# Anatomy of a Liquidity Shock on Non-banks

Nirupama Kulkarni

K. M. Neelima

Sonalika Sinha \*

September 5, 2023

#### **ABSTRACT**

### **Working Paper**

This paper investigates the anatomy of a liquidity shock in the non-banking sector in India in September 2018 using a unique supervisory database of non-banking financial companies (NBFCs) matched to their borrowers and lenders. Using a difference-in-differences methodology, we exploit ex-ante differences in NBFCs' exposure to liquidity mismatches as identification. We find that stressed firms experienced a significant decline in commercial paper growth, majorly attributed to mutual funds as they faced redemption pressure from investors. Firm size and provisioning requirements were the main mechanisms driving the impact of the shock for the stressed firms who could not substitute with alternate funding sources such as debentures or bank credit in the short run. Consequently, these firms cut down credit to their largest borrowers, and sectoral allocation of credit also declined. The banking sector predicated its support to non-banks based on their loan performance. While banks stepped in to support 'healthy' NBFCs, they *cut back* credit to unhealthy ones. Such selective bank support, or ringfencing by banks during the shock episode proved effective in averting the contagion of the liquidity shock to the traditional banking sector while continuing to support healthier firms. Such an approach can strike a balance between financial stability and targeted assistance.

JEL Codes: G01, G21, G23, G28

Keywords: Non-banking financial institutions, India, liquidity shock

<sup>\*</sup>Nirupama Kulkarni is Senior Research Director, CAFRAL (Promoted by Reserve Bank of India), (Email:nirupama.kulkarni@cafral.org.in), K.M. Neelima is Assistant Adviser in the Monetary Policy Department, Reserve Bank of India (Email:kmneelima@rbi.org.in), Sonalika Sinha is Manager (Research) in the International Department, Reserve Bank of India (Email:sonalikasinha@rbi.org.in). We are grateful to Manju Puri, Linda Goldberg, Björn Imbierowicz, Tarun Jain, Brijesh P, as well as participants of the CEBRA Annual Meeting 2023, DEPR Study Circle, and CAFRAL Brown Bag Series for their valuable inputs and comments on our paper. We gratefully acknowledge excellent research assistance by Sanika Ranadive. The views expressed in the paper are those of the authors and not necessarily the institution(s) to which they belong. Errors are purely our own.

# 1 Introduction

Maturity transformation makes asset-liability mismatches inherent in financial institutions. Though costly, governments can insure banks via lender-of-last resort (LOLR) and deposit insurance programs, and associated moral hazard challenges can be addressed through banking supervision (Tirole and Farhi, 2021). Non-banking financial institutions, on the other hand, have a similar structure of asset-liability mismatches but do not have access to insurance or LOLR, and are subject to relatively lighter regulations. In this paper, we examine the impact of a liquidity shock in September 2018 within India's non-bank financial companies (NBFCs). This shock triggered a withdrawal by short-term creditors, making it difficult for NBFCs to roll over their short-term debt. Our investigation examines the consequent impact on the non-banking sector, its relationship with the traditional banking sector, and the potential real effects. Non-bank crises often stem from funding instability and liquidity shocks, as emphasized by (Quirin Fleckenstein, 2020). Notably, in the Indian context, the non-bank sector contributes significantly, representing 20-30% of the credit flow within the economy, as highlighted in (Agarwal, 2023). Therefore, a shock within this sector is important to analyse.

Understanding shocks to non-banks matters for two prime reasons. First, the rise of non-banks holds serious financial stability implications (Aramonte et al., 2022; Buchak and Seru, 2018) as the real sector (firms and households) tends to increase direct borrowings from non-banks (Chernenko et al., 2022; Hodula et al., 2020). Even though the non-banking sector across countries have widely different institutional organisation, there is one thing in common - i.e. the increasing share of non-banks in the financial system poses common financial stability concerns for policymakers (Forbes et al., 2023; FSB, 2022). Second, the non-banking sector aids monetary policy transmission (Acharya, 2020) which can enable smoother transmission of credit through stability in interest rate spreads. Monetary cycles are closely related to fragility in the non-banking sector (Xiao, 2020).

We analyze the impact of a liquidity shock on short-term liquidity. For identification, we leverage variation in ex-ante exposure of firms to asset-liability mismatch which represents the rollover risk of the firms within a one-year period. This ex-ante exposure is uncorrelated with

balance-sheet firm characteristics before the shock. Using this identification, our research documents how the liquidity shock impacted firms' access to commercial paper and examines which source of funding was most impacted by the shock. Next, we examine the NBFC balance-sheet characteristics that were underlying the effects. We also focus on the relationship between non-banks and banks in response to the liquidity shock. Finally, we examine some real effects that explore the credit allocation by NBFCs to sectors and individual borrowers in response to the shock.

Our analysis uses a unique and confidential supervisory dataset, as reported to Reserve Bank of India (RBI), India's central bank. We match this balance sheet information with two important information sets. First is details about their lenders, encompassing traditional banks and other financial institutions. Second, we match the data with NBFC borrower entities, consisting of sectorwise and firm-level information on loans secured from the NBFCs. This integrated dataset enables us to establish a comprehensive network that connects NBFCs with their lending and borrowing counterparts. Complementing this dataset, we also incorporate supervisory data pertaining to bank balance sheets and performance metrics, particularly focused on traditional banks.

Our paper presents the following results:

*First*, stressed firms i.e. NBFCs with higher ex-ante asset-liability mismatch faced a greater decline in commercial paper funding, attributable primarily to the mutual funds investors, who pulled out of the market facing redemption pressures in response to the liquidity shock. CP growth of NBFCs with higher ex-ante exposure reduced by 14.51 pp in response to the shock.

Second, the stressed firms were unable to substitute with alternate financing. Looking into multiple categories of entities that subscribed to CPs, such as mutual funds, banks, debentures and other NBFCs, we report that mutual funds experienced maximum decline in CP growth– a decline of 10.62 pp<sup>1</sup>.

*Third*, the liquidity shock worked its way through larger NBFCs and those with less provisions to hedge against the losses. Using firm balance-sheet fundamentals to delineate the mechanism of the shock, we find that larger NBFCs with higher exposure suffered a 5.56 pp (S.E.= 2.28) decline

<sup>&</sup>lt;sup>1</sup>As of March 2020, mutual funds constituted the largest group of subscribers, accounting for 57% of the total, which increased to 66% as of December 2021.

in CP growth in response to the liquidity shock. Similarly, firms with less provisioning coverage were more impacted.

Fourth, we find that bank lending to high-exposure NBFCs was predicated on their loan performance. Bank lending to high-exposure NBFCs with low GNPA ratio (i.e. relatively 'healthier' firms) increased by 0.55 percentage points, while lending decreased to firms with higher NPAs (relatively 'weaker' firms) in response to the liquidity shock. These findings point to cleansing effect of the shock as banks reallocated fresh loans to healthier NBFCs and ringfenced themselves from weaker firms.

Fifth, we examine how the effect of the liquidity shock impacted NBFC credit and sectoral lending. The shock impacts credit allocation as stressed NBFCs cut down credit across all sectors viz., industry, services, and retail, with retail loans declining the most. Overall NBFC credit declined by 32.54 pp as a consequence of the shock. Particularly, NBFCs cut down credit to the retail sector by 29.78 pp, to the industrial sector by 15.68 pp, and to the services sector by 20.14 pp as a consequence of the shock.

*Sixth*, we report the real effect of the liquidity shock by capturing borrower-level lending. At the individual firm-level, high-exposure NBFCs pass on their credit constraints by reducing lending to their largest borrowing firms by 0.349 pp when faced with a liquidity shock *vis-a-vis* low-exposure NBFCs.

**Related Literature:** The rise of non-banks was expected to lead to better allocation of risk, improved credit and cost efficiency, and lower borrowing costs for households (Fuster and Vickery, 2019) and corporations. While a lot of these objectives hold true, fragilities in the sector can have serious financial stability implications. Therefore, understanding the anatomy of a shock on non-banks is critical.

Our paper contributes to three strands of literature.

First, our paper relates to the vast literature on bank fragility and contagions. We draw inspiration from rich empirical evidence on bank runs. Calomiris and Mason (1997) document the Chicago banking crisis dating back to the Great Depression in 1932, wherein failed banks had similar ex-ante characteristics as the surviving banks. Saunders and Wilson (1996) and Iyer and Puri

(2012) reveal that deposit insurance and bank-depositor relationships have played a significant role in bank runs from the Great Depression in 1930s to the Global Finance Crisis of 2008. while most of these studies have focused on banking crises or runs, there is lesser empirical evidence on non-banking crises and shocks, their underlying mechanisms, contagion effects, and real effects. Our paper adds to the extant literature by examining a non-banking shock.

Second, we relate to the literature on crisis-induced resource reallocation and its potential 'cleansing effects'. Bernanke (1983) revealed how financial crises can impact aggregate output by reducing the efficiency of credit allocation. Inflated costs and reduced access to credit can in turn suppress address demand. Hsieh and Klenow (2009) show that reallocating resources from unproductive firms to more productive firms enhances economic growth. The literature on resource reallocation aftershocks has two sides. One side argues that after a run, funds move to better private banks and improve credit discipline, as seen in the case of Argentina in the 1990s (Schumacher, 1998). In contrast, Bernanke (1983) brought to light that financial disruptions can reduce the efficiency of credit allocation. Our paper traces the impact of a liquidity shock and traces out the resulting implications for both banks and non-banks. Further, a shock to non-bank holds allocative consequences that are potentially distinct from banking run outcomes, and therefore critical to understand.

The *third* important strand of literature we relate to is the regulatory arbitrage and the resultant relationship between banks and non-banks. A critical reason why non-banks are flourishing is due to regulatory arbitrage. As emphasized by Hanson and Stein (2011), regulatory burdens on the traditional banking sector, in the form of rising capital requirements and greater scrutiny may reduce their balance sheet capacity and result in migration of banking activities towards non-banks that are more likely to mitigate such costs. The global financial crisis in 2008 triggered a broad push toward increased regulation of the financial sector. At the heart of the debate is the issue of capital requirements. In particular, (Admati and Pfleiderer, 2013) argue that banks should be subject to alternative or significantly higher capital requirements in order to mitigate risk-shifting incentives and increase financial stability (see also (Flannery, 2014); (Thakor, 2014)). On the other hand, increased regulation of banks may push intermediation into unregulated fi-

nancial institutions, including the "shadow banking" system.<sup>2</sup> While shadow banks may bring fresh funding or other efficiencies (e.g., new loan pricing technologies), unlike traditional banks they cannot issue insured liabilities nor access central bank liquidity during times of marketwide stress. Theoretical work emphasizes that these distinct sources of fragility at shadow banks might amplify risks in the financial system and reduce overall welfare ((Chretien and Lyonnet., 2018); (Farhi and Tirole, 2017); (Martinez-Miera and Repullo, 2018); (Plantin, 2015)), a concern echoed by practitioners and policymakers alike.<sup>3</sup> Despite its importance for the design of prudential regulation (Freixas and Peydr´o (2015);Hanson and Stein (2011)), there is limited empirical evidence on the relation between bank capital and shadow banking, and their potential risks to the financial system.

Through the remaining paper, **Section** 2 discusses institutional details of NBFCs in India, **Section** 3 discusses the data and summary statistics, **Section** 4 lays out the empirical design, **Section** 5 provides the main results of the analysis, **Section** 6 describes the impact on bank lending, **Section** 7 discusses impact on NBFC credit and finally **Section** 8 concludes.

# 2 Institutional Details of Non-banks in India

In India, non-banking financial companies or NBFCs have been in existence since the pre-independence era, and India's central bank, RBI began regulating the sector in 1964, making it one of the earliest central banks to do so. The business model of NBFCs relies on borrowings as a large section of the sector does not have access to deposits and even those that do, have access only to term deposits which are pricier than demand deposits that banks have. NBFCs primarily borrow from banks or by floating debentures and raise short-term funds by issuing commercial papers (CPs) which are typically subscribed by banks, mutual funds, or NBFCs.

<sup>&</sup>lt;sup>2</sup>We use the terms "shadow bank" and "non-bank" interchangeably when referring to financial institutions that provide credit without issuing insured liabilities. This is consistent with the Federal Reserve's (or Financial Stability Board's) definition of shadow banking as non-bank credit intermediation.

<sup>&</sup>lt;sup>3</sup>For example, "Risky borrowing is making a comeback, but banks are on the sideline," New York Times, June 11, 2019, www.nytimes.com/2019/06/11/business/risky-borrowing-shadow-banking.html, and "Banks and the next recession," Oliver Wyman, 2019, www.oliverwyman.com/our-expertise/insights/2019/may/banks-and-the-next-recession.html, describe "pro-cyclicality" in lending, whereas "The firesales problem and securities financing transactions," a speech by Jeremy Stein at the Federal Reserve Bank of New York on October 4, 2013, www.federalreserve.gov/newsevents/speech/stein20131004a.htm, points to potential connections from shadow banks to secondary market prices.

The NBFC sector has a prominent role in India's financial landscape, with total financial assets worth nearly ₹38 trillion (approx 0.4 trillion USD) in March 2022. The credit to GDP ratio of the sector grew from 8.6 per cent in 2013 to 12.3 per cent in 2022, and NBFC share in bank credit rose from 15 per cent in 2013 to 25 per cent in 2022. Over time, supervisory guidance has adapted to the dynamic nature of the sector. As also discussed in Acharya et al. (2013), RBI oversees the functioning of three non-bank entities<sup>4</sup> i.e. non-banking financial companies (NBFCs), All India Financial Institutions (AIFIs), and primary dealers (PDs). Within this, NBFCs are further categorised on the basis of the their type of activity or niche, which includes segments like vehicle financing, infrastructure lending, factoring, lending against gold, microfinance and more.

Based on activity, NBFCs are classified into multiple categories which are: (i) Asset Finance Companies (AFCs), (ii) Investment Companies (ICs), (iii) Loan Companies (LCs), (iv) Infrastructure Finance Companies (IFCs), (v) Core Investment Companies (CICs), Micro-Finance Institutions (NBFC-MFIs), Infrastructure Debt Funds (NBFC-IDF). Of these, categories *i*, *ii*, and *iii* were merged to form Investment and Credit Companies or **NBFC-ICCs**. We focus our main analysis on these ICC companies and also include a larger representative sample for robustness.

Based on liability structure, NBFCs are categorised as deposit-taking NBFCs (NBFCs-D) for deposit-collecting companies, and the others as non-deposit-taking NBFCs (NBFCs-ND)which are deemed as systemically important (NBFCs-ND-SI) if their asset size were above ₹5 Bn (approx USD 62 million). As of July 2022, 9640 NBFCs were registered with RBI 2022, of which 415 were NBFCs-ND-SI, 49 were NBFCs-D and the rest were NBFCs-ND (RBI, 2022).

#### 2.1 The NBFC liquidity shock explained:

The Indian non-banking financial company (NBFC) sector encountered a significant liquidity shock in 2018 due to the default of a prominent conglomerate on a short-term loan. This conglomerate was a NBFC-ICC with an intricate group structure and numerous subsidiaries, operating across diverse sectors including real estate, transportation, and financial services. The group held

<sup>&</sup>lt;sup>4</sup>In India, non-banking financial institutions (NBFIs) form a diverse group that includes entities like insurance companies, pension fund companies, alternative investment fund companies, all India financial institutions, primary dealers, merchant banking firms, stock exchanges, stock-broking/sub-broking companies, and *Nidhi* companiesRBI (2022)). *Nidhi* companies encourage and promote savings among its members, and provide them with credit facilities for their personal and business needs.

a substantial debt of ₹970 billion, out of which ₹570 billion had been borrowed from public sector banks. The central investment company within the group was registered under RBI as a core investment entity, primarily for lending to other group companies.

The crisis emerged when one of the group's subsidiaries defaulted on inter-corporate deposits from a financial institution (FI), sparking concerns about the larger company's liquidity challenges. The underlying reasons were attributed to various factors such as escalating interest rates, cost overruns, and stalled projects. This subsidiary's failure to repay a short-term loan to the same FI further escalated apprehensions among investors.

In response, credit rating agencies downgraded both the main company and its subsidiaries to "junk" status. This triggered a market sell-off, leading to a sharp decline in the stock prices of the company's listed entities. The ripple effect extended to the broader non-banking financial sector and housing finance companies (HFCs) as mutual funds, heavily invested in this sector, started withdrawing their investments. The interconnectedness of the financial system became apparent, prompting calls for enhanced regulation and risk management practices within the NBFC sector.

Following this, another significant mutual fund company sold commercial papers (CPs) of a major housing finance company (HFC) at a discounted rate, intensifying the panic in the financial markets. Stock prices plummeted by approximately 60% in intra-day trades. Notably, large NBFCs experienced substantial drops in their market capitalization, accompanied by rapid increases in yields, which translated to higher borrowing costs.

The stress extended to the secondary market for CPs, leading to a substantial spike in spreads. This made it difficult for certain NBFCs to raise CPs to meet short-term obligations, resulting in a few NBFCs and HFCs defaulting on their borrowings. As a consequence, the overall outstanding commercial paper in the economy contracted, and mutual funds reduced their exposure to CP holdings of NBFCs during this period.

To address the situation, the Reserve Bank of India (RBI) wielded its regulatory authority to restore confidence and stability. Measures included the removal of directors from NBFCs, taking control of their boards, and appointing administrators to enhance governance and safeguard the interests of depositors and creditors, among other actions.

#### 3 Data

In this study, we leverage data sourced from supervisory returns submitted by NBFCs on a quarterly cadence, meticulously cataloged within the RBI's databases. This dataset encompasses information drawn from three primary platforms: (i) the Company Off-Site Surveillance and Monitoring System (COSMOS), (ii) the business objects (BO) database, and (iii) the eXtensible Business Reporting Language (XBRL) platform. These returns constitute a fundamental component of RBI's offsite surveillance methodology applied to NBFCs, thus harboring the potential to yield profound analytical insights.

The regulatory returns are periodically updated due to the constantly evolving nature of the sector. Therefore, these data repositories offer a wealth of valuable information pertaining to the performance dynamics of NBFCs within the temporal span between consecutive inspection cycles. Moreover, they function as a proactive mechanism for early identification, acting as an advanced cautionary apparatus for forthcoming on-site inspections. Furthermore, these datasets enable the monitoring of evolving trends within the sector, thereby enhancing our capacity to grasp the sector's trajectory over time. Note that data across all classifications of NBFCs registered with the Reserve Bank are captured in these platforms.<sup>5</sup>.

The supervisory data we use in our study is novel and differs substantially from what is publicly available on NBFCs. *First*, the dataset encompasses the entire gamut of NBFCs, thus giving us a comprehensive representation of the sector. Deposit-taking and systemically important non-banks are required to file data on a quarterly basis.

Second, in addition to encompassing comprehensive balance sheets and profit and loss statements which are available publicly, the supervisory data covers a range of other dimensions such as asset classification, provisioning, asset-liability mismatch, Capital to Risk-Weighted Assets Ratio (CRAR), exposure of banks and other financial institutions to NBFCs, sectoral credit, non-performing assets (NPAs), public deposits held by NBFCs, interconnectedness with other financial entities, loan sales, securitization, and more. This detailed incorporation adds an additional layer of depth to our analysis. For instance, while the general data on Commercial Paper (CP) issuances

<sup>&</sup>lt;sup>5</sup>Except Housing Finance Companies which are supervised by National Housing Bank.

by NBFCs is publicly available, the dataset we utilize further dissects this information, revealing the distribution of CP holdings among banks, mutual funds, other investors, and the like. This level of granularity enriches the scope of our study.

Third, our analysis centers on evaluating their asset-liability mismatch during the time of the liquidity shock. To comprehensively assess the liquidity status of NBFCs, the data allows us to delve into the data concerning cash inflows, including elements such as interest income from investments, performing loans, and other operational activities. Additionally, we are able to scrutinize outflows, which include repayments tied to various forms of borrowings. The reported data is segregated based on different maturity periods, such as 0-7 days, 8-14 days, 15-30 days, 1-2 months, 2-3 months, 3-6 months, 6 months-1 year, 1-3 years, 3-5 years, and beyond 5 years. This intricate examination is conducted on a quarterly basis, as these data points are reported by NBFCs within their structural liquidity return. These returns essentially mirror the composition of the balance sheet: asset accruals correspond to inflows, whereas liability accruals correspond to outflows. By aggregating the total inflows and outflows within a specific maturity period, we can effectively compute the liquidity position of an NBFC during a given quarter. This methodology is particularly powerful in identifying instances where NBFCs experience mismatches across various maturity buckets within each period. Specifically, within any given quarter, we define a liquidity stress scenario for an NBFC in a certain maturity bucket when the outflows surpass the inflows, normalized against the outflows within the corresponding maturity bracket. In the context of our study, we consolidate all maturity buckets up to the 6 months to one-year range. This consolidation aids us in deriving a comprehensive view of the short-term liquidity position of an NBFC within a quarter.

Fourth, the dataset provides us with valuable insights into the extent of financial institutions' (FIs) exposure to NBFCs. This encompasses comprehensive information detailing the quantum of loans extended by each bank or financial institution to NBFCs, covering a range of financial instruments such as term loans, working capital facilities, debentures, commercial paper (CP), and other forms. This information is furnished on a quarterly basis, affording us a dynamic view of these interactions. Our analytical focus centers on 57 prominent NBFCs that collectively represent

a substantial 85 percent of the sector. This subset yields an average of 239 observations per quarter, ensuring robustness in our analysis. To augment the depth of our insights, we align this dataset with supervisory data pertaining to bank variables, drawn from scheduled commercial banks via the Off-Site Monitoring and Surveillance (OSMOS) mechanism.

Fifth, the dataset provides us with unique borrower-level insights of NBFCs, i.e. comprehensive information about top 20 individual borrowers of NBFCs. Further, we have access to their corresponding loan amount, all updated on a quarterly basis. Similar to the methodology adopted for bank/FI exposure data, our analysis relies on the Prowess-linked borrower data associated with the 57 selected NBFCs.

The period of analysis for our study is from June 2018 to March 2019 on a quarterly basis. Our main analysis focuses on a total of 332 investment and credit companies (ICCs) comprising half of the NBFC sector, which are predominantly privately-owned NBFCs. Their business activities are similar to those of banks—mainly lending to the retail, services, and industrial sectors, while some are also involved in investment activities. These NBFCs primarily rely on borrowing from banks and markets. Our analysis on the subset of NBFCs (57 NBFCs) is based on both ICCs and Infrastructure Finance Comapnies (IFCs), which are large companies specialised in lending to the infrastructure sector. We wanted to have comprehensive coverage of the sector while reducing the sample size which warranted the need for inclusion of IFCs.

As far as we know, our study is the first of its kind in the Indian context. While there have been some studies conducted by RBI that have utilized these supervisory data for empirical analysis, we are aware of only one other article that has done so (Acharya et al., 2013).

#### 3.1 Summary Statistics

Non-Banking Financial Companies (NBFCs) primarily rely on borrowing funds to sustain their operations. One strategy for short-term capital is issuing commercial paper (CPs), a debt instrument with a one-year repayment timeline. CPs are subscribed by entities like banks, mutual funds, other NBFCs, and more. Conversely, long-term funds come from bank loans and debentures. Banks offer loans like term loans (a substantial segment), working capital loans, cash credit, and overdrafts. They also subscribe to NBFCs' CPs and non-convertible debentures (NCDs), with

NCDs being a significant long-term borrowing avenue that can't be converted to equity.

Table 1 shows the range of financial metrics with both average trends and substantial variability, underscoring the multifaceted and heterogeneous nature of these measures across the NBFC sector. The specified variables are in terms of year-on-year growth. Each variable provides insights into crucial financial aspects and their diversity across firms.

"Ex-ante exposure" represents the potential difference between anticipated inflows and outflows against total outflows. With a mean of 1.8 and a standard deviation of 16.4, firms expect average inflows to surpass outflows, yet with considerable variation in their positions. "Borrowing growth" at a mean of 69.6 signifies firms' collective borrowing increase, but variability is evident with a standard deviation of 62.5. "CP growth," indicating changes in commercial paper issuance, has a mean of 18.0, and a standard deviation of 42.1 underlines moderate changes with substantial variance.

Similarly, "Bond growth," signifying shifts in bond issuances, shows a mean of 30.7 with a standard deviation of 53.5, highlighting moderate expansion yet considerable diversity. "Bank borrowing growth" indicates changes in bank borrowings, with a mean of 39.9 and a standard deviation of 58.1, indicating moderate growth with significant variability.

Continuing, "MF CP growth," reflecting mutual funds' CP subscriptions, has a mean of 13.6 and a standard deviation of 36.3, indicating moderate growth with variable outcomes. "Bank CP growth," showing bank subscriptions to CPs, records a mean of 6.0 and a standard deviation of 21.8, signifying limited growth with varying patterns. "NBFC CP growth," gauging subscriptions to NBFC-issued CPs, records a mean of 0.7 and a standard deviation of 6.8, suggesting minimal growth with low variability.

"Other CP growth," capturing subscriptions from non-bank/NBFC sources, reports a mean of 7.4 and a standard deviation of 28.0, depicting moderate growth with considerable variation. In terms of bank loans, "Bank term loans growth" shows a mean of 38.2 and a standard deviation of 66.9, indicating moderate growth with notable variance. "Bank working capital growth" at a mean of 13.9 and a standard deviation of 42.9 suggests modest growth with variability. "Bank cash loans growth," with a mean of 25.5 and a substantial standard deviation of 77.8, indicates

moderate growth with significant diversity. Lastly, "Bank overdraft loans growth" records a mean of 7.3 and a standard deviation of 27.5, showcasing slight growth with variability.

CP growth was on average lower than bank borrowings and borrowing via debentures. CP growth was driven by mutual funds while bank borrowings growth was largely on account of growth in term loans.

# 4 Identification and Empirical Design

We use a difference-in-differences framework to estimate how ex-ante exposures impacted NBFC borrowing/lending during the liquidity shock episode. We use the following baseline specification for our analysis:

$$\Delta Y_i = \alpha + \beta \times \text{Ex-Ante Exposure}_i + X_i + \epsilon_i \tag{1}$$

In Equation (1), we exploit heterogeneity in ex-ante short-term liquidity of NBFC 'i' during the shock, which indicates their asset-liability mismatch. The dependent variables of interest are - i) funding by CPs, ii) NBFCs borrowing from banks or bond market, and iii) NBFC credit and investments.  $Y_i$  denotes the change in the dependent variable(s), based on the average balance-sheet data for the pre-period i.e. between June 2018 and September 2018, and the post-period i.e. between December 2018 and March 2019. The main coefficient of interest,  $\beta$ , measures the impact of ex-ante exposure on the outcome variable.

The ex-ante exposure of NBFC *i* exploits variation in the short tenure bucket of less than one year, which we use as an indicator for the immediate funding requirements of the firm. We add up all maturity buckets upto one year, as explained in the previous section, to get this short-tenure bucket. The exposure variable is in net terms as it includes repayment of term loans to banks and CP obligations to be rolled over or repaid adjusting it with the incoming payments. The ex-ante exposure indicator is calculated using the following formula:

$$Short-term\ liquidity_i = \frac{Contractual\ Inflows\ -\ Contractual\ Outflows}{Total\ Outflows} \tag{2}$$

In Equation (2), **Short** – **termliquidity** $_i$  denotes the ability of NBFC 'i' to service or repay short-term borrowings within the one-year period. Low short-term liquidity implies outflows are more than inflows in a year, thus making the NBFC 'i' more prone to rollover risks, or the risk of being unable to repay debts within a one-year period. We interpret the liquidity indicator using a binary classification, where firms with below-median short-term liquidity denote higher ex-ante exposure and take a value of '1', while firms with above-median liquidity indicate lower ex-ante exposure and take a value of '0' based on NBFCs' short-term liquidity in June 2018 i.e. one quarter before the shock.

Finally, we control for a vector of NBFC-level characteristics such as NPA ratio, cash ratio and operating expense ratio as of June 2018.

#### 5 Main results

#### 5.1 Ex-ante Exposure Correlates

In this section, we discuss the funding patterns in NBFCs in response to the liquidity shock detailed in Section 2.1. Our main set of results is based on 332 ICCs which constitute approximately half of the NBFC sector by asset size.

We begin our analysis by discussing the relationship between NBFC exposure and balance sheet characteristics in the pre-period or the period preceding the liquidity shock which occurred in 2018. Doing so would rule out the problem of multicollinearity for the main specification. Accordingly, we follow the baseline specification using Equation (3) below:

$$\Delta \text{Ex-Ante Exposure}_i = \alpha + X_i + \epsilon_i$$
 (3)

where  $X_i$  are NBFC balance sheet characteristics such as operating expenses ratio (operating expenses/ total income), cash ratio (cash and bank balances/ total assets), and non-performing assets (NPA) ratio (NPA/total credit) of NBFCs. The dependent variable is  $Ex - AnteExposure_i$ , which is an indicator variable equal to one for NBFC 'i' if it had below-median short-term liquidity.

Table 2 reports the results of Equation (3). The regressions reveal a null effect, which means that high-exposure and low-exposure NBFCs did not differ on these ratios in the pre-shock period. This eliminates the scope for these pre-shock characteristics to have led to a differential impact between high and low-exposure NBFCs in the post-shock period. In the coming sub-sections, we delve into understanding the impact of the crisis. Note that these high-exposure NBFCs are also found to have similar ex-ante trends in profitability (operating expense) and asset performance (non-performing asset ratio) as on March 2018, i.e. before the shock.

#### 5.2 Impact of Shock on NBFCs

In this subsection, we investigate the impact of the liquidity shock on short-term funding of NBFCs. We exploit how heterogeneity in the ex-ante asset-liability mismatch of NBFCs impacted their commercial paper (CP) holdings when the shock occurred. We use the following specification:

$$\Delta CP_i = \alpha + \beta \times \text{Ex-Ante Exposure}_i + \epsilon_i \tag{4}$$

where the dependent variable of interest is  $CPgrowth_i$  i.e. growth in commercial papers subscribed by NBFC i.

Table 3 reports regression results from Equation (4) about the funding flows in NBFCs during the time of the shock in 2018. Panel A of Table 3 reports the impact on CP subscribed by all lenders i.e. mutual funds, banks, other NBFCs. We find that CP growth of NBFCs with higher exante exposure reduced by 14.51 pp (S.E.= 4.67) in response to the shock. Post the liquidity shock, markets became reluctant to lend to NBFCs due to the fear of potential defaults by other NBFCs. Consequently, NBFCs were liquidity-constrained and faced difficulties in debt repayments, particularly on loans with shorter maturities. In Panel A's columns (2) to (5), we investigate which types of entities that subscribed to CPs, such as mutual funds, banks, NBFCs, and others, declined the most. The decline in CP funding of NBFCs with higher exposure was mainly on account of withdrawals of mutual funds, the largest subscribers of NBFC CPs. Mutual funds subscribing to CPs of high-exposure NBFCs declined by 10.62 pp (S.E.= 4.054). Results show that it was the

weaker NBFCs – those with higher exposure – which were relatively more affected.

## 5.3 Mechanism of the Liquidity Shock

Panel B of Table 3 reports the interaction of CP growth with NBFC characteristics such as size (measured by log of total assets), provisioning coverage ratio (PCR) measured by provisioning over total non-performing assets and operating expense (measured by operating costs over total income). We utilize information on these NBFC characteristics to assess which characteristics caused a decline in CP growth for the NBFCs with high exposure. Columns (1)-(3) show the interaction term for firm exposure and characteristics, which is the coefficient of interest. Column (1) shows that larger firms (above-median total assets) with higher exposure suffered a 5.56 pp (S.E.= 2.28) decline in CP growth in response to the liquidity shock, as compared to smaller NBFCs with lower exposure. Column (2) shows that for NBFCs with higher exposure but also above-median PCR, the decline in CP growth was relatively lesser, as compared with firms below-median PCR with lower exposure. This indicates that the liquidity shock did not impact NBFCs with higher provisioning against impaired assets, as they had greater buffers against the erosion of market confidence in the short-term funding market. Finally, we examine the effect of the operating expense of NBFCs, an indicator of firm efficiency, which is measured by operating expenses to total income. Column (3) reports a null effect of firm inefficiency on CP funding.

The liquidity shock made its way through NBFC size and provisioning buffers to impact CP funding, and this effect was larger for firms with higher exposure. Firm efficiency did not play a significant role in driving the impact of the shock.

For robustness, we carry out a placebo test, as shown in Table 4 where we shuffle the period of the shock. A null result confirms that the results in response to the shock period are valid.

# 5.4 Impact on Alternate Sources of Funding

The shock impacted firms with higher exposure. But could these firms access alternate sources of finance? In response to the shock, the CP market faced redemption pressures, i.e. firms that had ex-ante short-term liquidity faced greater challenges in raising funds. Through this subsection, we analyse access to alternative funding sources during the liquidity shock and whether varying

levels of ex-ante exposure affected such access. We use Equation (5) below:

$$\Delta Borrowings_i = \alpha + \beta \times Ex-Ante Exposure_i + \epsilon_i$$
 (5)

where the dependent variable of interest is  $Borrowings_i$ . We report the impact of the liquidity shock on alternative sources of funding such as banks, debentures, mutual funds as well as total borrowings.

Table 5 reports the regression results from Equation (5). Overall borrowings, i.e. growth in total borrowings of NBFCs with high exposure declined by 58.8 pp (S.E.= 6.17) in response to the liquidity shock. Going further, we break down the overall decline in borrowings of these NBFCs. As reported earlier, we know that overall CP growth reduced by 14.5 pp (S.E.= 4.67), as explained earlier. However, the decline was not limited to the CP market. As the liquidity shock occurred, borrowings of high-exposure NBFCs from debentures reduced by 30.15 pp (S.E.= 5.79) possibly owing to lesser issuance of debentures by high-exposure NBFCs after their extant debt matured. Column (4) in Table 5 indicates at ring-fencing by banks which reduced lending to high-exposure NBFCs by nearly 46 pp (S.E.= 6.03) as a consequence of the shock. These banks did not provide fresh credit to 'riskier' NBFCs, thereby ensuring some degree of cleansing effect in the bank-NBFC relationship.

NBFCs were unable to tap into alternate sources of funding - be it from debentures or from the banking sector.

# 6 Impact on Bank Lending

Did banks ringfence themselves from the NBFCs? How did the bank-NBFC relation augur in response to the shock?

In this section, our focus shifts to examining the response of the traditional banking sector in the wake of the liquidity shock experienced within the NBFC sector. To answer this, we start by matching a sub-sample of NBFCs with their respective lenders i.e. banks, mutual funds, financial institutions, CPs, debentures, provident funds, pension funds, and insurance funds. This matching process yields a sub-sample of 57 NBFCs that serve as the foundation for this analysis.

These 57 firms range across all types of NBFCs and are representative of the interconnectedness of different financial entities with a specific NBFC during the shock quarter.

Equation (6) below is the baseline specification to identify the response of the banking system in response to the liquidity shock.

ΔBank Lending<sub>i</sub> = 
$$\alpha + \beta \times \text{Ex-Ante Exposure * Bank}_i + \epsilon_i$$
 (6)

where Bank is an indicator equal to 1 if the financial institution that the NBFC borrows from is a scheduled commercial bank and the role of banks is captured by the coefficient of the interaction term  $Ex - AnteExposure * Bank_i$ . We define the health of the NBFC based on their median gross non-performing assets as on March 2018. We present two specifications: one without accounting for time-invariant unobservable traits of Financial Institutions (FIs), i.e., without applying Financial Institutions' fixed effects (FI-FE), and the other incorporating FI-FE.

Table 6 reports the results from Equation (6), where column (1) of Panel A shows that NBFCs with substantial exposure encountered a reduction in funding from Financial Institutions (FIs). However, it's noteworthy that among these high-exposure NBFCs, those that maintained links with banks were still able to secure bank borrowings. Column(2) corroborates these findings through a higher coefficient upon factoring in a fixed-effect for financial institutions – as banks lending to NBFCs increased by 0.55 pp (S.E.= 0.203).

Going a step further, we delineate the distinct dynamics of bank lending to NBFCs predicated on their Gross Non-Performing Asset (GNPA) ratio. We use two separate classifications of NBFCs, notably "healthy" and "unhealthy," to ask which type of NBFCs received more bank borrowings?

Column (1) of Panel B shows that high-exposure NBFCs with low NPAs (healthy NBFCs) faced a decline in credit from FIs but those among these NBFCs which had a relationship with banks reported relatively higher borrowings after the shock. The specification with FI-FE also reports similar results.

Column (2) of Panel C in Table 6 reveals that FIs did reduce lending high-exposure NBFCs with higher NPA ratios. However, the interaction term reports a null effect on banks lending to unhealthy NBFCs, which further suggests a 'cleansing effect' as banks reallocated their loans to

good quality NBFCs after the crisis.

# 7 Impact on NBFC Credit

Did the liquidity constraints impact the credit allocation by NBFCs? We answer this question using sector-wise information in this section using the 332 ICCs used in Section 5.

We follow the following specification:

$$\Delta \text{Credit}_i = \alpha + \beta \times \text{Ex-Ante Exposure}_i + \epsilon_i \tag{7}$$

where  $Credit_i$  indicates the growth in credit by NBFCs. In Panel A of Table 6, we find that overall credit of high-exposure NBFCs declines by 32.54pp (S.E.= 8.71) during the shock episode. We find no statistically significant effect on all investments as well as the subdivisions- long-term and current investments.

Panel B reports NBFC credit to three sectors - retail, industry, and services. Credit to the retail sector declines maximum decline of 29.78 pp (S.E.= 4.84). Retail lending is composed of vehicle loans, gold loans, microfinance loans, education loans, consumer durables, etc. which are typically extended for relatively shorter tenures as compared to loans to other sectors. We find that NBFCs with greater ex-ante asset-liability mismatch reduce retail loans by a larger extent when faced with a liquidity shock, as compared to industry and services. An alternate possibility could be that being ICCs, these NBFCs already had a higher share in retail lending, which declined in the post-period in response to the shock.

Impact on the services sector comes next in line where credit declines by 20.14 pp (S.E.= 5.81). This implies reduced lending to trade and transport operators, among others.

Finally, NBFC lending to the industry sector, which is typical of longer-term infrastructure loans, declines by 15.67 pp (5.92).

In a nutshell, we find that retail credit by NBFCs suffers most in response to a liquidity shock while lending to the industry is relatively less impacted.

# 7.1 Borrower-level impact

In this subsection, we capture firm-level effects by exploiting borrower-level information of NBFCs. We track the lending history of individual NBFCs to identify their largest borrowers. This information helps us understand the firm-level effect of a liquidity shock on NBFCs by comparing the same entity borrowing from two NBFCs, one with greater ex-ante exposure to the liquidity shock and one with lower ex-ante exposure. We also control for time-varying borrower characteristics to delineate the credit supply of NBFCs from credit demand. To do this, we control for borrower-level demand for credit by using borrower\*time fixed effects as done in Khwaja and Mian (2008).

We use the following specification:

Firm Borrowing<sub>i,i</sub> = 
$$\alpha + \beta \times \text{Ex-Ante Exposure}_i + \text{Borrower FE} + \epsilon_i$$
 (8)

where Firm Borrowing $_{j,i}$  represents the log of firm j borrowing from NBFC i. We have two specifications for this equation- (1) where we do not control for borrower fixed effects (to control firms' demand for credit ) and (2) controlling for borrower fixed effects.

Table (7) Column (2) reports that high-exposure NBFCs cut down credit to firms by 0.349 pp (S.E.=0.094) when faced with a liquidity shock. This indicates that high-exposure NBFCs passed on their credit constraints to the borrowers in response to the shock relative to low-exposure NBFCs.

# 8 Conclusion

This paper is a guidebook for analysing the anatomy of a non-bank liquidity shock. We focus on an episode in India that occurred in September 2018, when a large non-banking financial company (NBFC) defaulted on its debt obligation which had ripple effects within the sector. Most notably, the impact of the shock remained contained within the sector due to ringfencing by the banking sector. Through our analysis, we anatomize how this happened.

Facing redemption pressures due to the default of a large company's debt, mutual funds withdrew from the commercial paper (CP) market. Consequently, NBFCs which relied on short-term commercial paper were faced with a liquidity shock as their CP funding declined. The decline was larger for NBFCs with a higher ex-ante asset-liability mismatch. Moreover, while the mutual fund losses were the highest, stressed NBFCs were unable to access alternate sources of funding like banks and debentures. The liquidity shock was higher for firms that were larger in size and had lesser provisioning buffers against loan losses.

Our study also decomposes the relationship of NBFCs with the traditional banking sector during stressed times. Our findings reveal a noteworthy trend: NBFCs in better financial health, characterized by less non-performing loans, experienced ongoing support from banks. Conversely, the banking sector took precautions to ringfence itself from relatively less sound financial institutions, particularly those burdened by larger amounts of non-performing assets (NPAs). At the borrower level, non-banks cut down credit to their largest borrowers in response to the shock. This underscores that a liquidity shock affecting non-banking entities carries tangible real effects, resulting in a reduction in credit allocation.

Through our analysis, we shed light on the effect of a liquidity shock on credit reallocation by non-banks in the short term. Stressed firms, i.e., those with higher ex-ante asset-liability mismatch passed on their credit constraints to the sectoral level. Our investigation uncovers that lending to the retail sector bore the brunt of this impact, whereas the effects on lending to services and the industrial sector were comparatively lesser.

We believe our study offers important takeaways for policy considerations. We show that ringfencing of the banking sector can be a potent strategy for banks to prevent contagion effects and preserve financial stability. Simultaneously, a liquidity shock in non-banks can have a cleansing effect which can expose weak fundamentals of non-banks such as higher exposure to rollover risk, less provisioning against losses, and high non-performing loans. Notably, the size of non-banks matters significantly in how they respond to crises.

Finally, our paper should be read with a few caveats. *First*, our study zeroes in on a specific liquidity shock that unfolded within India. While analogous mechanisms might apply to other economies, the resultant impact can hinge on the idiosyncrasies of the non-banking sector in each country. Institutional details about the non-banking space in India are detailed in Section 2 of

the paper. *Second*, our empirical evidence does not allow us to draw any welfare conclusions regarding the non-banking sector. In terms of assessing the impact at the borrower level, we were equipped to analyze the effects on the top 20 borrowers. Nonetheless, interesting insights could emerge from delving into the implications of the shock for small borrowers, which could yield more interesting insights about the cleansing effects of a shock. We encourage researchers with the appropriate data to delve into these aspects. *Third*, the demonetisation episode in 2016 in India could have impacted the ex-ante liquidity exposure of firms in our sample. However, in this paper, we have chosen to focus only on understanding the liquidity shock that occurred within the non-bank sector and its underlying implications for financial stability.

# References

- Acharya, Viral, 2020, Quest for restoring financial stability in India (Sage Publications Pvt. Limited).
- Acharya, Viral V, Hemal Khandwala, and T Sabri Öncü, 2013, The growth of a shadow banking system in emerging markets: Evidence from india, *Journal of International Money and Finance* 39, 207–230.
- Admati, P. M. DeMarzo M. Hellwig, A. R., and P. Pfleiderer, 2013, Fallacies, irrelevant facts, and myths in the discussion of capital regulation: Why bank equity is not expensive, *Working Paper, Stanford University*.
- Agarwal, Ruchir, 2023, The past future of indian finance, M-RCBG Associate Working Paper No. 212
- Aramonte, Sirio, Andreas Schrimpf, and Hyun Song Shin, 2022, Non-bank financial intermediaries and financial stability, *The Research Handbook of Financial Markets*.
- Bernanke, Ben, 1983, Nonmonetary effects of the financial crisis in propagation of the great depression, *American Economic Review* 73, 257–276.
- Buchak, Matvos G Piskorski T, G, and A Seru, 2018, Fintech, Regulatory Arbitrage, and the Rise of Shadow Banks, *Journal of Financial Economics* 130, 453–483.
- Calomiris, Charles W., and Joseph R. Mason, 1997, Contagion and bank failures during the great depression: The june 1932 chicago banking panic, *American Economic Review* 87, 863–883.
- Chernenko, Sergey, Isil Erel, and Robert Prilmeier, 2022, Why do firms borrow directly from non-banks?, *The Review of Financial Studies* 35, 4902–4947.
- Chretien, E., and V. Lyonnet., 2018, Traditional and shadow banks, Working Paper, Ohio State University.
- Farhi, E., and J. Tirole, 2017, Shadow banking and the four pillars of traditional financial intermediation, *Working Paper, Harvard University* 76, 973–992.
- Flannery, M. J., 2014, Maintaining adequate bank capital, *Journal of Money, Credit and Banking* 46, 157–80.
- Forbes, Kristin, Christian Friedrich, and Dennis Reinhardt, 2023, Stress relief? funding structures and resilience to the covid shock, *Journal of Monetary Economics*.
- Freixas, L. Laeven, X., and J.-L. Peydr´o, 2015, Systemic risk, crises and macroprudential policy, *Cambridge, MA: MIT Press*.

- FSB, Financial Stability, 2022, Global monitoring report on non-bank financial intermediation, *Financial Stability Board Report*, *December*.
- Fuster, M. Plosser P. Schnabl, A., and J. Vickery, 2019, The role of technology in mortgage lending, *Review of Financial Studies* 32, 1854–99.
- Hanson, A. K. Kashyap, S. G., and J. C. Stein, 2011, A macroprudential approach to financial regulation, *Journal of Economic Perspectives* 25, 3–28.
- Hodula, Martin, Ales Melecky, and Martin Machacek, 2020, Off the radar: factors behind the growth of shadow banking in europe, *Economic Systems* 44, 100808.
- Hsieh, Chang-Tai, and Peter J Klenow, 2009, Misallocation and manufacturing tfp in china and india, *The Quarterly Journal of Economics* 124, 1403–1448.
- Iyer, Rajkamal, and Manju Puri, 2012, Understanding Bank Runs: The Importance of Depositor-bank Relationships and Networks, *American Economic Review* 102, 1414–1445.
- Khwaja, Asim Ijaz, and Atif Mian, 2008, Tracing the Impact of Bank Liquidity Shocks: Evidence from an Emerging Market, *American Economic Review* 98(4), 1413–42.
- Martinez-Miera, D., and R. Repullo, 2018, Markets, banks and shadow banks, *Working Paper*, *CEMFI*.
- Plantin, G., 2015, Shadow Banking and Bank Capital Regulation, *Review of Financial Studies* 28, 146–175.
- Quirin Fleckenstein, German Gutierrez Gallardo Sebastian Hillenbrand, Manasa Gopal, 2020, Nonbank Lending and Credit Cyclicality, NYU Stern School of Business 59.
- RBI, 2022, Report on trend and progress of banking in india.
- Saunders, Anthony, and Berry Wilson, 1996, Contagious bank runs: evidence from the 1929–1933 period, *Journal of Financial Intermediation* 5, 409–423.
- Schumacher, Liliana B., 1998, Information and currency run in a system without a safety net: Argentina and the 'tequila' shock, *IMF Working Paper*.
- Thakor, A. V., 2014, Bank capital and financial stability: An economic trade-o or a faustian bargain?, *Annual Review of Financial Economics* 6, 185–223.
- Tirole, Jean, and Emmanuel Farhi, 2021, Shadow banking and the four pillars of traditional financial intermediation, *The Review of Economic Studies* 88, 2622–2653.
- Xiao, Kairong, 2020, Monetary transmission through shadow banks, *The Review of Financial Studies*

33, 2379–2420.

# Table 1 Summary Statistics

This table presents the summary statistics of all the variables for the NBFCs used in our analysis. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. It is shown in the table as ex-ante exposure (cont.). Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. The remaining growth variables are calculated using balance sheet variables and are average in the post-period to the average in the pre-period. Preperiod is between June 2018–September 2018, and the post-period is between December 2018 and March 2019. Data is from the Reserve Bank of India.

	Mean	SD
Ex-ante exposure (cont.)	1.8	16.4
Borrowing growth	69.6	62.5
CP growth	18.0	42.1
Bond growth	30.7	53.5
Bank borrowing growth	39.9	58.1
MF CP growth	13.6	36.3
Bank CP growth	6.0	21.8
NBFC CP growth	0.7	6.8
Other CP growth	7.4	28.0
Bank term loans growth	38.2	66.9
Bank working capital growth	13.9	42.9
Bank cash loans growth	25.5	77.8
Bank overdraft loans growth	7.3	27.5
Observations	318	

Table 2 Correlates of the Exposure Variable

The table presents the correlates of the exposure variable. The dependent variable in all columns is the ex-ante exposure. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. The RHS variables operating expense, cash ratio and NPA ratio in columns 1-3, respectively. Data is from the Reserve Bank of India. Observations are at the NBFC level for 318 NBFCs, one quarter before and after the shock. Robust standard errors are clustered at the firm level

	(1)	(2)	(3)
		Ex-ante E	Exposure
Operating Expense	-0.089		
	(0.071)		
Cash Ratio		0.127	
		(0.157)	
NPA Ratio			-0.000
			(0.001)
$\mathbb{R}^2$	0.006	0.003	0.000
N	254	253	223

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

Table 3
Impact on Commercial Paper Funding for NBFCs

Panel A presents the commercial paper growth around the ILFS crisis against the ex-ante exposure variable for NBFCs. The dependent variable is the growth in the total commercial paper subscribed by all lenders (column 1), mutual funds (column 2), banks (column 3), other NBFCs (column 4) and a catch-all category other (column 5). Pre-period is between June 2018–September 2018 and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Panel B shows the heterogeneity across size, provisioning ratio, and operating expenditure ratio. Size is measured as the log of assets, the provisioning ratio is 1 for above median values, and the operating ratio is the operating expenses to the total sales. The dependent variable is the total commercial paper growth between the pre- and post-period, defined as before. Observations are at the NBFC level for NBFCs, one quarter before and after the shock period. Robust standard errors are clustered at the firm level.

Panel A: Commercial Paper Growth

	(1)	(2)	(3)	(4)	(5)
Dependent variable:		Growth	CP subscribed l	Эy	
	All	MF	Bank	NBFC	Other
Ex-ante Exposure	-14.507***	-10.618***	-2.237	-0.340	-3.313
	(4.673)	(4.054)	(2.445)	(0.766)	(3.145)
$\mathbb{R}^2$	0.030	0.021	0.003	0.001	0.004
N	318	318	318	318	318

<sup>\*</sup>p < 0.10, \*p < 0.05, \*p < 0.01. Standard errors clustered at firm level.

Panel B: Heterogeneity in Commercial Paper Growth

	(1)	(2)	(3)
Dependent variables:		CP Growth	
	Size	Provisioning	OpEx
		ratio	ratio
Ex-ante Exposure	32.149**	-15.146***	-13.892**
	(13.062)	(4.589)	(5.859)
Ex-ante Exposure * Variable	-5.562**	0.785***	2.543
	(2.283)	(0.078)	(7.943)
Variable	11.809***	0.035	-17.516**
	(1.844)	(0.055)	(7.023)
$\mathbb{R}^2$	0.212	0.056	0.057
N	316	318	318

Table 4 Placebo effects for other periods

Panel A presents the commercial paper growth around the ILFS crisis against the ex-ante exposure variable for NBFCs. The dependent variable is the growth in the total commercial paper subscribed by all lenders (column 1), mutual funds (column 2), banks (column 3), other NBFCs (column 4) and a catch-all category other (column 5). Pre-period is between June 2018–September 2018 and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Panel B shows the heterogeneity across size, provisioning ratio, and operating expenditure ratio. Size is measured as the log of assets, the provisioning ratio is 1 for above median values, and the operating ratio is the operating expenses to the total sales. The dependent variable is the total commercial paper growth between the pre- and post-period, defined as before. Observations are at the NBFC level for NBFCs, one quarter before and after the shock period. Robust standard errors are clustered at the firm level.

#### **Commercial Paper Growth**

	(1)	(2)	(3)	(4)	(5)
Dependent variables:		CP gro	owth exp	osure	
	All	MF	Bank	NBFC	Other
Ex-ante Exposure	-10.804	-1.660	1.380	1.846	3.128
	(10.526)	(9.238)	(8.965)	(1.191)	(4.294)
$\mathbb{R}^2$	0.004	0.000	0.000	0.007	0.002
N	263	263	263	263	263

**Table 5 Impact on Alternate Funding Sources** 

This table presents the funding growth around the liquidity shock against the ex-ante exposure variable for NBFCs. The dependent variable is the growth in total funding (column 1), commercial paper (column 2), debentures (column 3), and banks (column 4). Pre-period is between 2018–September 2018 and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Observations are at the NBFC level for NBFCs, one quarter before and after the shock. Robust standard errors are clustered at the firm level.

	(1)	(2)	(3)	(4)
Dependent variables:		Growth in b	orrowing from	ı
	Total	CP	Debentures	Bank
Ex-ante Exposure	-58.802***	-14.507***	-30.147***	-46.015***
	(6.173)	(4.673)	(5.797)	(6.031)
$\mathbb{R}^2$	0.222	0.030	0.080	0.157
N	318	318	318	318

<sup>\*</sup>p < 0.10, \*\*p < 0.05, \*\*\*p < 0.01. Standard errors clustered at firm level.

Table 6
Bank Support During the Shock

This table presents the heterogeneity in borrowing from banks versus other financial institutions (FI) around the shock. The dependent variable is the change in borrowing between the pre- and post-period. Pre-period is between June 2018–September 2018 and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Bank is an indicator equal to 1 if the financial institution that the NBFC borrows from is a scheduled commercial bank. Column 2 includes FI fixed effects. In Panel A all NBFCs are included. Panel B (C) subsets to healthy (weak) NBFCs defined as those with below (above) median gross non-performing asset ratio as of June 2018. Data is from the Reserve Bank of India. Observations are at the FI-NBFC level. Standard errors are clustered at the NBFC level.

Panel A: All			
	(1)	(2)	
Dependent variables:	Growth in	n borrowing.	
Ex-ante Exposure	-0.290**	-0.359**	
	(0.134)	(0.176)	
Exposure * Bank	0.389***	0.555***	
_	(0.147)	(0.203)	
Bank	0.124**		
	(0.063)		
$\mathbb{R}^2$	0.018	0.415	
FI-FE	N	Y	
N	1064	1064	

Panel B: Healthy NBFCs			
	(1)	(2)	
Dependent variables:	Growth in	borrowing	
Ex-ante Exposure	-0.621***	-0.498*	
_	(0.092)	(0.254)	
Exposure * Bank	0.643***	0.626**	
	(0.121)	(0.281)	
Bank	0.055		
	(0.087)		
$\mathbb{R}^2$	0.029	0.445	
FI-FE	N	Y	
N	570	570	

Table 5
Bank Support During the Shock (contd.)

# Panel C: Weak NBFCs

	(1)	(2)	
Dependent variables:	Growth in	n borrowing	
Ex-ante Exposure	0.262	-0.162***	
	(0.273)	(0.000)	
Exposure * Bank	-0.252	0.228	
•	(0.294)	(0.222)	
Bank	0.305***		
	(0.108)		
$\mathbb{R}^2$	0.027	0.573	
FI-FE	N	Y	
N	492	492	

# Table 6 Impact on Credit and Investment

Panel A table presents the change in credit and investments around the shock against the ex-ante exposure variable for NBFCs. The dependent variable is the change in credit column 1) and all investments (column 2), long-term investments (column 3), and current investments (column 4). Pre-period is between June 2018–September 2018, and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Observations are at the NBFC level for NBFCs, one quarter before and after the shock period. Robust standard errors are shown. Panel B shows the impact on credit by industry. The dependent variables are the change in credit between the pre- and post-period for the retail (column 1), industry (column 2), and services (column 3). The remaining variables are as defined in Panel A.

#### Panel A:

	(1)	(2)	(3)	(4)	
Dependent variables		Growth in			
	Credit		Investments	3	
		All	Long-term	Current	
Ex-ante Exposure	-32.537***	-4.786	6.281	15.523	
	(8.714)	(9.169)	(8.806)	(18.113)	
$\mathbb{R}^2$	0.042	0.001	0.002	0.002	
N	318	318	318	318	

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

#### Panel B:

	(1)	(2)	(3)
Dependent variables:	-	Loan Growth	า
	Retail	Industry	Services
Ex-ante Exposure	-29.776***	-15.677***	-20.140***
_	(4.839)	(5.919)	(5.813)
$\mathbb{R}^2$	0.108	0.022	0.037
N	318	318	318

Standard errors in parentheses; \* p < 0.10, \*\* p < 0.05, \*\*\*  $\overline{p < 0.01}$ 

Table 7
Effect on borrower-level credit

This table presents the change in borrower-level credit around the shock against the ex-ante exposure variable for NBFCs. The dependent variable is (log of) firm borrowings. Pre-period is between June 2018–September 2018, and the post-period is between December 2018 and March 2019. Ex-ante exposure is the short-term (less than 1 year) asset-liability mismatch, defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Observations are at the NBFC-borrower level, one quarter before and after the shock. This table includes a fixed-effect for the NBFC borrowers to control for its impact on credit. Robust standard errors are shown.

	(1)	(2)
Dependent variables:	Log of firm borrowings	8
Ex-ante exposure	-2.772***	-0.349***
_	(0.050)	(0.094)
$\mathbb{R}^2$	0.159	0.883
Borrower-FE	N	Y
N	15988	14010

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

# Anatomy of a Liquidity Shock on Non-banks Online Appendix

Table A1 Channel: Heterogeneity Tests

This table presents the various channels through which NBFCs characteristics impact their CP borrowings. The tables shows the heterogeneity across size, provisioning ratio, CRAR, operating expenses, and cash ratio. The dependent variable is the CP growth in size (Column 1), provisioning ratio (Column 2), CRAR (Column 3), operating expenses (Column 4), and cash ratio (Column 5) respectively. Size is measured as the log of assets, the provisioning ratio is 1 for above median values, and the operating ratio is the operating expenses to the total sales. Pre-period is between June 2018–September 2018, and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Observations are at the NBFC level for NBFCs, one quarter before and after the shock. Robust standard errors are shown.

	(1)	(2)	(3)	(4)	(5)
		Dependent variables: CP Growth			
Variable:	Size	Provisioning	CRAR	OpEx	Cash
		ratio		ratio	ratio
Variable	8.657***	0.047	-0.110***	-17.462***	-24.907***
	(1.048)	(0.058)	(0.027)	(3.770)	(9.197)
$\mathbb{R}^2$	0.192	0.010	0.044	0.032	0.013
N	316	318	313	318	316

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

Table A2
Limited Effect on Commercial Real Estate

This table presents the limited effect on commercial real estate. The dependent variable is Services loan growth in Commercial RE (column 1), Trade (column 2) and Trnsport Operators (Column 3). Pre-period is between June 2018–September 2018, and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Observations are at the NBFC level for NBFCs, one quarter before and after the shock. Robust standard errors are shown.

	(1)	(2)	(3)
Dependent v	ariables: Servic	es Loan G	rowth
	Commercial	Trade	Transport
	RE		Operators
Ex-ante exposure	-5.385	-6.902**	-5.299**
	(4.438)	(3.157)	(2.516)
$\mathbb{R}^2$	0.005	0.015	0.014
N	318	318	318

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

# Table A3 Larger Effects on Smaller Service Firms

This table presents the larger effects on smaller service firms. The dependent variable is Services loan growth to small/micro (column 1), medium (column 2) and large (Column 3). Pre-period is between June 2018–September 2018, and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Observations are at the NBFC level for NBFCs, one quarter before and after the shock. Robust standard errors are shown.

	(1)	(2)	(3)	
Dependent variables: Services Loan Growth				
	Small/Micro	Medium	Large	
Ex-ante exposure	-7.862**	-4.072	-4.578	
•	(3.228)	(3.076)	(2.858)	
$\mathbb{R}^2$	0.019	0.006	0.008	
N	318	318	318	

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

# Table A4 Industry Firms

This table examines the effect on loans disbursed by high exposure NBFCs to industry on the basis of their size. The dependent variable is industry loan growth to small/micro (column 1), medium (column 2) and large (Column 3). Pre-period is between June 2018–September 2018, and the post-period is between December 2018 and March 2019. Growth is calculated using balance sheet variables and is the average in the post-period to the average in the pre-period. Short-term (less than 1 year) asset-liability mismatch is defined as the ratio of the short-term contractual cash inflows minus the short-term contractual cash outflows to the total outflows. Ex-ante exposure is 1 for below median values of the short-term asset-liability mismatch. Data is from the Reserve Bank of India. Observations are at the NBFC level for NBFCs, one quarter before and after the shock. Robust standard errors are shown.

	(1)	(2)	(3)	
Dependent variables: Industry Loan Growth				
	Small/Micro	Medium	Large	
Ex-ante exposure	-4.324	-6.038*	-3.569	
	(3.239)	(3.112)	(3.299)	
$\mathbb{R}^2$	0.006	0.012	0.004	
N	318	318	318	

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