# How Does Bank Lending To Non-Banks Affect Credit Allocation And Systemic Risk *

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**Abstract**

Using loan-level administrative data and a regulatory shock that induced some banks to redirect lending from non-financial firms to Non-Bank Financial Institutions (NBFIs), we find that firms dependent on such banks witness a contraction in total borrowing and experience worse real outcomes. NBFIs use additional bank lending to make new loans, increasing lender competition and causing reallocation of credit towards smaller, younger, and riskier firms. Overall, this reallocation of capital is efficient. Additionally, we exploit the unexpected failure of a large NBFI to show that idiosyncratic shocks in the NBFI sector can spread via bank-NBFI connections, reducing credit availability across the economy. Our findings highlight the tradeoffs associated with bank-NBFI connections, underscoring the importance of transparency in these linkages.

**Keywords:** Financial Intermediation, Non-Banks, Capital Regulation, Systemic Risk

**JEL Classification:** E58, G21, G23, G28, G32

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# I Introduction

> "Given the increasing importance of non-bank financial companies in the financial system, the increasing interconnectedness between banks and non-banks merits close attention. ... Needless to state that such concentrated linkages may create a contagion risk." – Shaktikanta Das (Governor, Reserve Bank of India)[1]

Banks have played an important role in the growth of non-bank financial intermediaries (NBFIs). In the U.S., bank lending to NBFIs recently surpassed $1 trillion, paralleling similar rise in Europe and other emerging markets. Banks' increasing exposure to the NBFI sector is concerning because it may enable banks to shift credit away from creditworthy borrowers. Furthermore, bank-NBFI connections may increase systemic risk in the economy whereby stresses in the opaque NBFI sector can spill over to other firms via bank balance sheets. Bank regulators worldwide have acknowledged these concerns and have cited lack of transparent data as an impediment to addressing them.[2] We ask two questions in this paper. First, how does banks' lending to NBFIs affect credit allocation in the economy? Second, do banks transmit idiosyncratic shocks of the NBFI sector to unrelated non-financial firms?

We answer these questions using administrative loan-level data on banks and NBFIs in India. To answer the first question, we exploit a regulatory change where the Reserve Bank of India reduced risk weights on certain types of NBFIs. We find that banks responded by shifting their lending activity from non-financial firms towards policy-favored NBFIs. Unable to find new lenders, these firms suffered a decline in total borrowing and adverse real outcomes. On the flip side, NBFIs that benefited from the policy channeled additional bank lending towards their own borrowers. Overall, the policy led to increased lender competition and credit reallocation towards smaller, younger, and riskier firms.

Then, we answer the second question by examining the unexpected failure of a large NBFI and by showing that banks connected to that NBFI reduced lending to their unrelated corporate borrowers. Once again, these borrowers suffer in terms of credit availability and exhibit worse real outcomes. Such banks also reduce lending to unrelated NBFIs, who in turn, respond by shrinking their own lending activity. This leads to an amplified contraction in credit supply. Overall, our findings suggest that bank-NBFI nexus exposes bank-dependent borrowers to two risks – crowding out when their banks increase lending to NBFIs ("substitution risk") and exposure to shocks in the non-bank sector through interconnected banks

[1] See link.

[2] Both U.S. and Europe have proposed rules requiring banks to disclose their investments into non-bank entities so that they can be regulated if required.

("contagion risk").

Our data comes from the register of secured credit maintained by the Registrar of Companies (RoC) under the Ministry of Corporate Affairs in India. Both borrowers and lenders must report the loans to the RoC within 30 days of originating it. Lenders have strong incentives to report all the loans, as any unreported loan is treated as unsecured in the event of liquidation. Furthermore, if a lender fails to register a loan, the borrower can take another loan using the same collateral voiding the claim of the first lender. These institutional features ensure that our data contains the near universe of secured credit in India as is accurately reported.

Indian banks give a large share of credit to NBFIs. The fraction of bank credit to NBFIs grew from near zero in 2002 to 14% in 2022. The NBFIs, in turn, give loans to non-financial firms. Thus, both banks and NBFIs have loan assets and earn interest income on them. However, since NBFIs are not allowed to raise deposit funding, they are either unregulated or lightly-regulated. Thus, regulators have little insight or control over how NBFIs choose the firms they lend to. This presents a regulatory arbitrage opportunity where banks can indirectly lend to sectors where regulators don't allow them to lend directly.

The Reserve Bank of India (RBI), citing a need for counter-cyclical policy in the face of high credit growth in certain sectors, lowered the risk weights for banks' exposure to the NBFI sector. Specifically, the risk weight on NBFIs rated BBB and above was lowered from 125% to 100%, and that on NBFIs rated below BBB was lowered from 150% to 100%. Notably, the change only applied to the NBFIs having assets over the threshold of INR 1,000 Million (denoted as systemically important or NBFC-SI). The smaller NBFIs and non-financial firms did not experience any change in their risk weights.[3] We exploit the exogenous decrease in the banks' cost of lending to NBFIs to study how bank-NBFI connections form and how they affect bank borrowers.

First, we use aggregated loan-level data at the borrower-lender-year level to show that banks responded to the policy change by shifting their lending activity towards NBFIs benefiting from the change in risk weights. Specifically, we use difference-in-difference analysis to show that in the 5-year period following the policy change in 2009, bank lending to NBFI relative to NBFC-Non-SI and non-financial firms increased by 4.3 p.p. (or 42% relative to the sample mean). We use lender×year fixed effects to get within-bank estimate of the policy response. Furthermore, we employ borrower×lender and borrower-characteristics×year fixed effects to ensure that endogenous matching and borrower characteristics (size, age, and

[3]We use firms and corporates interchangeably throughout the text. Similarly, we use NBFI and NBFC-SI interchangeably throughout the text. In case of NBFC-Non-SI, we mention them explicitly as such.

rating) are not driving our results.

We then address the concern that NBFI borrowers may have different trajectories compared to other borrowers using three robustness tests. First, event study estimates show the lack of pre-trends and also show that banks' response coincided with the policy shock and was persistent. Next, we find that the banks increased lending only to NBFIs above the INR 1 Trillion policy cutoff and not to those below it, supporting the notion that risk-weight reduction lead to bank response. Finally, we use a triple-difference specification to show that banks with lower capital adequacy ratio (CAR) responded more strongly, which is expected since such capital constrained banks are more likely to respond to easing of capital regulations. The triple-difference specification is useful since it allows us to employ borrower×year fixed effects to address the concern that our results are driven by unobservable borrower-level differences between NBFI and other borrowers of the bank. Overall, our findings indicate that banks responded to the risk-weight change by tilting their lending activity towards NBFIs.

We then examine what types of banks, in terms of their ex-ante exposure to the NBFI sector, respond more strongly to the policy change. Theoretically, it is ambiguous which banks will respond more aggressively. Banks with no NBFI exposure may decide to continue that way if they do not have the skill to lend to the NBFI sector. On the other hand, banks with high levels of NBFI exposure may also lack response if there is some upper limit on the desired level of NBFI exposure. Consistent with the latter conjecture, we find that banks with low ex-ante exposure to NBFIs respond more aggressively by cutting their lending activity to firms and diverting it to NBFIs. In other words, we find that the policy shock induced banks there were previously focusing solely on firms to switch towards NBFIs.

Next, we examine firms that were the pre-existing borrowers of such "aggressively-switching banks". We find that these firms experience a decline in bank borrowing which is not compensated by getting more loans from other banks or NBFIs. Consequently, such firms experience lower asset growth, sales growth, and profitability. These results suggest that, in the presence of switching frictions between borrowers and lenders, bank lending to the NBFI sector can come at the cost to their non-financial borrowers. We term this risk of bank substituting their traditional borrowers for NBFI lending as "substitution risk".

Next, we shed light on how the lending behavior of NBFIs is likely determined by the infusion of bank funding. If NBFIs use additional bank loans merely to reduce reliance on other less desirable financing sources (e.g., debentures, commercial papers, etc.), there would be no impact on the size of NBFIs loan-book. Absent any change in NBFIs' lending behavior, the regulation would induce a surplus transfer from banks' corporate borrowers towards NBFIs in form of lower cost of debt capital. On the other hand, NBFIs may deploy

the proceeds from bank towards making new loans. In this case, NBFIs would respond by increasing their lending activity. We examine the overall lending by NBFIs and find that they indeed increase lending to firms, both relative to banks as well as on absolute basis. We also find that NBFIs increase lending to NBFC-Non-SI (relative to banks), indicating that the policy change increased the average length of intermediation chain and associated opaqueness of the lending lending ecosystem.

Bank-NBFI connections have also potential benefits in terms of liquidity transformation. For NBFIs, bank loans can provide long-term stable financing relative to their alternative source of financing (e.g., short-term commercial paper). This can mitigate duration mismatch problem for them as they typically make illiquid loans. In other words, greater bank financing after the policy change may enable NBFIs to make bigger and longer-maturity loans to their borrowers. We find that the size and maturity of NBFI-loans increased after the policy was implemented relative to bank-loans, even after controlling for unobservable borrower-level factors. Thus, bank-NBFI connections can provide funding stability to NBFIs indirectly benefiting their borrowing firms.

Additional bank lending may also impact the quality of loans originated by the NBFIs. First, NBFIs may specialize in borrowers with weaker balance sheets who traditionally lack access to bank finance. Second, additional bank debt might increase overall leverage and risk-shifting incentives for NBFIs, tilting their portfolio towards a riskier set of borrowers (Jensen and Meckling (1976)). On the flip side, greater involvement of banks might increase monitoring of NBFIs lending activity, forcing them to switch towards safer and better quality borrowers (Diamond (1984)). We find that after the policy change, NBFIs direct lending primarily towards smaller, younger, and lower rated firms. These results suggest that bank-NBFI connections enable flow of bank credit towards firms with weaker balance sheets.

How NBFIs direct bank lending also has implications for lender competition. Several papers show that non-banks differentiate from banks through the use of technology and may complement or substitute bank lending in the economy (Gopal and Schnabl (2022)). We find that NBFIs increase their lending towards firms that are more bank dependent, implying that they increase lender competition for such firms. At a more aggregate level, we also find that they tilt their lending towards districts with more bank presence, implying an increase in regional lender competition.

While NBFIs may eat up the share of bank lenders, whether they increase aggregate credit supply depends on the overlap between bank borrowers and NBFI borrowers. An NBFI may recycle the debt it receives from a bank by lending to the borrowers that would have otherwise received loans from the same bank. This is plausible since banks may transmit

private information about their borrower base to the NBFIs they lend to. Such recycling would leave the overall credit availability unaffected by the policy change. On the other hand, NBFIs may strategically lower their asset commonality with their bank lenders in order to minimize correlation between their health and the health of their lenders. Finally, bank may not want to lend more the NBFIs that would compete with them, ex-post. We find that unlike their tilt towards bank dependent firms, NBFIs seem to avoid targeting firms that are related to their own bank lender. These results are consistent with the idea that NBFIs and their bank lenders find it beneficial to not compete for the same set of firms. A positive implication is less systemic risk arising out of asset commonality problems. Consistently, we find that NBFIs also stay away from regions that their lender banks dominate in. Although, we find that they lend more to industries served by their banks, consistent with the idea of information sharing between banks and NBFIs.

Finally, we evaluate the aggregate effects of the credit reallocation driven by the policy change. Industries more exposed to the "aggressively-switching banks" show a decline in the dispersion of marginal productivity of capital, indicating improved within-industry capital allocation (Hsieh and Klenow (2009)). To quantify these effects relative to a counterfactual without the policy, we use the methodology of Sraer and Thesmar (2023), which measures the policy's impact on allocative efficiency by analyzing the distribution of marginal productivity of capital at the industry level. Our results show that the reduction in risk weights increased aggregate productivity by 9.4%, driven primarily by more efficient within-industry credit allocation. This productivity gain also led to an increase in aggregate economic output.

We then proceed to the next part of our analysis which highlights the systemic risk arising due to bank-NBFI connections. Some of the systemic risk concerns that regulators have expressed have started to materialize. A notable example is the 2024 bankruptcy of First Credit, a fintech company, which forced First & Peoples Bank, a local bank in Kentucky, to write off approximately $18 million in loans. This financial strain led the FDIC and Kentucky's Department of Financial Institutions to impose a consent order on the bank. The incident further underscores the risks associated with the opaque relationships between banks and non-banking financial institutions (NBFIs). Among the measures ordered by regulators, First & Peoples was required to identify the borrowers that its associated fintech companies were lending to — a detail the bank reportedly had not been aware of.[4]

To explore the systemic risk arising from bank-NBFI linkages, we study the unexpected and precipitous downfall of a large NBFI in India called the Infrastructure Leasing & Financial Services (IL&FS) group. IL&FS was a large conglomerate that financed and implemented

[4]See FT article dated August 18, 2024.(link)

infrastructure projects across India. Facing construction delays, cost overruns, and corporate governance issues, the group defaulted on its loan and commercial paper obligations in September 2018. The default was plausibly unexpected, as IL&FS had the highest credit rating of AAA right before it defaulted.

We find that banks exposed to the IL&FS group companies responded to the crisis by cutting their lending to their non-IL&FS borrowers drastically. Specifically, we find that IL&FS-exposed banks reduced lending to their non-financial borrowers by 1.1 p.p. (or 14%). To address the concern that stress in certain industries may jointly affect IL&FS default and lower firm demand for loans, we exclude all firms that operate in the same industry as any of the IL&FS group companies. Unable to find alternative lenders, these firms experienced a decline in overall borrowing along with lower asset growth, sales growth, leverage, and profitability. Overall, these results show that lending practices of the lightly-regulated NBFIs can adversely affect the borrowers of banks funding such non-bank lenders.

Finally, we document an amplification effect that occurs when the contagion risk originates from idiosyncratic shocks to NBFIs instead of those to non-financial firms. In the aftermath of the IL&FS crisis, doubts were raised about the quality of loans originated by even the non-IL&FS NBFIs. We find that banks exposed to IL&FS reduced lending to their unrelated NBFI borrowers by 5.8 p.p. (or 48%). Since these NBFIs have their own borrower base, they pass on the negative credit supply shock to those borrowers. In particular, we show that corporate borrowers of the NBFCs which in turn borrow from banks exposed to IL&FS default also suffer a significant decline in credit supply, with economic magnitude comparable with decline experienced by corporate borrowers directly borrowing from the affected banks. These second round contagion effects are a unique feature of the setting where idiosyncratic shocks originate from the NBFI sector and are likely to be crucial in economies with significant bank-NBFI linkages.

Our paper is related to the large literature on shadow banks (see Adrian et al. (2018) for review). The shadow banking sector has seen a rapid growth over the past two decades. The growth has been driven by technological advancements (Buchak et al. (2018)), bank regulations (Irani et al. (2021)), demand for covenant-lite loans and synergies between bank and non-bank debt (Chernenko et al. (2022); Haque et al. (2024)), and institutional investors' demand for high yielding securities (Bhardwaj et al. (2022)). Alternatively, higher capital requirements may require banks to curtail lending, with the unmet demand being met by non-banks (Gopal and Schnabl (2022); Lee et al. (2023)). Regulatory arbitrage can incentivize banks to gain exposure to highly-rated shadow banks, that in turn, finance lower-rated entities (Plantin (2015); Acharya et al. (2013)). We show that bank regulations specifically targeting

the NBFI sector can deepen the bank-NBFI connections by directly inducing banks to lend to NBFIs. We also show that such connections expose banks to the risks taken by NBFIs and present systemic risk implications for the entire economy.

Second, our paper speaks to the vast literature on bank capital regulation. Capital requirements mitigate moral hazard in the presence of public safety nets provided to banks (Merton (1977)). Under Basel-II, these requirements were linked to asset risk and several papers discuss the pros-and-cons of such model-based regulation (Kashyap et al. (2004); Repullo and Suarez (2013); Behn et al. (2016)). A related literature studies capital regulation in presence of a shadow banking sector (Farhi and Tirole (2021); Begenau and Landvoigt (2022); Buchak et al. (2024)).Separate from these papers, we study a capital regulation model that features differential treatment for equally-rated non-financial firms and NBFIs. Several policy makers have argued against the "one-size-fits-all" model of capital regulation and have advocated for a special treatment for NBFIs. Our papers sheds lights on some of the tradeoffs involved in designing capital regulations targeted towards the NBFI sector.

Third, our paper is related to the literature on financial contagion and network linkages (Brunnermeier (2009)). The connections between intermediaries can transmit idiosyncratic shocks of one borrower to another via interconnected banks (Allen and Gale (2000); Gennaioli et al. (2013); Elliott et al. (2014)). In general, intermediation chains, where capital flows from households to firms via multiple intermediaries, can drastically affect credit availability and systemic risk (Adrian and Shin (2010); Donaldson and Micheler (2018)). We study networks between banks and NBFIs which have been a key focus of regulators because of the opaque structure of NBFI entities. We show that such networks adversely affect non-financial firms borrowing from the banks lending to NBFIs. Additionally, we document an indirect contagion effect which spreads to the firms who borrow from NBFIs who, in turn, rely on such banks. Through the lens of the IL&FS episode, our study also highlights a novel channel (bank-NBFI connections) through which stresses in the real-estate sector can spillover to the corporate sector.

The papers closest to ours are Jiang (2023) and Acharya et al. (2024), which also study non-banks that are financed by traditional banks. However, these two papers focus on the mortgage market and commercial real estate market, respectively. In contrast, we focus on the corporate borrowers and show the effect of bank-NBFI connections on credit allocation and real outcomes of non-financial firms. Furthermore, we focus on systemic risk arising from the NBFI sector and spreading to non-financial firms via bank balance sheets, which is not the focus of Jiang (2023) or Acharya et al. (2024).

# II Background

## A NBFI Background in India

Non-Bank Financial Institutions (NBFIs) or more popularly called in India as Non-Bank Finance Companies (NBFCs) emerged in India in 1960's and were initial regulated under Companies Act. However, due to the growth in the number of NBFIs, the chit fund frauds in 1970's, and the growing complexity of the lending ecosystem, the NBFI sector was brought under the Reserve Bank of India's regulatory control starting from early 1990's. In particular, the RBI Act 1934 was amended to include Chapters III to specifically put the regulatory structure in place for NBFIs. The term NBFI was defined formally under the RBI Act 1934 for the first time in 1997, and all the NBFI were required to register themselves with RBI. An implication of this regulatory overhaul of 1997-98 was that the number of NBFIs dropped from 51, 929 in 1996 to mere 7,855 in 1999. In 2008, right before the policy enactment on risk-weight reduction, there were 12,809 NBFIs registered with RBI.

RBI classifies the NBFIs into various types depending upon whether they accept public deposits (deposit taking NBFC) or not (non-deposit taking NBFC or NBFC-ND). It also classifies them by the area of operation - Asset Finance Companies (AFC) which primarily invests in physical assets, Investment Companies (IC) which invests in securities, Housing Finance Companies (HFC), Infrastructure Finance Companies (IFC), Loan Companies (LC), Micro Finance Institutions (NBFC-MFI), and so on. The 2006 regulation defined the "systemically important" NBFCs (NBFC-SI) to mean the NBFC with assets above 1 billion INR at the end of the previous financial year. The NBFC-ND-SI (Systemically important, Non-Deposit Taking NBFC) were subjected to Capital to Risk-weighted Assets Ratio (CRAR) of 10%, which was further enhanced to 12% in 2010, and 15% in 2011. NBFC-ND-SI were also subjected to the limits on exposure to single-entity to limit the systemic risk. With the capital adequacy ratios in place, RBI felt more comfortable for banks to have direct exposure to NBFC-ND-SI segment. With the additional purpose of providing these systemically important NBFCs with relatively stable funding to limit the systemic risk in the financial markets, RBI reduced the risk-weights applicable for banks on loans to NBFC-ND-SI segment of NBFI sector.

RBI has been more aggressive than other central banks and regulators in regulating the NBFI sector. In 2021 it adopted the scale-based regulation subjecting larger NBFIs to more stringent liquidity and capital adequacy provisions. More recently, RBI increased the risk-weights on consumer loans, including those issued by NBFIs, to curb the household debt in

India. Out study shed light on one of the important policy changes in the history of ebb and flow of RBI regulations over the NBFI sector.

Now we shed some light on nature of NBFI financing and lending in India utilizing data from RBI's Report on Trend and Progress of Banking in India 2022-23[5] and RBI's Financial Stability Report 2024.[6]

**Nature of NBFI Lending in India:** Contrary to the perception that NBFIs specialize in unsecured credit, secured credit forms 69.5% of the NBFIs loan book in India as of March 2023. This is important for us as our credit register is that of secured loans. Some of the largest NBFIs in India focus exclusively on retail credit (durable goods credit, vehicle financing etc). Hence, there could be a concern whether industry credit as captured in our credit register contains meaningful fraction of aggregate NBFI lending. However, share of NBFI loans to industry (37%) dominate the share of NBFI loans going to retail segment (30%) as of March 2023, allaying such concerns.

**NBFI Liabilities:** Bank borrowings with 37.8% share of total borrowing and debentures with 36.1% share constitute the two largest and equally dominant sources of funding for Indian NBFI sector. Banks provide additional funding to NBFI by subscribing to the commercial papers, and even part of the debentures. In aggregate, 40.06% of NBFI financing comes from the commercial banks. The composition of NBFI financing has changed dramatically in India over time. For example in 2008 only 21.52% of total external financing was contributed by borrowings.[7] Assuming most of the NBFI borrowings are from banks, it is clear that banks have significantly expanded their footprint on the liability side of the NBFIs over past decade and half. The policy enactment of risk-weight reduction did contribute to accelerate the bank lending to NBFIs as our evidence suggests. In particular, the consolidated data from RBI reports over the years document the fall in the importance of commercial papers as a source of funding for NBFIs.

## B Risk Weight Change in 2009

Central banks in many countries follow "risk weight" based approach requiring banks to hold capital in proportion to the risk weight attached with each loan. Risk weights are used extensively both to limit risk taking by the financial institutions by attaching higher risk

[5]https://rbi.org.in/Scripts/AnnualPublications.aspx?head=Trend+and+Progress+of+Banking+in+India
[6]https://www.rbi.org.in/Scripts/PublicationReportDetails.aspx?UrlPage=ID=1162
[7]Decomposition of borrowings by banks is not available in 2008.

weights to the riskier categories of credit segments, as well as to promote or restrict credit flow to the specific sectors.

Reserve Bank of India (RBI) adopted the risk weight approach around 2004/05 in response to BASEL II norms. Risk weights attached to the corporate credit were governed by the credit rating obtained by the corporate borrower from the approved rating agency.[8] Recognizing the potential for systemic risk, RBI adopted a cautious approach and levied risk weights of 125% for NBFIs with credit rating above BB and 150% risk weights for unrated NBFIs or NBFIs with credit rating of BB or below. This meant that lending to better rated NBFIs was significantly more costly for banks in terms of capital requirements than lending to similarly rated non-financial corporate borrower. This kept the banks-NBFI connections under the check with banking credit to NBFI's being only 3.54% and 8.68% in October 2008 relative to the aggregate non-food credit, and aggregate credit to Industry respectively.

However in November 2008, RBI lowered the risk weights attached to the credit provided by banks to an important category of NBFIs, namely NBFC-ND-SI (NFBIs which are non-deposit taking and systemically important). Specifically, the risk weights for NBFC-ND-SI rated BBB and above was lowered from 125% to 100%, whereas that for NBFC-ND-SI rated below BBB (and unrated ones) was lowered from 150% to 100%.[9] NBFIs with asset size above INR 1000 Million (approximately $20 Million using October 2008 exchange rate) as per the latest audited financial statements were categorized as "Systemically Important" (SI) under the extant RBI guidelines as on the date of the circular.

The motivation offered by the RBI while enacting this policy change was as follows: "The aforesaid prudential requirements were prescribed in view of the continued high credit growth observed in specific sectors." Hence, the policy was not motivated by the capital or liquidity shocks within the NBFI sector. Figure 1 plots the risk weight attached to the loans to NBFI borrowers, and non-financial corporate borrowers, before and after the implementation of RBI policy. There was no change in the risk weight for non-financial firms as well as for NBFIs which were not categorized as systemically important. Notably, risk weights for NBFC-ND-SI category came down to 100% irrespective of the credit rating of the NBFI. The lower rated NBFIs received the maximum benefit of 50 basis points of reduction on the risk weight.

[8]For example, loans to AAA rated non-financial corporate borrower have always attracted 20% risk weight in India.

[9]The policy was announced via circular dated 15 November 2008 (RBI.No.2008-09/282) titled "Review of Prudential Norms – Provisioning for Standard Assets and Risk Weights for Exposures to Corporates, Commercial Real Estate and NBFC- ND-SI"

# III Data

We use variety of data sources in this paper. We describe them below.

## A Borrower-Lender Linkages

We use the universe of secured credit register in India maintained by the Registrar of Companies (RoC) under the aegis of the Ministry of Corporate Affairs (MCA) to understand the borrower-lender loan connections. Secured loans are known as "charges" under the Companies Act 2013. The data provides a unique charge identification number, the name of the company that is creating a charge (borrower), and charge-holder in whose favor the charge is being created (lender), the amount of the charge, the date of charge initiation (loan origination date), date of charge satisfaction (loan repayment date) if satisfied already, and a dummy indicating if any modification has been made to the charge over the charge's life. Unfortunately, we do not see the interest rate details or the details of assets pledged under the charge.

The legal framework in India ensures that our data is accurate and comprehensive. Specifically, Section 77 of The Companies Act 2013 mandates that all the borrowers creating a charge (i.e., taking a loan) must register such a charge with the RoC within thirty days of creating it. In some cases, RoC may extend the time limit to register the charges up to three sixty days. If a company still fails to register the charge, then the charge-holder (i.e., the lender) may apply to the RoC to register the charge. Section 79 further specifies that any modifications to the charge shall also need to be registered following the process and timelines as mentioned in Section 77.

The non-registration of a charge has two consequences under The Companies Act 2013. When a company enters the liquidation, the non-registered charge is *void against liquidator*, which means that a liquidator can ignore the secured charge and treat it at par with other unsecured creditors. A non-registered charge is also *void against any creditor*, which means that if a company creates a new charge using the same set of assets/collateral in favor of any other creditor and that new charge gets registered first, then the original charge is void, and would be considered as unsecured in the liquidation process. Given these provisions, non-registration of a charge is extremely costly for lenders, and because lenders have the ability to register the charge if the borrower fails to do so, it is unlikely that a secured charge is not recorded in the RoC's register of charges. This allows us to interpret the register as the near-universe of secured credit in India. The data has been used by an increasing set

of papers studying financial intermediation within India (see, for example, Kashyap et al. (2023)).

We construct an annual loan book for each borrower-lender pair showing the amount outstanding between each pair net of any repayments done till the date. A new loan between the pair is identified if the amount outstanding goes up from one year to the next.

## B Financial and Real Outcomes

We merge the credit register data with Prowess database which records the financial and accounting information for nearly 50,000 public and private Indian firms. Prowess includes both non-financial and financial firms. In particular it includes roughly 10,000 NBFIs which bodes well for our paper. In particular, the Prowess database records detailed information on firm's balance sheet items such as assets, fixed assets and its composition, bank and non-bank debt, equity etc. It also provides information relating to the revenues, costs, and profitability of a company, as well as details of credit rating. Prowess database has been used by multiple researchers earlier (Bertrand et al. (2002); Lilienfeld-Toal et al. (2012); Vig (2013)).

For each year, we observe multiple credit ratings on both short-term and long-term securities that are issued by various credit rating agencies in India. We pick the latest of all such ratings separately for short-term and long-term securities for every financial year which runs from April to March of next year. Using standard conversion practices, we assign a rating scale from 1 to 7 with 1 being lowest and 7 being the highest rating. Many firms have no rating for a given financial year. We mark them as Unrated and consider this to be the lowest rating category with numeric of 0.

We use other datasets from Reserve Bank of India (RBI) such as aggregate time series data on total Indian banking deposits and loans, as well as the master list of the NBFCs registered with RBI. We merge the RBI list of NBFCs closer to the risk-weight policy enactment and merge it with list of NBFCs as defined in Prowess. The intersection of the two provides us with our final list of NBFCs we consider in our analysis.

## C Summary Statistics

India, in line with rest of the world, has witnessed a substantial transformation of its credit ecosystem in the past two decades. We start summarizing our data by providing aggregate trends in secured credit across several dimensions. Figure 2 panel (a) shows the allocation of bank credit over the years. Bank credit outstanding has grown from INR 8 Trillion in 2002 to

INR 40 Trillion in 2022. Notably, while banks lent almost exclusively to corporate borrowers in 2002, the fraction of bank lending going to NBFIs reached 14% in 2022. Bank regulations, like the risk weight change of 2009, played a crucial role in redirecting bank credit towards NBFIs. Figure 2 panel (b) shows how lender composition of firms have evolved over the years. Aggregate borrowing by the corporate sector was INR 7 Trillion in 2002 and rose to INR 55 Trillion in 2022. While firms were extremely bank dependent in 2002, the fraction of corporate credit financed by NBFIs reached 35% in 2022. Overall, these results suggest that NBFIs have played an increasingly important role in credit allocation and are a substantial player in the economy.

Next, we provide summary statistics of key variables used in the analysis in Table 1. Panel (a) shows statistics at the loan level. The annual probability of a new loan in our sample is 10%. The average size of a typical loan is INR 363 Million and the average maturity is 5 years. Panel (b) provides statistics for firms. There are 23,979 unique firms in our sample. The average firm has INR 4.5 Billion in assets, is 21 years of age, and has a credit rating score of 0.51 (out of 5) on its long-term loans. Its sales is INR 2.8 Billion and leverage (debt/assets) is 42%. Its gross profitability, measured as EBITDA/Sales is 13% and the average return on assets is -19%. Borrower Exposure, a measure of firm's exposure to the 2009 policy change and formally defined in Section C.1, has an average value of 0.47. The average likelihood of a firm issuing at least one loan in a given year is 27%. The corresponding likelihood for a bank loan is 24% and for a NBFI loan is 6.5%. On average, a firm as INR 2 Billion in total borrowing. Out of the total outstanding credit, 9% is from NBFIs.

Panel (c) provides summary statistics for NBFIs. There are 1,207 total NBFI-SI in our sample. Out of these, 1,149 appear as borrowers and 181 appear as lenders. There are 123 NBFIs that appear as both borrowers and lenders. A typical NBFI has INR 84 Billion in total assets, is 22 years in age, and has a credit rating score of 3 (out of 5). Panel (d) provides summary statistics for banks. There are 146 banks in our sample. The average outstanding credit for a bank is INR 239 Billion. Out of this, 6.5% is allocated to NBFIs. The average fraction of credit allocation to NBFIs in 2008 (which serves as bank exposure to the policy shock) is 7.4%. The average capital adequacy ratio is 16%.

**Difference Between Bank-dependent and NBFI-dependent Borrowers** How do bank-dependent borrowers differ from those that borrow from NBFIs? To answer this question, we divide the nonfinancial firms in our sample into three groups. The first and the second group is firms whose outstanding credit comprises entirely of bank loans and NBFI loans, respectively. The third group is firms who borrow from both banks and NBFIs. In

2008 (i.e., year prior to the RBI policy change), bank-dependent firms and NBFI-dependent firms accounted for 16.8% and 9.2% of the total outstanding credit, respectively. A vast majority (74%) of outstanding credit belongs to firms who borrow from both sources.

We present key characteristics of the three group of firms in Table A1. Bank-dependent firms tend to be larger and older compared to NBFI-dependent firms. Banks appear to specialize in lending to firms with higher leverage and profitability. These findings on profitability align with Chernenko et al. (2022), who show that low-profitability firms in the U.S. rely predominantly on non-banks for credit. Firms with access to both banks and NBFIs are generally larger, older, more leveraged, and more profitable than those relying exclusively on either source.

# IV Results on Capital Allocation

## A Substitution of Credit Towards NBFIs

From the bank's perspective, NBFI lending became less costly than previously after the policy enactment, creating a strong incentive for the banks to substitute nonfinancial firms with NBFC-ND-SI borrowers (treated NBFIs). In this section, we document the evidence supporting this substitution. First, we begin by plotting the bank credit to the NBFI sector relative to the aggregate credit to the nonfinancial firms (Figure A1). The uptick in the lending to the NBFI sector is visible over the next two financial years after the policy enactment. The NBFI credit relative to industry increased from 8.45% before the policy enactment to 11.79% by mid-2011.[10]

Next, we leverage our rich loan-level data from the credit register to estimate the substitution more formally using standard differences-in-differences (DiD) methodology. In particular, we estimate the following model for the financial years 2004 to 2015 (i.e., five years before and after the policy change).

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Borrower}_{b,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{l,t} + \alpha_{X(b,2008),t} + \varepsilon_{b,l,t} \tag{1}$$

where $b$, $l$, and $t$ indexes the borrower, bank lender, and the financial year respectively.

[10]The aggregate data as published by the RBI does not distinguish between SI and non-SI NBFIs. However, 75% of the total credit to NBFI was accounted for by the NBFI-ND-SI category in our credit register. An important benefit of using published regulatory credit data is that it also covers unsecured credit, which is not covered by the credit registry maintained by the Ministry of Corporate Affairs.

$1(Loan)_{b,l,t}$ is a dummy which takes a value of one if a new loan originates between the lender $l$ and the borrower $b$ at time $t$. NBFI Borrower$_{b,2008}$ indicates that the borrower is a treated NBFI, and Post RW Change is a dummy which takes a value of one for financial years after the 2009 change in risk weights. The coefficient of interest $\beta$ estimates whether the probability that a bank originates a loan to a treated NBFI relative to the control borrowers differs significantly in the years following the policy enactment (relative to the years prior to the enactment). The substitution effect predicts a positive $\beta$.

We estimate the model using "within bank" variation in loan origination across treated and untreated borrowers (Jiménez et al. (2014)). In particular, our model includes the lender × time fixed effects ($\alpha_{l,t}$), so that we compare the loan origination by a *given lender* to the treated NBFIs relative to the control borrowers. This controls for any unobservable fluctuations in bank characteristics such as capital adequacy, bad loans, aggregate credit growth, or bank's risk taking preferences. Notably, it also controls for deposit flows to each bank, which is important as the deposit flight from public banks to private banks was an important way in which the financial crisis affected the Indian banking system (Acharya et al. (2023)).

We additionally control for the lender-borrower pair fixed effects ($\alpha_{b,l}$) which forces the comparison relative to the mean probability of loan origination between a given pair (Paligorova and Santos (2017)). We can not absorb borrower× time fixed effects as the treatment is at the borrower level. However our model includes rich set of ex-ante borrower characteristics × time fixed effects ($\alpha_{X(b,2008),t}$). In particular, we include ex-ante quintile-buckets of size × time, quintile-buckets of age × time, and credit rating category × time fixed effects thereby comparing the outcomes to the NBFIs and firms having similar size, age, and credit rating profile ex-ante.

Table 2 present the results. We begin by estimating a model without any fixed effects in column 1. We obtain $\beta$ of 0.046 which is statistically significant at 1% level and economically very large. This indicates that the difference in the annual probability of loan origination for the treated NBFIs relative to control borrowers (namely firms and NBFC-Non-SI) jumped by 4.6 pp. from the five year period prior to enacting the policy to the five year period after the policy enactment. Economically this is a 42% increase (relative to the mean probability of 10.2%) in the probability of loan origination to the treated NBFIs. The coefficient remains stable at 0.046 (column 2) and drops only marginally to 0.043 (column 3) even after saturating the model with varying level of fixed effects. In a nutshell, Table 2 documents that banks substituted the credit away from control borrowers (primarily nonfinancial firms) towards treated NBFIs in response to reduction in risk-weights by RBI.

### A.1 Robustness

Next, we address the concern that comparing the loan outcomes of NBFIs with a nonfinancial corporate borrowers, even within the similar ex-ante size, age, and credit rating bucket may violate the assumptions underlying the differences-in-differences methodology. E.g., it is plausible that these two types of borrowers are exposed to differentially evolving economic conditions around the time of the financial crisis. We address this concern in three ways.

**Event Study** First, we next present the DiD estimates as an event study around the policy enactment that confirm the parallel trends assumption. In particular, we estimate the following specification:

$$1(\text{Loan})_{b,l,t} = \sum_{t=2004}^{2009} \beta^t \times \text{NBFI Borrower}_{b,2008} \times 1_t + \alpha_{b,l} + \alpha_{l,t} + \alpha_{X(b,2008),t} + \varepsilon_{b,l,t}$$

Here, $1_t$ is a set of dummy variables indicating years from 2004 to 2014. Figure A2 plots the results of the event study analysis.[11] There is no visible pre-trend in the relative fraction of bank credit being allocated to the treated NBFIs. Starting from the financial year 2009, we see the loan origination probability increase for the treated NBFIs relative to other borrowers. The coefficient in 2008 (relative to the base of 2004) is 0.024 but statistically insignificant. This can be explained by the anticipation effect as there were active discussions prior to the RBI policy enactments and some of the banks might have pre-empted the substitution (Loipersberger (2018)). While it is not possible to empirically test the parallel trends assumption, the lack of visible pre-trends suggests that it likely holds in our setting.

**Treated vs. Untreated NBFIs** Next, it is plausible that the substitution results are driven by bank credit flowing into the broader NBFI sector for reasons unrelated to the risk-weight reduction. This is an important concern as the RBI policy timing coincides with the onset of the financial crisis, which may have created an economic and regulatory environment inducing the banks to move away from their traditional lending model. E.g., the crisis may have reduced the credit demand from bank-dependent firms, prompting banks to lend more to the NBFI sector. To show that our results are driven by the RBI risk weight policy, we exploit the fact that the policy was only applicable to the subset of NBFIs having assets over

[11] The timeline follows financial year in India, so that the year 200x represent the estimates for the financial year ended on March 200x.

the cutoff of INR 1 Billion. We estimate the following specification:

$$1(\text{Loan})_{b,l,t} = \sum_{k=1}^{4} \beta^k \times \text{NBFC Size Group}^k_{b,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{l,t} + \alpha_{X(b,2008),t} + \varepsilon_{b,l,t}$$

Here, we classify NBFC borrowers into four size groups based on their total assets in 2008. These are <15, 15-1,000, 1,000-15,000, and >=15,000 (expressed in INR Millions). NBFC Size Group$^k_{b,2008}$ is an indicator variable that equals one if the NBFC $b$ lies in size group $k$ in 2008, and zero otherwise. Figure 3 plots the substitution effect for various categories of NBFIs relative to the firms (control group). As evident, the substitution effect is statistically and economically significant only for the set of NBFIs that experienced a reduction in risk weights. These results suggest that the substitution pattern documented above is driven by the RBI policy and not by any other concurrent change in economic or regulatory environment.

**Capital Adequacy Test** Finally, we perform a triple-difference test which not only allow us to effectively control for the borrower's credit demand, but also highlights the economic channel through which the substitution effect operated. The incentives to substitute out firms by now cheaper NBFI credit should be strongest for the capital constrained banks. To test this hypothesis, we split the banks in to below-median and above-median Capital Adequacy Ratios (CAR) at the end of the financial year 2008. We then use the Khwaja and Mian (2008) methodology and do a "within-borrower" test to check if the substitution towards treated NBFIs was stronger by the Low CAR banks relative to High CAR banks. Specifically, we estimate the following model:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Borrower}_{b,2008} \times \text{Post RW Change}_t \times \text{Low Bank CAR}_{l,2008} \quad (2)$$

$$+ \alpha_{b,l} + \alpha_{l,t} + \alpha_{b,t} + \varepsilon_{b,l,t} \quad (3)$$

where Low Bank CAR$_{l,2008}$ denotes the dummy indicating if the bank has below-median CAR ratio at the end of financial year 2008. Crucially, we can now absorb the borrower's credit demand by including borrower $\times$ time fixed effects ($\alpha_{b,t}$) and focus on how the credit supply to the same borrower differ after the RBI policy enactment. Columns 1-3 of Table A2 show that $\beta > 0$, indicating that the switch towards treated NBFIs was stronger among banks with low CAR ratio. Column 1-2 do not include borrower $\times$ year fixed effects. First we note that the coefficient on NBFI Borrower$_{b,2008}$ $\times$ Post RW Change$_t$ is positive and significant at 0.023 in Column 1. This is the evidence documented so far that the lenders originated more loans to treated NBFIs post the RBI policy enactment. However, what is interesting is that the coefficient on triple interaction NBFI Borrower$_{b,2008}$ $\times$ Post RW Change$_t$ $\times$ Low Bank CAR$_{l,2008}$ is

economically larger at 0.037 and statistically significant at less than 1% level. This indicates that Low CAR banks substituted towards treated NBFIs with greater probability.

Next, we interpret these coefficients economically. The loan origination probability from the High CAR banks for the treated NBFIs (relative to control borrowers) goes up by 21.90% post RBI policy enactment. However, the same goes up by additional 35.28% for the group of Low CAR banks. Our preferred specification is Column 3 which includes the borrower $\times$ year fixed effects. With the inclusion of these fixed effects the baseline DiD coefficient can not be estimated now. The coefficient on the triple interaction however is large (0.028) and statistically significant. Economically, the loan origination probability between the treated NBFIs and the Low CAR Bank goes up by additional 26.66%. Overall, these results show that the increase in bank lending towards NBFIs is driven by the change in capital regulations and not by a change in borrower loan demand.

# B Heterogeneity in Bank Response

Evidence presented thus far establishes that, in response to the change in RBI risk weight policy, an average bank substituted their lending away from nonfinancial firms and towards NBFI borrowers. We conjecture that the strength of this substitution crucially depends on the given bank's exposure to the risk weight policy shock, as measured by its ex-ante (prior to 2009) exposure to the NBFI borrowers. In particular, we measure bank's ex-ante exposure to treated NBFI borrowers (namely NBFC-ND-SI) as

$$\text{NBFI Holding}_{l,2008} = \sum_{b \in \text{NBFI}} \left( \frac{\text{Credit}_{b,l,2008}}{\text{Credit}_{l,2008}} \right) \tag{4}$$

where $\text{Credit}_{b,l,2008}$, and $\text{Credit}_{l,2008}\text{Credit}_{l,2008}$ denotes the credit outstanding between the lending bank $l$ and borrower $b$, and the aggregate loan book size of the lender bank $l$ respectively, both measured prior to the policy enactment. 80 out of 157 lending banks in our data had positive exposure to the NBFI borrowers as of 2008, with mean, median, and the $75^{th}$ percentile NBFI Holding of 5.10%, 0.01%, and 7.88% respectively. Conditional on having positive ex-ante exposure to NBFI borrowers, the mean and median of the exposure are 10% and 7.81% respectively. Hence, a large number of banks had significant exposure to treated NBFIs prior to the policy change.

How should high vs. low ex-ante exposure to NBFI borrowers affect bank's credit supply to the NBFIs (treated) vs. nonfinancial firms (control)? We build our hypothesis by analyzing the strength of *substitution* and *income* effect facing the lender banks with differential

exposure to NBFI borrowers. With the change in relative risk-weights between NBFI and corporate borrowers, *all* lender banks would optimally tilt their portfolios towards NBFI borrowers as these now require less capital charge than before. However, this *substitution effect* is likely to be stronger for the lender banks with ex-ante low NBFI holdings. High NBFI holding banks may already be sufficiently exposed to the NBFI sector and hence their incentives to lend even more are likely to be weaker.

At the same time, the high NBFI holding banks also receive a positive *income effect* through the improvement to their capital adequacy ratios. This happens because their outstanding exposures to the NBFI borrowers now attract lower capital charge, freeing up regulatory capital for these banks. For example, given that the risk-weight reductions are either 25 or 50 basis points (depending on the NBFI rating catogory), a 10% NBFI holding can translate into a 2.5 to 5 percentage points increase in bank capital. This *income effect* should allow these banks to expand the credit to *all* the borrowers, including credit to firms. Hence, we expect the high NBFI holding banks to improve credit to both NBFIs (treated) and firms (control). On the contrary, a low NBFI holding bank experiences little to no change in the regulatory treatment their outstanding exposures. With no income effect at play, these banks expand credit to NBFI borrowers by cutting it from their corporate borrowers.

To test these hypothesis formally, we begin by estimating a following model to trace the lending of banks with heterogeneous exposure to NBFI borrowers ex-ante

$$1(\text{Loan})_{b,l,t} = \beta \times \text{Low NBFI Holding}_{l,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \varepsilon_{b,l,t} \tag{5}$$

Here, we split the bank lenders into below- and above-median groups of NBFI Holdings, where NBFI Holding for a bank is the fraction of all outstanding loans given the treated NBFI borrowers in 2008. We then estimate the above model separately for the NBFI borrowers and the corporate borrowers. $\beta$ captures the relative response of banks with low ex-ante NBFI exposure. The model is estimated with only borrower×lender fixed effect so that we can document the effect on both low- and high-NBFI holding groups. Figure 4 plots the coefficients from the two separate regressions.

The results as plotted in Figure 4 are consistent with our hypothesis. First, the probability of loan origination to the NBFI borrowers goes up for both the high NBFI holding banks (experiencing both the substitution and the income effect) and the low NBFI holding banks (experiencing only the substitution effect). However, the positive income effect allows high NBFI holding banks to also expand their lending to firms. In particular, the probability of a new loan to a corporate borrower goes up by 1.56 percentage points for high NBFI exposure banks. For banks with low NBFI holding, the substitution towards NBFI borrowers comes

at the expense of firms. The new loan origination probability between a low NBFI exposure bank and a corporate borrower goes down by 1.16 pp. relative to the pre-period, and by 2.73 pp. relative to the high NBFI holding bank group. Overall, the substitution from corporate borrowers towards NBFI borrowers is much stronger among banks with low NBFI holding ex-ante.

Next, we strengthen the above evidence by estimating a richer empirical model that compares the loan outcomes for firms and NBFI borrowers in the same regression using a triple difference strategy. In particular, we estimate the following model

$$\begin{aligned} 1(\text{Loan})_{b,l,t} &= \beta \times \text{NBFI Borrower}_{b,2008} \times \text{Post RW Change}_t \times \text{Low NBFI Holding}_{l,2008} \\ &\quad + \alpha_{b,l} + \alpha_{l,t} + \alpha_{b,t} + \varepsilon_{b,l,t} \end{aligned} \tag{6}$$

Compared to the model in equation 5, $\beta$ now estimates the increase in the loan origination by the banks with low ex-ante NBFI exposure (relative to those with high ex-ante NBFI exposure) to NBFI borrowers (relative to corporate borrowers). The results are documented in Table 3. In column 1, we begin by estimating the model with the borrower×lender fixed effects as before, but additionally absorb lender×time fixed effects, which allows us to compare the lending of the same bank to the corporate vs NBFI borrowers after absorbing any bank-level fluctuations. The coefficient on the NBFI borrowers×Post RW Change of 0.04 is statistically significant, confirming the substitution from firms to NBFI borrowers by high NBFI holding banks from pre- to post-period.

More importantly, the triple interaction coefficient of NBFI Borrower × Post RW Change × Low NBFI Holding is positive and statistically significant, suggesting that banks with low NBFI holding substitute even more strongly towards NBFI borrowers in the post period. In particular loan origination probability increases by 34.46% from pre- to post-period relative to the mean loan origination probability for high NBFI exposure banks, but by much larger 52.88% for low NBFI exposure banks.

In columns 2 and 3 we gradually saturate the model and continue to obtain qualitatively and quantitatively similar results. In Column 2 we additionally absorb the borrower characteristics×time fixed effects to control for the fact that loan demand in the post-period might evolve differently for borrowers that differ in terms of size, age, and credit ratings. In Column 3, which is our most saturated model, we absorb borrower×time fixed effects additionally, which controls for the any borrower specific time-varying credit demand, and isolates the credit supply. Intuitively, these set of fixed effect allows us to compare the credit supply to the same firm from two banks with heterogeneous ex-ante NBFI exposure. The

diff-in-diff coefficient is not estimated as we zoom in a particular borrower-year combination and exploit the variation across the lenders of the same borrower in terms of ex-ante NBFI holding. The coefficient on triple interaction is 0.021, larger than the estimates in column 1.

Overall, Figure4 and Table 3 provides a compelling evidence that lender bank's ex-ante exposure to the treated NBFI borrowers shapes up their credit supply in the post-period. In particular, banks with low ex-ante NBFI exposure substitute aggressively towards NBFI borrowers at the expense of their corporate borrowers.

# C Borrower-Level Outcomes

## C.1 Credit Supply

The loan level estimates so far suggests a shift of credit supply away from firms towards treated NBFIs. Do these loan level estimates imply an overall reduction in the credit supply for firms? Potentially, corporate borrowers could find new bank lenders if their existing lenders substitute them out in favor of NBFIs. More importantly, the corporate borrowers could obtain new loans from the treated NBFIs which received a bout of funding from the banks after the RBI policy enactment. Both these channels imply a negative credit supply estimate at the loan level but not at the firm level. On the other hand, it is well known that relationships are sticky and finding new lenders in the short time is not easy. NBFIs may specialize in a separate class of firms, or may even divert credit to the non-corporate segment, making it difficult for the affected firms to fill the credit gap.

With this motivation, we next estimate the borrower level credit supply after the RBI policy enactment as is done in Jiménez et al. (2020). We first define the borrower's exposure to the *substitution risk* as the borrower's ex-ante dependence on the group of banks which are more likely to substitute firms in favor of treated NBFIs, namely the banks with low ex-ante NBFI holding. As evidence from the last section shows, these banks substitute the credit towards NBFIs and away from corporate borrowers more aggressively in response to the risk weight reduction. Hence, firms relying on these set of banks are most vulnerable to being substituted out. Thus, we define our borrower's exposure to the RBI policy as

$$\text{Borrower Exposure}_{b,2008} = \sum_{l \in \text{Banks}} \left( \frac{\text{Credit}_{b,l,2008}}{\text{Credit}_{b,2008}} \right) \times 1 \left( \text{Low NBFI Holding}_{l,2008} \right) \quad (7)$$

This measures the fraction of the ex-ante credit to a given corporate borrower $b$ which is financed by banks in the low ex-ante NBFI holding group. Average borrower exposure is

0.468 indicating that 47% of the ex-ante credit is at the substitution risk.

Next, we provide descriptive evidence comparing firms with high and low exposure to substitution risk. Table A3 shows that firms with high exposure are larger, older, and safer in terms of credit rating. Equipped with our measure of borrower's exposure to the substitution risk, we next examine the effect of the policy on new loan originations. Specifically, we estimate the following model on the borrower-year panel:

$$1(\text{Loan})_{b,t} = \beta \times \text{Borrower Exposure}_{b,2008} \times \text{Post RW Change}_t + \alpha_b + \alpha_{X(b,2008),t} + \varepsilon_{b,t} \quad (8)$$

where $1(\text{Loan})_{b,t}$ is an indicator variable that equals one if corporate borrower $b$ took at least one new loan from a group of lender considered in the regression. The model is estimated for three distinct set of lenders: bank lenders, treated NBFI lenders (NBFI), and the union of these two sets. Estimating the model separately over the set of lenders allows us to attribute the change in the borrower's overall credit supply to various set of lenders. The model has borrower fixed effects, and the quintile bins for the ex-ante characteristics $\times$ year fixed effects, as before.

The results are summarized in Table 4. We estimate the model for set of banks (column 1), treated NBFIs (Column 2), and both set of lenders (Column 3). Column 1 shows that higher borrower exposure to the *substitution risk* reduces the probability of such a firm obtaining any new loan from a bank, and this reduction is statistically significant. Economically, a one standard deviation higher borrower exposure to the RBI policy implies a 9.28% reduction in probability of that borrower obtaining at least one new loan from banks. Do NBFI lenders fill this credit void? Column 2 answers this question in negative. Post the RBI policy enactment, the probability of obtaining at least one new loan from the treated NBFIs go up by 0.02 pp. (Column 2) which is statistically and economically insignificant.

Given that exposed borrowers experience a credit cut from bank lenders, and no improvement in credit supply from NBFI lenders, it is clear that the substitution risk hurts the borrowers by reducing the overall credit supply to them. Column 3 documents this effect – more exposed firms suffer a substantial decline in the probability of obtaining a new loan. Economically, a one standard deviation higher borrower exposure to the RBI policy implies a 9.44% reduction in probability of that borrower obtaining at least one loan from banks or NBFIs. Overall, our borrower level estimation suggests that when banks substitute their credit towards NBFIs, their nonfinancial borrowers experience an overall drop in the credit supply.

### C.2 Real Outcomes

Does the reduction in credit supply impact the real outcomes for the firms connected to the aggressively-switching banks? We reestimate the model in equation 8 but using various real outcomes as the outcome variables:

$$Y_{b,t} = \beta \times \text{Borrower Exposure}_{b,2008} \times \text{Post RW Change}_t + \alpha_b + \alpha_{X(b,2008),t} + \varepsilon_{b,t} \quad (9)$$

where $Y_{b,t}$ is the real outcome of interest for corporate borrower $b$. Table 6 document the results. Consistent with lower total borrowing, we find that firms experience a reduction in total leverage. Interestingly, we also find an increase in the cost of debt, proxied by the total interest expense scaled by lagged debt. This suggests that the exposed firms experienced a reduction in credit availability both across the extensive and the intensive margin. We also observe that exposed firms experience a sharp deterioration in asset growth, revenue growth, and a variety of profitability and return measures. Column 1 (2) estimates that from pre- to post-period, a one standard deviation higher exposure to substitution risk for a firm implies a 12.62% (7.45%) smaller assets (sales) relative to the unexposed firm. Since we absorb ex-ante borrower size, age, and rating buckets × time fixed effects, these coefficients show the relative growth in assets and revenue of two firms with similar observable characteristics. Columns 4 and 5 document the deterioration in measure of profitability (EBITDA/Sales and ROA). For example, column 5 estimates that a one standard deviation higher borrower exposure to substitution risk implies a 9.96 percentage points reduction in return on assets, which is economically very large given that mean return on assets in the sample of our firms is just 1.11%.

**Robustness: Deposit Flight Vs. Exposure to Shock** Acharya et al. (2023) document a run on some of the branches of private sector banks in India in the aftermath of the 2008 global financial crisis. Deposits migrated mainly to government-owned public sector banks (PSBs), which were considered safe haven by most depositors. Is it possible that our result documenting a drop in credit supply to borrowers exposed to the risk-weight shocks through their bankers is driven by the deposit flight experienced by their banks around the same time as the risk-weight shock? We rule out this concern in multiple ways.

First, although there could have been a deposit flight from some of the branches of the private banks, there was no aggregate deposit run on the private banks in 2008/09. The aggregate deposits in Indian private banks increased by 14. 87%, and a median private bank experienced a deposit growth of 15.43% during the financial year 2008/09. Only one major

private bank (namely, ICICI Bank) experienced negative deposit growth during the financial year 2008-09. Second, a necessary condition for the deposit flight episode to confound our results is that the private banks likely experiencing deposit flight are also the ones less exposed ex-ante to the NBFI sector, so the customers of these banks are vulnerable to substitution risk post the risk-weight shock. However, we find that the ex-ante mean exposure as of 2008 to the NBFIs is similar across private and public sector banks (4.91% for the private banks and 6.06% for public sector banks). More importantly, the correlation between the ex-ante NBFI exposure of a bank and the deposit growth during 2008/09 is 0.12 and statistically insignificant. Collectively, these descriptive statistics offer suggestive evidence that our results are not driven by the deposit flight channel.

To further rule out the possibility, we estimate a horse race between borrowers' exposure to the risk-weight shock and the deposit-flight channel. To this end, we define the borrower's exposure to deposit flight as follows

$$\begin{aligned} \text{Borrower Deposit Flight Exposure}_{b,2009} &= \sum_{l \in \text{Banks}} \left( \frac{\text{Credit}_{b,l,2008}}{\text{Credit}_{b,2008}} \right) \\ &\times \quad 1\left(\text{Low}\,\Delta\ \ln(\text{Deposits})_{l,2009}\right) \end{aligned} \tag{10}$$

where $1\left(\text{Low}\,\Delta\ \ln(\text{Deposits})_{l,2009}\right)$ denotes the dummy variable assuming value 1 if the percentage change in the deposits for a bank lender $l$ during the financial year 2008/09 is below the median deposit growth rate. Using specification from equation 8. In particular, we estimate the following specification

$$\begin{aligned} 1(\text{Loan})_{b,t} &= \beta_1 \times \text{Borrower Exposure}_{b,2008} \times \text{Post RW Change}_t + \alpha_b \\ &+ \beta_2 \times \text{Borrower Deposit Flight Exposure}_{b,2009} + \alpha_{X(b,2008),t} + \varepsilon_{b,t} \end{aligned} \tag{11}$$

The results are presented in Table 5. In column 1, we begin by reproducing the result that one unit higher borrower exposure to substitution risk implies a 6.10 percentage points reduction in the probability that the borrower obtains a loan from any lender during the financial year. Economically, this translates into a reduction in the probability of obtaining a loan of 10.11% (relative to the mean probability) for one standard deviation higher borrower exposure to substitution risk. In Column 2, we highlight the impact of deposit flight on the probability of obtaining a loan. The estimate suggests that one standard deviation higher exposure to deposit flight reduces the probability of borrower obtaining any loan by 1.58 percentage points or 5.31% relative to the mean probability. Column 2 corroborates the

result in Acharya et al. (2023) that the credit supply reduced in the aftermath of the 2008 crisis for borrowers dependent upon the banks experiencing deposit flight.

In column 3, we put the two mechanisms to compete against each other. We obtain virtually unchanged estimates on both the exposure measures, suggesting that the two channels operated independently of each other. Columns 4 and 5, taken together, document as expected that the reduction in credit supply following the deposit flight and risk weight substitution is mainly concentrated within bank lenders and not the NBFI lenders. Overall, we present evidence that substitution risk materially affected borrowers independently and on top of any adverse credit supply effects experienced by the borrowers due to the deposit flight channel.

# D Anatomy of NBFI Response

The results so far document that increased bank financing to the treated NBFIs comes at the expense of bank-dependent nonfinancial firms. Moreover, firms experiencing this *substitution effect* also suffer real consequences in terms of slower asset and revenue growth, and lower profitability.

To fully understand the policy's impact on credit allocation, we analyze the lending behavior of treated NBFIs post-enactment. Specifically, we examine how treated NBFIs utilize increased bank financing, which types of firms they lend to, whether the policy influences loan contract terms, and, finally, the implications for competition between banks and NBFIs.

## D.1 Loan Origination

First we examine whether NBFIs increase their lending activity in the post period. It is possible that NBFIs use additional bank lending to merely refinance their existing loans or to substitute away from other, more expensive forms of financing (namely debentures and commercial paper). In this case, additional bank loans due to the RBI policy would reflect a surplus transfer from exposed nonfinancial firms towards NBFIs. Alternatively, it is possible that NBFIs channel additional bank lending to firms in form of new loans.

We answer this question both in absolute and relative terms. We begin by estimating a very parsimonious model to measure absolute increase in loan origination probability for NBFI lenders as follows;

$$1(\text{Loan})_{b,l,t} = \gamma \times \text{Post RW Change}_t + \alpha_{b,l} + \varepsilon_{b,l,t} \tag{12}$$

The model is estimated on the sample of corporate borrowers and NBFI lenders. The model estimates if within a corporate borrower and NBFI lender pair, the probability of a new loan increases from pre- to post-policy period. Column 1 of Table A6 document the result. We obtain $\gamma$ of 0.028 which is also statistically significant indicating that from pre- to post policy enactment period, the loan origination probability goes up by 32.94% relative to the unconditional mean for a given borrower-lender pair.

It could be that in the post policy enactment period, credit demand of firms increased for both bank and NBFI lenders, driving the above result. Alternatively, credit demand could be higher in the post-period for the firms served by the NBFI lenders. Hence, we estimate a richer model tackling these concerns. In particular, we estimate the increase in loan origination from NBFI lenders *relative* to bank lenders for the *same* firm by estimating the following model:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Lender}_{l,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{b,t} + \varepsilon_{b,l,t} \qquad (13)$$

where, we absorb borrowers$\times$ time fixed effect to soak up the credit demand by borrowers and compare the credit supply to a given borrower from NBFI lenders relative to bank lenders. Specifically, $\beta$ measures the change in the probability that a NBFI lender issues a new loan to a firm, relative to such increase by a bank lending to the same firm. Table 7 documents the results. In column 1, we begin by absorbing just borrower$\times$lender fixed effects as a baseline. We find that $\beta$ is 0.018, which is statistically significant and represent a 17.82% increase in the unconditional probability of loan issuance. Specification in column 1 compares the rate of loan origination for NBFI lenders to bank lenders and takes care of the fact that the result is not driven by a general time trend. But it could still be that the firm dependent upon NBFI lenders are different than the average firm in terms of size, age, or industry and experienced faster than average growth in credit demand. To tackle this concern, we include borrower characteristic$\times$time fixed effects, where we include size, age, and rating of the corporate borrower. The $\beta$ in column 2 is hardly unchanged both in terms of statistical and economic significance.

In Column 3, we saturate the model with stringent borrower$\times$time fixed effect, thereby absorbing any unobserved credit demand for a given firm and allowing comparison of loan origination for a given borrower across NBFI and bank lenders. We again obtain statistically significant $\beta$ of 0.02. Economically, the estimate implies that the likelihood of a NBFI lender originating a new loan is 19.80% higher relative to bank lenders as we move from pre- to post policy period. These results suggest that the treated NBFIs increased their lending to nonfinancial firms, both in absolute terms and relative to banks.

Next, we examine how the policy affected the length of the intermediation chain. Banking regulators might lack perfect visibility of the entire network. As a result, assessing risks in the system can be challenging.[12]. Granular data on bank-NBFI connections enables us to better explore the risk inherent in such networks. Since banks may not internalize the impact of systemic risk due to their investments, they may have incentives to obfuscate their lending activities in order to avoid any regulatory cost. One way banks can do that is by deepening the unregulated part of the credit intermediation chain. In other words, banks can induce their NBFI borrowers to lend to other NBFIs, which in turn lend to even more NBFIs, creating a complex intermediation chain. Such chains are harder for regulators to analyze, especially because the NBFI sector is less regulated than banks, and might have little social value. On the flip side, increasing the length of the chain can be efficient if it increases the borrowing capacity of the ultimate borrower (i.e., the non-financial firm) by lowering the liquidation cost after an interim shock (He and Li (2022)). We examine this possibility by studying whether NBFIs that get higher bank funding increase their lending disproportionately more to other NBFIs. Table A5 shows that NBFIs increased lending to NBFC-Non-SI more than the banks. These results are consistent with the idea that banks utilized the policy shock to lengthen the intermediation chain likely increasing the opacity of the lending ecosystem.

Another important implication of this result is explaining why we cannot use NBFC-Non-SI (i.e., the untreated NBFIs) as the control group when understanding the lending behavior of NBFC-SI (i.e., the treated NBFIs) in response to the policy change. Since NBFC-Non-SI themselves experience loan inflow from the treated NBFC-SI, potentially enabling them to make more loans, comparing their lending volume to that of treated NBFC-SIs will lead to biased estimates. This leads us to either look at lending by NBFC-SIs in isolation (i.e., Table A6) or relative to banks (i.e., Table 7).

### D.2 Terms of Loan Contract

Obtaining stable funding is one of the critical challenge any NBFI faces as it lacks the access to deposit franchise. NBFI search for funding in the wholesale market by issuing short-term commercial papers to mutual funds and banks. However, with a revised policy on the risk-

[12]The importance of understanding lending networks comprehensively is emphasized by Jackson and Pernoud (2021) who mention — "Accordingly, and partly spurred by the lessons learned from the 2008 financial crisis, assessments of systemic risk that involve nontrivial portions of the network as beginning to emerge... This is an important advance in the assessment of systemic risk, but much more is needed, especially outside of Europe and for the growing shadow banking system, which falls outside of most jurisdictions."

weight in India, NBFI lenders secured relatively stable funding in the form of bank loans. We conjecture that this should feed in to the terms of contract offered by the NBFI lenders. With this motivation, we study the implications of the policy for the average ticket size and the maturity of the loans issued by the NBFI lenders after the policy enactment. We use exactly the same model with borrower×year fixed effects as we used to estimate the loan origination by NBFI lenders in equation 13;

$$Y_{b,l,t} = \beta \times \text{NBFI Lender}_{l,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{b,t} + \varepsilon_{b,l,t} \tag{14}$$

where $Y_{b,l,t}$ can be logarithm of the loan size on the new loans originated between lender $l$ and borrower $b$, or loan maturity (in months). The model is estimated on corporate borrowers and both the NBFI and bank lenders as above.

Table 8 presents the results. All columns absorb borrower×lender fixed effects. Columns 1 and 3 additionally absorb borrower characteristics×year fixed effects, while columns 2 and 4 additionally absorb borrower×year fixed effects. Using either specifications we obtain that the change from pre- to post-period in loan size and maturity is larger for the loans issued by NBFI lenders relative to the bank lenders. In Columns 1 and 3, the $\beta$ is identified by comparing the two set of lenders for the corporate borrowers with the same ex-ante characteristics such as size, age, and rating, while for columns 2 and 4, the $\beta$ estimates the change in loan contract terms for the *same borrower* across two set of lenders. Estimate from column 2 implies that relative to bank lenders, the loan size grew by 34.8% more for NBFI lender, controlling for the overall credit demand of that borrower from pre- to post-period. Column 4 indicates that relative to bank lender, maturity of loan issued by NBFI lenders grew by 6 months more from pre- to post-period. This is economically large relative increase (roughly 9.97%) relative to the average maturity of 5 years in our data.

How do we interpret our results? Any financial institution's lending decision is guided by two objectives; first is the *duration matching* on the asset and liability side of its balance sheet so that the valuation effects from interest rate fluctuations are minimized. As NBFI lenders obtain more of the funding from bank lenders in the form of medium term loans having longer maturity than short-term commercial papers, we expect NBFI to issue longer tenure loans to firms to better match the duration of the asset and liability side after the policy. Our evidence is consistent with the duration matching exercise of NBFI lenders.

Second is the objective of *cash flow matching* so that the loan portfolio generates cash-flows matching with anticipated deposits or commercial paper repayments, so that liquidity crunch is minimized. When NBFI has on its liability side a sequence of commercial papers maturing at various points in time, smaller loan size across a wider set of borrowers allows NBFIs

to create a continuous cash-flow structure matching the needs on the liability side. Lumpy or larger loan sizes across a few borrowers are difficult to manage for a typical NBFI as it creates a *bullet* cash flow structure where the NBFI faces liquidity surpluses when these loans pay-off but is in liquidity deficit most of the times when CP's are maturing on continuous basis. Hence, cash-flow matching objective forces NBFC to provide smaller loans to a larger cross-section of the borrowers. Our evidence is again consistent with the cash-flow matching objective of an NBFI. It is important to note that the results on loan size are not driven by NBFI trying to penetrate larger borrowers after the policy enactment. The borrower×year fixed effects imply that for a *given borrower*, size of the NBFI issues loans grows much faster than those issued by banks from pre- to post-period.

### D.3 Types of Borrowers

We next investigate if the expanded credit supply of NBFI lenders promote financial inclusion by providing credit to potentially credit constrained firms. We extend our model of equation 13 to include triple interaction between post-policy period dummy, NBFI lender, and borrower characteristics, and consider size, age, and credit rating as three characteristics. Our choice of borrower characteristic is parsimonious and follows recent literature suggesting that more complex measures of credit constraints may not identify the constrained firms (Farre-Mensa and Ljungqvist (2015)). Again the model is saturated with borrower×lender and borrower×year fixed effects, so that we estimate the credit supply of NBFI lenders relative to the bank lenders for the same given borrower.

Table 9 document the results. In columns 1-3 we consider the triple interaction with dummies for smaller, younger, and lower credit rating borrowers respectively[13] and obtain strong positive $\beta$. The results therefore suggest that post the policy enactment, loan origination probability to smaller, younger, and low rated firms increased more for NBFI lenders relative to bank lenders. For example, column 1 shows that loan origination probability rises by 17.47% (0.018/0.103 where 0.103 is the unconditional loan origination probability) more for NBFI lenders (relative to bank lenders) as we move from pre- to post-period for medium and large sized borrowers. But for small sized borrowers, the loan issuance probability rises by additional 13.60% (0.014/0.103 ) for for NBFI lenders (relative to bank lenders). Columns 2 and 3 repeat the analysis for younger and low-rated firms. Column 4 includes all the three characteristics in one regression. Size loses its statistical and economic significance, but age and rating retains the significance and has comparable magnitudes.

[13]We define small and young firms as the smallest and youngest one-third borrowers as 2008 financial year end. Borrower rated BBB or below is assigned Low rating dummy of 1.

Hence, we provide a compelling narrative that credit re-allocates from larger, older, and top rated firms to smaller, younger, and low rated borrowers. One can interpret this result as a financial inclusion with one caveat that with borrower×year fixed effects, the model estimates intensive margin of financial inclusion for potentially credit constrained firms.

### D.4 Competition to Bank Lenders?

There are two interesting and related questions that arise when we study the credit reallocation due to stronger bank-NBFI connections in the post policy period. First is whether NBFI lend to the new class of borrowers or the same set of borrowers already served by the banks providing more credit to these NBFI lenders after the policy enactment. This can happen for at least two reasons. There could be an active information sharing between bank and NBFI lender about the borrower quality, which naturally results into these NBFIC-SI lenders lending to the same set of borrowers. A second reason could be that after the policy enactment, banks now find it cheaper to lend indirectly to poorly rated firms by routing the loans through NBFI lenders. This is a reasonable hypothesis to conjecture given the evidence in the previous sub-section that NBFI sharply increases the lending to poorly rate firms relative to bank lenders in the post-period. If true, then the risk weight reduction policy would push the credit risk out of the banking system only to find NBFI sector laden with bad assets a few years later. In case there is a overlap in the set of borrowers (*related borrowers*) served by the bank and the NBFI funded by such bank (the "asset commonality" problem), then it not only limits the scope for financial inclusion but also can potentially increase fragility in the financial system.

Second question is if the asset commonality problem is not present, then whether NBFI lenders penetrate the traditional bank lending market and increase the credit market competition, or access the segments of borrowers not served by by the traditional banks and thereby promote financial inclusion.

We investigate these interesting questions and document the results in Table 10. In particular, for Panel A, we estimate the following model

$$1(\text{Loan})_{b,l,t} = \gamma \times \text{Post RW Change}_t \times \text{Borrower Characteristic}_{b,2008}\alpha_{l,t} + \alpha_{b,l} + \varepsilon_{b,l,t} \quad (15)$$

We consider three characteristics encoded in following three dummy variables; Bank Corporate, Bank Region, and Bank Industry; Respectively these dummies take the value of 1 for firms which are heavily bank dependent ("Bank Corporate") or located in bank dependent districts ("Bank Regions"), or belong to industries heavily dependent on bank financing

("Bank Industry"). The model is estimated for NBFI lenders and all the corporate borrowers and absorbs lender×year fixed effects, so that we trace the lending for a given NBFI lender across corporate borrowers with high vs. low dependence on bank financing.

Column 1 shows that for NBFI lenders, the probability of issuing a loan to a firm heavily dependent on the bank financing rises from pre- to post-period. The rise is statistically and economically large. Loan origination to a bank dependent borrower rises by by 106% from pre- to post-period for a NBFI lender, holding the credit supply of that lender. Hence, risk-weight reduction on NBFI loans provide expanded credit capacity in the hands of NBFI lenders and in turn NBFI lenders create more competition in the credit markets by tapping in to the borrowers traditionally served by the banks. Columns 2 (3) finds that there is a economically meaningful (albeit with modest statistical significance) rise in loan issuance probability to the firms in the regions (belonging to industries) which are traditionally bank dependent.

Panel B investigates if policy magnifies the "asset commonality" problem. In particular, we are interested in finding if the increase in the loan issuance probability by NBFI lender to the bank-dependent borrowers post policy is driven by set of borrowers already served by the banks which finance the NBFI in 2008 ("Related Bank Corporate") or by new class of borrowers.[14] We find no evidence that NBFI lend disproportionately more to the *related borrowers* (column 1) or in the regions with strong presence of banks lending to the NBFI (column 2) in the post-policy period. If anything, NBFI reduce the lending disproportionately in the related regions, albeit the statistical significance of this result is modest. There is a weak evidence that NBFI lend disproportionately more within the *related industries* (column 3). This could be a result of banks specializing in lending to a particular industry selecting to lend more to the NBFI's also specializing in the same industry, as bank can evaluate the NBFI's portfolio more efficiently.

Overall our results in Panel A and B taken together provide a strong evidence that bank-NBFI connections does not exacerbate the asset commonality problem. Instead, NBFIs create more competition in the credit market by tapping into unrelated firms dependent on bank financing from banks not lending to the NBFI in question.

## E Aggregate Effects of Credit Reallocation

The evidence presented so far shows that the increase in bank lending to NBFIs led to the reallocation of credit towards smaller, younger, and riskier borrowers. What is the aggregate

[14]Related Bank Corporate dummy takes a value of 1 for a firm that is served by NBFI lender's in 2008.

effect of such a reallocation? To answer this question, we rely on the methodology recently developed by Sraer and Thesmar (2023). In their methodology, the aggregate effect of a policy depends on how it affects the distribution of the output-to-capital ratio, proxied by the log of marginal productivity of capital (log-MRPK).

In particular, the change in total factor productivity (TFP) and output depends on the policy-induced change in the variance of log-MRPK, the mean of log-MRPK, and the covariance of log-MRPK and sales. To implement this methodology, we define industry of a firm according to the industry group code provided by Prowess. Overall, we have 150 unique industries in our sample. Then, for each industry-year pair, we calculate the three moments by calculating the MRPK as the ratio of sales to assets and aggregating across all firms within that pair. We calculate each industry's exposure to the policy change (Industry Exposure) as the fraction of all outstanding credit that a given industry has from Low NBFI Holding banks. Thus, an industry with higher Industry Exposure can be thought of as a industry more exposed to banks' switching activity. We also create a binary variable (High Industry Exposure) that indicates that a given industry has above-median level of Industry Exposure.

To estimate how exposure to the RBI policy affected the three moments of output-to-capital ratio, we estimate the following model:

$$\mathrm{Y}_{s,t} = \beta \times \text{Industry Exposure}_{s,2008} \times \text{Post RW Change}_t + \alpha_s + \alpha_t + \varepsilon_{s,t}$$

where $s$ and $t$ indexes the industry and the financial year respectively. $\mathrm{Y}_{s,t}$ denotes the moments calculated for industry $s$ in year $t$. We employ industry ($\alpha_s$) and time ($\alpha_t$) fixed effects and cluster standard errors at the industry level. Table 11 documents the results. Columns 1, 3, and 5 show results corresponding to the continuous Industry Exposure measure, whereas Columns 2, 4, and 6 show results corresponding to the binary High Industry Exposure measure. We find that industries more exposed to the RBI policy experienced a significant decline in the dispersion of marginal productivity of capital. This suggests that the reallocation of bank credit away from firms and towards NBFIs increased the efficiency of capital allocation. The effect on average MRPK is insignificant, but that on the coveriance term is negative, indicating that the policy led to high capital availability for more productive firms.

To aggregate the effects, we follow Sraer and Thesmar (2023) and use the estimates corresponding to the binary exposure measure. The change in the key moments are: $\Delta\Delta\sigma^2(s) = -0.295$, $\Delta\Delta\mu(s) = 0.079$, and $\Delta\Delta\sigma_{MRPK,py}(s) = -0.377$. We use the calibration parameters from David and Venkateswaran (2019) and Sraer and Thesmar (2023) and set the capital share in production to 0.33 and the price elasticity of demand to 6.0, corresponding to $\theta =$

0.85. We calculate $\phi_s$ and $\kappa_s$, the pre-period share of total sales and capital of industry $s$ directly from the firm-level panel.

The overall change in total factor productivity (TFP) is calculated as:

$$\begin{aligned}\Delta log(TFP) \approx & \underbrace{-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1}^{S}\kappa_s\Delta\Delta\sigma^2(s)}_{9.8\%} \\ & \underbrace{-\frac{\alpha}{2}\left(1+\frac{\alpha\theta}{1-\theta}\right)\sum_{s=1}^{S}(\phi_s-\kappa_s)\left(\Delta\Delta\mu(s)+\Delta\Delta\sigma_{MRPK,py}(s)+\frac{1}{2}\frac{\alpha\theta}{1-\theta}\Delta\Delta\sigma^2(s)\right)}_{-0.4\%} \\ & \approx 9.4\%\end{aligned}$$

Our estimation implies that the gains from reallocation of capital due to the policy change are substantial. Within-industry reallocation contributes 9.8% to the TFP growth, whereas spillover effects across industries lower TFP growth by 0.4%. Overall, there is a 9.4% growth in aggregate productivity.

The overall change in output is calculated as:

$$\begin{aligned}\Delta log(Y) &\approx -\frac{\alpha(1+\epsilon)}{1-\alpha}\sum_{s=1}^{S}\phi_s\left(\Delta\Delta\mu(s)+\frac{1}{2}\frac{\alpha\theta}{1-\theta}\Delta\Delta\sigma^2(s)+\Delta\Delta\sigma_{MRPK,py}(s)\right) \\ &\approx 21.9\%\end{aligned}$$

Thus, the aggregate output increased by 21.9%. Overall, these results imply the the reallocation of capital due to the reduction of risk weights increased aggregate productivity and output in the economy. These positive effects are driven by more efficient capital allocation within industries.

# V Results on Systemic Risk

## A Background of IL&FS Crisis

Infrastructure Leasing & Financial Services Limited (IL&FS) which went into liquidation in 2019 was established in 1987 as an RBI registered Core Investment Company with the primary objective of funding the infrastructure projects via its subsidiaries. IL&FS grew into one of the largest NBFI in the country with 302 subsidiaries across segments like infrastructure,

highways, energy, and finance. The IL&FS had three main shareholders at the time of the establishments namely, The Central Bank of India, The Unit Trust of India, both of which are public-sector undertakings (PSU), and HDFC Ltd. Strong backing by PSU's allowed IL&FS to acquire a quasi-PSU status in the debt market, allowing it to expand its debt relatively easily. At the time of the default at the end of financial year 2018, IL&FS had amassed total debt of close to 1 trillion INR, and its debt-equity ratio grew from 10 to 16 in a matter of a year. At 16.8, the leverage was roughly thrice more than the NBFC sector. Apart from unsustainable debt, IL&FS suffered from investing into unviable projects or projects which faced difficulties in completion due to difficulties in land acquisition etc. The severe asset-liability duration mismatch created panic amongst the mutual fund and other investors that dried up the liquidity for IL&FS, triggering a wave of defaults.

The trouble started when in June of 2018, IL&FS Transportation Networks (INTL) delayed payment of 4.5 billion INR to Small Industries Development Bank of India (SIDBI) triggering a panic and immediate downgrade of ITNL's credit rating. This was followed by group's founder and Chairman stepping down, and in another default in August of 2018 by its flagship financial arm/subsidiary. Indian Government took control of the management with the aim of efficient liquidation.

The IL&FS crises had significant spillover onto NBFC and mutual fund sectors. Debt mutual funds had large direct exposure to the IL&FS group, and with panic setting in, mutual fund investors responded by increasing their redemption requests. The first blow to NBFC sector came when DSP Mutual Fund dumped 3 billion INR worth of commercial papers of another NBFC, Dewan Housing Finance Limited (DHFL) in late September 2018, possibly to satisfy the redemption requests. However, market interpreted the action as a signal of systemic trouble in the NBFC sector. This triggered a panic sell-off in equities of largest of the NBFCs in India. For example Bajaj Finserve, the largest retail NBFC, with minimal direct exposure to the IL&FS sectors (energy, infrastructure etc.) saw its equity price collapsing by roughly 25% between September and October of 2018.

More importantly, the liquidity dried up for NBFCs as banks and mutual funds virtually stopped rolling over the commercial papers and debt. Consequently, DHFL defaulted with drying up of liquidity creating further worsening of the situation for other NBFCs. Borrowing costs rose by roughly 10% for a typical NBFC and largest six NBFCs captured half of the total debt issuance by the NBFC sector highlighting the trouble most other NBFC faced to obtain funding after the IL&FS crises.[15]

[15]https://qz.com/india/1860466/how-indias-nbfc-crisis-deepened-from-ilfs-defaults-to-covid-19

# B Systemic Impact of IL&FS Failure

The 2008 risk-weight reduction on the loans to NBFCs provided the impetus for formation of bank-NBFC connections. We are now interested in studying the credit market outcomes and real effects of such bank-NBFC connections in the economy. In an event that a large borrower defaults on the bank loan, it is likely that the deterioration in bank's health spillovers to other borrowers of that bank. However, if some of these other borrowers are financial institutions like NBFCs, then the credit contraction to those clients by the bank further spillovers to the borrowers of such NBFCs. We aim to test this narrative in our empirical tests.

Prowess data provides us with the identity of the parent company for all the subsidiaries. We are able to locate 142 subsidiaries of IL&FS group in our credit register.

## B.1 Bank Exposure to IL&FS and Lending

To this end we first define the bank lender's exposure to IL&FS at the end of financial year 2017-18 as follows

$$\text{Bank ILFS Exposure}_{l,2018} = \sum_{b} \left( \frac{\text{Credit}_{b,l,2018}}{\text{Credit}_{l,2018}} \right) \times 1\left(ILFS_b\right) \tag{16}$$

where $1\left(ILFS_b\right)$ is a dummy variable if borrower $b$ is any of the IL&FS group subsidiary in our data. Prowess data provides us with the identity of the parent company for all the subsidiaries. Using this information and merging with our credit register, we are able to locate 142 subsidiaries of IL&FS group. Bank's exposure to ILFS is then simply the fraction bank's total loan outstanding towards any of the IL&FS group company.

34 commercial banks had a positive exposure to IL&FS in 2018. Conditional on having exposure, the mean, median, and $90^{th}$ percentile of bank IL&FS exposure is 4.64%, 0.59%, and 14.72%. While the financial condition of various ILFS subsidiaries had been deteriorating since June 2018, the downgrade of the ILFS parent entity on September 17, 2018, had a large impact on banks with substantial exposure to the group. Even large banks saw a sharp decline in their stock prices following the announcement. In Figure A3, we illustrate how the stock prices of two major banks with significant IL&FS exposure—Yes Bank and Syndicate Bank—reacted to the downgrade. As is evident from the figure, the negative effects on banks connected to ILFS were both swift and substantial.

Next, we trace the lending outcomes for the banks with high vs. low direct exposure to

IL&FS group using a following model

$$1(\text{Loan})_{b,l,t} = \beta \times \text{High Bank ILFS Exposure}_{l,2018} \times \text{Post ILFS}_t + \alpha_{b,l} + \alpha_{b,t} + \varepsilon_{b,l,t} \quad (17)$$

where $1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if an borrower $b$ took a new loan from a bank lender $l$ in year $t$, and zero otherwise. High Bank ILFS $\text{Exposure}_{l,2018}$ is an indicator variable that equals one if bank $l$ had an above-median exposure to ILFS group in 2018 as defined in Equation 16, and zero otherwise. because IL&FS defaults occurred during the financial year 2018-19, Post $\text{ILFS}_t$ equals one for year 2019 onwards. We absorb borrower×year to absorb any unobserved changes to the credit demand of the borrower around the same time the IL&FS crises took place, which is a likely scenario. Additionally, we absorb the borrower×lender fixed effects as before so as to resolve the concern of endogenous matching between certain types of borrowers with certain specific types of lenders. Such endogeneous matching can drive the results if such matching gain pace after the IL&FS crises.

We begin by considering the dynamics around IL&FS crises of new loan origination between banks and NBFI borrowers (excluding IL&FS group NBFIs) in column 1. Holding the credit demand of such NBFIs, the credit supply declines to NBFIs more severely after the IL&FS crises from banks having higher ex-ante exposure to IL&FS group. The decline is statistically and economically significant, with an additional reduction in loan origination probability for high IL&FS exposure banks by 5.8 percentage points (pp.) or by 47.5% (relative to mean probability of loan origination to a NBFI borrower of 12.2%) relative to the banks with low IL&FS exposure.

In column 2 we consider corporate borrowers and find that high IL&FS exposure banks cut credit more aggressively after the crises even to the corporate borrowers. The additional reduction from high IL&FS exposure banks is 1.1 pp. or 13.5% (relative to mean probability of loan origination to corporate borrower of 8.1%). The result that bank's credit supply to corporate borrowers decline due to IL&FS exposure is robust to excluding industrial sectors in which IL&FS group companies were active (i.e., Infrastructure, Construction, and Electricity), to further bolster our argument that the result is not driven by drop in the credit demand. In column 4 we show that exposure to IL&FS is special. We measure bank's exposure to NBFI sector in 2018 in similar fashion in which we measure bank's IL&FS exposure. However, we find that it is te IL&FS exposure and not the NBFI exposure that drive the decline in credit supply.

Taken together we find that banks exposed to the troubled IL&FS bank did cut credit to both corporate and NBFI borrowers. However, NBFIs experienced a decline in credit supply

at least three times as large as experienced by a corporate borrower. Our results contribute to the literature on two dimensions; First it shows that banks cut the credit to NBFI borrowers much more severely. To this extent the average spillover effects estimated in the literature so far are underestimated. Second, the result highlights that the second-round spillover effects when these NBFI borrowers cut the credit to their borrowers are potentially economically large.

### B.2 Aggregate Credit Supply at Borrower Level

Having shown that exposed banks cut lending to its NBFI and corporate borrowers, we next trace if these borrowers are able to substitute the bank with a new lender unaffected by the IL&FS crises, and restore the credit supply to pre-crises levels. To this end, we define the exposure of a borrower to IL&FS crises through its bank lenders as follows;

$$\text{Borr. ILFS Exposure}_{b,2018} = \sum_{l \in \text{Banks}} \left( \frac{\text{Credit}_{b,l,2018}}{\text{Credit}_{b,2018}} \right) \times \text{ILFS Exposure}_{l,2018} \tag{18}$$

where $Credit_{b,l,2018}$ and $Credit_{b,2018}$ respectively denote the credit outstanding between borrower $b$ and bank lender $l$, and total borrowings of borrower $b$, and ILFS $\text{Exposure}_{l,2018}$ is the bank's exposure to IL&FS crises as defined in Equation 16. That is, Borrower's exposure to IL&FS is the weighted average of exposure of its bank lenders to IL&FS. Given that borrowers have multiple bank lenders at a point in time, borrower exposure to IL&FS has a smaller mean, median, and $90^{th}$ percentile of 0.46%, 0.22%, and 0.83%.

The credit supply at the borrower level is estimated using following model on the borrower×year panel;

$$\begin{aligned} 1(\text{Loan})_{b,t} &= \beta \times \text{High Borrower ILFS Exposure}_{b,2018} \times \text{Post ILFS}_t && (19) \\ &+ \alpha_b + \alpha_{X(b,2018),t} + \varepsilon_{b,t} && (20) \end{aligned}$$

where $1(\text{Loan})_{b,t}$ is the dummy indicating whether borrower $b$ was able to obtain even a single loan from a set of lenders considered in the regression during year $t$, High Borrower ILFS $\text{Exposure}_{b,2018}$ is the dummy for above-median borrower exposure to IL&FS. We absorb borrower fixed effects, and borrower characteristics×year fixed effects so that we estimate the change in credit for a given borrower from before to after the IL&FS crises in response to High exposure to IL&FS crises relative to Low exposure borrowers within the same characteristic bucket.

In column 1 we consider the borrower's credit from all the banks to find that the probability of a borrower obtaining any bank loan drops more severely from pre- to post-ILFS crises for

highly exposed borrowers to IL&FS crises. In column 2 we find that NBFI lenders do extend more credit to these exposed borrowers, but not enough to compensate for the decline in bank credit supply (column 3). On the net basis we find that a highly exposed borrower to the IL&FS crisis suffers an additional decline in probability of obtaining any loan of 24.68% relative to the mean probability of obtaining any loan from any lender during the year for a corporate borrower. The magnitude seems large relative to the borrower's indirect exposure to IL&FS crises. However, such was a panic in the Indian financial markets that a mere positive exposure (rather than the actual extent of exposure) dried up the credit supply for even the corporate borrowers only indirectly related to IL&FS crisis.

Table 14 investigate if there is a heterogeneity in the severity of a drop in credit supply to the exposed borrowers. We find no evidence that smaller, or younger corporate borrowers are hurt more due to exposure to IL&FS crisis. However, borrowers with low credit rating and having higher ex-ante dependence on banks are hurt more. This is consistent with the hypothesis that after the crisis, lenders would be more cautious to lend to lower rated borrowers. On the other hand, higher bank dependency implies limited connections of such corporate borrowers with NBFCs which results in a more severe credit contraction for such firms post the IL&FS crisis.

Lastly, we document in Table 15 that IL&FS exposure induced credit contraction affects the real outcomes for the exposed borrowers. We absorb the borrower fixed effects, and and borrower characteristics×year fixed effects as before as we estimate the real effects on the borrower×year panel. Borrowers with higher IL&FS exposure suffer additional decline of 3.1% and 6.6% in its size measured by total assets, and revenues respectively. The credit contraction also lowers the leverage for such borrowers. However, the borrowers on the net bass suffer as their profitability drops by additional 0.88 pp. or by 7.36% on the mean profitability ratios in our sample.

### B.3 Contagion Due to Banks-NBFI Connections

Now we address the question used to motivate this section which is whether existing bank-NBFI connections amplify adverse effects of a large borrower default? As explained in the motivation to this section, bank-NBFI connection has the potential to spread the default induced credit contraction to the corporate borrowers whose NBFI lenders borrow from directly affected bank.

Therefore, a corporate borrower could be affected by the default either because that borrower borrows from the affected bank, or because it borrows from a NBFI which in turn

borrow from the affected bank. We call former the first round effects of default and later the second round effect of default. To understand the relative role of the first and second round effects, we first define the the two exposure measures for any given corporate borrower. The first round measure is defined by

$$\text{Borr. ILFS Exposure}^{1}_{b,2018} = \sum_{l \in \text{Banks}} \left( \frac{\text{Credit}_{b,l,2018}}{\text{Credit}_{b,2018}} \right) \times 1(\text{ILFS Exposure}_{l,2018}) \tag{21}$$

This is akin to our Borrower Exposure to ILFS measure, except that instead of continuous ILFS Exposure of a bank lender, we consider a dummy ($1(\text{ILFS Exposure}_{l,2018})$) indicating any positive exposure by a bank to IL&FS. Let the banks with direct exposure to IL&FS be denoted by $ld$. Then the second round measure is defined as

$$\text{Borr. ILFS Exposure}^{2}_{b,2018} = \sum_{l \in \text{NBFC}} \left( \frac{\text{Credit}_{b,l,2018}}{\text{Credit}_{b,2018}} \right) \times 1(\text{Credit}_{l,ld,2018}) \tag{22}$$

This measure computes the share of borrowings for a given corporate issued by NBFI lender which borrow from banks directly exposed to ILF&FS group.

Note that the second round effects are absent in the economy where Bank-NBFC connections are absent. Therefore, the contraction in corporate credit after IL&FS crisis in response to the second round exposure via NBFIs provides a good estimate of both the contagion and amplification effects of bank-NBFI connections. For the corporate borrowers having both first and second round exposure to IL&FS, the response of credit to second round exposure provides an estimate of amplification effects of bank-NBFI connections. For the corporate borrowers having only indirect second round exposure to IL&FS, the response of credit to second round exposure provides an estimate of contagion due to bank-NBFI connections, as these corporate borrowers are more likely to be shielded in an economy without bank-NBFI connections.

To test the relative significance of first and second round ILFS exposures, we employ a following horse race model on corporate borrowers$\$times$year panel

$$\begin{aligned} 1(\text{Loan})_{b,t} = {} & \beta_1 \times \text{Borrower ILFS Exposure Via Banks}_{b,2018} \times \text{Post ILFS}_t \\ & + \beta_2 \times \text{Borrower ILFS Exposure Via NBFC}_{b,2018} \times \text{Post ILFS}_t \\ & + \alpha_b + \alpha_{X(b,2018),t} + \varepsilon_{b,t} \end{aligned}$$

$1(\text{Loan})_{b,t}$ is an indicator variable that equals one if corporate borrower $b$ took at least one new loan from any lender during the year $t$ and zero otherwise. As before, we absorb borrower

fixed effects, and borrower characteristics×year fixed effects.

Table 16 report the results. We first use only first round (column 1) and second round (column 2) exposure to ILFS individually. Both the exposure measures predicts an additional decline in probability of obtaining any loan for a corporate borrower relative to borrowers without exposure to ILFS. In column 3, we run a horse race between the two effects. The coefficients hardly change as compared to columns 1 and 2, and retain their statistically significance at 1% confidence level. Economically, both the first and second round exposure to ILFS are strong. A one-standard-deviation higher first (second) round exposure implies an additional decline in probability of obtaining any loan for a corporate borrower of 1.13 pp. (1.89 pp.). Relative to mean probability of obtaining a loan during the year, these translates into an additional decline of 4.28% (8.04%) for first (second) round exposure to ILFS. This suggests that a corporate borrower with one standard deviation higher first and second round exposure to ILFS will experience an amplified decline of 12.87% in probability of obtaining a loan. And borrowers with only second round exposure get hit by an additional 8.04% decline in loan probabilities relative to the economy where bank-NBFI connections are absent. This is the contagion effect.

Our results highlight that even if corporate borrowers having second round exposure to ILFS are far more disconnected from ILFS compared to borrowers with first round exposure, the credit contraction experienced by the former group of corporate borrowers is almost twice as strong. This result can be explained using two observations. First, results in table 12 shows that banks with direct exposure to ILFS cut credit much more strongly for NBFI borrowers. Second, the fact that even non-exposed bank lenders and mutual funds virtually stopped lending to NBFIs, compounded the financing troubles for a typical NBFI around ILFS crisis.

To conclude, we provide a very strong amplification and contagion effects on credit supply of bank-NBFI connections.

# VI Conclusion

Our paper provides a complete account of how credit allocation changes in the economy is response to the regulations incentivizing banks to lend to NBFCs, and the contagion effects of such bank-NBFC connections. We provide a strong evidence that the lowering of risk-weights on bank loans to NBFCs increased lending by banks to NBFCs at the expense of the corporate borrowers, and these corporate borrowers found it difficult to obtain credit from NBFCs to fill the credit gap leftover by the banks. However, we highlight that NBFCs are

more likely to lend to smaller, younger, and low rated firms, thereby promoting financial inclusion.

Using a large scale default of IL&FS group in 2018, we document the contagion effect of bank-NBFC connections by showing that not only borrowers of the banks with direct IL&FS exposure suffered a decline in credit and deterioration in real outcomes, but these adverse effects extended to the borrowers only indirectly exposed to IL&FS via their NBFC lender which in turn borrow from directly affected banks.

Overall, our paper shed light on hitherto understudied consequences of bank-NBFC connections. Our paper provides interesting policy insights. In particular it highlights that NBFCs might reallocate the credit to credit constraints firms, but bank-NBFC connections also sows the seeds of contagion.

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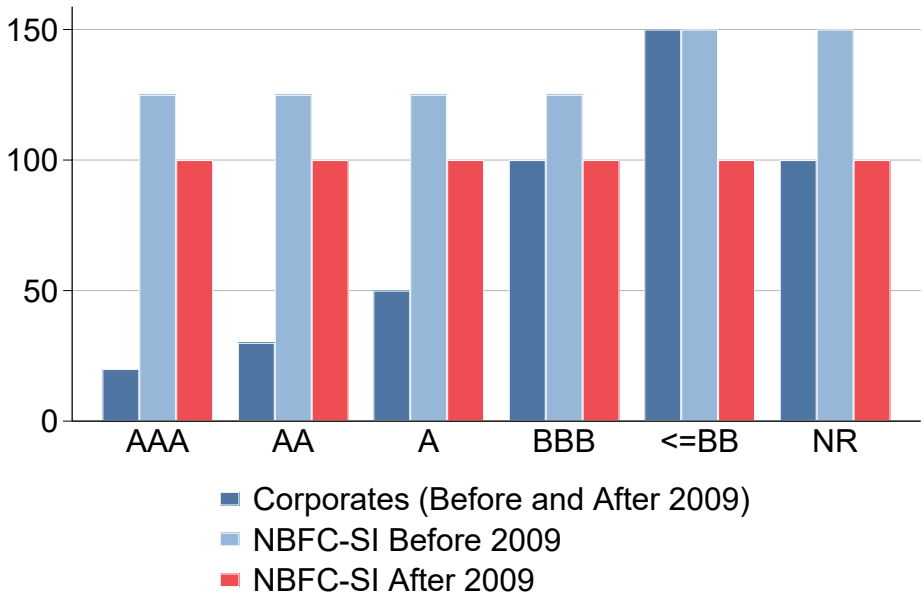
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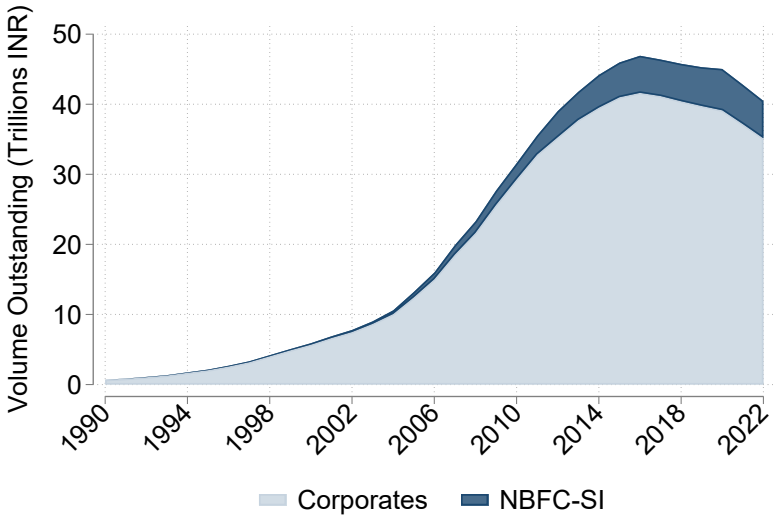
# VII Figures and Tables

**Figure 1: Risk Weights Before and After 2009**

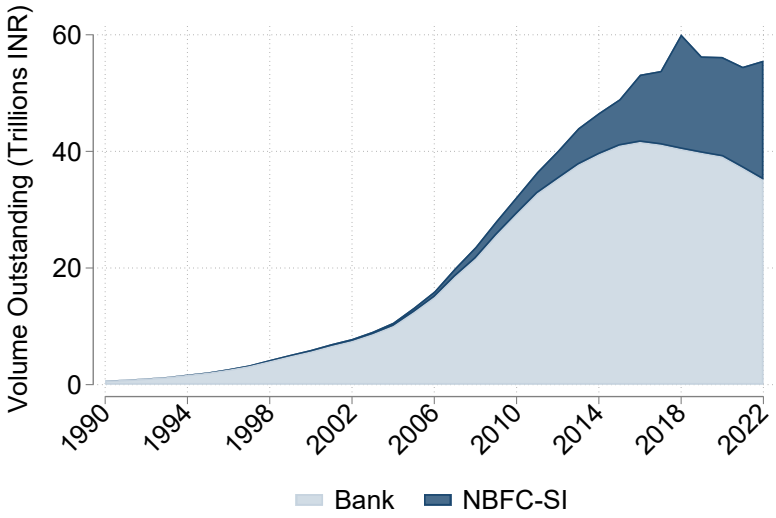



**Notes**: Figure 1 shows rating-wise risk weights (in %) for banks' exposure to corporates and systemically important NBFCs before and after the 2009 change.

**Figure 2: Aggregate Summary Statistics**



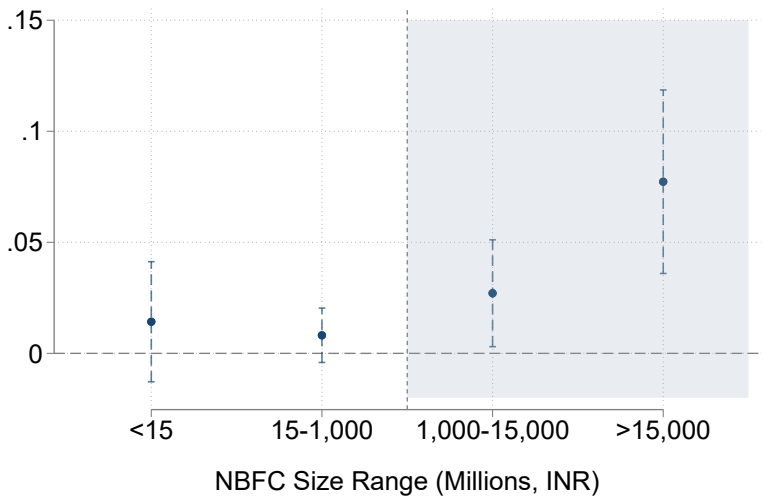

**(a) Composition of Bank Borrowers**




**(b) Composition of Lenders to Corporates**

**Notes**: Figure 2 shows the composition of bank borrowers (Panel (a)) and the composition of lenders to the corporate section (Panel (b)).

**Figure 3: Robustness: Effect Across NBFC Size Groups**

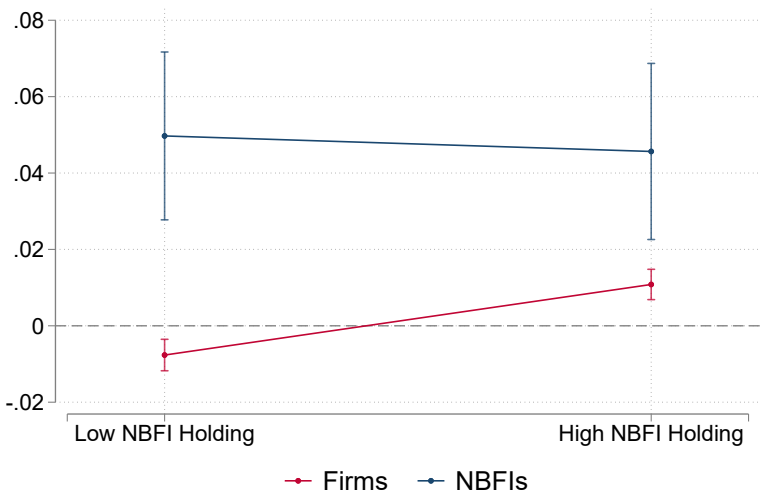



**Notes**: Figure 3 shows that, after 2009, banks increased lending primarily to NBFCs classified as systemically important (i.e., those with more than INR 1,000 Million in assets) in 2008. The sample contains all types of borrowers and bank lenders and covers the period from 2004 to 2014. The empirical specification is:

$$1(\text{Loan})_{b,l,t} = \sum_{k=1}^{4} \beta^k \times \text{NBFC Size Group}^k_{b,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{l,t} + \alpha_{X(b,2008),t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. We classify NBFC borrowers into four size groups based on their total assets in 2008. These are <15, 15-1,000, 1,000-15,000, and >=15,000 (expressed in INR Millions). NBFC Size Group$^k_{b,2008}$ is an indicator variable that equals one if the NBFC $b$ lies in size group $k$ in 2008, and zero otherwise. Post RW Change$_t$ equals one for year 2009 onwards. $\alpha_{b,l}$, $\alpha_{l,t}$, and $\alpha_{X(b,2008),t}$ denote borrower-lender, lender-year, and borrower-characteristics-year fixed effects, respectively. We use pre-2009 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Figure 4: Heterogeneity in Bank Response**




**Notes**: Figure 4 shows that banks with less prior-NBFI holdings substituted away from their corporate borrowers. The red line corresponds to Corporate borrowers and the blue line corresponds to NBFI borrowers. The sample contains bank lenders and covers the period from 2004 to 2014. The empirical specification is:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{Low NBFI Holding}_{l,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. Low NBFI $\text{Holding}_{l,2008}$ is an indicator variable that equals one if bank lender $l$ had below-median fraction of all its lending going towards NBFI in 2008. Post RW $\text{Change}_t$ equals one for year 2009 onwards. The figure plots coefficients corresponding to both Low and High NBFI Holding for both Coporates and NBFI. $\alpha_{b,l}$ denotes borrower-lender fixed effects. We cluster standard errors at the borrower level.

**Table 1: Summary Statistics**

| | Obs | Mean | SD | Median |
|---|---|---|---|---|
| **Panel (a): Loans** | | | | |
| 1(Loan) (per Year) | 695125 | 0.100 | 0.300 | 0.000 |
| Loan Size (INR Millions) | 69461 | 363.449 | 374.805 | 200.000 |
| Loan Maturity (Years) | 54020 | 4.885 | 3.421 | 4.250 |
| **Panel (b): Firms** | | | | |
| 1(Loan) (per Year) | 173669 | 0.273 | 0.446 | 0.000 |
| 1(Loan) Bank (per Year) | 173669 | 0.235 | 0.424 | 0.000 |
| 1(Loan) NBFI (per Year) | 173669 | 0.065 | 0.246 | 0.000 |
| Total Borrowing (INR Billions) | 173669 | 2.006 | 9.239 | 0.139 |
| Borrowing from NBFI (%) | 139050 | 9.217 | 24.483 | 0.000 |
| Borrower Exposure | 173669 | 0.468 | 0.476 | 0.386 |
| Assets (INR Billions) | 173669 | 4.529 | 39.172 | 0.342 |
| Age (Years) | 173669 | 20.513 | 17.388 | 17.000 |
| Credit Rating Score | 173669 | 0.513 | 1.082 | 0.000 |
| Sales (INR Billions) | 147633 | 2.808 | 10.354 | 0.376 |
| Leverage (%) | 150336 | 42.411 | 28.986 | 45.216 |
| EBITDA/Sales (%) | 167215 | 13.201 | 24.762 | 9.233 |
| ROA (%) | 127052 | -19.329 | 474.908 | 30.863 |
| **Panel (c): NBFIs** | | | | |
| Assets (INR Billions) | 1502 | 83.576 | 248.172 | 12.332 |
| Age (Years) | 1502 | 21.667 | 14.805 | 18.000 |
| Credit Rating Score | 1502 | 2.960 | 1.930 | 4.000 |
| **Panel (d): Banks** | | | | |
| Total Lending (INR Billions) | 1602 | 238.520 | 749.782 | 18.105 |
| Lending to NBFI (%) | 1602 | 6.517 | 9.491 | 2.742 |
| Lending to NBFI Pre 2009 (%) | 1602 | 7.442 | 9.231 | 5.202 |
| Bank CAR (%) | 1317 | 16.157 | 8.371 | 13.080 |

**Notes**: Table 1 shows summary statistics of key variables used in the paper.

**Table 2: Bank Lending After 2009: NBFI vs. Other Borrowers**

| | 1(Loan) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| NBFI Borrower × Post RW Change | 0.046*** | 0.046*** | 0.043*** |
| | (0.011) | (0.011) | (0.011) |
| NBFI Borrower | -0.004 | | |
| | (0.008) | | |
| Post RW Change | 0.007*** | | |
| | (0.002) | | |
| Obs | 447068 | 447068 | 447068 |
| Borrower × Lender FE | | ✓ | ✓ |
| Lender × Year FE | | ✓ | ✓ |
| Borrower Size Group × Year FE | | | ✓ |
| Borrower Age Group × Year FE | | | ✓ |
| Borrower Rating × Year FE | | | ✓ |
| Y-Mean | 0.102 | 0.102 | 0.102 |
| Adj. R-sq | 0.001 | 0.101 | 0.102 |

**Notes**: Table 2 shows that banks increased lending to NBFI after the 2009 change in relative risk weights. The sample contains all types of borrowers and bank lenders and covers the period from 2004 to 2014. The empirical specification in Column (3) is:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Borrower}_{b,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{l,t} + \alpha_{X(b,2008),t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. $\text{NBFI Borrower}_{b,2008}$ is an indicator variable that equals one if $b$ is classified as a systemically important NBFC in 2008, and zero otherwise. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\alpha_{b,l}$, $\alpha_{l,t}$, and $\alpha_{X(b,2008),t}$ denote borrower-lender, lender-year, and borrower-characteristics-year fixed effects, respectively. We use pre-2009 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Table 3: Effect of Banks' Prior NBFI Holdings**

| | 1(Loan) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| NBFI Borrower × Post RW Change × Low NBFI Holding | 0.015* | 0.016* | 0.021*** |
| | (0.009) | (0.009) | (0.008) |
| NBFI Borrower × Post RW Change | 0.040*** | 0.037*** | |
| | (0.012) | (0.012) | |
| Obs | 413683 | 413683 | 413683 |
| Borrower × Lender FE | ✓ | ✓ | ✓ |
| Lender × Year FE | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | | ✓ | |
| Borrower Age Group × Year FE | | ✓ | |
| Borrower Rating × Year FE | | ✓ | |
| Borrower × Year FE | | | ✓ |
| Y-Mean | 0.104 | 0.104 | 0.104 |
| Adj. R-sq | 0.102 | 0.103 | 0.105 |

**Notes**: Table 3 shows that banks with lower lending to NBFI prior to 2009 switched more aggressively towards NBFI after the 2009 change in relative risk weights. The sample contains all types of borrowers and bank lenders and covers the period from 2004 to 2014. The empirical specification in Column (3) is:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Borrower}_{b,2008} \times \text{Post RW Change}_t \times \text{Low NBFI Holding}_{l,2008} + \alpha_{b,l} + \alpha_{l,t} + \alpha_{b,t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. $\text{NBFI Borrower}_{b,2008}$ is an indicator variable that equals one if $b$ is classified as a systemically important NBFC in 2008, and zero otherwise. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\text{Low NBFI Holding}_{l,2008}$ is an indicator variable that equals one if bank lender $l$ had below-median fraction of all its lending going towards NBFI in 2008. $\alpha_{b,l}$, $\alpha_{l,t}$, and $\alpha_{b,t}$ denote borrower-lender, lender-year, and borrower-year fixed effects, respectively. We cluster standard errors at the borrower level.

**Table 4: Impact on Corporate Borrowers (Total Borrowing)**

| | 1(Loan) | | |
|---|---|---|---|
| | Bank | NBFI | All |
| | (1) | (2) | (3) |
| Borrower Exposure × Post RW Change | -0.058*** | 0.002 | -0.059*** |
| | (0.006) | (0.003) | (0.006) |
| Obs | 99231 | 99231 | 99231 |
| Borrower FE | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | ✓ | ✓ | ✓ |
| Borrower Age Group × Year FE | ✓ | ✓ | ✓ |
| Borrower Rating × Year FE | ✓ | ✓ | ✓ |
| Y-Mean | 0.287 | 0.287 | 0.287 |
| SD(Borrower Exposure) | 0.459 | 0.459 | 0.459 |
| Adj. R-sq | 0.305 | 0.260 | 0.321 |

**Notes**: Table 4 shows that corporate borrowers related to more exposed banks experienced a decline in total borrowing. The sample contains corporate borrowers and covers the period from 2004 to 2014. The empirical specification is:

$$1(\text{Loan})_{b,t} = \beta \times \text{Borrower Exposure}_{b,2008} \times \text{Post RW Change}_t + \alpha_b + \alpha_{X(b,2008),t} + \varepsilon_{b,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if corporate borrower $b$ took at least one new loan from a bank lender (Column (1)), NBFI lender (Column (2)), or any lender in year $t$, and zero otherwise. $\text{Borrower Exposure}_{b,2008}$ is the fraction of total credit that borrower $b$ has from the set of low NBFI holding banks in 2008. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\alpha_b$ and $\alpha_{X(b,2008),t}$ denote borrower and borrower-characteristics-year fixed effects, respectively. We use pre-2009 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Table 5: Impact of Deposit Flight on Corporate Borrowers (Total Borrowing)**

| | 1(Loan) | | | | |
|---|---|---|---|---|---|
| | All | | | Bank | NBFI SI |
| | (1) | (2) | (3) | (4) | (5) |
| Post RW Change × Borrower Exposure | -0.061*** | | -0.064*** | -0.068*** | 0.006* |
| | (0.007) | | (0.008) | (0.009) | (0.003) |
| Post RW Change × Borrower Deposit Flight Exposure | | -0.047*** | -0.053*** | -0.062*** | 0.013*** |
| | | (0.009) | (0.010) | (0.010) | (0.005) |
| Obs | 99231 | 94510 | 94510 | 94510 | 94510 |
| Borrower FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Borrower Age Group × Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Borrower Rating × Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Y-Mean | 0.287 | 0.298 | 0.298 | 0.264 | 0.067 |
| SD(Borrower Exposure) | 0.476 | | 0.474 | 0.474 | 0.474 |
| SD(Deposit Flight) | | 0.337 | 0.337 | 0.337 | 0.337 |
| Adj. R-sq | 0.321 | 0.315 | 0.316 | 0.295 | 0.263 |

**Notes**: Table 5 shows that corporate borrowers related to more exposed banks experienced a decline in total borrowing even after controlling for the borrower's exposure to the deposit flight experienced by its bankers. The sample contains corporate borrowers and covers the period from 2004 to 2014. The empirical specification is:

$$\begin{aligned} 1(\text{Loan})_{b,t} &= \beta_1 \times \text{Borrower Exposure}_{b,2008} \times \text{Post RW Change}_t + \alpha_b \\ &+ \beta_2 \times \text{Borrower Deposit Flight Exposure}_{b,2009} + \alpha_{X(b,2008),t} + \varepsilon_{b,t} \end{aligned}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if corporate borrower $b$ took at least one new loan from any lender (Column 1-3), a bank lender (Column (4)), or an NBFI lender (Column (5)) in year $t$, and zero otherwise. $\text{Borrower Exposure}_{b,2008}$ is the fraction of total credit that borrower $b$ has from the set of low-exposure banks in 2008. $\text{Borrower Deposit Exposure}_{b,2009}$ is the weighted average of the bank's deposit growth during the financial year 2008/09, where weights are the fraction of total credit that borrower $b$ obtains from the bank lender $l$. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\alpha_b$ and $\alpha_{X(b,2008),t}$ denote borrower and borrower-characteristics-year fixed effects, respectively. We use pre-2009 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

## Table 6: Impact on Corporate Borrowers (Real Outcomes)

| | Leverage | Cost of Debt | Log Assets | Log Sales | EBITDA/Sales | ROA |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post RW Change × Borrower Exposure | -0.034*** | 0.547* | -0.275*** | -0.164*** | -0.602 | -0.217** |
| | (0.005) | (0.297) | (0.024) | (0.027) | (0.419) | (0.095) |
| Obs | 85463 | 67726 | 99231 | 85678 | 95397 | 77604 |
| Borrower FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Borrower Age Group × Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Borrower Rating × Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Y-Mean | 0.409 | 0.448 | 5.930 | 5.795 | 14.536 | 0.011 |
| SD(Borrower Exposure) | 0.460 | 0.447 | 0.459 | 0.454 | 0.458 | 0.459 |
| Adj. R-sq | 0.662 | 0.009 | 0.877 | 0.876 | 0.421 | 0.362 |

**Notes**: Table 6 shows that corporate borrowers related to more exposed banks experienced worse real outcomes. The sample contains corporate borrowers and covers the period from 2004 to 2014. The empirical specification is:

$$\mathrm{Y}_{b,t} = \beta \times \text{Borrower Exposure}_{b,2008} \times \text{Post RW Change}_t + \alpha_b + \alpha_{X(b,2008),t} + \varepsilon_{b,t}$$

$\mathrm{Y}_{b,t}$ is a set of outcomes (Leverage, Cost of Debt, Assets, Sales, and Profitability) for borrower $b$ in year $t$. Borrower $\text{Exposure}_{b,2008}$ is the fraction of total credit that borrower $b$ has from the set of low NBFI holding banks in 2008. Post RW $\text{Change}_t$ equals one for year 2009 onwards. $\alpha_b$ and $\alpha_{X(b,2008),t}$ denote borrower and borrower-characteristics-year fixed effects, respectively. We use pre-2009 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Table 7: Corporate Borrowing After 2009: NBFI vs. Banks**

| | 1(Loan) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| NBFI Lender × Post RW Change | 0.018*** | 0.019*** | 0.020*** |
| | (0.003) | (0.003) | (0.003) |
| Post RW Change | 0.008*** | | |
| | (0.002) | | |
| Obs | 466266 | 466266 | 466266 |
| Borrower × Lender FE | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | | ✓ | |
| Borrower Age Group × Year FE | | ✓ | |
| Borrower Rating × Year FE | | ✓ | |
| Borrower × Year FE | | | ✓ |
| Y-Mean | | | 0.101 |
| Adj. R-sq | 0.099 | 0.102 | 0.098 |

**Notes**: Table 7 shows that corporates increased borrowing from NBFI after the 2009 change in relative risk weights. The sample contains corporate borrowers and both bank and NBFC lenders and covers the period from 2004 to 2014. The empirical specification in Column (3) is:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Lender}_{l,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{b,t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. $\text{NBFI Lender}_{l,2008}$ is an indicator variable that equals one if $l$ is classified as a systemically important NBFC in 2008, and zero otherwise. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\alpha_{b,l}$, $\alpha_{X(b,2008),t}$ and $\alpha_{b,t}$ denote borrower-lender, borrower-characteristics-year, and borrower-year fixed effects, respectively. We use pre-2009 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Table 8: Effect on Loan Contracts**

| | Loan Size | | Loan Maturity | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| NBFI Lender × Post RW Change | 0.356*** | 0.348*** | 0.526** | 0.488* |
| | (0.109) | (0.131) | (0.255) | (0.291) |
| Obs | 10970 | 10970 | 10970 | 10970 |
| Borrower × Lender FE | ✓ | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | ✓ | | ✓ | |
| Borrower Age Group × Year FE | ✓ | | ✓ | |
| Borrower Rating × Year FE | ✓ | | ✓ | |
| Borrower × Year FE | | ✓ | | ✓ |
| Y-Mean | 19.210 | 19.210 | 4.897 | 4.897 |
| Adj. R-sq | 0.592 | 0.560 | 0.487 | 0.460 |

**Notes**: Table 8 shows the change in loan contract terms after the 2009 change. The sample contains corporate borrowers and both bank and NBFC lenders and covers the period from 2004 to 2014. Each observation corresponds to a borrower-lender-year combination conditional on a new loan being taken. The empirical specification in Columns (2) and (4) is:

$$\text{Y}_{b,l,t} = \beta \times \text{NBFI Lender}_{l,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{b,t} + \varepsilon_{b,l,t}$$

$\text{Y}_{b,l,t}$ is Loan Size (i.e., log of loan amount) in Columns (1) and (2) and Loan Maturity (in years) in Columns (3) and (4) for new loans taken by borrower $b$ from lender $l$ in year $t$. NBFI $\text{Lender}_{l,2008}$ is an indicator variable that equals one if $l$ is classified as a systemically important NBFC in 2008, and zero otherwise. Post RW $\text{Change}_t$ equals one for year 2009 onwards. $\alpha_{b,l}$ and $\alpha_{b,t}$ denote borrower-lender and borrower-year fixed effects, respectively. We cluster standard errors at the borrower level.

**Table 9: Corporate Borrowing After 2009: Heterogeneous Impact**

| | 1(Loan) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| NBFI Lender × Post RW Change | 0.018*** | 0.016*** | -0.004 | -0.006 |
| | (0.003) | (0.003) | (0.009) | (0.009) |
| × Low Borrower Size | 0.014*** | | | 0.008 |
| | (0.005) | | | (0.005) |
| × Low Borrower Age | | 0.017*** | | 0.014** |
| | | (0.006) | | (0.006) |
| × Low Borrower Rating | | | 0.030*** | 0.024** |
| | | | (0.009) | (0.010) |
| Obs | 564339 | 564339 | 564339 | 564339 |
| Borrower × Lender FE | ✓ | ✓ | ✓ | ✓ |
| Borrower × Year FE | ✓ | ✓ | ✓ | ✓ |
| Y-Mean | 0.103 | 0.103 | 0.103 | 0.103 |
| Adj. R-sq | 0.091 | 0.091 | 0.091 | 0.091 |

**Notes**: Table 9 shows how lending composition of different types of corporate borrowers changed after the 2009 change in relative risk weights. It sheds light on how the 2009 policy affected loan market segmentation between bank and NBFC lender base. The sample contains all corporate borrowers and both bank and NBFC lenders and covers the period from 2004 to 2014. The empirical specification in Column (3) is:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Lender}_{b,2008} \times \text{Post RW Change}_t \times \text{Borrower Characteristic}_{b,2008} + \alpha_{b,l} + \alpha_{b,t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. NBFI $\text{Lender}_{b,2008}$ is an indicator variable that equals one if $l$ is classified as a systemically important NBFC in 2008, and zero otherwise. Post RW $\text{Change}_t$ equals one for year 2009 onwards. Borrower $\text{Characteristic}_{b,2008}$ indicates a set of characteristics (size, age, and rating) for borrower $b$ in 2008. $\alpha_{b,l}$ and $\alpha_{b,t}$ denote borrower-lender and borrower-year fixed effects, respectively. We cluster standard errors at the borrower level.

## Table 10: NBFC Lending and Asset Commonality

### Panel A: All Banks

| | 1(Loan) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post RW Change × Bank Corporate | 0.094*** | | |
| | (0.009) | | |
| Post RW Change × Bank Region | | 0.045* | |
| | | (0.025) | |
| Post RW Change × Bank Industry | | | 0.014 |
| | | | (0.028) |
| Obs | 92629 | 92629 | 92629 |
| Borrower × Lender FE | ✓ | ✓ | ✓ |
| Lender × Year FE | ✓ | ✓ | ✓ |
| Y-Mean | 0.088 | 0.088 | 0.088 |
| Adj. R-sq | 0.177 | 0.175 | 0.175 |

### Panel B: Related Banks

| | 1(Loan) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post RW Change × Related-Bank Corporate | -0.011 | | |
| | (0.009) | | |
| Post RW Change × Related-Bank Region | | -0.027* | |
| | | (0.016) | |
| Post RW Change × Related-Bank Industry | | | 0.022* |
| | | | (0.011) |
| Obs | 109306 | 109306 | 109306 |
| Borrower × Lender FE | ✓ | ✓ | ✓ |
| Lender × Year FE | ✓ | ✓ | ✓ |
| Y-Mean | 0.086 | 0.086 | 0.086 |
| Adj. R-sq | 0.169 | 0.169 | 0.169 |

**Notes**: Table 10 shows lending behavior of NBFI after the 2009 change. The sample contains all types of borrowers and NBFI lenders and covers the period from 2004 to 2014. The empirical specification is:

$$1(\text{Loan})_{b,l,t} = \gamma \times \text{Post RW Change}_t \times \text{Borrower Characteristic}_{b,2008} + \alpha_{b,l} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. Bank Corporate, Bank Region, and Bank Industry indicate corporates, districts and regions heavily dependent on bank debt (Panel A). Related-Bank Corporate, Region, and Industry correspond to corporates, districts, and industries served by NBFI $l$'s bank lenders in 2008 (Panel B). Post RW Change$_t$ equals one for year 2009 onwards. $\alpha_{b,l}$, $\alpha_{b,t}$, and $\alpha_{l,t}$ denotes borrower-lender, borrower-year, and lender-year fixed effects. We cluster standard errors at the borrower level.

**Table 11: Aggregate Effects of Credit Reallocation**

| | Var(MRPK) | | Mean(MRPK) | | Cov(MRPK Sa | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6 |
| Post RW Change × Industry Exposure | -0.777 | | 0.163 | | -0.746** | |
| | (0.478) | | (0.128) | | (0.327) | |
| Post RW Change × High Industry Exposure | | -0.295* | | 0.079 | | -0.37 |
| | | (0.175) | | (0.053) | | (0.15 |
| Obs | 1631 | 1631 | 1631 | 1631 | 1631 | 163 |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Y-Mean | 1.539 | 1.539 | -0.640 | -0.640 | 1.386 | 1.38 |
| SD(Borrower Exposure) | 0.283 | 0.497 | 0.283 | 0.497 | 0.283 | 0.49 |
| Adj. R-sq | 0.641 | 0.639 | 0.954 | 0.954 | 0.508 | 0.50 |

**Notes**: Table 11 shows the aggregate effects of credit reallocation due to the RBI risk weight policy. The sample covers the period from 2004 to 2014. The empirical specification is:

$$\mathrm{Y}_{s,t} = \beta \times \text{Industry Exposure}_{s,2008} \times \text{Post RW Change}_t + \alpha_s + \alpha_t + \varepsilon_{s,t}$$

where $s$ and $t$ indexes the industry and the financial year respectively. Industry is defined using the Prowess industry group code variable. $\mathrm{Y}_{s,t}$ denotes the moments calculated for industry $s$ in year $t$. Industry $\text{Exposure}_{s,2008}$ is the fraction of outstanding credit in industry $s$ from Low NBFI Holding banks in 2008. High Industry $\text{Exposure}_{s,2008}$ indicates one for industry with above-median level of Industry Exposure. Post RW $\text{Change}_t$ equals one for year 2009 onwards. We employ industry ($\alpha_s$) and time ($\alpha_t$) fixed effects and cluster standard errors at the industry level.

**Table 12: Bank Lending After ILFS**

| | 1(Loan) | | | |
|---|---|---|---|---|
| | NBFC | Corporate | | |
| | (1) | (2) | (3) | (4) |
| High Bank ILFS Exposure × Post ILFS | -0.058*** | -0.011*** | -0.010*** | -0.011*** |
| | (0.010) | (0.004) | (0.004) | (0.004) |
| High Bank NBFC Exposure × Post ILFS | | | | -0.033 |
| | | | | (0.033) |
| Obs | 26998 | 185140 | 177335 | 185140 |
| Borrower × Lender FE | ✓ | ✓ | ✓ | ✓ |
| Borrower × Year FE | ✓ | ✓ | ✓ | ✓ |
| Y-Mean | 0.122 | 0.081 | 0.079 | 0.081 |
| Adj. R-sq | 0.107 | 0.016 | 0.002 | 0.016 |

**Notes**: Table 12 shows that banks exposed to ILFS curtailed lending to unrelated NBFCs and Corporates. The sample contains all bank lenders and covers the period from 2017 to 2020. We exclude all ILFS-affiliated borrowers. The empirical specification is:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{High Bank ILFS Exposure}_{l,2018} \times \text{Post ILFS}_t + \alpha_{b,l} + \alpha_{b,t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if an NBFC borrower (in Column (1)) or a Corporate borrower (in Columns (2) to (4)) $b$ took a new loan from a bank lender $l$ in year $t$, and zero otherwise. High Bank ILFS $\text{Exposure}_{l,2018}$ is an indicator variable that equals one if bank $l$ had an above-median exposure to ILFS group in 2018, and zero otherwise. Post $\text{ILFS}_t$ equals one for year 2019 onwards. In Column (3), we exclude all borrowers from ILFS-related sectors (i.e., Infrastructure, Construction, and Electricity). $\alpha_{b,l}$ and $\alpha_{b,t}$ denote borrower-lender and borrower-year fixed effects, respectively. We cluster standard errors at the borrower level.

**Table 13: Impact of ILFS on Corporate Borrowers (Total Borrowing)**

| | 1(Loan) | | |
|---|---|---|---|
| | Bank | NBFI | Total |
| | (1) | (2) | (3) |
| High Borrower ILFS Exposure × Post ILFS | -0.097*** | 0.023*** | -0.058*** |
| | (0.005) | (0.004) | (0.006) |
| Obs | 76427 | 76427 | 76427 |
| Borrower FE | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | ✓ | ✓ | ✓ |
| Borrower Age Group × Year FE | ✓ | ✓ | ✓ |
| Borrower Rating × Year FE | ✓ | ✓ | ✓ |
| Y-Mean | 0.169 | 0.102 | 0.235 |
| Adj. R-sq | 0.272 | 0.313 | 0.305 |

**Notes**: Table 13 shows that corporate borrowers related to ILFS-exposed-banks experienced a decline in total borrowing. The sample contains corporate borrowers and covers the period from 2017 to 2020. We exclude all ILFS-affiliated borrowers. The empirical specification is:

$$1(\text{Loan})_{b,t} = \beta \times \text{High Borrower ILFS Exposure}_{b,2018} \times \text{Post ILFS}_t + \alpha_b + \alpha_{X(b,2018),t} + \varepsilon_{b,t}$$

$1(\text{Loan})_{b,t}$ is an indicator variable that equals one if corporate borrower $b$ took at least one new loan from a bank lender (Column (1)), NBFI lender (Column (2)), or any lender in year $t$, and zero otherwise. High Borrower ILFS $\text{Exposure}_{l,2018}$ is an indicator variable that equals one if corporate borrower $b$ had an above-median fraction of credit from ILFS-related banks in 2018, and zero otherwise. Post $\text{ILFS}_t$ equals one for year 2019 onwards. $\alpha_b$ and $\alpha_{X(b,2018),t}$ denote borrower and borrower-characteristics-year fixed effects, respectively. We use pre-2019 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Table 14: Heterogeneous Impact of ILFS on Corporate Borrowers**

| | 1(Loan) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| High Borrower ILFS Exposure × Post ILFS | -0.058*** | -0.046*** | -0.025 | 0.010 |
| | (0.009) | (0.009) | (0.018) | (0.011) |
| × Low Borrower Size | 0.007 | | | |
| | (0.012) | | | |
| × Low Borrower Age | | -0.014 | | |
| | | (0.011) | | |
| × Low Borrower Rating | | | -0.032* | |
| | | | (0.019) | |
| × Bank Dependent | | | | -0.098*** |
| | | | | (0.012) |
| Post ILFS × Low Borrower Size | 0.016* | | | |
| | (0.009) | | | |
| Post ILFS × Low Borrower Age | | -0.002 | | |
| | | (0.009) | | |
| Post ILFS × Low Borrower Rating | | | 0.038** | |
| | | | (0.016) | |
| Post ILFS × Bank Dependent | | | | 0.192*** |
| | | | | (0.010) |
| Obs | 76918 | 76918 | 76918 | 76918 |
| Borrower FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |
| Y-Mean | 0.235 | 0.235 | 0.235 | 0.235 |
| Adj. R-sq | 0.305 | 0.305 | 0.305 | 0.312 |

**Notes**: Table 14 shows what type of corporate borrowers related to ILFS-exposed banks experienced a decline in total borrowing. The sample contains corporate borrowers and covers the period from 2017 to 2020. We exclude all ILFS-affiliated borrowers. The empirical specification is:

$$\begin{aligned}1(\text{Loan})_{b,t} = \gamma \times \text{High Borrower ILFS Exposure}_{b,2018} \times \text{Post ILFS}_t \times \text{Borrower Characteristic}_{b,2018} \\ + \beta \times \text{High Borrower ILFS Exposure}_{b,2018} \times \text{Post ILFS}_t \\ + \delta \times \text{Borrower Characteristic}_{b,2018} \times \text{Post ILFS}_t + \alpha_b + \alpha_t + \varepsilon_{b,t}\end{aligned}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if corporate borrower $b$ took at least one new loan from any lender in year $t$, and zero otherwise. High Borrower ILFS Exposure$_{l,2018}$ is an indicator variable that equals one if corporate borrower $b$ had an above-median fraction of credit from ILFS-related banks in 2018, and zero otherwise. Borrower Characteristic$_{b,2018}$ indicates a set of characteristics (size, age, rating, and bank-dependence) for borrower $b$ in 2018. Post ILFS$_t$ equals one for year 2019 onwards. $\alpha_b$ and $\alpha_t$ denote borrower and year fixed effects, respectively. Low Borrower Size and Low Borrower Age indicate assets and age in the bottom three quintiles. Low Borrower Rating indicates a credit rating of BBB or below. Finally, Bank Dependent indicates that the borrower borrows exclusively from banks. We cluster standard errors at the borrower level.

**Table 15: Impact of ILFS on Real Outcomes**

| | Log Assets | Log Sales | Leverage | PBITDA/Sales |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| High Borrower ILFS Exposure × Post ILFS | -0.031*** | -0.066*** | -0.015*** | -0.881** |
| | (0.007) | (0.014) | (0.002) | (0.383) |
| Obs | 76427 | 70821 | 65449 | 74032 |
| Borrower FE | ✓ | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | ✓ | ✓ | ✓ | ✓ |
| Borrower Age Group × Year FE | ✓ | ✓ | ✓ | ✓ |
| Borrower Rating × Year FE | ✓ | ✓ | ✓ | ✓ |
| Y-Mean | 6.527 | 6.230 | 0.401 | 11.954 |
| Adj. R-sq | 0.979 | 0.933 | 0.869 | 0.554 |

**Notes**: Table 15 shows that corporate borrowers related to ILFS-exposed banks experienced worse real outcomes. The sample contains corporate borrowers and covers the period from 2017 to 2020. We exclude all ILFS-affiliated borrowers. The empirical specification is:

$$\mathrm{Y}_{b,t} = \beta \times \text{High Borrower ILFS Exposure}_{b,2018} \times \text{Post ILFS}_t + \alpha_b + \alpha_{X(b,2018),t} + \varepsilon_{b,t}$$

$\mathrm{Y}_{b,t}$ is a set of outcomes (Assets, Sales, Leverage, and Profitability) for borrower $b$ in year $t$. High Borrower ILFS $\text{Exposure}_{l,2018}$ is an indicator variable that equals one if corporate borrower $b$ had an above-median fraction of credit from ILFS-related banks in 2018, and zero otherwise. Post $\text{ILFS}_t$ equals one for year 2019 onwards. $\alpha_b$ and $\alpha_{X(b,2018),t}$ denote borrower and borrower-characteristics-year fixed effects, respectively. We use pre-2019 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Table 16: Contagion Effects of Bank-NBFC Connections**

| | 1(Loan) | | |
|---|---|---|---|
| | Total | Tota | Total |
| | (1) | (2) | (3) |
| Post ILFS×Borr. ILFS Exposure Via Banks (1st Round) | -0.019*** | | -0.025*** |
| | (0.006) | | (0.006) |
| Post ILFS×Borr. ILFS Exposure Via NBFC (2nd Round) | | -0.125*** | -0.138*** |
| | | (0.021) | (0.021) |
| Obs | 76427 | 76427 | 76427 |
| Borrower FE | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | ✓ | ✓ | ✓ |
| Borrower Age Group × Year FE | ✓ | ✓ | ✓ |
| Borrower Rating × Year FE | ✓ | ✓ | ✓ |
| Y-Mean | 0.235 | 0.235 | 0.235 |
| SD (1st Round Exposure) | 0.454 | | 0.454 |
| SD (2nd Round Exposure) | | 0.137 | 0.137 |
| Adj. R-Sq. | 0.304 | 0.305 | 0.305 |

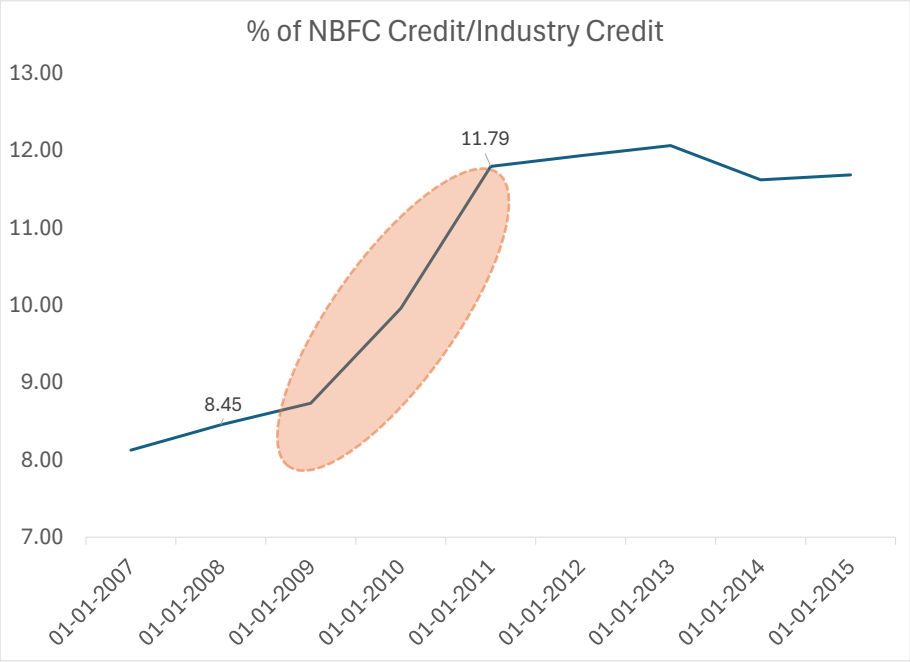
**Notes**: Table 16 shows that corporate borrowers related to ILFS-exposed-banks (1st round exposure) or to NBFC lenders borrowing from ILFS affected banks (2nd round exposure) experienced a decline in total borrowing. The sample contains corporate borrowers and covers the period from 2017 to 2020. We exclude all ILFS-affiliated borrowers. The empirical specification is:

$$\begin{aligned} 1(\text{Loan})_{b,t} = \beta_1 \times \text{Borrower ILFS Exposure Via Banks}_{b,2018} \times \text{Post ILFS}_t \\ + \beta_2 \times \text{Borrower ILFS Exposure Via NBFC}_{b,2018} \times \text{Post ILFS}_t \\ + \alpha_b + \alpha_{X(b,2018),t} + \varepsilon_{b,t} \end{aligned}$$

$1(\text{Loan})_{b,t}$ is an indicator variable that equals one if corporate borrower $b$ took at least one new loan from any lender during the year $t$ and zero otherwise. Borrower ILFS Exposure Via $\text{Banks}_{l,2018}$ and Borrower ILFS Exposure Via $\text{NBFC}_{l,2018}$ are as defined in equations 21 and 22 Post $\text{ILFS}_t$ equals one for year 2019 onwards. $\alpha_b$ and $\alpha_{X(b,2018),t}$ denote borrower and borrower-characteristics-year fixed effects, respectively. We use pre-2019 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

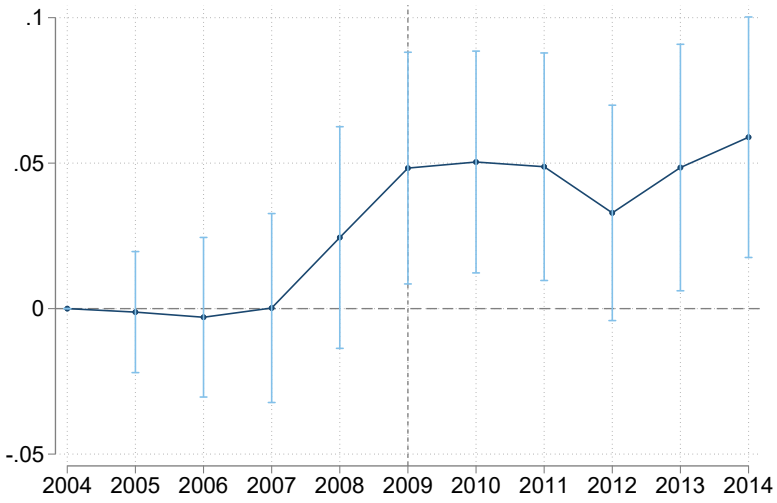
# VIII Appendix

**Figure A1: Aggregate Trends in the RBI Data**




**Notes**: Figure A1 shows the trend in bank credit to the NBFI sector relative to the aggregate credit to the nonfinancial industry. This figure is plotted using the aggregate data published on the RBI website and it covers both secured and unsecured credit.

**Figure A2: Bank Lending After 2009: NBFI vs. Other Borrowers (Event Study)**

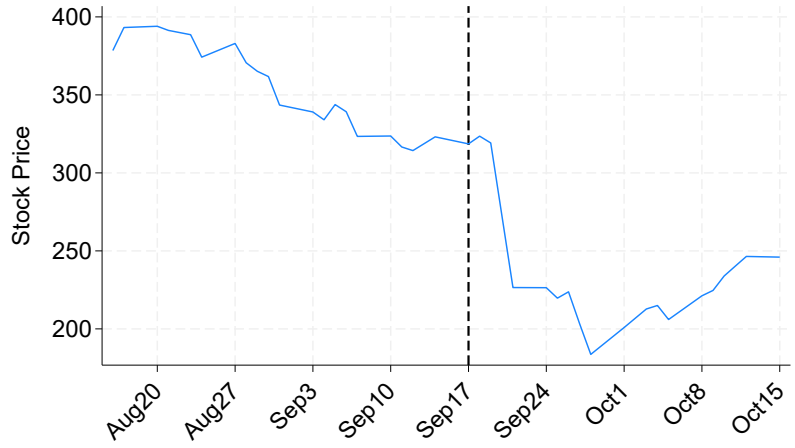



**Notes**: Figure A2 uses event study analysis to show that banks increased lending to NBFI after the 2009 change in relative risk weights. The sample contains all types of borrowers and bank lenders and covers the period from 2004 to 2014. The empirical specification is:

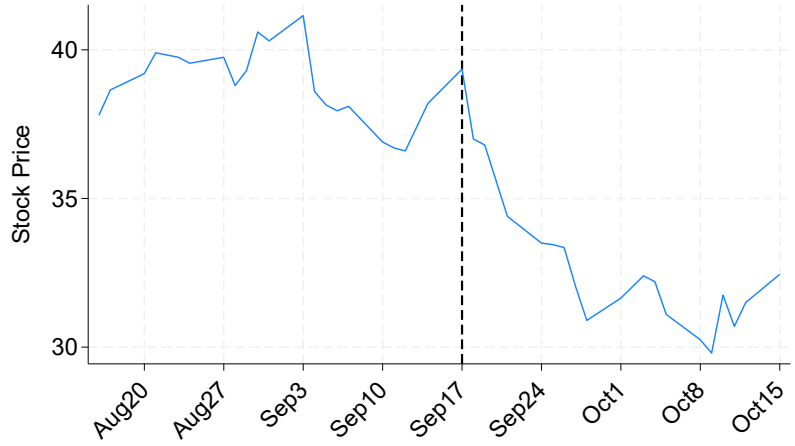
$$1(\text{Loan})_{b,l,t} = \sum_{t=2004}^{2009} \beta^t \times \text{NBFI Borrower}_{b,2008} \times 1_t + \alpha_{b,l} + \alpha_{l,t} + \alpha_{X(b,2008),t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. NBFI $\text{Borrower}_{b,2008}$ is an indicator variable that equals one if $b$ is classified as a systemically important NBFC in 2008, and zero otherwise. $1_t$ are dummy variables indicating years from 2004 to 2014. $\alpha_{b,l}$, $\alpha_{l,t}$, and $\alpha_{X(b,2008),t}$ denote borrower-lender, lender-year, and borrower-characteristics-year fixed effects, respectively. We use pre-2009 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Figure A3: Bank Stock Price Reaction to IL&FS Downgrade**




**(a) Yes Bank**




**(b) Syndicate Bank**

**Notes**: Figure A3 shows the stock price reaction of two large banks having a substantial amount of IL&FS exposure to the news of IL&FS defaulting on its loan obligations and being downgraded to D by Indian Credit Rating Agencies. These are Yes Bank (2.65% exposure) and Syndicate Bank (2.24% exposure). The vertical dashed line denote September 17th – the date when IL&FS was downgraded to D (See Link).

**Table A1: Difference Between Bank-dependent and NBFI-dependent Firms**

| | Bank | NBFI | Both | (Bank - NBFC) |
|---|---|---|---|---|
| Total OS Loan (INR Million) | 784 | 431 | 3,466 | 353*** |
| Assets (INR Million) | 2,371 | 1,223 | 8,202 | 1,148 |
| Age (Years) | 18.10 | 15.21 | 23.14 | 2.89*** |
| Leverage Ratio | 0.43 | 0.39 | 0.50 | 0.04** |
| ROA | 0.16 | -0.65 | 0.39 | 0.81* |

**Notes**: Table A1 shows the difference in firms whose outstanding credit in 2008 came from Banks, NBFIs, and Both sources.

**Table A2: Robustness: Effect of Low Bank CAR**

| | 1(Loan) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| NBFI Borrower × Post RW Change × Low Bank CAR | 0.037*** | 0.037*** | 0.028** |
| | (0.012) | (0.012) | (0.011) |
| NBFI Borrower × Post RW Change | 0.023** | 0.021** | |
| | (0.010) | (0.010) | |
| Obs | 391252 | 391252 | 391252 |
| Borrower × Lender FE | ✓ | ✓ | ✓ |
| Lender × Year FE | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | | ✓ | |
| Borrower Age Group × Year FE | | ✓ | |
| Borrower Rating × Year FE | | ✓ | |
| Borrower × Year FE | | | ✓ |
| Y-Mean | 0.105 | 0.105 | 0.105 |
| Adj. R-sq | 0.099 | 0.101 | 0.102 |

**Notes**: Table A2 shows that banks with lower capital adequacy ratios increased lending to NBFI more after the 2009 change in relative risk weights. The sample contains all types of borrowers and bank lenders and covers the period from 2004 to 2014. The empirical specification in Column (3) is:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Borrower}_{b,2008} \times \text{Post RW Change}_t \times \text{Low Bank CAR}_{l,2008} + \alpha_{b,l} + \alpha_{l,t} + \alpha_{b,t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. $\text{NBFI Borrower}_{b,2008}$ is an indicator variable that equals one if $b$ is classified as a systemically important NBFC in 2008, and zero otherwise. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\text{Low Bank CAR}_{l,2008}$ is an indicator variable that equals one if bank lender $l$ had below-median capital adequacy ratio in 2008. $\alpha_{b,l}$, $\alpha_{l,t}$, and $\alpha_{b,t}$ denote borrower-lender, lender-year, and borrower-year fixed effects, respectively. We cluster standard errors at the borrower level.

**Table A3: Univariate Analysis: Corporates with Low and High Exposure**

| | All Corporates | | | | Low Exposure | | High Exposure | | T-Test |
|---|---|---|---|---|---|---|---|---|---|
| | N | Mean | Median | SD | N | Mean | N | Mean | |
| Log(Assets) | 99,245 | 5.8 | 5.82 | 2.28 | 44,924 | 5.34 | 54,321 | 6.18 | 0.84*** |
| Age (Years) | 99,245 | 21.42 | 17 | 17.78 | 44,924 | 19.14 | 54,321 | 23.3 | 4.16*** |
| Credit Rating | 99,245 | 0.25 | 0 | 0.91 | 44,924 | 0.16 | 54,321 | 0.32 | 0.16*** |

**Notes**: Table A3 shows the difference in characteristics of firms with high and low value of Borrower Exposure.

**Table A4: Heterogeneous Impact on Corporates: Alternative FE**

| | 1(Loan) | | |
|---|---|---|---|
| | Bank | NBFI | All |
| | (1) | (2) | (3) |
| **Panel (A): Borrower Size** | | | |
| Post RW Change × Low Borrower Size | 0.023*** | -0.007* | 0.022*** |
| | (0.006) | (0.004) | (0.006) |
| **Panel (B): Borrower Age** | | | |
| Post RW Change × Low Borrower Age | 0.017*** | 0.014*** | 0.028*** |
| | (0.006) | (0.003) | (0.006) |
| **Panel (C): Borrower Rating** | | | |
| Post RW Change × Low Borrower Rating | 0.047*** | 0.021** | 0.046*** |
| | (0.013) | (0.011) | (0.013) |
| Obs | 99231 | 99231 | 99231 |
| Borrower FE | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |
| Y-Mean | 0.251 | 0.066 | 0.287 |
| Adj. R-sq | 0.301 | 0.259 | 0.318 |

**Notes**: Table A4 shows credit reallocation across different types of firms after the 2009 change. The empirical specification is:

$$1(\text{Loan})_{b,t} = \gamma \times \text{Post RW Change}_t \times \text{Borrower Characteristic}_{b,2008} + \alpha_b + \alpha_t + \varepsilon_{b,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if corporate borrower $b$ took at least one new loan from any lender in year $t$, and zero otherwise. Borrower $\text{Characteristic}_{b,2008}$ indicates a set of indicator variables for borrower characteristics like size, age, and rating for borrower $b$ in 2008. Low Borrower Size and Low Borrower Age indicate assets and age in the bottom three quintiles. Low Borrower Rating indicates a credit rating of BBB or below. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\alpha_b$ and $\alpha_t$ denote borrower and year fixed effects, respectively. We cluster standard errors at the borrower level.

**Table A5: Borrowing After 2009: NBFI vs. Banks**

**Panel A: NBFI Borrowers**

| | 1(Loan) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| NBFI Lender × Post RW Change | -0.022 | -0.013 | -0.014 |
| | (0.016) | (0.016) | (0.016) |
| Post RW Change | 0.050*** | | |
| | (0.012) | | |
| Obs | 35350 | 35350 | 35350 |
| Borrower × Lender FE | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | | ✓ | |
| Borrower Age Group × Year FE | | ✓ | |
| Borrower Rating × Year FE | | ✓ | |
| Borrower × Year FE | | | ✓ |
| Y-Mean | 0.133 | 0.133 | 0.133 |
| Adj. R-sq | 0.136 | 0.148 | 0.180 |

**Panel B: NBFC-Non-SI Borrowers**

| | 1(Loan) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| NBFI Lender × Post RW Change | 0.013** | 0.011* | 0.008 |
| | (0.006) | (0.006) | (0.006) |
| Post RW Change | 0.001 | | |
| | (0.004) | | |
| Obs | 33630 | 33630 | 33630 |
| Borrower × Lender FE | ✓ | ✓ | ✓ |
| Borrower Size Group × Year FE | | ✓ | |
| Borrower Age Group × Year FE | | ✓ | |
| Borrower Rating × Year FE | | ✓ | |
| Borrower × Year FE | | | ✓ |
| Y-Mean | 0.041 | 0.041 | 0.041 |
| Adj. R-sq | 0.087 | 0.090 | 0.107 |

**Notes**: Table A5 shows whether non-corporate borrowers increased borrowing from NBFI after the 2009 change in relative risk weights. The sample contains NBFI borrowers in Panel A and NBFC-Non-SI borrowers in Panel B. The sample includes both bank and NBFC lenders and covers the period from 2004 to 2014. The empirical specification in Column (3) is:

$$1(\text{Loan})_{b,l,t} = \beta \times \text{NBFI Lender}_{l,2008} \times \text{Post RW Change}_t + \alpha_{b,l} + \alpha_{b,t} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. $\text{NBFI Lender}_{l,2008}$ is an indicator variable that equals one if $l$ is classified as a systemically important NBFC in 2008, and zero otherwise. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\alpha_{b,l}$, $\alpha_{X(b,2008),t}$ and $\alpha_{b,t}$ denote borrower-lender, borrower-characteristics-year, and borrower-year fixed effects, respectively. We use pre-2009 size quintiles, age quintiles, and rating categories as borrower characteristics. We cluster standard errors at the borrower level.

**Table A6: NBFC Lending After 2009: Absolute Basis**

| | 1(Loan) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Post2009 | 0.028*** | | | | |
| | (0.002) | | | | |
| Post RW Change × Low Borrower Size | | 0.006 | | | 0.001 |
| | | (0.004) | | | (0.004) |
| Post RW Change × Low Borrower Age | | | 0.017*** | | 0.015*** |
| | | | (0.004) | | (0.004) |
| Post RW Change × Low Borrower Rating | | | | 0.024*** | 0.020*** |
| | | | | (0.007) | (0.007) |
| Obs | 125601 | 125508 | 125508 | 125508 | 125508 |
| Borrower × Lender FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lender × Year FE | | ✓ | ✓ | ✓ | ✓ |
| Y-Mean | 0.085 | 0.085 | 0.085 | 0.085 | 0.085 |
| Adj. R-sq | 0.151 | 0.175 | 0.175 | 0.175 | 0.175 |

**Notes**: Table A6 shows lending behavior of NBFI after the 2009 change. The sample contains all types of borrowers and NBFI lenders and covers the period from 2004 to 2014. The empirical specification is:

$$1(\text{Loan})_{b,l,t} = \gamma \times \text{Post RW Change}_t \times \text{Borrower Characteristic}_{b,2008} + \alpha_{b,l} + \varepsilon_{b,l,t}$$

$1(\text{Loan})_{b,l,t}$ is an indicator variable that equals one if borrower $b$ took a new loan from lender $l$ in year $t$, and zero otherwise. Borrower $\text{Characteristic}_{b,2008}$ indicates a set of indicator variables for borrower characteristics like size, age, and rating for borrower $b$ in 2008. Low Borrower Size and Low Borrower Age indicate assets and age in the bottom three quintiles. Low Borrower Rating indicates a credit rating of BBB or below. $\text{Post RW Change}_t$ equals one for year 2009 onwards. $\alpha_{b,l}$ denotes borrower-lender fixed effects. We cluster standard errors at the borrower level.