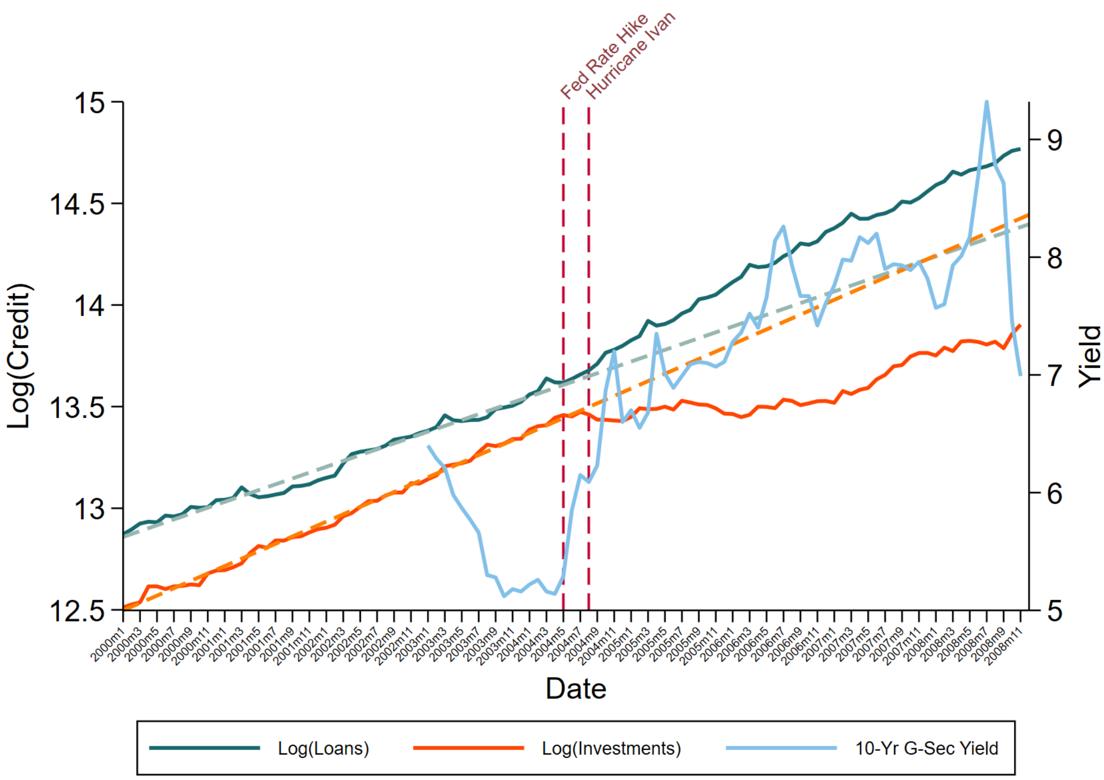
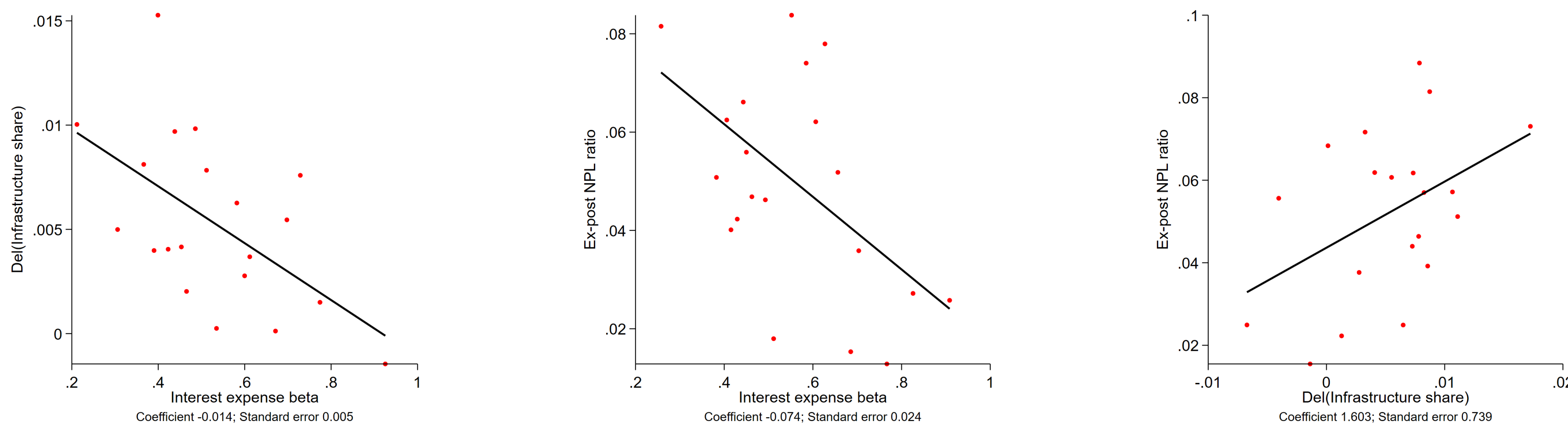


Figure 4
Interest expense beta and ex-post non-performing loan ratio

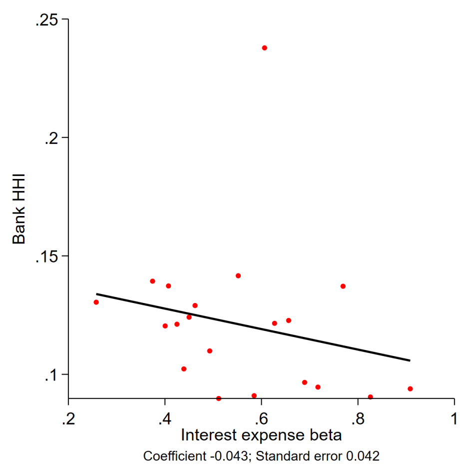
Panel (a) shows a bin scatter plot of the average increase in infrastructure share in total lending against the interest expense betas. Panel (b) shows the bin scatter plot of ex-post NPL ratio of banks against the interest expense betas. Panel (c) shows the bin scatter plot of ex-post NPL ratio of banks against the share of infrastructure sector. Ex-post NPL ratio refers to the ratio of non-performing loans to total loans averaged over 2014, 2015 and 2016 for each bank. This is done to capture the three year period subsequent to the initiation of RBI's Asset Quality Review. Infrastructure lending refers to loans towards construction, metals, mining, and electricity, gas & water sectors. The interest expense betas are calculated by regressing the quarterly change in each bank's interest expense rate on the contemporaneous and previous three changes in the RBI Repo rate. The sample consists of banks with at least 30 quarterly observations from 2002 to 2016 (43 banks). Sample starts from 2002 because Repo rate used as a monetary policy instrument since then. The bin scatter plot groups banks into 20 bins by interest expense beta and plots the average ex-post NPL ratio within each bin. The data are sourced from Banking Statistical Returns (RBI) and CMIE Prowess.



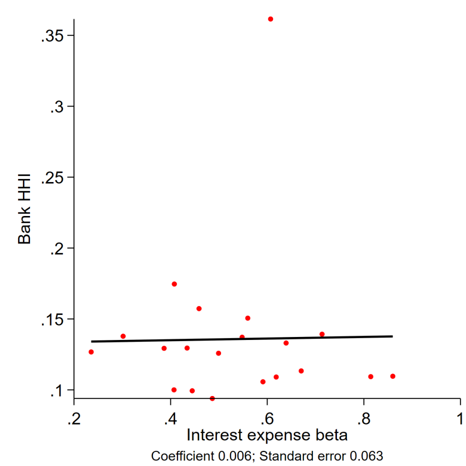
(a) Interest expense beta and infra **(b) Interest expense beta and NPL** **(c) Infrastructure share and NPL**

Figure 5
Interest expense beta and deposit market concentration

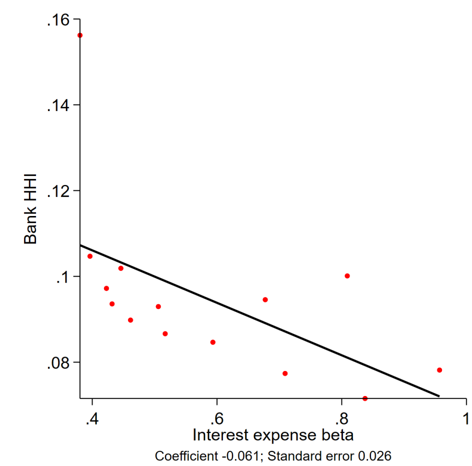
The figure below shows a bin scatter plot of interest expense betas against the bank HHI. To calculate the bank HHI, we first calculate a district HHI by computing each bank's share of the total deposits in the district and summing the squared shares. Bank-HHI is then equal to the weighted average of the district HHI, where the weights are determined by the fraction of deposits raised in each district where the bank operates. The betas are calculated by regressing the quarterly change in each bank's interest expense rate on the contemporaneous and previous three changes in the RBI Repo rate. The sample consists of banks with at least 30 quarterly observations from 2002 to 2016 (43 banks). Sample starts from 2002 because Repo rate used as a monetary policy instrument since then. The bin scatter plot groups banks into 20 bins by bank HHI and plots the average interest expense betas within each bin. The data are sourced from Banking Statistical Returns (RBI) and CMIE Prowess.



(a) Interest expense beta



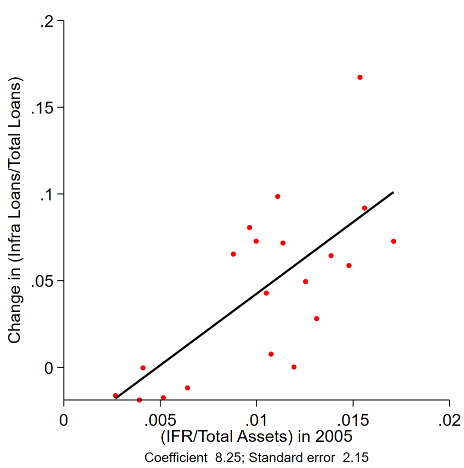
(b) Public Sector Banks



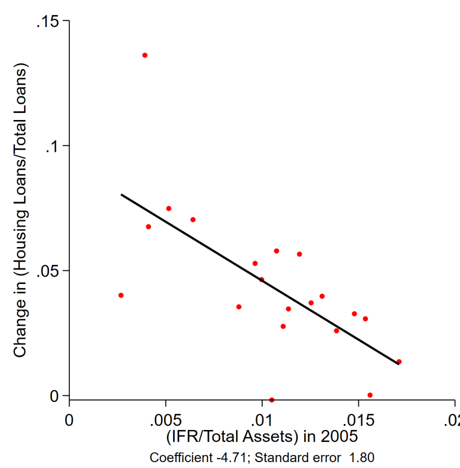
(c) Private Sector Banks

Figure 6
Bank lending pattern and Investment Fluctuation Reserve ratio

Panel (a) shows the bin scatter plot of the change in the average ratio of each bank's infrastructure loans from 2001-2005 to 2006-2010 against the ratio of banks' investment fluctuation reserves to total assets in 2005. Bank's average ratio of infrastructure loans to total loans is calculated separately for the time periods 2001-2005 and 2006-2010. The difference in the average ratio in 2006-2010 and average ratio in 2001-2005 is then used on the y-axis. Panel (b) shows the bin scatter plot of the change in the average ratio of each bank's housing loans from 2001-2005 to 2006-2010 against the ratio of banks' investment fluctuation reserves in 2005 to total assets in 2005. Bank's average ratio of housing loans to total loans is calculated separately for the time periods 2001-2005 and 2006-2010. The difference in the average ratio in 2006-2010 and average ratio in 2001-2005 is then used on the y-axis. Infrastructure lending refers to bank loans towards sectors associated with infrastructure including construction, metals, mining and electricity, gas & water. Housing lending refers to loans classified under 'Personal - Loans for Housing' category in BSR. We use the ratio of investment fluctuation reserve to total assets as a proxy for deposit franchise. The bin scatter plot groups banks into 20 bins by IFR to total assets ratio in 2005 and plots the average of each bin's change in Infra to total loans from 2001-2005 to 2006-2010 within each bin. Results remain robust for variations in the pre- or post-period. The data are sourced from Banking Statistical Returns (RBI) and CMIE Prowess.



(a) IFR ratio in 2005 and Infra lending



(b) IFR ratio in 2005 and Housing lending

Figure 7
Investment Fluctuation Reserve in 2004 and Outstanding Infrastructure Loans

The figure below shows the event study estimates obtained from a fixed effects panel regressions to assess the relevance of ex-ante investment fluctuation reserves in 2004 for infrastructure lending as described in equation 6. The dependent variable is the ratio of outstanding bank-district level infrastructure loans in a given year relative to the infrastructure loans in 2002. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}_t$ is an indicator variable which takes the value 1 for year t, and 0 otherwise. Exposure measure $\mathbb{1}\{\text{IFR ratio}_{2004,i}\}$ takes the value 1 for banks with above median share of investment fluctuation reserves to total assets in 2004, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the year dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. Bank-district and district-year fixed effects are included as indicated. The data are annual and cover 31 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are double-clustered at the district and year level.

$$\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}} = \alpha_{d,t} + \delta_{i,d} + \sum_{\tau=1999}^{2016} \beta_\tau \times \mathbb{1}\{\text{IFR ratio}_{2004,i}\} \times \mathbb{1}_t + X_{2004,i} + \epsilon_{id,t}$$

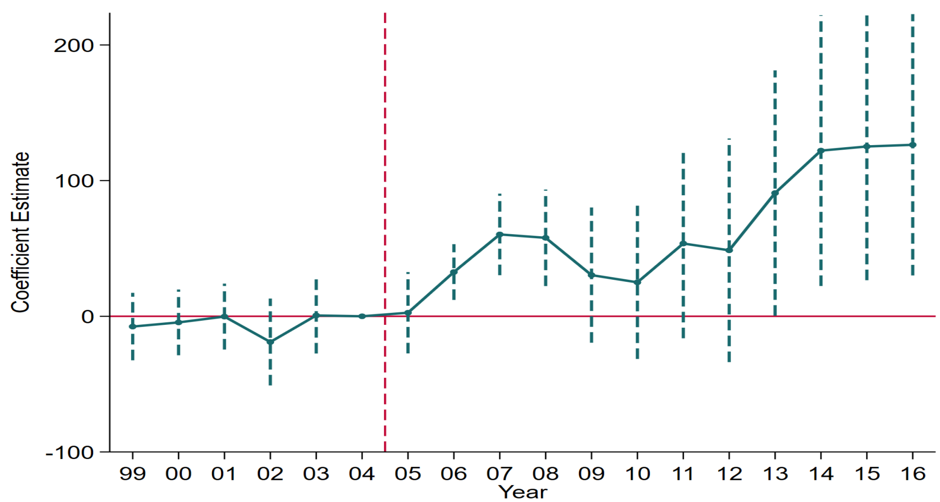


Figure 8
Investment Fluctuation Reserve in 2004 and Interest Rate on Outstanding Infrastructure Loans

The figure below shows the event study estimates obtained from a fixed effects panel regressions to assess the relevance of ex-ante investment fluctuation reserves in 2004 for interest rate on outstanding infrastructure loans as described in equation 8. The dependent variable Infra Int $\text{Rate}_{id,t}$ is the interest rate on outstanding infrastructure loans. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}_t$ is an indicator variable which takes the value 1 for year t, and 0 otherwise. Exposure measure $\mathbb{1}\{\text{IFR ratio}_{2004,i}\}$ takes the value 1 for banks with above median share of investment fluctuation reserves to total assets in 2004, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the year dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. Bank-district and district-year fixed effects are included as indicated. The data are annual and cover 31 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are double-clustered at the district and year level.

$$\text{Infra Int Rate}_{id,t} = \alpha_{d,t} + \delta_{i,d} + \sum_{\tau=1999}^{2016} \beta_\tau \times \mathbb{1}\{\text{IFR ratio}_{2004,i}\} \times \mathbb{1}_t + X_{2004,i} + \epsilon_{id,t}$$

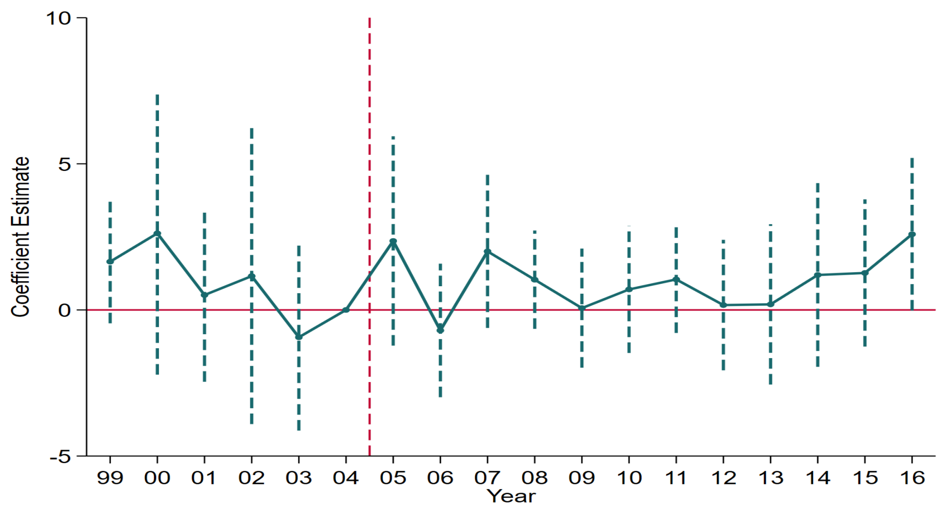


Figure 9

Interest Expense Beta in 2004 and Outstanding Infrastructure Loans

The figure below shows the event study estimates obtained from a fixed effects panel regressions to assess the relevance of ex-ante interest expense sensitivity of banks for infrastructure lending as described in equation 10. The dependent variable is the ratio of outstanding bank-district level infrastructure loans in a given year relative to the infrastructure loans in 2002. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}_t$ is an indicator variable which takes the value 1 for year t, and 0 otherwise. Exposure measure $\mathbb{1}\{\text{Expense Beta}_{2004,i}\}$ takes the value 1 for banks with above median interest expense beta, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the year dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. Bank-district and district-year fixed effects are included as indicated. The data are annual and cover 28 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are double-clustered at the district and year level.

$$\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}} = \alpha_{d,t} + \delta_{i,d} + \sum_{\tau=1999}^{2016} \beta_\tau \times \mathbb{1}\{\text{Expense Beta}_{2004,i}\} \times \mathbb{1}_t + X_{2004,i} + \epsilon_{id,t}$$

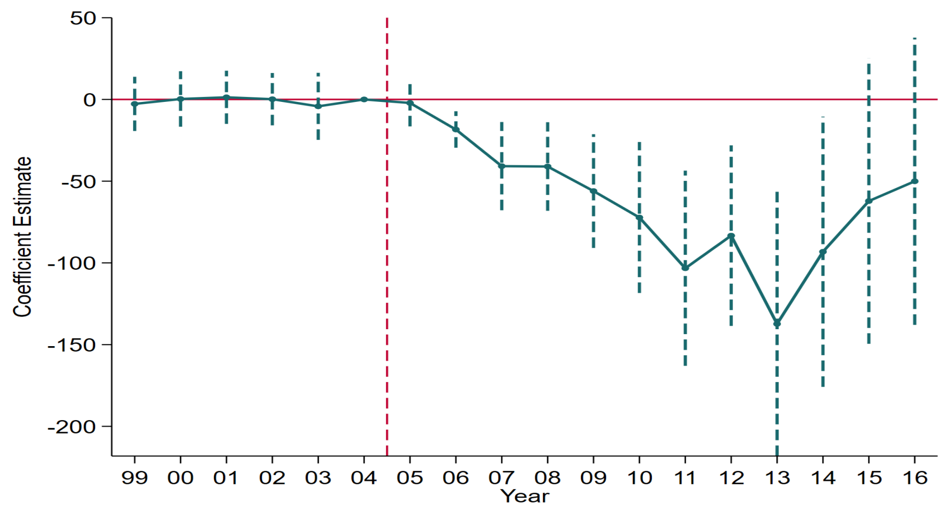


Figure 10
Interest Expense Beta and Interest Rate on Outstanding Infrastructure Loans

The figure below shows the event study estimates obtained from a fixed effects panel regressions to assess the relevance of ex-ante interest expense sensitivity of banks for infrastructure lending as described in equation 12. The dependent variable Infra Int Rate$_{id,t}$ is the interest rate on outstanding infrastructure loans. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}_t$ is an indicator variable which takes the value 1 for year t, and 0 otherwise. Exposure measure $\mathbb{1}\{\text{Expense Beta}_{2004,i}\}$ takes the value 1 for banks with above median interest expense beta, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the year dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. Bank-district and district-year fixed effects are included as indicated. The data are annual and cover 28 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are double-clustered at the district and year level.

$$\text{Infra Int Rate}_{id,t} = \alpha_{d,t} + \delta_{i,d} + \sum_{\tau=1999}^{2016} \beta_\tau \times \mathbb{1}\{\text{Expense Beta}_{2004,i}\} \times \mathbb{1}_t + X_{2004,i} + \epsilon_{id,t}$$

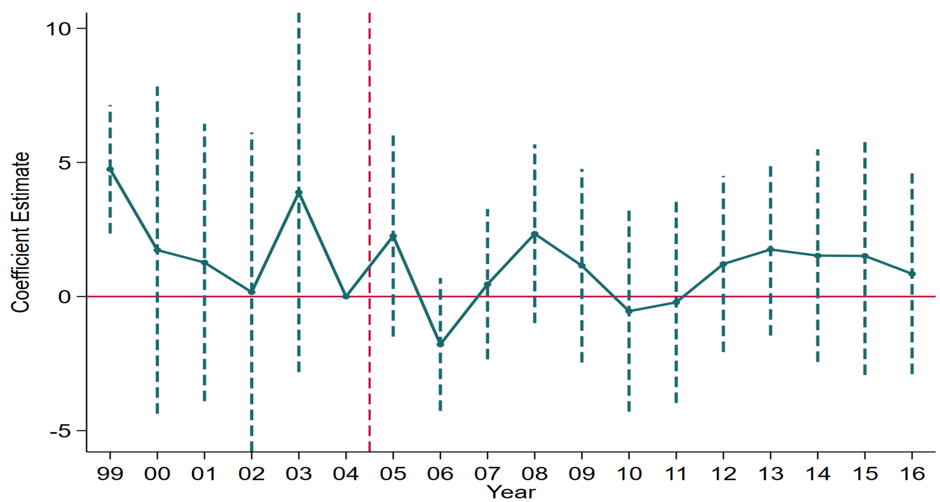


Table 1
State-ownership and interest sensitivity matching

The table below provides estimates of the relation between state-ownership of banks and interest expense rate sensitivity to changes in the RBI Repo rate using a panel estimation procedure for equation 2. The dependent variables for column 1 and 2 is the change in interest expenses and for columns 3 and 4 is change in interest income rate. $\mathbb{1}\{PSB_i\}$ is an indicator variable which takes the value 1 for public sector banks and 0 for private sector or foreign banks. Column 1 presents the first-stage results with contemporaneous and three lagged values of ΔRepo Rate interacted with the PSB dummy as the explanatory variable and column 2 presents the second-stage results with predicted value of ΔInterest Expenses from the first stage as the explanatory variable. ΔRepo Rate is the change in the RBI Repo rate from one quarter to the next. Bank and quarter fixed effects are included as indicated. The data are quarterly and cover 48 Indian commercial banks from 2002 to 2016 (because Repo rate used as a monetary policy instrument since 2002). In subsequent results for the main analysis, 5 banks are thrown out due to missing values of investment fluctuation reserves. These results remain robust to using the sample of 43 banks as well. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

$$\text{First stage: } \Delta\ \text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3}\left(\beta^0_{\tau,psb} + \beta^1_{\tau,psb}\mathbb{1}\{PSB_i\}\right)\Delta\text{RepoRate}_{t-\tau} + \epsilon_{i,t}$$

$$\text{Second stage: } \Delta\ \text{IntInc}_{i,t} = \lambda_i + \theta_t + \delta\Delta\widehat{\text{IntExp}}_{i,t} + \epsilon_{i,t}$$

	First stage		Second stage	
	(1)	(2)	(3)	(4)
$\beta^1_{\tau,psb}$	−0.111***	−0.094*		
	(0.037)	(0.054)		
$\Delta\widehat{IntExp}$			1.131***	1.083**
			(0.378)	(0.465)
Bank FE	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes
Obs.	2,053	2,053	2,053	2,053
No. of banks	48	48	48	48
R^2	0.152	0.512	0.095	0.536

Table 2
Deposit market concentration in 2005 and interest sensitivity matching

The table below provides estimates of the relation between banks' deposit market concentration and interest expense sensitivity to changes in the RBI Repo rate equation 3. The dependent variable is the change in the interest expense rate of bank i from quarter t-1 to t. This variable is regressed against contemporaneous and three lagged values of ΔRepo Rate interacted with the bank's deposit market concentration (bank-HHI) in 2005 (pre-event year in the subsequent analysis) as the explanatory variable. Columns (1) and (2) provide results for the sample with all banks, whereas columns (3) and (4), and (5) and (6) provide separate results for the sub-sample with public sector banks and private sector banks. To calculate the bank HHI, we first calculate district level HHI by computing each bank's share of the total deposits in the district and summing the squared shares. Bank-HHI is then equal to the weighted average of the district HHI, where the weights are determined by the fraction of deposits raised in each district where the bank operates. The variable $\mathbb{1}\{High\ HHI_{2005,t}\}$ takes the value 1 for above median bank HHI in 2005 and 0 otherwise. Bank and quarter fixed effects are included as indicated. The data are quarterly from 2002 to 2016 (because Repo rate used as a monetary policy instrument since 2002). Standard errors are block-bootstrapped by quarter with 1,000 iterations. The sample consists of 43 Indian commercial banks. In order to ensure the comparability of all results analysing potential determinants of deposit franchise, 5 banks are thrown out due to missing values of investment fluctuation reserves in all subsequent results.

$$\Delta \text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3} \left(\beta^0_{\tau HHI} + \beta^1_{\tau HHI} \times \mathbb{1}\{\text{High HHI}_{2005,t}\} \right) \Delta \text{RepoRate}_{t-\tau} + \epsilon_{i,t}$$

	All banks		Public Sector Banks		Private Sector Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$\beta^1_{\tau HHI}$	−0.098***	−0.096**	−0.045	−0.044	−0.183***	−0.191***
	(0.031)	(0.043)	(0.047)	(0.073)	(0.042)	(0.043)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Obs.	1,871	1,871	1,251	1,251	620	620
No. of banks	43	43	28	28	15	15
R^2	0.156	0.511	0.155	0.577	0.165	0.499

Table 3
IFR ratio in 2005 and interest rate sensitivity

The table below provides estimates of the relation between banks' investment fluctuation reserves and interest expense sensitivity to changes in the RBI Repo rate for equation 4. The dependent variable is the change in the interest expense rate of bank i from quarter t-1 to t. This variable is regressed against contemporaneous and three lagged values of ΔRepo Rate interacted with with an indicator variable for above median bank's investment fluctuation reserve (IFR) in 2005 (pre-event year in the subsequent analysis) as the explanatory variable. Columns (1) and (2) provide results for the sample with all banks, whereas columns (3) and (4), and (5) and (6) provide separate results for the sub-sample with public sector banks and private sector banks. We compute IFR rate as the ratio of investment fluctuation reserves to total assets in 2005. We derive the median bank investment fluctuation rates by ownership in 2005. The variable $\mathbb{1}\{High\ IFR_{2005,t}\}$ takes the value 1 for above median investment fluctuation reserve ratio in 2005 and 0 otherwise. Bank and quarter fixed effects are included as indicated. The data are quarterly from 2002 to 2016 (because Repo rate used as a monetary policy instrument since 2002). Standard errors are block-bootstrapped by quarter with 1,000 iterations. The sample consists of 43 Indian commercial banks. 5 banks are thrown out due to missing values of investment fluctuation reserves. In order to ensure the comparability of all results analysing potential determinants of deposit franchise, 5 banks are thrown out due to missing values of investment fluctuation reserves.

$$\Delta\text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3}\left(\beta^0_{\tau IFR} + \beta^1_{\tau IFR} \times \mathbb{1}\{\text{High IFR}_{2005,t}\}\right)\Delta\text{RepoRate}_{t-\tau} + \epsilon_{i,t}$$

	All banks		Public Sector Banks		Private Sector Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$\sum \beta_{\tau IFR}$	−0.086***	−0.070**	−0.063***	−0.045	−0.167*	−0.161*
	(0.022)	(0.033)	(0.012)	(0.046)	(0.083)	(0.085)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Obs.	1,871	1,871	1,251	1,251	620	620
No. of banks	43	43	28	28	15	15
R^2	0.154	0.509	0.156	0.578	0.166	0.500

Table 4
Investment Fluctuation Reserve in 2004 and Outstanding Infrastructure Loans

The table below provides estimates of a difference-in-differences regression to assess the relevance of ex-ante investment fluctuation reserves in 2004 for infrastructure lending as described in equation 5. The dependent variable is the ratio of outstanding bank-district level infrastructure loans in a given year relative to the infrastructure loans in 2002. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}\{\text{Post}_{2004,t}\}$ is an indicator variable which takes the value 1 for years post 2004, and 0 otherwise. Exposure measure takes the value 1 for banks with above median share of investment fluctuation reserves to total assets in 2004, and 0 otherwise. $\text{X}_{2004,i}$ refers to bank level controls interacted with the post period dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. Bank-district and district-year fixed effects are included as indicated. The data are annual and cover 31 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are double-clustered at the district and year level.

$$\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}} = \alpha_{d,t} + \delta_{i,d} + \beta \times \mathbb{1}\{\text{High IFR ratio}_{2004,i}\} \times \mathbb{1}\{\text{Post}_{2004,t}\} + \text{X}_{2004,i} + \epsilon_{id,t}$$

	1	2	3
$\text{Post}_{2004} = 1$	86.759***		
	(23.435)		
High IFR $\text{Ratio}_{2004} = 1$	10.323**		
	(4.851)		
$\text{Post}_{2004} = 1 \times$ High IFR $\text{Ratio}_{2004} = 1$	39.206*	66.498**	69.668**
	(22.534)	(28.963)	(31.441)
Controls	No	No	Yes
Bank-District FE	No	Yes	Yes
District-Year FE	No	Yes	Yes
Observations	50510	50510	50510
No. of districts	416	416	416
No. of banks	31	31	31
R^2	0.005	0.572	0.572

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5
Investment Fluctuation Reserve in 2004 and Interest Rate on Outstanding Infrastructure Loans

The table below provides estimates of a difference-in-differences regression to assess the relevance of ex-ante investment fluctuation reserves in 2004 for interest rate on infrastructure lending as described in equation 7. The dependent variable is the interest rate charged on infrastructure loans in a given year. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}\{\text{Post}_{2004,t}\}$ is an indicator variable which takes the value 1 for years post 2004, and 0 otherwise. Exposure measure takes the value 1 for banks with above median share of investment fluctuation reserves to total assets in 2004, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the post period dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. Bank-state and state-year fixed effects are included as indicated. The data are annual and cover 31 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are double-clustered at the state and year level.

$$\text{Infra Int Rate}_{id,t} = \alpha_{d,t} + \delta_{i,d} + \beta \times \mathbb{1}\{\text{High IFR ratio}_{2004,i}\} \times \mathbb{1}\{\text{Post}_{2004,t}\} + X_{2004,i} + \epsilon_{id,t}$$

	1	2	3
$\text{Post}_{2004} = 1$	-3.588^{***}		
	(0.670)		
$\text{High IFR Ratio}_{2004} = 1$	-0.821^{***}		
	(0.269)		
$\text{Post}_{2004} = 1 \times \text{High IFR Ratio}_{2004} = 1$	0.649	0.484	0.309
	(0.455)	(0.676)	(0.599)
Controls	No	No	Yes
Bank-State FE	No	Yes	Yes
State-Year FE	No	Yes	Yes
Observations	6257	6257	6257
No. of States	31	31	31
No. of banks	32	32	32
R^2	0.018	0.327	0.329

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6
Interest Expense Beta and Outstanding Infrastructure Loans

The table below provides estimates of a difference-in-differences regression to assess the relevance of ex-ante interest expense sensitivity for infrastructure lending as described in equation 9. The dependent variable is the ratio of outstanding bank-district level infrastructure loans in a given year relative to the infrastructure loans in 2002. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}\{\text{Post}_{2004,t}\}$ is an indicator variable which takes the value 1 for years post 2004, and 0 otherwise.Exposure measure takes the value 1 for banks with above median interest expense beta, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the post period dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. Bank-district and district-year fixed effects are included as indicated. The data are annual and cover 28 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are double-clustered at the district and year level.

$$\frac{\text{Infra}_{id,t}}{\text{Infra2002}_{id}} = \alpha_{d,t} + \delta_{i,d} + \beta \times \mathbb{1}\{\text{High Expense Beta}_{2004,i}\} \times \mathbb{1}\{\text{Post}_{2004,t}\} + X_{2004,i} + \epsilon_{id,t}$$

	1	2	3
$\text{Post}_{2004} = 1$	119.251^{***}		
	(27.913)		
High Expense $\text{Beta}_{2004} = 1$	-3.629		
	(2.817)		
$\text{Post}_{2004} = 1 \times$ High Expense $\text{Beta}_{2004} = 1$	-60.354^{**}	-62.634^{**}	-61.506^{**}
	(22.990)	(25.185)	(25.807)
Controls	No	No	Yes
Bank-District FE	No	Yes	Yes
District-Year FE	No	Yes	Yes
Observations	35584	35584	35584
No. of districts	373	373	373
No. of banks	28	28	28
R^2	0.006	0.542	0.542

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7
Interest Expense Beta and Interest Rate on Outstanding Infrastructure Loans

The table below provides estimates of a difference-in-differences regression to assess the relevance of ex-ante interest expense sensitivity for interest rate on infrastructure lending as described in equation 11. The dependent variable is the interest rate charged on infrastructure loans in a given year. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}\{\text{Post}_{2004,t}\}$ is an indicator variable which takes the value 1 for years post 2004, and 0 otherwise. Exposure measure takes the value 1 for banks with above median interest expense beta, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the post period dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. Bank-state and state-year fixed effects are included as indicated. The data are annual and cover 28 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are double-clustered at the state and year level.

$$\text{Infra Int Rate}_{id,t} = \alpha_{d,t} + \delta_{i,d} + \beta \times \mathbb{1}\{\text{High Expense Beta}_{2004,i}\} \times \mathbb{1}\{\text{Post}_{2004,t}\} + X_{2004,i} + \epsilon_{id,t}$$

	1	2	3
$\text{Post}_{2004} = 1$	-3.504^{***}		
	(1.083)		
$\text{High Expense Beta}_{2004} = 1$	0.603		
	(1.536)		
$\text{Post}_{2004} = 1 \times \text{High Expense Beta}_{2004} = 1$	-1.029	-1.313	-0.916
	(1.490)	(1.883)	(1.730)
Controls	No	No	Yes
Bank-State FE	No	Yes	Yes
State-Year FE	No	Yes	Yes
_cons	Yes	No	No
Observations	4384	4384	4384
No. of States	29	29	29
No. of banks	28	28	28
R^2	0.022	0.354	0.355

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8
Interest sensitivity matching: Panel estimation

The table below provides estimates of a difference-in-differences regression to assess the relevance of ex-ante investment fluctuation reserves in 2004 for infrastructure lending as described in equation 13. The dependent variable is the change in the log of outstanding infrastructure credit in 2007 relative to the log of outstanding infrastructure credit in 2004. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}\{\text{Post}_{2004,t}\}$ is an indicator variable which takes the value 1 for years post 2004, and 0 otherwise. Exposure measure takes the value 1 for banks with above median share of investment fluctuation reserves to total assets in 2004, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the post period dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. District fixed effects are included as indicated. The data are annual and cover 30 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are clustered at the district level.

$$\Delta\text{Log}(\text{Infra}_{2007-2004,id}) = \alpha_d + \beta \times \mathbb{1}\{\text{High IFR ratio}_{2004,i}\} + \epsilon_{id}$$

	1	2	3
High IFR ratio$_{2004}$	0.141**	0.222***	0.218***
	(0.067)	(0.071)	(0.073)
Controls	No	No	Yes
District FE	No	Yes	Yes
Observations	2765	2765	2765
No. of districts	418	418	418
No. of banks	30	30	30
R^2	0.002	0.155	0.169

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9
Interest sensitivity matching: Panel estimation

The table below provides estimates of a difference-in-differences regression to assess the relevance of ex-ante investment fluctuation reserves in 2004 for infrastructure lending as described in equation 13. The dependent variable is the change in the log of outstanding infrastructure credit in 2007 relative to the log of outstanding infrastructure credit in 2004. Infrastructure loans refer to bank loans towards construction, mining, and electricity, gas & water sectors. $\mathbb{1}\{\text{Post}_{2004,t}\}$ is an indicator variable which takes the value 1 for years post 2004, and 0 otherwise. Exposure measure takes the value 1 for banks with above median interest expense beta, and 0 otherwise. $X_{2004,i}$ refers to bank level controls interacted with the post period dummy variable. Controls include the following bank level variables: total assets in 2004, share of metropolitan deposits to total deposits in 2004, and indicator variable for state or private ownership. District fixed effects are included as indicated. The data are annual and cover 26 Indian commercial banks from 1999 to 2016 in an unbalanced panel. Standard errors are clustered at the district level.

$$\Delta\text{Log}(\text{Infra}_{2007-2004,id}) = \alpha_d + \beta \times \mathbb{1}\{\text{High Expense Beta}_{2004,i}\} + \epsilon_{id}$$

	1	2	3
High Expense Beta_{2004}	-0.259^{***}	-0.218^{**}	-0.179^{**}
	(0.086)	(0.090)	(0.091)
Controls	No	No	Yes
District FE	No	Yes	Yes
Observations	1903	1903	1903
No. of districts	378	378	378
No. of banks	26	26	26
R^2	0.005	0.204	0.215

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Banking Catch-22: Trading off Mark-to-Market and Default Risk in the presence of Guaranteed Deposits

Online Appendix

A Bank interest rate risk hedging in India

We seek to explore whether the lending behaviour of Indian banks is linked to their deposit franchise through the incentive to hedge against interest rate risk. Figure A1 shows that the average net interest margins and return on assets of Indian banks were indeed quite stable in the face of significant RBI Repo rate movements, implying that banks may be matching the Repo rate sensitivities of their interest income and interest expenses. In this section, we formally test for this by using the 'cash flow approach'. In this approach, we estimate the impact of changes in the RBI Repo rate on banks' interest income, interest expenses, and return on assets (ROA). The intuition behind this is straightforward: if a bank is unhedged against interest rate risk due to, for instance, floating rate assets and fixed rate liabilities, a decrease in the RBI Repo rate should result in a corresponding decrease in the interest income with the interest expenses remaining unchanged. Relatedly, such an unhedged bank's ROA should display a higher sensitivity to changes in the interest rate, given that interest income and interest expenses are important components in the calculation of ROA[7]. Therefore, measures of the sensitivity of a banks' interest income and interest expense to the RBI Repo rate should serve as useful indicators of the extent to which a bank is hedged against interest rate risk. The interest rate sensitivity of banks is estimated using Equation 1.

where $\Delta IntExp_{i,t}$ is the change in bank i's interest expense rate from t-1 to t, $\Delta RepoRate_t$ is the change in the RBI Repo rate from t-1 to t, and α_i are bank fixed effects. The interest expense rate measures the total quarterly interest expenses (total interest expenses on deposits, wholesale funding, and other liabilities) divided by quarterly average assets and then annualized (multiplied by four). We allow for three lags of the RBI Repo rate changes to capture the cumulative effect of

[7]Note that return on assets is calculated as the sum of net interest margin and fee income net of operating costs and loan losses

the RBI Repo rate changes over a full year. The estimate for bank i's expense beta is then the sum of the coefficients in the above regression, i.e. $\sum_{\tau=0}^{3} \beta_{i,\tau}$. Using the above regression specification, we also obtain the interest income and ROA betas, thus deriving the three estimates used in the subsequent analysis: β_i^{Inc}, β_i^{Exp}, β_i^{ROA}.

A.1 Summary statistics

Table A1 provides the summary statistics on interest income beta, interest expense beta, and ROA beta for the full sample and separately for public and private sector banks. The average expense and income beta are 0.568 and 0.559, meaning that interest expense and interest income increase by 57 bps and 56 bps, respectively, for every 100 bps increase in the RBI Repo rate. Public sector banks are characterised by expense and income betas of 0.532 and 0.541 whereas private sector banks show a similar difference in magnitudes of expense and income betas, which are 0.614 and 0.606, respectively. These statistics seem to imply that even in the relative scarcity of explicit hedging instruments, Indian banks are quite well hedged against interest rate risks. Relative to the results in Drechsler et al. (2021), the ROA beta is of a higher magnitude, 0.133 as opposed to 0.032, implying that banks in India are less hedged relative to the US.

A.2 Cross-sectional Analysis

To begin with, we conduct an informal cross-sectional test of the extent to which banks match interest sensitivities of their income and expenses.

Figure A2 provides a binned scatter plot to show the extent of sensitivity matching. It groups banks into 20 bins by expense beta and plots the average income beta for each bin. We find strong matching between banks' interest income and expense betas. Ordinary least squares regression of interest income beta on interest expense beta yields a coefficient of 0.741 for the sample.

Figure A3 supports the above evidence by showing that interest rate sensitivity of banks' return on assets is largely unrelated to that of interest expenses. Additionally, as also evidenced in the summary statistics, the values of ROA betas are much smaller than those for interest income and expense betas, implying that income and expense sensitivity matching shields the banks' profitability from interest rate changes.

A.3 Panel analysis

In this section, we use a panel regression to test the extent to which banks match interest sensitivity of their income and expenses. As highlighted by DSS, the panel setup imposes a more stringent test of sensitivity matching relative to cross-sectional regressions of interest income beta on interest expense beta, because the panel setup tests whether banks match sensitivities lag by lag, instead of an average across all four lags. We run the following two-stage regressions to derive the extent of sensitivity matching:

$$\text{First stage: } \Delta\text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta\text{RepoRate}_{t-\tau} + \epsilon_{i,t}$$

$$\text{Second stage: } \Delta\text{IntInc}_{i,t} = \lambda_i + \theta_t + \delta \Delta\widehat{IntExp}_{i,t} + \epsilon_{i,t} \tag{14}$$

The first stage is based on the original regression specification (eq. 1) for deriving the expense betas. In the second stage, we run a panel regression of interest income on the fitted value of interest expense beta from the first stage, controlling for individual and time fixed effects. The coefficient δ measures the extent to which changes in interest expenses induced by changes in the RBI Repo rate are matched by changes in the interest income. A value of δ close to one corresponds to a bank hedged against interest rate risk, since any variation in interest expenses due to a change in interest rate is perfectly compensated by a similar change in the interest income.

Since the betas are themselves estimated, there is a need to correct the standard errors. As in Drechsler et al. (2021), we address this issue by using block bootstrap, wherein the data are sampled in blocks to give the same correlation structure as in the original data. Taking a block to be the cross-section of banks in a given quarter enables us to capture the cross sectional correlation within a quarter. We estimate the betas and the beta matching regression for each of these samples and compute the distribution of coefficients to construct the standard errors.

Table A2 presents the panel regression results. We obtain a coefficient estimate of 0.996. This implies that a 100 bps increase in interest expenses induced by a change in RBI Repo rate is associated with a 99.6 bps increase in the interest income. Therefore, these results indicate that banks in India manage interest rate sensitivities on the asset and liability sides to ensure their Net Interest

Margins and Return on Assets is protected. Note that unlike the Drechsler et al. (2021) analysis where there is only interest rate risk, and can therefore always hedge themselves fully against this risk, banks in emerging economies such as India may face incomplete asset markets whereby hedging against interest rate risk comes at the cost of default risk. Given this context, strong hedging against interest rate risk by banks is a notable result.

Finally, Table A3 computes a similar two stage panel regression, with change in the return of assets of firm i from t-1 to t used as the dependent variable as follows:

$$\text{First stage: } \Delta\text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta\text{RepoRate}_{t-\tau} + \epsilon_{i,t}$$
$$\text{Second stage: } \Delta\text{ROA}_{i,t} = \lambda_i + \theta_t + \delta\Delta\widehat{IntExp}_{i,t} + \epsilon_{i,t} \tag{15}$$

As expected, changes in interest expenses on account of changes in the RBI Repo rate have no significant effect on the firm profitability implying hedging of interest rate risk.

Figure A1
Aggregate time series

The figure below shows the aggregate time series of central bank repo rate (CB Rate), net interest margin (NIM) and return on assets (ROA). The data are annual from CMIE Prowess, 2002 to 2020 (because Repo rate used as a monetary policy instrument since 2002). Net interest margin is calculated as the difference between interest income and interest expense divided by total assets. Return on assets is calculated as the sum of net interest margin and fee income net of operating costs and loan losses.

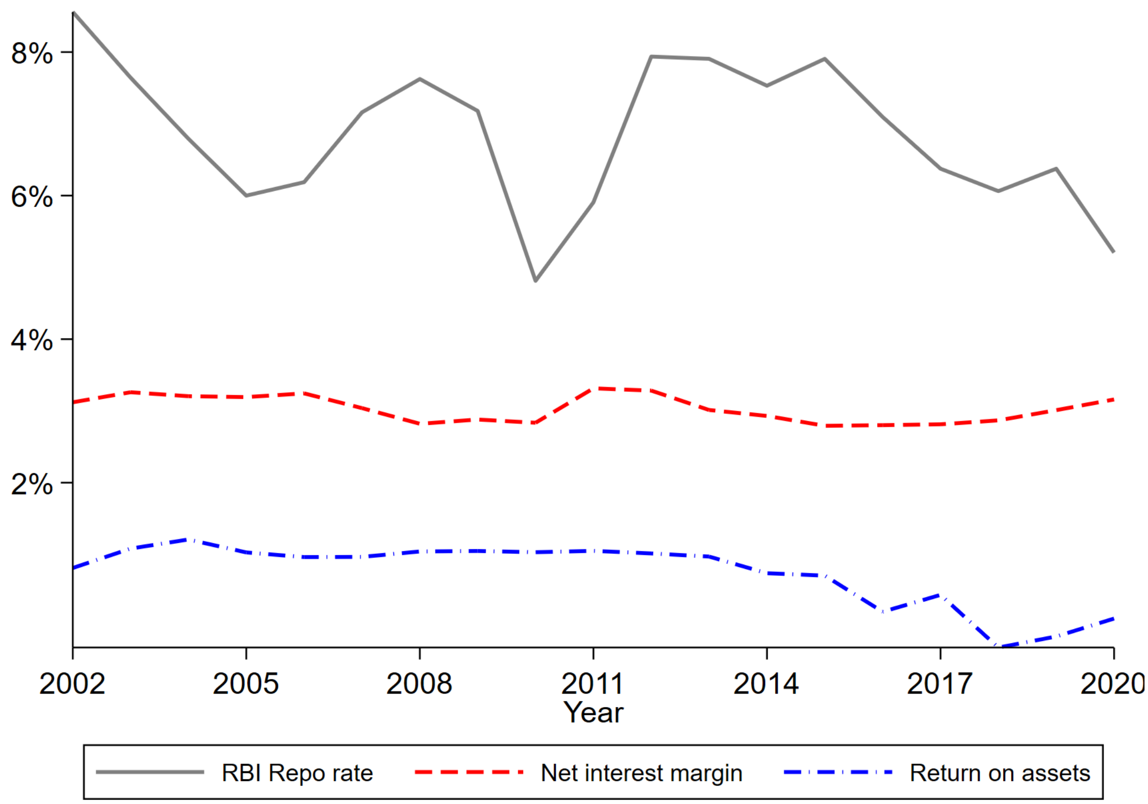
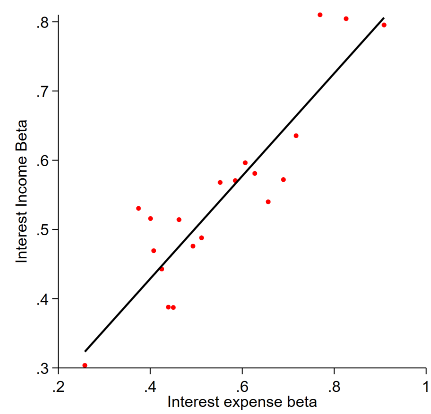


Figure A2
Interest income and interest expense matching

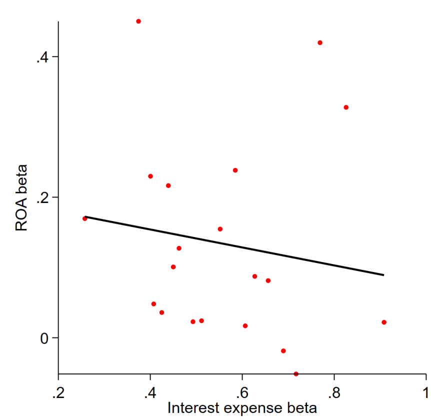
The figure below shows bin scatter plots of interest expense and interest income betas for all banks with at least 30 quarterly observations. The betas are calculated by regressing the quarterly change in each bank's interest expense rate, interest income rate on the contemporaneous and previous three changes in the RBI Repo rate. The bin scatter plot groups banks into 20 bins by interest expense beta and plots the average income beta within each bin. The sample consists of 43 banks from 2002 to 2016 (because Repo rate used as a monetary policy instrument since 2002). The data are sourced from Banking Statistical Returns (RBI) and CMIE Prowess.



Coefficient 0.741; Standard error 0.110

Figure A3
Return on assets and interest expense matching

The figure below shows bin scatter plots of interest expense and ROA betas for all banks with at least 30 quarterly observations. The interest expense betas are calculated by regressing the quarterly change in each bank's interest expense rate, interest income rate on the contemporaneous and previous three changes in the RBI Repo rate. The bin scatter plot groups banks into 20 bins by interest expense beta and plots the average ROA beta within each bin. The sample consists of 43 banks from 2002 to 2016 (because Repo rate used as a monetary policy instrument since 2002). The data are sourced from Banking Statistical Returns (RBI) and CMIE Prowess.



Coefficient -0.128; Standard error 0.188

Table A1
Summary Statistics

The table below provides summary statistics on bank characteristics. It displays the sample mean coupled with standard deviation (in parenthesis) for each variable. The sample consists of Indian commercial banks with at least 30 quarterly observations from 2002 to 2016 (43 banks). Interest expense betas are calculated by regressing the change in a bank's interest expense rate on the contemporaneous and three previous quarterly changes in the RBI repo rate and summing up the coefficients (see equation (1)). Interest income betas are calculated analogously. Column (1), (2) and (3) report the results for all banks, public sector banks and private sector banks respectively. TFE refers to time fixed effects.

	(1)	(2)	(3)
	All banks	Public Sector Banks	Private Sector Banks
Expense Beta (TFE)	0.5679	0.5317	0.6135
	(0.178)	(0.157)	(0.206)
Income Beta (TFE)	0.5587	0.5414	0.6058
	(0.180)	(0.142)	(0.238)
ROA Beta (TFE)	0.1337	0.1279	0.1547
	(0.197)	(0.153)	(0.278)
Expense Beta (No TFE)	0.5757	0.5391	0.6197
	(0.206)	(0.217)	(0.176)
Income Beta (No TFE)	0.5650	0.5467	0.6123
	(0.210)	(0.208)	(0.217)
ROA Beta (No TFE)	0.1388	0.1348	0.1602
	(0.205)	(0.171)	(0.275)
Asset repricing maturity	3.1946	3.4157	2.8767
	(0.480)	(0.317)	(0.492)
Liability repricing maturity	2.1186	2.3926	1.7385
	(0.884)	(0.949)	(0.568)
Log avg. assets	13.5554	13.9621	12.8948
	(1.091)	(0.795)	(1.280)
Loan/Assets	0.6545	0.6588	0.6450
	(0.0360)	(0.0271)	(0.0501)
Securities/Assets	0.3455	0.3412	0.3550
	(0.0360)	(0.0271)	(0.0501)
Deposits/Assets	0.9432	0.9584	0.9197
	(0.0857)	(0.0563)	(0.125)
IFR ratio 2005	0.0288	0.0117	0.0082
	(0.115)	(0.00383)	(0.00309)
Long-term investment ratio 2005	0.2294	0.2617	0.1774
	(0.0986)	(0.0719)	(0.123)
Observations	43	28	15

Table A2
Interest sensitivity matching: Panel estimation

The table below provides estimates of the matching of interest income and interest expense sensitivities to changes in the RBI Repo rate for equation 14. The dependent variable in the second stage regression is the change in the interest income rate (interest income divided by assets) from quarter t-1 to t and $\Delta IntExp_{i,t}$ is the change in the interest expense rate of bank i from t-1 to t. $\widehat{IntExp}_{i,t}$ is the predicted value of change in interest expense rate from the first stage regression. ΔRepo Rate is the change in the RBI Repo rate from one quarter to the next. Bank and quarter fixed effects are included as indicated. The data are quarterly and cover 48 Indian commercial banks from 2002 to 2016 (because Repo rate used as a monetary policy instrument since 2002). In subsequent results for the main analysis, 5 banks are thrown out due to missing values of investment fluctuation reserves. These results remain robust to using the sample of 43 banks as well. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

$$\text{First stage: } \Delta\text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta \text{ Repo Rate}_{t-\tau} + \epsilon_{i,t}$$

$$\text{Second stage: } \Delta \text{ IntInc}_{i,t} = \lambda_i + \theta_t + \delta \Delta \widehat{\text{IntExp}}_{i,t} + \epsilon_{i,t}$$

	All banks		Public Sector Banks		Private Sector Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widehat{IntExp}$	0.996***	0.902***	1.132**	0.964**	0.861***	0.825***
	(0.122)	(0.075)	(0.235)	(0.102)	(0.113)	(0.071)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Obs.	2,053	2,053	1,330	1,330	723	723
No. of banks	48	48	30	30	18	18
R^2	0.130	0.563	0.149	0.619	0.116	0.574

Table A3
Interest expense and ROA matching: Panel estimation

The table below provides estimates of the matching of return of assets and interest expense sensitivities to changes in the RBI Repo rate for equation 15. The dependent variable in the second stage regression is the change in the return on assets from quarter t-1 to t and $\Delta IntExp_{i,t}$ is the change in the interest expense rate of bank i from t-1 to t. $\widehat{IntExp}_{i,t}$ is the predicted value of change in interest expense rate from the first stage regression. ΔRepo Rate is the change in the RBI Repo rate from one quarter to the next. Bank and quarter fixed effects are included as indicated. The data are quarterly and cover 48 Indian commercial banks from 2002 to 2016 (because Repo rate used as a monetary policy instrument since 2002). In subsequent results for the main analysis, 5 banks are thrown out due to missing values of investment fluctuation reserves. These results remain robust to using the sample of 43 banks as well. Standard errors are block-bootstrapped by quarter with 1,000 iterations.

$$\text{First stage: } \Delta\ \text{IntExp}_{i,t} = \alpha_i + \delta_t + \sum_{\tau=0}^{3} \beta_{i,\tau} \Delta\text{RepoRate}_{t-\tau} + \epsilon_{i,t}$$

$$\text{Second stage: } \Delta\text{ROA}_{i,t} = \lambda_i + \theta_t + \delta\Delta\widehat{\text{IntExp}}_{i,t} + \epsilon_{i,t}$$

	All banks		Public Sector Banks		Private Sector Banks	
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\widehat{IntExp}$	−0.468	−0.428	−0.087	−0.237	−0.645	−0.330
	(0.596)	(0.530)	(0.170)	(0.188)	(1.037)	(0.746)
$\sum \gamma_\tau$	0.404		0.191*		0.555	
	(0.338)		(0.106)		(0.665)	
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes
Obs.	2,052	2,052	1,330	1,330	722	722
No. of banks	48	48	30	30	18	18
R^2	0.028	0.087	0.035	0.183	0.033	0.078