Do Intermediaries Help Mitigate the Contagious Effects of Runs?*

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December 30, 2025

Abstract

In this paper, we examine the behavior of financial intermediaries during a run involving mutual funds and shadow banks. Our setting is based in India, where investors fund shadow banks via debt mutual funds. For our analysis, we exploit the unexpected failure of a large shadow bank. The failure of a shadow bank potentially signals distress in the industries where it operates. Investors plausibly revised their beliefs after this information event and exited mutual funds with a high allocation to shadow banks, irrespective of whether these banks operate in similar industries as the failed shadow bank (affected shadow banks). This investor response would have spread contagion to shadow banks operating in different industries (unaffected shadow banks). Mutual funds, however, selectively reduced allocation to affected shadow banks and shielded unaffected ones from the investor run. On the other hand, closed-end funds, facing no redemption pressure, held onto their allocation in shadow banks. Therefore, the fundamentals themselves did not warrant liquidation. Overall, the intermediary's choice to liquidate certain shadow banks minimized the inefficiency caused by the run. We highlight this liquidation choice as a hitherto unexplored role of intermediaries.

Keywords: Bank Runs, Contagion, Financial Intermediaries, Mutual Funds, Shadow Banks

JEL Codes: G20, G23, G01

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1 Introduction

Liquidity creation is an essential role of financial intermediaries.[1] Nevertheless, the same role opens up the possibility of runs, which arouse inefficient asset liquidation by the intermediaries (Diamond and Dybvig (1983)). To our knowledge, all theoretical studies on runs consider banks with a representative project.[2] Hence, in such models, asset liquidation implies liquidating the representative project. However, in practice, there is rich heterogeneity across projects. An information event could raise concerns regarding the viability of specific projects but not others. In such a scenario, during a run, an intermediary's choice to liquidate specific (other viable) projects could mitigate (amplify) the social costs of runs. This choice is particularly important when runs arise from coordination failure due to imperfect knowledge of fundamentals.[3]

To understand such liquidation choices, we study the behavior of intermediaries during a run involving mutual funds and shadow banks in India. Understanding their behavior is vital for three reasons. First, the shadow banking system is highly vulnerable to runs as investors are not covered by deposit insurance (Foley-Fisher et al. (2020), Schmidt et al. (2016), Li et al. (2021)). Second, in the shadow banking sector, financial intermediation is performed by a chain of institutions, and each link in the chain is vulnerable to run (Foley-Fisher et al. (2020)). Hence, a panic-driven action by a group at one end of the chain could lead to contagious effects at the other end of the chain. Finally, a series of shadow bank runs could precipitate a financial crisis, as happened in the case of the Great Recession (Bernanke (2010); Gorton (2010); Gertler et al. (2020)).[4]

In this paper, we show that intermediaries help reduce the social cost of liquidations and, thereby, minimize the inefficiencies caused by investor runs. They do so by shielding relatively healthier projects from the adverse consequences of investor runs. Therefore, though intermedi-

[1] Diamond and Dybvig (1983); Gorton and Pennacchi (1990); Diamond and Rajan (2001); Berger and Bouwman (2009)

[2] Diamond and Dybvig (1983); Chari and Jagannathan (1988); Chen (1999); Goldstein and Pauzner (2005)

[3] Goldstein and Pauzner (2005)

[4] During the global financial crisis, there were widespread runs in the shadow banking sector. For example, there were runs on the repo market (Gorton and Metrick (2012); Krishnamurthy et al. (2014)), asset-backed commercial paper market (Kacperczyk and Schnabl (2010); Covitz et al. (2013)), and money-market mutual funds (Schmidt et al. (2016)).

aries are susceptible to runs, their choice of liquidation minimizes the inefficiency arising from runs. We highlight this liquidation choice as a hitherto unexplored role of intermediaries.

We present a simplified example to illustrate this point. Consider an economy with heterogeneous projects. There are three agents in the economy - shadow banks, mutual funds, and mutual fund investors (henceforth, investors). Mutual funds finance projects via shadow banks. The projects belong to two sectors - infrastructure and non-infrastructure. Shadow banks specialize in lending to a sector — infra (non-infra) oriented shadow banks primarily fund projects in the infra (non-infra) sector. Mutual funds can accurately gauge the health of each sector but not the health of a specific project. The health of the sector materializes after mutual funds have made the investments. Mutual fund investors are, however, uninformed. When the state of the economy is realized at a later date, the prospects turn out to be unfavorable for the infra sector but favorable for the non-infra sector. However, on average, the projects in both sectors are still viable. A project is viable when the cash flows are adequate to meet the repayment obligations.

In this setting, suppose a shadow bank with high idiosyncratic exposure to unviable projects fails, taking the investors by surprise. The informed mutual funds know that the shadow bank's failure is idiosyncratic, and the sectors' health does not warrant termination of funding (Goldstein and Pauzner (2005)). However, uninformed mutual fund investors read the failure of the shadow bank as a signal about the overall health of the shadow banking sector and withdraw from mutual funds (Chen (1999)). Due to their uninformed nature, investors' withdrawal does not depend on funds' exposure to infra-oriented shadow banks. Facing redemption pressure from their investors, mutual funds are forced to reduce exposure to shadow banks, thereby triggering early liquidation of their borrowers' projects. Nevertheless, informed mutual funds can selectively withdraw from infra-oriented shadow banks. Note that non-infra projects potentially have a higher realizable value than infra projects, making the liquidation discount for non-infra projects higher than that of infra projects. Thus, the selective withdrawal by informed intermediaries from infra-oriented shadow banks can minimize inefficiency arising from early liquidation.

Coming to the specifics of our empirical setting, India has a category of institutions called non-banking financial companies (NBFCs) that provide bank-like financial services. The credit originated by NBFCs was approximately 20% of total commercial bank credit. The liabilities of NBFCs are majorly comprised of debentures, bank borrowings, and commercial papers. As of December 2017, NBFCs borrowed 40% of funds from banks, 37% of funds from mutual funds, and 19% from insurance companies. Hence, mutual funds were a significant source of funds for NBFCs. NBFCs, in turn, constituted a significant share ($\approx$ 35%) of mutual funds' assets under management (AUM).

In September 2018, Infrastructure Leasing & Financial Services (IL&FS) Financial Services, a 100% subsidiary of the IL&FS group and a systemically important NBFC, defaulted on its short-term liabilities. There were a series of defaults by several IL&FS group companies around the same period. Most of these companies were rated high investment grade at the time of default; hence, the event took market participants by surprise. Therefore, the IL&FS failure was potentially unanticipated and provides an ideal setting to study the behavior of investors and mutual funds following an adverse signal about the NBFC sector.

The failure of IL&FS signals the potential distress in the industries where it operates (henceforth, IL&FS industries). We find that these industries fared worse on several dimensions of financial health, including profitability, solvency, and leverage, prior to the collapse of IL&FS. Hence, the collapse of IL&FS probably revealed the severity of stress in these industries. We identify NBFCs that operate in IL&FS industries as affected. Specifically, affected NBFCs are those NBFCs with above median value of loans outstanding with the IL&FS industries as of 30th June 2018. The remaining NBFCs are classified as unaffected.

We begin our analysis by examining mutual fund investors' withdrawal decisions in response to the crisis. We find that investors redeem differentially more from mutual funds with high NBFC allocation. In terms of economic magnitude, mutual funds with high NBFC allocation experienced 15 percentage points (pp) higher outflows compared to other funds over three months following the collapse of IL&FS. The economic magnitude is comparable to runs documented in the literature.[5] Additional analysis reveals that investors' redemption decision was related to overall NBFC allocation but not affected NBFC allocation.

The above result can be explained using a framework in which investors revise their beliefs after an information event (Chen (1999); Metrick (2024)). The mutual fund investors likely consider the failure of IL&FS as a signal of trouble in other NBFCs, thereby triggering a self-fulfilling panic. Though there are mutual funds as another layer between the investors and the NBFCs in our setting, a payoff externality arises as redemption costs are not reflected in NAV at the time of redemption; instead, they are borne by investors staying invested in the fund (Chen et al. (2010)). As the direct exposure of mutual funds to the IL&FS group was small (0.35%), financial contagion arising from direct exposure to IL&FS cannot explain the mutual fund investors' response.

We now turn to the next link in the intermediation chain – the open-ended mutual funds. We ask - how do open-ended mutual funds meet the redemption pressure? We find that that mutual funds reduced exposure to affected NBFCs to meet the redemption pressusre. They reduced exposure to affected NBFCs by 13.4pp more compared to unaffected NBFCs in a difference-in-differences sense. A plausible explanation is that since the redemption pressure is tied to NBFC allocation, mutual funds reduce exposure to NBFCs, hoping that lower NBFC allocation may stem the outflows. Moreover, the pay-off structure of the managers incentivize them to maximize performance (Sirri and Tufano (1998), Gaspar et al. (2006)). Hence, the well-informed mutual fund managers choose to liquidate their investments in NBFCs affected by the crisis compared to other NBFCs.

Nevertheless, there remains an open question about whether mutual funds' decision to reduce exposure to affected NBFCs is driven by deterioration in the fundamentals of the infra sector or redemption pressure. Goldstein and Pauzner (2005) argue that when fundamentals are below a certain threshold, it is efficient for all investors to run. Hence, the question is whether the fundamentals of the sector funded by affected NBFCs' were so bad that the mutual funds would have reduced allocation, irrespective of the redemption pressure.

[5] For instance, while examining the impact of the Eurozone crisis, Chernenko and Sunderam (2014) find a 9.9% decline in AUM for a one standard deviation increase in mutual funds' Eurozone exposure. During the week following the Lehman default, Kacperczyk and Schnabl (2013) document a 3.3pp higher outflows for a one standard deviation increase in mutual funds' risk exposure.

To answer the above question, we rely on closed-ended funds, which do not face redemption pressure. We do not find any evidence of closed-ended funds reducing exposure to affected NBFCs. Thus, the reduction in allocation by open-ended funds to affected NBFCs seems to be driven by the redemption pressure. The result supports our assumption that the infrastructure projects were viable. Moreover, the behavior of the closed-end fund also suggests that even the withdrawal by the open-ended funds from affected NBFCs does not trigger a strategic complementarity between the two types of funds (Goldstein and Pauzner (2005)).

A reader could wonder if the closed-end funds could have increased their exposure to NBFCs when the underlying projects were viable. We find closed-end funds increased their exposure to unaffected NBFCs. Note that since NBFCs are specialized, a closed-end fund would require time to conduct the necessary due diligence before investing in an NBFC. However, persistent selling by open-ended funds may bring down a few affected NBFCs before the evaluation is complete, if not immediately. Furthermore, closed-end funds are significantly smaller in size when compared to open-ended funds. As a result, they may not be able to absorb the entire selling by open-ended funds. Therefore, closed-end funds are likely to prefer unaffected NBFCs.

Finally, we provide suggestive evidence for the two implicit assumptions in our analysis. First, the termination of funding by mutual funds could have triggered early liquidation of NBFC borrowers' projects. We show that withdrawal by mutual funds indeed increases the likelihood of liquidation of projects funded by affected NBFCs. Second, social costs of early liquidation are higher when projects belonging to non-IL&FS industries are liquidated. We find that liquidations in non-IL&FS industries attract higher penalties by the financial markets than those by IL&FS industries. The evidence suggests that the liquidations of projects funded by unaffected NBFCs are indeed relatively more inefficient.

Overall, the main takeaway that emerges from the above analysis is that the failure of an NBFC may trigger a contagious run by uninformed investors. This run would have forced projects into early liquidation, though the projects are fundamentally viable. However, an informed intermediary may choose to liquidate relatively low-return projects. In a counterfactual scenario, where investors fund projects directly, even some of the high-return projects may have been potentially liquidated. Therefore, informed intermediaries are able to minimize the inefficiency arising from contagious runs.

A limitation of our study is that we do not observe the behavior of the retail investors investing directly in the NBFCs. Our conclusions about the behavior of retail investors are based on observing their investments with mutual funds. This is because regulatory restrictions prevent NBFCs from raising demand deposits. The NBFCs are largely funded through bonds and commercial papers, which have negligible retail participation.

Our paper is related to multiple strands of literature. We contribute to the literature that documents various roles played by the financial intermediaries. The literature has documented various roles such as liquidity creation (Diamond and Dybvig (1983); Gorton and Pennacchi (1990)), delegated monitoring (Diamond (1984); Boot and Thakor (1997)), screening (Manove et al. (2001)), information production (Leland and Pyle (1977); Boyd and Prescott (1986)), risk-sharing (Allen and Gale (1997)). We show that intermediaries also help in reducing the social cost of liquidations and minimizing the inefficiencies caused by runs.

Within the broader financial intermediation literature, we contribute to the emerging literature on intermediation chains. Glode and Opp (2016) and Glode et al. (2019) document that the presence of even moderately-informed intermediaries can incentivize efficient trading behavior in OTC markets. He and Li (2022) demonstrate that intermediation chains help insulate the underlying projects from negative fundamental shocks, resulting in greater borrowing capacity. In their case, the insulation arises from the liquidation of the intermediary's asset instead of the underlying project. In our setting, we demonstrate insulation based on the intermediary's ability to identify and liquidate bad assets on behalf of the investors.

We contribute to the literature that studies the phenomenon of bank runs. In a seminal paper, Diamond and Dybvig (1983) show that the demand deposit contracts that facilitate liquidity provision have a bank-run equilibrium. In their model, bank runs can result due to sun-spot events. The studies that followed attempted to investigate the causes of bank runs (Chari and Jagannathan

(1988), Chen (1999), Goldstein and Pauzner (2005)). The above studies document that causes of bank runs can range from incorrect interpretation of signals originating from large liquidity-driven withdrawals or bank failures to bad economic fundamentals. Further, studies have also examined the policy responses such as suspension of convertibility or deposit insurance (Ennis and Keister (2009), Dávila and Goldstein (2023)).

The empirical studies on bank runs outside financial crises are limited because such events are sporadic. Iyer and Puri (2012) and Iyer et al. (2016) document factors that affect depositors' behavior during runs. Blickle et al. (2024) examine bank run during a financial crisis and find that unsophisticated depositors withdraw from both failing and surviving banks. Runs have also been shown to exist in the shadow banking industry (Foley-Fisher et al. (2020), Schmidt et al. (2016), Li et al. (2021), Frydman et al. (2015)). We contribute to the literature by showing that the presence of intermediaries helps mitigate the social cost of liquidations triggered by runs.

Finally, we also contribute to the literature on contagion. A strand of literature on financial contagion investigates the spread of contagion from one geographical region to another through financial intermediaries (Allen and Gale (2000), Anderson et al. (2019), Calvo and Mendoza (2000), Peek and Rosengren (2000)). Studies have also specifically shown that interbank connections can result in the spread of contagion (Iyer and Peydro (2011), Acemoglu et al. (2015), Gofman (2017)). Chernenko and Sunderam (2014) examine contagion in the case of mutual funds. They document that funds exposed to the Eurozone crisis suffered outflows, and as a result, non-European issuers were adversely affected. The literature has primarily shown that intermediaries amplify the effects of financial contagion. In contrast to the above studies, we show that intermediaries could potentially minimize the inefficient liquidations due to runs.

2 Institutional Setting

2.1 Non-Banking Financial Companies

As mentioned in Section 1, the shadow banks we refer to in this study are Non-banking financial companies (NBFCs or non-banks). NBFCs are institutions that provide bank-like financial services. Their services include extension of loans and advances, purchase of bonds issued by the Government, or other marketable securities. Apart from being registered under the Companies Act (1956), the NBFC must also be registered with the Reserve Bank of India (RBI). The RBI regulates the financial activities of NBFCs by adhering to the guidelines specified in Chapter III B of the Reserve Bank of India Act, 1934.[6] As of 31st March 2018, the total credit provided by NBFCs stood at Indian Rupee (INR) 17,643 billion or USD 270 billion, which is approximately 20% of the total commercial bank credit in India.[7]

The RBI classifies NBFCs into 12 types based on their type of activities, such as extending credit to disadvantaged groups, financing infrastructure projects, and acquisition of receivables. For instance, NBFC-Infrastructure Finance Company (IFC) specializes in providing infrastructure loans, and NBFC-Core Investment Company provides loans to group companies. Similarly, Housing Finance Companies (HFCs) are a niche category of NBFCs with a focus on finance for housing, which are regulated by the National Housing Bank (NHB).[8] The RBI also classifies NBFCs based on their systemic importance; NBFCs with an asset size of more than Indian Rupee (INR) 5 billion are considered systemically important as their activities have a bearing on the financial stability.[9]

A significant difference between banks and NBFCs is that NBFCs cannot raise demand deposits. Further, only a subset of NBFCs are permitted to raise term deposits. In aggregate, deposits constitute a negligible portion (≈1.5%) of NBFCs' balance sheet.[10] The liabilities of NBFCs are

[6] https://www.rbi.org.in/Scripts/BS_ViewMasCirculardetails.aspx?id=12218

[7] https://www.rbi.org.in/Scripts/PublicationsView.aspx?id=18745 & https://www.rbi.org.in/Scripts/PublicationsView.aspx?id=21580

[8] Since 2019, the regulation of Housing Finance Companies (HFCs) is carried out by the RBI

[9] https://www.rbi.org.in/SCRIPTs/FAQView.aspx?Id=92

[10] Deposits constitute the largest portion of banks' balance sheet (≈75%); https://www.rbi.org.in/Scripts/PublicationsView.aspx?id=18743

majorly comprised of debentures, bank borrowings, and commercial papers. NBFCs borrowed 40% of funds from banks, 37% of funds from debt mutual funds, and 19% from insurance companies.[11] Therefore, the fraction of NBFCs' liabilities that are directly funded by unsophisticated (for example, retail) investors is negligible. They fund the liabilities of NBFCs indirectly via mutual funds.

2.2 Debt Mutual Funds

As noted in Section 2.1, debt mutual funds are a significant source of funds for NBFCs. Debt mutual funds primarily invest in bonds or other debt securities, including treasury bills, commercial papers, certificates of deposit, government securities, and corporate bonds. As per the Association of Mutual Funds in India (AMFI), a nodal association of mutual funds, the total assets under management (AUM) with open-ended debt mutual funds at the end of March 2018 was approximately INR 10 trillion ($\approx$ 12% of bank credit).[12] The same number stands at INR 1.5 trillion for closed-end debt funds. At the end of March 2018, approximately 35% of the open-ended funds' AUM was invested in debt securities of NBFCs. Mutual funds are one of the major investors in the commercial papers of NBFCs.[13]

Open-ended debt mutual funds provide daily liquidity to investors, i.e., an investor can place a redemption request on any day, and the funds are credited to the investor's bank account within 2-3 working days. For a redemption request placed before the cut-off time of 3 pm, the same day's Net Asset Value (NAV) is applicable; otherwise, the following day's NAV is applicable. Note that alternate pricing rules (such as swing pricing) were not in place during our study timeline (Jin et al. (2022); Capponi et al. (2020)). Therefore, withdrawal by a few investors may impose a negative externality on those staying invested in the fund. This externality arises as funds are forced to conduct costly and unprofitable trades following significant outflows (Chen et al. (2010)). Thus, the first-mover advantage may exacerbate outflows during market stress.

[11] https://rbi.org.in/scripts/PublicationReportDetails.aspx?UrlPage=&ID=887

[12] https://portal.amfiindia.com/spages/ammar2018repo.pdf

[13] See: https://www.rbi.org.in/scripts/BS_ViewBulletin.aspx?Id=18995#

2.3 The IL&FS crisis

As noted in Section 1, our study surrounds the failure of a large NBFC, Infrastructure Leasing & Financial Services (IL&FS). IL&FS is a core investment company and serves as the holding company of the IL&FS group. It was founded in 1987 by several institutions to meet the infrastructure needs of the country. Its business operations are spread across multiple subsidiaries. As of 31st March 2018, the size of the consolidated balance sheet was INR 1,158 billion or USD 17.8 billion. The group had a consolidated debt of approximately INR 1,000 billion or USD 15.4 billion, which is approximately 1.15% of total bank credit.

In September 2018, IL&FS Financial Services, a 100% subsidiary of subsidiary of IL&FS and a systemically important NBFC, defaulted on its short-term liabilities. There were a series of defaults by several IL&FS group companies around the same period. Most of these companies were rated high investment grade at the time of default; hence, the event took market participants by surprise.[14] Subsequent to the default, the rating agencies downgraded the ratings of the short-term and long-term liabilities of IL&FS group companies.[15] Moreover, the Government of India intervened and constituted a new board in October 2018 since the existing board was deemed to have failed to discharge its duties.[16]

As of August 2018, the total exposure of mutual funds to IL&FS group was INR 52 billion or 0.35% of the debt mutual funds' AUM. Though the mutual funds' direct exposure to IL&FS was small, in the aftermath of the IL&FS collapse, there was heavy redemption from debt mutual funds. During the month of September 2018, the AUM declined by 9% for an average fund, while the same figure stood at 12% for mutual funds with high allocation to NBFCs. Subsequently, as illustrated in Figure 1, mutual funds gradually reduced their allocation to NBFCs; the share of assets invested in NBFC securities declined from 35% in August 2018 to 24% in December 2019.[17] The panic response by investors exacerbated the crisis in all likelihood. Bernanke (2018)

[14] https://indianexpress.com/article/explained/ilfs-defaults-nbfc-whiplash-understanding-the-debt-market-crisis-5374379/

[15] We cannot examine the stock market reaction as this IL&FS Financial Services is not listed

[16] http://www.ilfsindia.com/significant-developments-post-2018.aspx

[17] As a response to the crisis, the Reserve Bank of India allowed banks to provide partial credit enhancement to

echoes a similar sentiment in the context of the Great Recession. He notes that the unusual severity of the Great Recession was primarily due to panic in funding markets.

3 Stylized Example

We now present a stylized example to provide intuition behind our study. Let us consider an economy with heterogeneous projects belonging to infrastructure and non-infrastructure sectors. These prospects transpire at a later date. The economy has three agents - non-banks, mutual funds, and mutual fund investors. Mutual funds finance projects via non-banks. The non-banks specialize in lending to a sector. This specialization enables non-banks with better screening and monitoring. We label the non-banks specializing in the infrastructure (non-infrastructure) as infra (non-infra) oriented.

Further, each non-bank funds multiple long-term projects. A project gives a non-zero return upon success and zero otherwise. All projects are equally viable at the time of investment decision. A project is viable if it can fully meet the repayment obligations. There are three potential states of the project. In the first state, the corresponding sector's prospects are favorable, and the probability of success is relatively high. In the second state, the prospects are unfavorable, and the probability of success is relatively low; however, the projects are still viable. A third state of the project is when it is unviable.

Mutual funds invest in non-banks and hold a time-varying portfolio of non-banks. Note that each mutual fund invests in both types of non-banks. However, there is heterogeneity across mutual funds, with some having high exposure to infra-oriented non-banks. Since the non-banks are not diversified, the mutual funds need to incur monitoring costs (Diamond (1984)). Assume that these costs go into gauging the health of the sector in which non-bank specializes. Finally, mutual funds face strategic complementarities in their decision to renew investments in non-banks (Foley-Fisher

bonds issued by NBFCs, with an explicit end-use restriction of refinancing existing debt (see `https://rbi.org.in/Scripts/NotificationUser.aspx?Id=11407&Mode=0`). However, based on the ratings in the CMIE Prowess database, we do not find significant take-up during our sample period.

et al. (2020)).

In this context, the information set differs across agents. Non-banks receive precise signals about the health of their underlying projects. Having invested resources in monitoring, mutual funds can broadly gauge the health of a sector and a non-bank's exposure to each sector. However, mutual funds are uninformed about the health of a non-bank's projects. Finally, the investors are neither informed about non-bank's exposure to a sector nor about a sector's health. They can only observe portfolio holdings of mutual funds with a lag. Based on the lagged portfolio holdings, investors can infer a mutual fund's exposure to non-banks.

For the sake of illustration, we consider three stages. Mutual funds complete their investments in non-banks in the first stage. The state of each sector is realized during the second stage. Finally, the payoffs are realized in the third stage. Note that mutual funds may be forced to go for early liquidation during the second period if there is redemption pressure from investors, which can happen even if the fundamentals are viable. Assume that such early liquidation returns a fixed component and a discounted portion of the realizable payoff if there was no liquidation. The realizable payoff is significantly larger in firms belonging to sectors with favorable prospects compared to firms in sectors with unfavorable prospects.

Assume that when the economic fundamentals are realized, they turn out to be favorable for the non-infrastructure sector but unfavorable for the infrastructure sector. In this state, the projects are, on average, still viable, but infra projects have a relatively low probability of success. Further, assume that this probability is above a threshold such that panic-driven runs by mutual funds are not triggered (Goldstein and Pauzner (2005)).

Against this backdrop, consider a non-bank that funds the infrastructure sector. This non-bank fails unexpectedly, thereby triggering a crisis in the shadow-banking sector.[18] The failure of a non-bank is an information event that could call the solvency of the entire shadow banking sector into question in the eyes of uninformed mutual fund investors. However, note that non-banks, in general, are viable as the underlying projects are viable, on average. In this study, we examine the

[18]Note that even if the infra-projects are on average viable, the shadow bank could have failed because it has idiosyncratic exposure to unviable projects.

behavior of investors and mutual funds after the information event.

Let us consider mutual fund investors first. Though the failure of a non-bank may be idiosyncratic, the uninformed investors have an incentive to act on this noisy information, as demonstrated by Chen (1999). The incentive arises from the first-come, first-serve rule, and negative payoff externality among investors. Since they are uninformed, they cannot differentiate whether the failure is idiosyncratic or driven by the non-viability of projects in a sector.[19] As a result, they withdraw their investments in mutual funds with high allocation to non-banks, questioning the solvency of shadow banking sector. The exposure of mutual funds to infra (non-infra) oriented non-banks does not matter as investors are uninformed.

A reader could ask why the investors do not wait for the informed mutual funds to liquidate first. We identify three reasons why investors cannot base their decisions on mutual funds. First, strategic complementarity arises in open-ended mutual funds as redemption costs are not reflected in NAV at the time of redemption; instead, they are borne by investors staying invested in the fund (Chen et al. (2010)). Second, investors observe mutual funds' actions with a delay. Third, investors cannot differentiate between liquidity-driven withdrawals and information-driven withdrawals (Chari and Jagannathan (1988)). Therefore, even if the investors observe the non-renewals by mutual funds, it is difficult for them to pin the non-renewals to the health of certain non-banks.

We now turn to mutual funds' response. In the absence of redemption pressure, mutual funds would have held on to their investments in non-banks, as they are aware that both sectors' probability of success is above the threshold for panic-run (Goldstein and Pauzner (2005)). Therefore, the extent of deterioration in the fundamentals of the sectors themselves does not warrant liquidation.[20] However, facing redemption pressure from investors, mutual funds are forced to liquidate some portion of their portfolios. In this scenario, mutual funds can minimize the social cost of runs by liquidating infra-oriented non-banks (thereby, projects). In a counterfactual scenario, when investors fund the non-banks directly, under the same redemption decision, the social cost

[19] The idea is similar to the one proposed by Chari and Jagannathan (1988), where investors confuse liquidity-driven withdrawals for information-driven withdrawals

[20] In fact, even redemption demand-driven withdrawals by open-ended mutual funds do not change the threshold enough to trigger a run by closed-ended mutual funds.

from inefficient liquidation would have been higher as some non-infra projects would have been liquidated.

We present a numerical example to elucidate this point further. Let us assume that each project requires one unit of investment and let the return from a successful project be two units. Assume that the probability of success is 0.8 when prospects are favorable, 0.6 when prospects are unfavorable, and 0.2 when prospects are unviable. Suppose there are 100 non-banks of each type, and each non-bank funds 100 projects. Therefore, the total investment in each sector is 10000. Assume that non-banks raise the entire capital from mutual funds. Thus, the total investment by mutual funds is 20000. Assume that early liquidation of a project returns 0.1 unit plus 50% of realizable payoff if there was no liquidation. The fixed component may be treated as land whose value does not depend on the state.

The state of the world is then realized, and a non-bank fails. Seeing the failure of a non-bank, suppose 20% of the investors withdraw their investments from mutual funds.[21] Therefore, mutual funds are forced to liquidate 4000 units of their investment in non-banks to meet the redemption pressure. Mutual funds can minimize the inefficiency from early liquidation by liquidating a portion of infra-oriented non-banks. The social cost of inefficient liquidation is 2000 (i.e., $4000 \times 0.6 \times 2 - 4000 \times 0.1 - 0.5 \times 4000 \times 0.6 \times 2$). Consider a counterfactual scenario where investors funded nonbanks directly. Under the same redemption decision by investors, the social cost of inefficient liquidation would have been 2400 (i.e., $2000 \times 0.8 \times 2 + 2000 \times 0.6 \times 2 - 4000 \times 0.1 - 0.5 \times 2000 \times 0.8 \times 2 - 0.5 \times 2000 \times 0.6 \times 2$). Therefore, informed intermediaries are able to minimize the inefficiency arising from contagious runs. We demonstrate the above-hypothesized chain of events using the collapse of IL&FS as the setting.

[21] All investors do not withdraw since they delay withdrawals to acquire additional information akin to He and Manela (2016)

4 Data

We now describe our data source, sample construction, and present the descriptive statistics. Table A1 of the Online Appendix summarizes the list of key variables used in our study. We source the data from four databases - 1) Morningstar database, 2) Prowess database, 3) Refinitv Eikon database, 4) Ministry of Corporate Affairs, and 5) Capex database. We elaborate on the process followed to obtain and match the various groups of data below.

First, we obtain the debt mutual funds' portfolio holdings from the Morningstar database. The Indian debt funds disclose the portfolio information at a monthly frequency. The data fields include fund identifier, fund name, International Securities Identification Number (ISIN) of the debt instrument, instrument name, and the value invested. We obtain the monthly returns of the mutual funds from the Morningstar Direct platform.[22] The platform provides the respective fund's category and an identifier indicating open-ended/closed-ended funds.

Second, we use the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE) to obtain NBFCs' and firms' financial information. Note that the Prowess database does not have a data field to identify whether the company is an NBFC. Hence, we match the Prowess company names with the list of NBFC names mentioned on the Reserve Bank of India's website.[23] We perform a similar match with the names of Housing Finance Companies (HFCs) mentioned on the National Housing Bank's website.[24] We group them along with other NBFCs and proceed with our analysis.

Third, we rely on the Refinitiv Eikon database to obtain the list of debt instruments issued by an NBFC. The data fields include the name of the company, ISIN of the debt instrument, issuance date, and maturity date. Since we do not have a common identifier linking the Eikon and Prowess databases, we use a string-matching algorithm on the company names and supplement this approach with a manual match for verification. The ISIN of debt instrument facilitates our identification of the amount of funding provided by a mutual fund to an NBFC.

[22]Note that the return information is available at the share-class level.
[23]https://www.rbi.org.in/scripts/bs_nbfclist.aspx/
[24]https://nhb.org.in/list-of-companies/

Fourth, the Ministry of Corporate Affairs (MCA) maintains a secured loan register, which contains the list of all secured loans for which a "charge" has been created.[25] Note that charge creation refers to a legal claim by the borrower on its assets in favor of the lender. In the absence of charge creation, the lender loses the privilege of being a secured lender. Hence, it is reasonable to expect that a charge is created for all the secured loans. The data fields include the borrower's Corporate Identification Number (CIN), lender name, charge creation date, charge amount, and charge satisfied date. We identify the NBFCs' lending information by matching the lender names against Prowess names.

Finally, we obtain the project-level data from the CapexDx database maintained by CMIE. Specifically, we download the "Project Events" file from the database. The file provides information about the firm identifier, project identifier, event, and the date corresponding to the project event. Note that events could be related to various milestones, such as environmental clearance, land acquisition, construction, and machinery installation. For our analysis, we consider project events associated with the stalling of the projects. We list such project events in Table A2 of the Online Appendix.

4.1 Sample Construction & Descriptive Statistics

We first consider the universe of all open-ended debt funds that appear in our sample. Note that Indian debt funds offer several share classes (investment plans) to investors; however, the underlying portfolio remains the same across different share classes. Hence, we conduct the analysis at the fund level.[26] For our study, we exclude 'Government Bond' funds as these funds had close to 0% of AUM invested in NBFCs as of March 2018. We present the classification of debt funds and our identification of 'Government Bond' funds in Section A1 of the Online Appendix. Our final sample comprises 293 open-ended debt funds, as illustrated in Panel A of Table 1. We work with this final sample of open-ended funds (except in Section 7).

[25] `https://www.mca.gov.in/mcafoportal/showIndexOfCharges.do`

[26] For obtaining the fund-level returns, we compute the average returns across different share classes

We mention the waterfall of NBFC sample construction in Panel B of Table 1. To identify the sample NBFCs, we first consider the NBFCs funded by at least one of our sample open-ended mutual funds as of 31st March 2018. Note that the Indian financial year is from 1st April to 31st March of the following year. Hence, 31st March 2018 corresponds to the end of last financial year before the collapse of IL&FS. We then exclude NBFCs with a loan book value lower than Indian Rupee (INR) 10 billion. Finally, we exclude NBFCs that do not appear in our loan register database. Our final sample consists of 82 NBFCs.

To examine the investors' response, we construct a panel at the fund-month level and consider a timeline of three months before and after the collapse of IL&FS, i.e., June 2018 to November 2018. We obtain 1,561 observations using this approach. The descriptive statistics are reported in Panel C of Table 1. To examine the full impact of mutual funds' response, we consider a slightly longer one-year timeline, i.e., March 2018 to March 2019, as mutual funds may adjust their portfolios with a lag after experiencing outflows.[27] We construct a balanced panel at the fund-NBFC-month level to examine the mutual funds' response. Note that we have a total of 282,818 fund-NBFC-month observations. We report the descriptive statistics in Panel D of Table 1.

For our study, we require NBFCs' exposure to firms operating in similar industries as IL&FS, as described later in Section 4.2. In order to arrive at this NBFC-level measure, we create a firm-lender-quarter level panel of outstanding loans using the MCA data. We start with a panel of all firm-lender-quarter observations having a lending relationship at the end of quarter $t-1$. Next, during the quarter t, we add a firm-lender pair to the data whenever the lender extends a new loan to the firm and drop the firm-lender pairs whenever the firm fully repays the outstanding loan to the lender. The above steps lead to 416,920 firm-lender-quarter observations from June 2017 to March 2020. As shown in Panel E of Table 1, NBFCs issue new loans in 5% of the outstanding firm-lender-quarter observations.

[27] We obtain similar results even if we consider the six-month timeline

4.2 Exposure of NBFCs to IL&FS Crisis

As discussed in Section 2.3, the collapse of the IL&FS group was unexpected by the market participants. This collapse may be driven by unfavorable prospects for projects in industries to which IL&FS lent.[28] To verify whether the prospects were unfavorable, we examine the health of borrowers in industries to which IL&FS lent. We present the test methodology and results in Section A2 of the Online Appendix. The results indicate that firms belonging to IL&FS industries fared worse on several dimensions of financial health, including solvency, profitability, and leverage. These results indicate that IL&FS industries' prospects were probably unfavorable, i.e., projects' probability of success was relatively lower.

The above results indicate that those NBFCs that operate in similar industries as IL&FS are likely to be affected by the crisis, as unfavorable industries' prospects are now public information. A reader could ask why the investors did not see through the unfavorable prospects based on annual financial information. We argue that investors may not have factored in the severity of stress in IL&FS industries. The collapse of IL&FS is an information event for investors based on which they may revise their beliefs. To support the above argument, we examine the stock market reaction of NBFC stocks to IL&FS crisis.

Our first step is to identify NBFCs operating in IL&FS industries. For each NBFC, we compute the fraction of loans outstanding with the IL&FS industries as of 30th June 2018, i.e., the end of the last quarter before the IL&FS crisis. We define affected (unaffected) NBFCs as the NBFCs with above (below) the median value of this proportion.

We next examine the stock market reaction by considering the sample of listed NBFCs. We scale an NBFC's share price by the price as of 1st January 2018 and plot the average scaled price in Figure 2a. In Figure 2b, we plot the average scaled share price of affected and unaffected NBFCs separately. The figure indicates that affected NBFCs under-performed prior to the collapse of IL&FS, which is expected based on the adverse financial health of borrowers belonging to IL&FS

[28] As explained in Section A2 of Online Appendix, the top three industries to which IL&FS lent are 'Construction,' 'Real estate activities,' and 'Electricity.' We identify these industries as 'IL&FS' industries. Firms belonging to these three industries accounted for approximately 75% of IL&FS group's loan book.

industries at the end of 31st March 2018. In the aftermath of the collapse of IL&FS, initially, there was a panic, and prices of both affected and unaffected NBFCs crashed. However, the prices of unaffected NBFCs eventually recovered to the pre-crisis levels, but those of affected NBFCs continued to slide downward.

5 Investors' Exit from Mutual Funds

We examine how different players reacted to the collapse of IL&FS. Our first set of hypotheses deals with the mutual fund investors' reaction. We measure investors' reaction using the net monthly flow for each fund. Our null hypothesis (i.e., 1A) is that investors do not redeem in response to the collapse of IL&FS. No reaction is possible if the investors were fully informed and identified the underlying sectors as viable. The two alternate hypotheses deal with how investors redeemed their investments from mutual funds. If the investors were not fully informed, the collapse of IL&FS presented an information event after which they may have revised their beliefs (Chen (1999)).

Under the first alternate hypothesis, we consider the possibility of investors being imperfectly informed. While they may accurately assess a non-bank's exposure to a sector, they may be uninformed about the sector's health. As a result, they may read the failure of IL&FS as unviability of the infrastructure sector. In such a scenario, they should have exited mutual funds with high allocations to NBFCs affected by the crisis, which leads to our first alternate hypothesis (i.e., 1B).

However, it is also possible that investors were totally uninformed and failed to identify the NBFCs affected by the crisis. In the above scenario, they may have reacted only based on mutual funds' overall NBFC allocation and not their affected NBFC allocation, which leads to our second alternate hypothesis (i.e., 1C). We summarize our first set of hypotheses below.

- **Hypothesis 1A**: Investors do not redeem in response to the collapse of IL&FS.

- **Hypothesis 1B**: Investors were imperfectly informed in their redemption decision; they factored in mutual funds' allocation to NBFCs more affected by the crisis

* **Hypothesis 1C**: Investors were uninformed in their redemption decision; they only factored in the overall allocation of mutual funds to NBFCs (Chen (1999))

With the objective of disentangling the various scenarios discussed above, we proceed to examine the investors' reaction. We first assess whether investors reacted to the event. Following the standard practice in literature (Agarwal and Zhao (2019)), we define the net flow as shown below:

$$Flow_{i,t} = \frac{AUM_{i,t} - AUM_{i,t-1}(1+r_t)}{AUM_{i,t-1}} \tag{1}$$

where $Flow_{i,t}$ is net flow into fund i and month t, AUM is the total assets under management at the end of month t, and r_t is the fund's return in month t. A negative value of flow indicates investors' redemption from the fund.

We divide mutual funds into two groups based on their allocation to NBFCs. For measuring allocation, we first compute the total investment of a fund in NBFC securities as of the end of August 2018, i.e., the month before the collapse of IL&FS. We then divide the fund's total investment in NBFCs by the fund's AUM and call it the fund's allocation to NBFCs. Finally, we divide the funds into two groups - 1) a set of funds lying above the median value of allocation to NBFCs and 2) a set of funds lying below the median value of allocation to NBFCs. We identify the former set as funds with high NBFC allocation and the latter set as funds with low NBFC allocation.

We now plot the average monthly fund flows separately for the two groups of mutual funds, i.e., those with high and low allocations to NBFCs. Figure 3 illustrates the univariate evidence. We find that both groups witnessed significant outflows post the collapse of IL&FS. However, the quantum of outflows was significantly higher in the case of mutual funds with high NBFC allocation. The above univariate result indicates that the investors redeemed their investments from funds that had a higher proportion of AUM invested in NBFCs post-IL&FS crisis. Having presented the univariate evidence, we now formally test the investors' reaction using the following specification.

$$Flow_{i,t} = \beta_0 + \beta_1 High\_NBFC\_Alloc_i \times Post_t + \\ \beta_2 High\_NBFC\_Alloc_i + \beta_3 Post_t + X_{i,t} + \gamma_i + \zeta_t + \varepsilon_{i,t} \quad (2)$$

We organize the data at the fund-month level. $Flow$ represents the net inflow into the fund i and month t.[29] $High\_NBFC\_Alloc$ takes the value of one if the fund has above median allocation to NBFCs as of August 2018 and zero otherwise. *Post* in equation (2) takes a value of one from September 2018 onwards and zero otherwise.

X represents a vector of fund-month-level control variables. We control for the known determinants of fund flows – fund's performance and fund size (Sirri and Tufano (1998)). Our measure of the fund's performance is the return over and above the category's average return in the previous month. We proxy for fund size by the logarithm of fund AUM at the end of the previous month. We control for the interaction between the performance and an indicator identifying negative performance. This interaction term captures the concave flow-performance relationship documented in the case of debt funds (Goldstein et al. (2017)). We also control for the lagged fund flow (Agarwal and Zhao (2019)). Finally, we control for the fund's liquidity, proxied by the share of AUM invested in corporate bonds, to address the effects of financial fragility (Goldstein et al. (2017)). γ_i and ζ_t denote the fund and month fixed effects. We cluster the standard errors at the fund level.

Table 2 presents the results. In column (1), we only include *Post* as the explanatory variable and do not include any fixed effects. In column (2), we estimate the specification (2) above with fund fixed effects. Finally, in columns (3) and (4), we include fund and month-fixed effects. The full set of control variables listed above are also included in column (4). If the investors did not react to the crisis, i.e., if hypothesis 1A were true, we should expect the coefficient of $High\_NBFC\_Alloc \times Post$ to be close to zero.

Consider column (1). The coefficient of *Post* is -0.032, implying that, on average, mutual funds

[29] We winsorize the dependent variable at the 5% and 95% levels

witnessed 3.2pp lower flows per month in the post-period compared to the pre-period. In the rest of the three columns, the coefficients on the interaction term, $High\_NBFC\_Alloc \times Post$, are negative and significant. Consider column (4), which contains our final specification. The coefficient of the interaction term is -0.05, which implies that mutual funds with high NBFC allocation witnessed lower flows of 5pp per month after the crisis compared to other funds in a difference-in-differences sense. Further, as shown in Figure 3, the two groups experienced similar flows before the collapse of IL&FS, which enables us to reject the presence of pre-trends.

To understand the economic magnitude of the flows, we consider three months following the collapse of IL&FS. We find that mutual funds with high NBFC allocation experienced 15pp (i.e., 5×3) higher outflows compared to other funds' flows during the three months. The magnitude is economically significant given the findings of extant literature: for instance while examining the impact of the Eurozone crisis, Chernenko and Sunderam (2014) find a 9.9% decline in AUM for a one standard deviation increase in mutual funds' Eurozone exposure. During the week following the Lehman default, Kacperczyk and Schnabl (2013) document a 3.3pp higher outflows for a one standard deviation increase in mutual funds' risk exposure. In summary, our result enables us to reject the null hypothesis that investors do not react to the crisis.

5.1 Do Investors Differentiate the Type of Exposure?

Having shown that the investors do react to the crisis, we next examine whether investor reaction is consistent with an imperfectly informed or uninformed explanation (i.e., hypothesis 1B versus 1C). To disentangle the two remaining hypotheses, we need to test whether the mutual funds' allocation to NBFCs more affected by the crisis mattered for the observed reaction of the investors. We identified the affected NBFCs operating in similar industries as IL&FS in Section 4.2.

We ask whether, conditional on the overall NBFC exposure of funds, the type of NBFC exposure of the respective funds affected the investors' exit decision. Accordingly, we create two additional mutual fund groups based on the proportion of AUM invested in affected NBFCs' securities as of the end of August 2018. We call the group with the above (below) median allocation to affected NBFCs as high (low) affected-NBFC allocation. We use the following specification to formally examine whether investors' exit was dependent on the type of NBFC allocation.

$$Flow_{i,t} = \beta_0 + \beta_1 High\_NBFC\_Alloc_i \times Post_t + \beta_2 High\_Aff\_NBFC\_Alloc_i \times Post_t + \\ \beta_3 High\_NBFC\_Alloc_i + \beta_4 High\_Aff\_NBFC\_Alloc_i + \beta_5 Post_t + X_{i,t} + \gamma_i + \zeta_t + \varepsilon_{i,t} \quad (3)$$

We organize the data at the fund-month level. $Flow$ represents the net inflow into the fund i and month t. $High\_Aff\_NBFC\_Alloc$ takes the value of one if the fund has above median allocation to affected NBFCs as of August 2018 and zero otherwise. The rest of the variables continue to have the same definitions as mentioned in Section 5. If our hypothesis 1B were true, we should expect the coefficient of $High\_Aff\_NBFC\_Alloc \times Post$ to be negative and significant and the coefficient of $High\_NBFC\_Alloc \times Post$ to be statistically indistinguishable from zero. On the other hand, if our hypothesis 1C were true, we should expect the coefficient of $High\_Aff\_NBFC\_Alloc \times Post$ to be statistically indistinguishable from zero and the coefficient of $High\_NBFC\_Alloc \times Post$ to be negative and significant.

We present the results in Panel B of Table 3. Consider column (2), which contains our final specification with fund and month fixed effects and fund-month level controls. Note that the coefficient of $High\_NBFC\_Alloc \times Post$ is -0.061 and statistically significant. The economic magnitude is similar to that observed in Section 5. However, the coefficient of $High\_Aff\_NBFC\_Alloc \times Post$ is lower in absolute magnitude and statistically insignificant. The regression results also support the thesis that investors were inattentive to the type of NBFC allocation. Investors only factored in overall NBFC allocation in their exit decisions.

6 Mutual Funds' Exit from NBFCs

As illustrated in Figure 3, mutual funds faced significant outflows following the collapse of IL&FS. Hence, mutual funds needed liquidity to meet the redemption pressure. The funds had two alternatives: 1) manage the liquidity through their cash balances or liquid assets; 2) liquidate a part of their NBFC portfolio. Accordingly, our second set of hypotheses deals with what mutual funds do with their existing NBFC allocation to meet the redemption pressure.

Extant literature has identified that mutual funds sell their liquid assets first while meeting investor redemptions (Ma et al. (2022)). Similarly, in our case, open-ended mutual funds could have sold treasuries to meet the redemption demand. The null hypothesis (i.e., 2A) is that mutual funds do not reduce their investments in NBFCs. However, as we have shown in Section 5, investors' redemption decision is tied to mutual funds' NBFC exposure. Holding onto NBFC allocation may trigger a run by new batch of investors waiting for additional information (He and Manela (2016)). Therefore, mutual funds may have opted to reduce exposure to NBFCs, potentially anticipating a decline in redemption pressure.

The two alternate hypotheses deal with how mutual funds alter their allocation to NBFCs to meet the demand for funds. The mutual funds may choose to spread the non-renewals of NBFC securities to both types of NBFCs to avoid a situation where concentrated withdrawals on a subset of NBFCs trigger strategic complementarity, resulting in runs (Goldstein and Pauzner (2005)). The above option leads to our first alternate hypothesis (i.e., 2B) - mutual funds run on both types of NBFCs. Alternatively, the mutual funds may choose to concentrate the reduction in exposure towards NBFCs affected by the crisis. The above option leads to our second alternate hypothesis (i.e., 2C). We summarize our second set of hypotheses below.

- **Hypothesis 2A**: Mutual funds do not reduce their investments in NBFCs.
- **Hypothesis 2B**: Mutual funds reduce their investments in NBFCs, without distinction.
- **Hypothesis 2C**: Mutual funds reduce their investments in affected NBFCs more.

We proceed to examine the reaction of mutual funds. As a first step, we plot the average amount invested by mutual funds in debt securities issued by NBFCs. We estimate the average investment for affected and unaffected NBFCs separately and plot them month by month. Figure 4 presents the univariate analysis. We observe a significant decline in mutual fund investments in affected

NBFCs' securities post the collapse of IL&FS. However, the average investment in unaffected NBFCs remained at the pre-crisis levels. Therefore, mutual funds channeled the redemption pressure to affected NBFCs and shielded unaffected NBFCs. We now formally test the mutual funds' response using the following specification.

$$
\begin{aligned}
Investment_{i,n,t} = \beta_0 + \beta_1 Aff\_NBFC_n \times Post_t + \\
\beta_2 Aff\_NBFC_n + \beta_3 Post_t + \gamma_i + \theta_n + \zeta_t + \varepsilon_{i,n,t} \quad (4)
\end{aligned}
$$

We organize the data at fund i, NBFC n, and month t level. The dependent variable, *investment*, is the value of investment by mutual fund i in NBFC n at the end of the month t. Aff_NBFC is an indicator variable that is set to one if the NBFC is classified as affected and zero otherwise. *Post* is an indicator variable that takes the value of one from September 2018 onwards and zero otherwise. γ_i, θ_n, and η_t denote fund, NBFC, and month fixed effects, respectively. We cluster the standard errors at the fund level.

The estimates of the above specification measure the differential reduction in investments in affected NBFCs. Before presenting the estimates of differential effect, we ask whether there was an overall reduction in investments to NBFCs after the ILFS crisis. To test the above we regress *Investment* on *Post*. We present the results in Table A5 of the Online Appendix. We find that mutual funds reduced their allocation to NBFCs after the crisis. This behavior is also evident from Figure 4, where we plot the mutual funds' investment in affected/unaffected NBFCs. Therefore, this result enables us to reject the null hypothesis (i.e., hypothesis 2A) that mutual funds do not reduce their investments in NBFCs.

Next, Panel A of Table 4 presents the results of differential impact. For the first two columns, the dependent variable is the logarithm of one plus the mutual fund's investment in commercial papers (CP) of an NBFC. For columns (3) and (4), the dependent variable is the logarithm of one plus mutual fund's investment in bonds of an NBFC. We consider the logarithm of one plus the total (i.e., CP plus Bond) investment as the dependent variable in the last two columns. Note that we use a balanced panel in this specification and fill zeroes for fund-NBFC pairs where a fund does not hold an NBFC's security. Therefore, we add one to the holding amount before taking a logarithm.

We present the results from our baseline specification with the fund, NBFC, and month fixed effects in odd-numbered columns. Even-numbered columns contain our most stringent specification with fund $\times$ month and fund $\times$ NBFC fixed effects. The inclusion of fund $\times$ month fixed effects addresses any time-varying heterogeneity at the fund-month level. Further, using fund $\times$ NBFC fixed effects absorbs any time-invariant heterogeneity across fund-NBFC pairs. If the mutual funds did not differentiate between two types of NBFCs (i.e., if hypothesis 2B were true), we expect the coefficient of $Aff\_NBFC \times Post$ to be statistically indistinguishable from zero.

Consider column (2), which contains our most stringent specification. The coefficient of interaction term ($Aff\_NBFC \times Post$) is -0.116, implying that mutual funds reduced investment in commercial papers of affected NBFCs by 11.6pp compared to their investment in unaffected NBFCs in a difference-in-differences sense, post the IL&FS-crisis. When we examine the bond investment in column (4), the decline in investment in affected NBFCs stands at 4pp more when compared to their investment in unaffected NBFCs. In aggregate, mutual funds' investment in affected NBFCs declined by 13.4pp compared to their investment in unaffected NBFCs in a difference-in-differences sense, as indicated by the coefficient of interaction term in column (6). Moreover, Figure 4 enables us to reject pre-trends as an explanation for our finding. In summary, mutual funds reduced their investments more in affected NBFCs and shielded unaffected NBFCs from the crisis.[30]

Poisson Regression - Cohn et al. (2022) find that using the logarithm of one plus the outcome variable in a linear regression could lead to biased estimates. They suggest using a Poisson regression instead. Therefore, we use a Poisson model to estimate the coefficients in Equation (4). We present the results in Panel B of Table 4. The dependent variables are commercial paper investment in columns (1)-(2), bond investment in columns (3)-(4), and total investment in columns

[30]We conduct a robustness test to examine the impact on primary issuance of NBFCs. We describe the approach and present the results in Table A6 of the Online Appendix

(5)-(6). Notice that we obtain directionally similar results. However, the economic magnitude is on the higher side. As indicated by the coefficient of $Aff\_NBFC \times Post$ in column (6), we find that mutual funds' investment in affected NBFCs declined by 9.7pp compared to their investment in unaffected NBFCs in a difference-in-differences sense.

Robustness with Mutual Funds' AUM share - There could be a concern that the decline in mutual funds' investment in affected NBFCs is a mechanical outcome. As illustrated in Figure 4, on average, mutual funds' investment in affected NBFCs was significantly higher than in unaffected NBFCs before the crisis. If the mutual funds reduced their investment in all securities proportionately after the crisis, our finding of a greater decline in affected NBFC investment could be a mechanical outcome. To address this concern, we organize our data at a fund-NBFC type-month level and use the portfolio share of affected (unaffected) NBFCs as the dependent variable. We present the results in Table A7 of the Online Appendix. The results indicate that the portfolio share of affected NBFCs declined by 2.1pp compared to that of unaffected NBFCs in a difference-in-differences sense.

6.1 Does the reduction in NBFC allocation help?

As observed in Section 6, mutual funds reduced their investment in NBFCs following the IL&FS crisis. This reduction may be driven by mutual funds' anticipation of a decline in redemption pressure. We now investigate how investors responded to the reduction in NBFC allocation. Note that, as discussed in Section 5.1, investors did not differentiate on the type of NBFC exposure; therefore, we measure their response to the reduction in overall NBFC allocation using the following specification.

$$
\begin{aligned}
Flow_{i,t} = \beta_0 + \beta_1 High\_NBFC\_Alloc_i \times Post_t \times \Delta NBFC\_Share_{i,t} + \beta_2 High\_NBFC\_Alloc_i \times Post_t \\
+ \beta_3 \Delta NBFC\_Share_{i,t} \times Post_t + \beta_4 High\_NBFC\_Alloc_i \times \Delta NBFC\_Share_{i,t} + \beta_5 High\_NBFC\_Alloc_i + \\
\beta_6 High\_Aff\_NBFC\_Alloc_i + \beta_7 Post_t + X_{i,t} + \gamma_i + \zeta_t + \varepsilon_{i,t} \quad (5)
\end{aligned}
$$

We organize the data at the fund-month level. $Flow$ represents the net inflow into the fund i and month t. $\Delta NBFC\_Share$ is the change in NBFC allocation between $t-2$ and $t-1$. A negative value of $\Delta NBFC\_Share$ indicates that the mutual fund reduced allocation towards NBFCs between two months. The remaining variables have the same definition, as mentioned in Section 5. We cluster the standard errors at the fund level.

Table 5 presents the results. The dependent variable is the fund flow across both columns. We include fund and month fixed effects in both columns. Further, column (2) also includes fund-month level control variables mentioned in Section 5. Consider column (2), which contains our final specification. Note that the coefficient of $High\_NBFC\_Alloc \times Post \times \Delta NBFC\_Share$ is -0.602. This result implies that when mutual funds with high NBFC allocation reduced their allocation towards NBFCs, the redemption pressure subsided. The above finding also motivates our alternative hypotheses that mutual funds may have chosen to reduce exposure to NBFCs to meet the demand for funds, as pointed out in Section 6.

7 Behavior of Closed-end Funds

We now examine the behavior of closed-end funds where there is no redemption pressure. As a first step, we plot the average amount invested by mutual funds in debt securities issued by an NBFC separately for affected and unaffected NBFCs. Figure 5 presents the univariate analysis. Notice that the average amount invested in unaffected NBFCs increased from INR 36 billion in August 2018 to INR 44 billion in March 2019. However, the average amount invested in affected NBFCs remained at the pre-crisis levels. Therefore, closed-end mutual funds increased their allocation towards unaffected NBFCs after the IL&FS crisis. Having presented the univariate evidence, we formally examine the closed-end funds' response using the following specification.

$$Investment_{i,n,t} = \beta_0 + \beta_1 Unaff\_NBFC_n \times Post_t + \beta_2 Unaff\_NBFC_n + \beta_3 Post_t + \gamma_i + \theta_n + \zeta_t + \varepsilon_{i,n,t} \quad (6)$$

We organize the data at fund i, NBFC n, and month t level. The dependent variable, *investment*, is the value of investment by closed-end fund i in NBFC n at the end of the month t. $Unaff\_NBFC$ is an indicator variable that is set to one if the NBFC is classified as unaffected and zero otherwise. *Post* is an indicator variable that takes the value of one from September 2018 onwards and zero otherwise. γ_i, θ_n, and η_t denote fund, NBFC, and month fixed effects, respectively. The standard errors are clustered at the fund level.

We present the results with just *Post* as explanatory variable in Table A8 of the Online Appendix. We find that closed-end funds increased their allocation to NBFCs after the crisis, as also indicated by Figure 5. Table 6 presents the results. In Panel A, we use logarithm of one plus the CP/Bond/Total investment as dependent variables, and in Panel B, we use the absolute value of CP/Bond/Total investment as the dependent variables. Panel A and Panel B report the results from Linear and Poisson regressions, respectively. Consider column (6) in Panel B, which contains our final specification. Note that the coefficient of $Unaff\_NBFC \times Post$ is 0.103, implying that closed-end funds' investment in unaffected NBFCs increased by approximately 10.3pp compared to their investment in affected NBFCs in a difference-in-differences sense.

The above result helps resolve two puzzles. First, it confirms that the fundamentals of the projects were above the threshold below which mutual funds would have run irrespective of investors' behavior. Second, it shows that the non-renewals by open-ended funds does not trigger a run by other investors on affected NBFCs.

7.1 Discussion on Closed-End Funds' Behavior

Having observed investors' and open-ended mutual funds' responses, we examine the behavior of closed-end funds in Section 7 for several reasons. First, there could be a question of how open-ended funds would have responded in the absence of redemption pressure. If the funds' decision to withdraw investments in affected NBFCs is fundamental-driven, then open-ended funds would have withdrawn even in the absence of redemption pressure. However, if closed-ended funds hold on to their investments in affected NBFCs, then fundamentals themselves did not warrant liquidation.

Second, observing the behavior of closed-ended funds also answers the question of whether an entity not facing redemption pressure can help avoid inefficient liquidations of viable projects. The closed-ended funds could achieve the above by potentially increasing their allocation to viable NBFCs. Accordingly, in theory, they may either increase allocation to affected or unaffected NBFCs. However, we argue that closed-end funds are better off in increasing allocation to unaffected type, which we find in Section 7.

Note that NBFCs are specialized in our case. Hence, a closed-end fund would require time to conduct the necessary due diligence before investing in an NBFC. However, the persistent selling by open-ended funds may bring down a few affected NBFCs before the evaluation is complete, if not immediately. Further, note that price pressure would be temporary if fundamentals themselves do not change due to selling. However, when there is persistent selling, there could no longer be an arbitrage opportunity as expected returns are revised upwards.

In such a scenario, closed-end funds may be reluctant to consider increasing allocation to affected NBFCs. Moreover, as highlighted in Section 2.2, closed-end funds are smaller in size compared to open-end funds. Hence, closed-end funds may not be able to absorb the entire selling of affected NBFCs by open-ended funds. Therefore, closed-end funds are likely to emulate open-ended funds and prefer unaffected NBFCs (Abreu and Brunnermeier (2003)). Noticing that the selling of unaffected NBFCs is substantially lower in magnitude, closed-ended funds probably increased allocation to unaffected NBFCs.

8 Evidence of Mitigating Inefficient Liquidation

As discussed in Section 1 and Section 3, we argue that mutual funds in our setting mitigated the social cost of investor runs by directing the redemption pressure to affected NBFCs. Our claim hinges on two crucial assumptions. First, the termination of funding by mutual funds could trigger early liquidation of NBFC borrowers' projects, leading to a social cost. Second, the degree of inefficiency is higher when projects belonging to non-IL&FS industries are liquidated. We now examine the plausibility of these assumptions.

8.1 Does termination of funding trigger liquidation?

Several studies document the adverse impact on borrowers when lenders get into trouble (Khwaja and Mian (2008); Chernenko and Sunderam (2014); Chopra et al. (2021)). Hence, we expect an adverse impact on NBFCs when mutual funds terminate funding. The trouble in NBFCs is likely to spill over to their borrowers. For our analysis, a direct test to gauge the trouble would be observing the project liquidation by NBFCs' borrowers. In the absence of funding, NBFCs' borrowers are likely to discontinue projects or sell the projects to an outside entity. Unfortunately, our data does not allow us to observe project liquidations at the NBFC-borrower pair level.

Nevertheless, we test the thesis using the available data on the status of projects at the borrower level. We examine the likelihood of projects being stalled before completion. To be precise, stalling does not equate with liquidation, as projects could be stalled for various reasons (such as problems with land acquisition). However, all liquidations are likely to show-up as stalled project events in our data. Note that affected NBFCs witnessed greater withdrawal of funding. Hence, we expect a higher likelihood of stalled projects in the case of borrowers dependent on affected NBFCs. We use the following specification to test this hypothesis.

$$\begin{aligned} Stalled_{i,t} = \beta_0 + \beta_1 Aff\_NBFC\_Dep_i \times Post_t + \beta_2 Unaff\_NBFC\_Dep_i \times Post_t + \\ \beta_3 Aff\_NBFC\_Dep_i + \beta_4 Unaff\_NBFC\_Dep_i + \beta_5 Post_t + \gamma_i + \zeta_t + \varepsilon_{i,t} \quad (7) \end{aligned}$$

Our data are organized at firm i - quarter t level. We consider a five-year timeline spanning 31st March 2016 to 31st March 2020. To mitigate any effect due to anticipation, we exclude the one-year period around the event, i.e., 1st April 2018 to 31st March 2019. The dependent variable is an indicator variable that is set to one if at least one of the firm's projects stalled during the quarter and zero otherwise. Aff_NBFC_Dep ($Unaff\_NBFC\_Dep$) indicates whether a borrower is dependent on affected (unaffected) NBFCs. A borrower is classified as affected (unaffected) NBFC dependent when the fraction of loans outstanding (as % of assets) with affected (unaffected) NBFCs exceeds 10% as of June 2018, i.e., the last quarter before the collapse of IL&FS. *Post* is an indicator variable set to one from September 2018 and zero otherwise. γ and ζ denote the firm and quarter fixed effects. The standard errors are clustered at the industry level.

We present the results in Panel-A of Table 7. Consider column (3), which contains our preferred specification. The coefficient of $Aff\_NBFC\_Dep \times Post$ is 0.024, implying that borrowers dependent on affected NBFCs witnessed a 2.4pp increase in the likelihood of projects being stalled when compared to non-NBFC dependent borrowers. On the other hand, there is no significant difference in likelihood for borrowers dependent on unaffected NBFCs, as indicated by the coefficient of $Unaff\_NBFC\_Dep \times Post$. The finding suggests that reduced funding to affected NBFCs potentially resulted in the liquidation of their borrowers' projects.

8.2 Liquidation Cost for IL&FS Industries versus Other Industries

We now consider the assumption of differential cost when a project is liquidated early in IL&FS industries vis-à-vis other industries. An ideal test would be to compare the liquidation values in both industries. Unfortunately, we do not observe the liquidation discount in practice. Therefore, we rely on the next best alternatives. Our first approach is to compare the health of industries based on financial information. As discussed in Section 4.2, firms belonging to IL&FS industries fared worse on several dimensions of financial health. Therefore, early liquidation of projects belonging to relatively healthy non-IL&FS industries could entail a higher social cost.

Nevertheless, there is a shortcoming with the above approach as it is backward-looking in nature. As a result, we adopt a forward-looking approach by considering the market reaction around project stalling. Note that when a positive-NPV project is liquidated, there should be a decline value of the firm. Accordingly, we expect to find a negative stock price reaction around the liquidation of a positive-NPV project. A large negative return around project stalling indicates a higher social cost of early liquidation. For our analysis, we continue to proxy stalling for liquidation, as discussed in Section 8. We compute the one-week return around the date when a project stalled.[31] Our idea is to compare the average returns for IL&FS industries versus other industries.

We present the average returns in Panel-B of Table 7. We are constrained by the number of observations in the post period as we have only one year before the onset of the COVID crisis. Note that the average return around project stalling is -2.5% for firms belonging to non-IL&FS industries when compared to 0.32% for firms belonging to IL&FS industries in the aftermath of the IL&FS crisis. However, there is no significant difference in returns around stalling before the crisis. Our findings do not change when we consider market-adjusted abnormal returns. In summary, this result indicates that early liquidation likely entailed higher costs in the case of non-IL&FS industries.

A concern with the evidence presented above could be that markets misjudged the viability of infra-companies. Accordingly, a reader may worry that the market's muted response when infra-projects get liquidated cannot be interpreted as lower liquidation loss in the infra sector but is explained by the market's misjudgment of the sector. Two pieces of evidence suggest that the above argument is less likely. First, the closed-end funds held onto their investments in affected NBFCs. Hence, it is not the case that all market participants exited affected NBFCs. Second, we examine stalled events beginning six months after the collapse of IL&FS. It is unlikely that markets have continued to misjudge the viability of infra-companies for so long. Nevertheless, we evaluate the market reaction to project stalling in a sample limited to firms with high foreign institutional investor (FII) stakes (greater than 10%). FIIs are likely to be informed investors and, therefore, less susceptible to misjudging the state of the sector. We present the results in Panel-C of Table 7. We find that market reaction was muted even when we consider stalled events of firms with a high presence of such informed investors.

[31] For example, for a project stalled on 12th April 2019, we consider the return from 10th to 16th April 2019

9 Conclusion

In this paper, we highlight a hitherto unexplored role of financial intermediaries in mitigating the contagious effects of runs. To demonstrate the above role, we study the response of mutual fund investors and mutual fund managers to the collapse of a large NBFC (IL&FS) in India. We find that uninformed mutual fund investors withdraw their investments from mutual funds with high allocations to the NBFC sector, irrespective of mutual funds' allocation to more affected NBFCs. On the other hand, informed mutual fund managers redirect the investors' redemption towards NBFCs that have high common exposure with IL&FS. The findings indicate that the presence of an intermediary between the investors and NBFCs helps reduce the social costs of liquidations and mitigates the contagion.

A caveat is in order. We do not claim that the presence of an intermediary is uniformly better under all circumstances. Adding another layer of intermediation could aggravate agency frictions. For instance, mutual funds could engage in return-smoothing behavior. As a result, NAVs of mutual funds could be stale. Opportunistic traders could withdraw from over-valued funds, thereby exacerbating the risk of fund runs. Moreover, another round of maturity transformation by intermediaries could heighten financial fragility.

A limitation of our setting is that we do not have NBFCs directly funded by retail investors. Our conclusions related to the contrasting behaviors of mutual fund investors and mutual funds are based on observing the behavior of retail investors investing through mutual funds. Nevertheless, our study underscores the role of intermediaries in mitigating contagions. Policymakers would do well to consider such self-correcting mechanisms when laying down the policies for avoiding panic-based runs.

10 Figures & Results

Figure 1: MUTUAL FUNDS' SHARE OF NBFCS

In this figure, we plot the fraction of assets invested in debt securities of NBFCs.

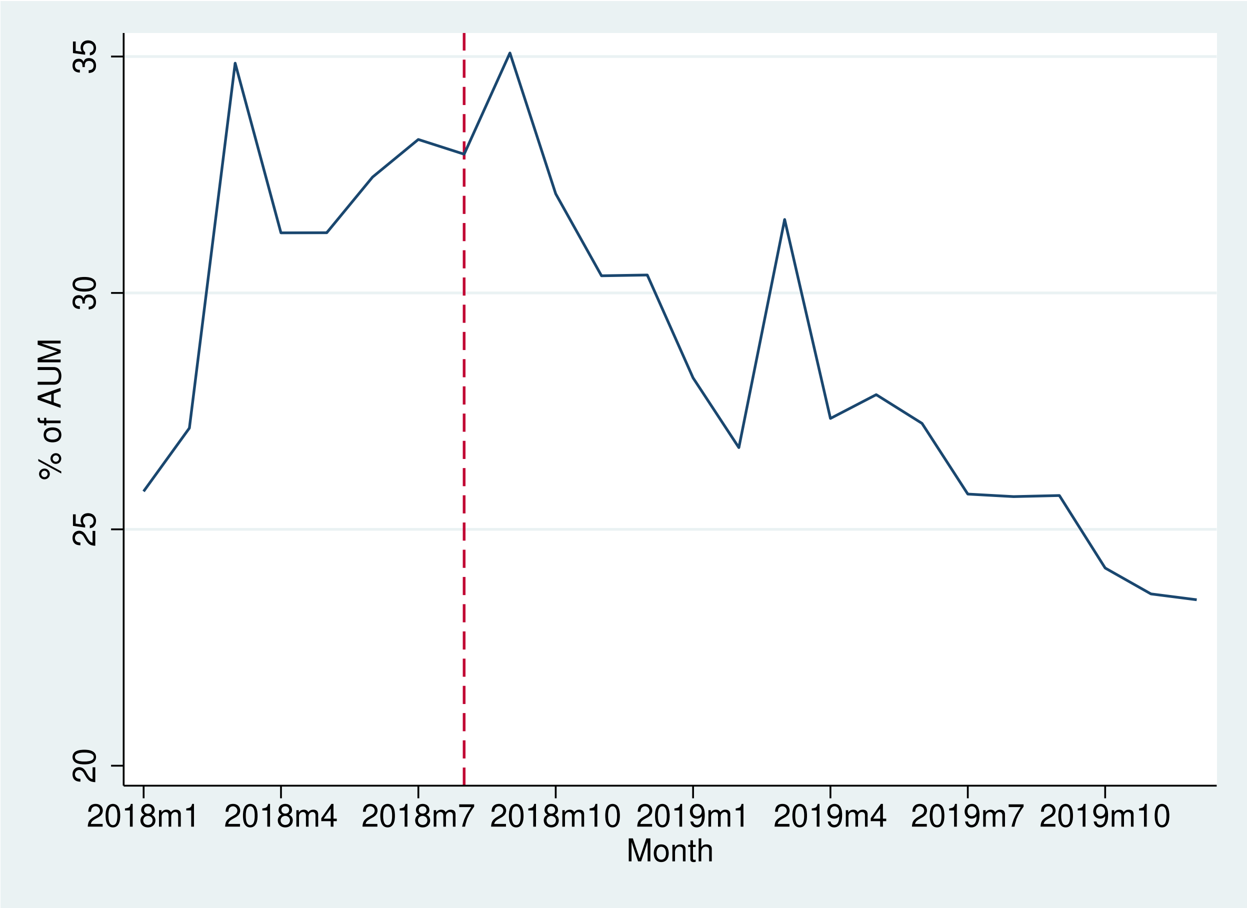
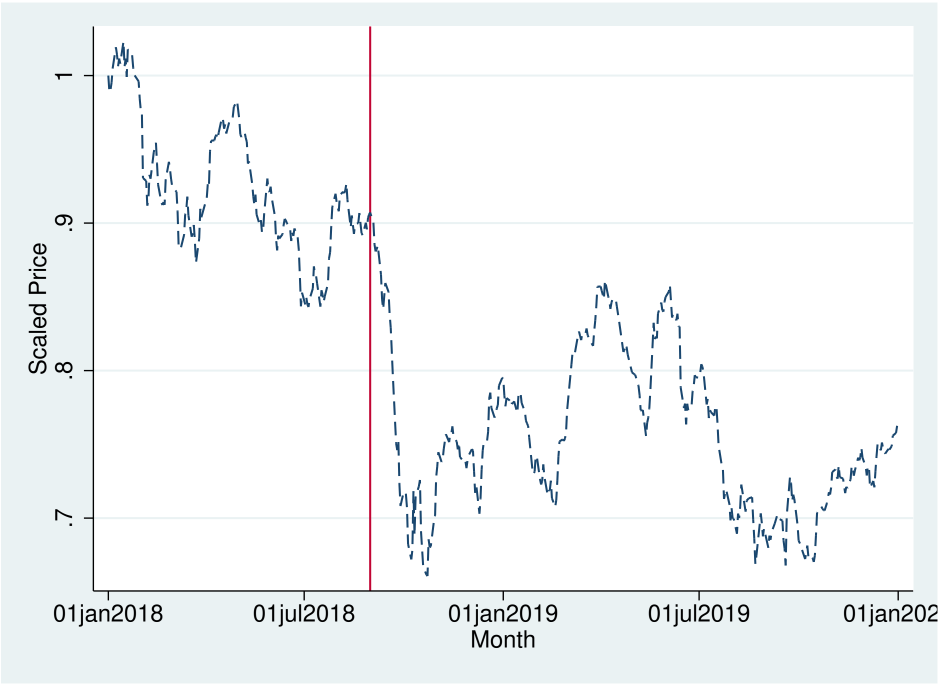
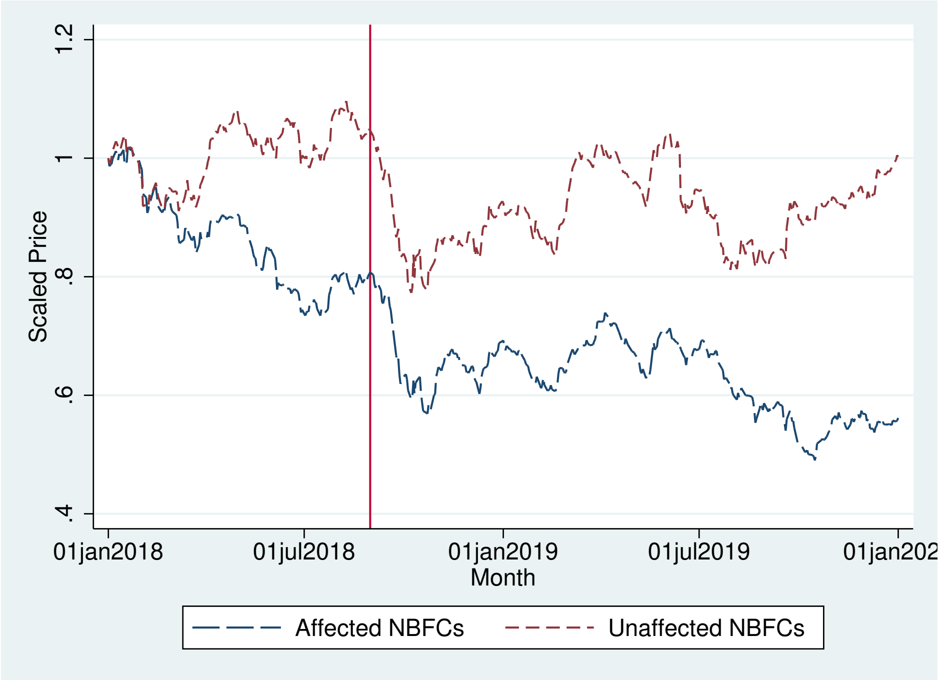


Figure 2: Stock Prices of NBFCs Post IL&FS Crisis

In this figure, we plot the average stock price of listed NBFCs. We scale the stock price with price as of 1st January 2018. In Panel A, we plot the average scaled price for all NBFCs. In Panel B, we plot the scaled price for affected and unaffected NBFCs separately. The red line indicates 31st August 2018.



(a) Average Scaled Price of All NBFCs



(b) Average Scaled Price of Affected and Unaffected NBFCs

Figure 3: IMPACT OF NBFC EXPOSURE ON FUND FLOWS

In this figure, we plot the average fund flows based on the mutual fund allocation to NBFCs. Note that the allocation is defined as the fraction of the total fund's assets invested in NBFC instruments. The dotted line indicates August 2018, i.e., the month before the collapse of IL&FS.

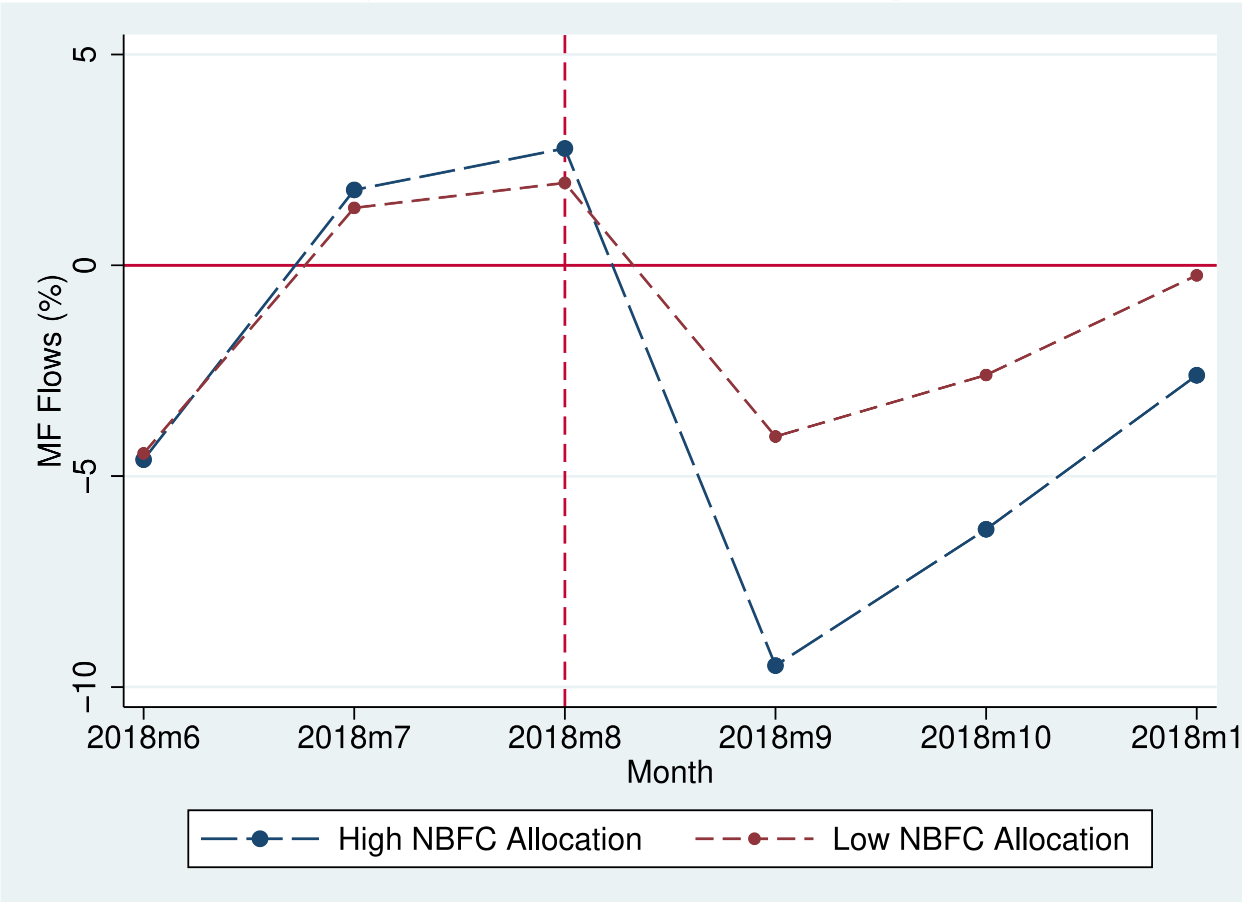


Figure 4: MUTUAL FUNDS' EXIT FROM NBFCS

In this figure, we plot the average amount invested by all open-ended mutual funds in affected and unaffected NBFCs separately. Note that the average amount is represented in Indian Rupee (INR) billion. The dotted line indicates August 2018, i.e., the month before the collapse of IL&FS.

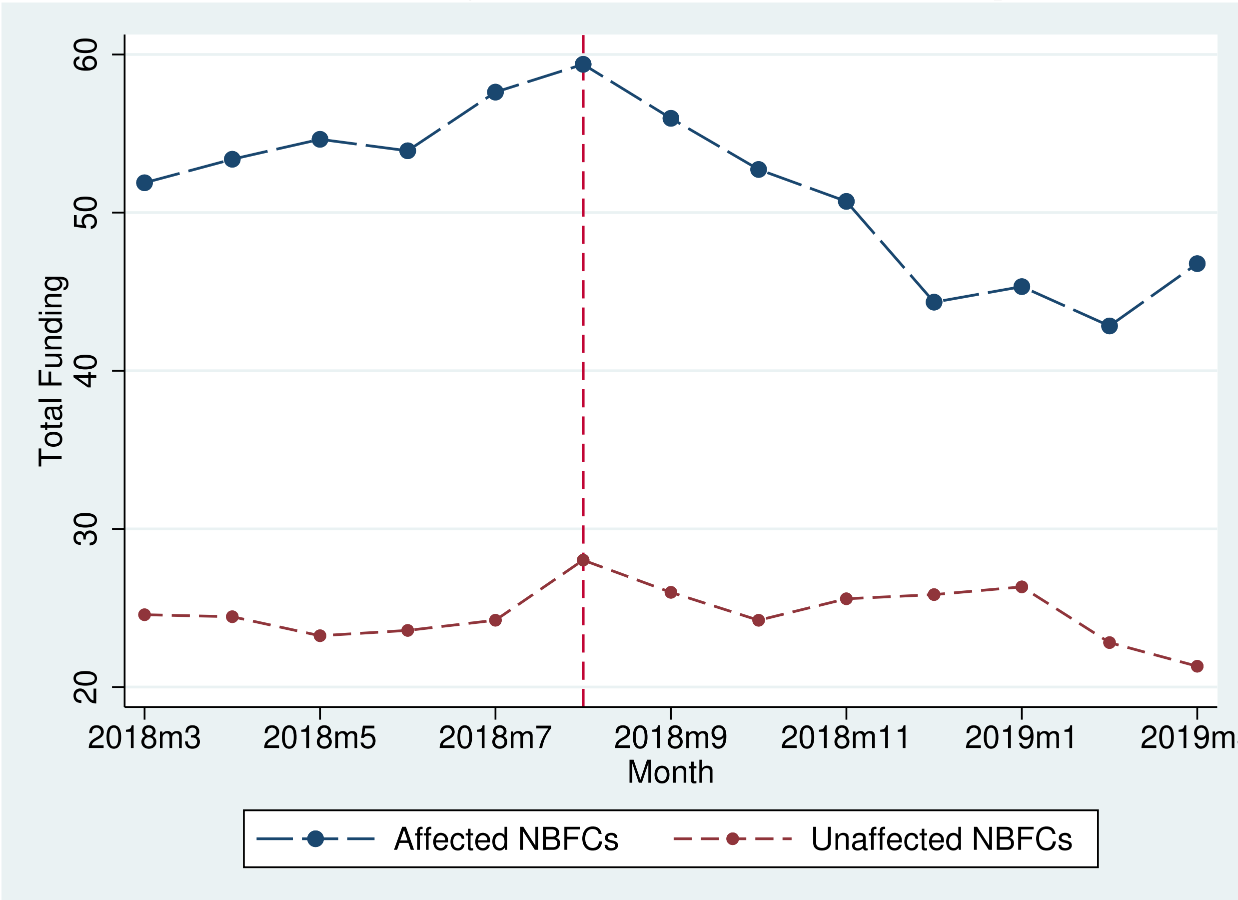


Figure 5: CLOSED-END FUNDS' ALLOCATION TO NBFCS

In this figure, we plot the average amount invested by all closed-end mutual funds in affected and unaffected NBFCs separately. Note that the average amount is represented in Indian Rupee (INR) billion. The dotted line indicates August 2018, i.e., the month before the collapse of IL&FS.

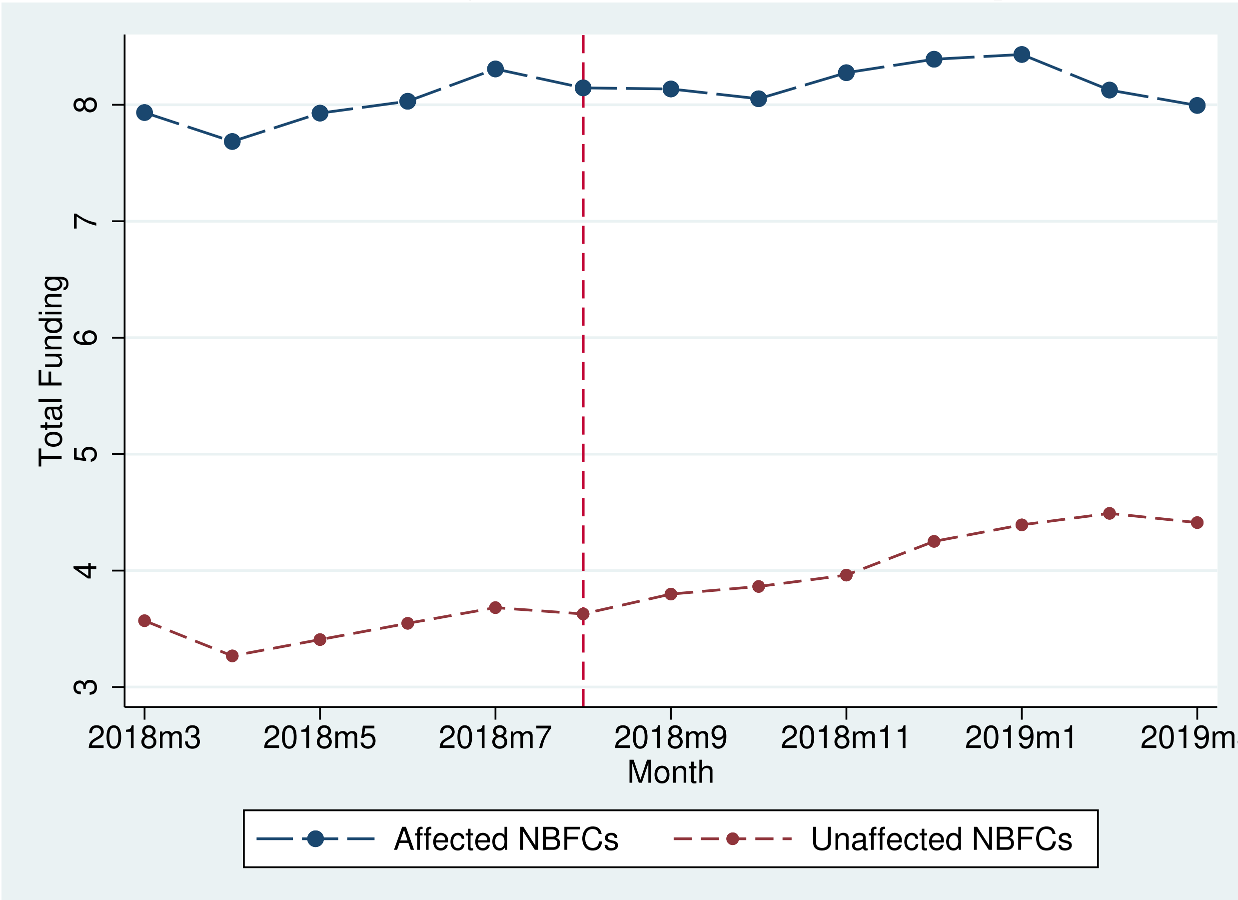


Table 1: SAMPLE CONSTRUCTION & DESCRIPTIVE STATISTICS

This table reports the details of sample construction

Panel A - Mutual Funds Sample	
Number of open-ended funds	333
Number of open-ended funds after excluding Government-Bond funds	293
Number of closed-ended funds	1242

Panel B - NBFCs Sample	
Number of NBFCs funded by at least one open-ended fund as of 31st March 2018	117
Number of NBFCs with value of loan book more than INR 10 billion	96
Number of NBFCs that appear in the loan-register database	82

Panel C - Descriptive Statistics (Fund-Month Level)

	N	Mean	Median	St. Dev.	p25	p75
Flow (%)	1,501	-2.23	-2.26	12.02	-7.08	0.90
Fund Size (INR Million)	1,555	42,446.99	12,442.15	79,415.58	2,301.77	51,709.36
Return (%)	1,497	0.40	0.46	0.27	0.26	0.55
Excess Return (%)	1,497	0.00	0.02	0.44	-0.06	0.10
NBFC Share (%)	1,555	26.54	27.06	14.58	15.98	37.10

Panel D - Descriptive Statistics (Fund-NBFC-Month Level)

	N	Mean	Median	St. Dev.	p25	p75
CP Invesment (INR Million)	282,818	71.47	0.00	743.13	0.00	0.00
Bond Invesment (INR Million)	282,818	72.00	0.00	565.67	0.00	0.00
Total Invesment (INR Million)	282,818	143.48	0.00	966.16	0.00	0.00

Panel E - Descriptive Statistics (Firm-Lender-Quarter Level)

	N	Mean	Median	St. Dev.	p25	p75
$\mathbb{1}_{\text{FreshLoan}}$	416,920	0.05	0.00	0.22	0.00	0.00
FreshLoan (INR Million)	416,920	27.18	0.00	655.03	0.00	0.00
Loan Outstanding (INR Million)	416,920	915.55	35.00	8,487.10	7.20	196.00

Table 2: IMPACT OF NBFC EXPOSURE ON FUND FLOWS

Our data are organized at the fund-month level. The dependent variable is the magnitude of fund flow, as defined in Section 5. *High_NBFC_Alloc* takes the value of one if the fund has above median allocation to NBFCs as of August 2018 and zero otherwise. *Post* takes a value of one from September 2018 and zero otherwise. We include the fund's performance, size, and flow, as well as the fund category's size and flow as control variables. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	*Flows*			
	(1)	(2)	(3)	(4)
High_NBFC_Alloc × Post		-0.040***	-0.040***	-0.050***
		(0.012)	(0.012)	(0.013)
Post	-0.040***	-0.021**		
	(0.006)	(0.009)		
Observations	1,501	1,501	1,501	1,493
R^2	0.028	0.273	0.322	0.376
Fund FE		Yes	Yes	Yes
Month FE			Yes	Yes
Fund Controls				Yes

Table 3: DOES THE REDEMPTION DEPEND ON THE TYPE OF NBFC ALLOCATION?

This table examines whether the investors' exit was dependent on the type of NBFC allocation. In Panel A, we present the average flows for mutual funds with high (low) affected NBFC allocation after conditioning on the overall NBFC allocation. In Panel B, our data are organized at the fund-month level. The dependent variable is the magnitude of fund flow, as defined in Section 5. $High\_NBFC\_Alloc$ takes the value of one if the fund has above median allocation to NBFCs as of August 2018 and zero otherwise. $High\_Aff\_NBFC\_Alloc$ takes the value of one if the fund has above median allocation to affected NBFCs as of August 2018 and zero otherwise. *Post* takes a value of one from September 2018 and zero otherwise. We include the fund's performance, size, and flow, as well as the fund category's size and flow as control variables. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	*Flows*	
	(1)	(2)
High_NBFC_Alloc × Post	-0.054***	-0.065***
	(0.015)	(0.015)
High_Aff_NBFC_Alloc × Post	0.021	0.022
	(0.015)	(0.015)
Observations	1,501	1,493
R^2	0.323	0.377
Fund FE	Yes	Yes
Month FE	Yes	Yes
Fund Controls		Yes

Table 4: MUTUAL FUNDS' EXIT FROM NBFCS

This table demonstrates how mutual funds responded to the redemption pressure. Our data are organized at the fund-NBFC-month level. Panel A and Panel B report the results from Linear and Poisson regressions, respectively. In Panel A, the dependent variable is the logarithm of one plus the value of commercial paper investment in columns (1)-(2), the logarithm of one plus the value of bond investment in columns (3)-(4), the logarithm of one plus the value of total investment in columns (5)-(6). In Panel B, the dependent variables are commercial paper investment in columns (1)-(2), bond investment in columns (3)-(4), and total investment in columns (5)-(6). Across both the panels, odd-numbered columns include fund, NBFC, month fixed effects and even-numbered columns include Fund × Month, Fund × NBFC fixed effects. Aff_NBFC is an indicator variable identifying affected NBFCs. *Post* is an indicator variable that takes the value of one from September 2018 and zero otherwise. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Panel A	*log(1+CP Invst.)*		*log(1+Bond Invst.)*		*log(1+Tot Invst.)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Aff_NBFC × Post	-0.112***	-0.116***	-0.047***	-0.040***	-0.137***	-0.134***
	(0.018)	(0.019)	(0.015)	(0.015)	(0.022)	(0.022)
Observations	282,818	282,654	282,818	282,654	282,818	282,654
R^2	0.169	0.532	0.251	0.802	0.262	0.720
Fund FE	Yes		Yes		Yes	
NBFC FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Fund × Month FE		Yes		Yes		Yes
Fund × NBFC FE		Yes		Yes		Yes

Panel B	*CP Invst.*		*Bond Invst.*		*Tot Invst.*	
	(1)	(2)	(3)	(4)	(5)	(6)
Aff_NBFC × Post	-0.209***	-0.214***	-0.010	0.001	-0.127***	-0.097***
	(0.053)	(0.060)	(0.046)	(0.050)	(0.036)	(0.036)
Observations	187,442	27,123	227,342	28,471	272,896	49,828
Fund FE	Yes		Yes		Yes	
NBFC FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Fund × Month FE		Yes		Yes		Yes
Fund × NBFC FE		Yes		Yes		Yes

Table 5: INVESTORS' RESPONSE TO REDUCTION IN NBFC ALLOCATION

Our data are organized at the fund-month level. The dependent variable is the magnitude of fund flow, as defined in Section 5. *High_NBFC_Alloc* takes the value of one if the fund has above median allocation to NBFCs as of August 2018 and zero otherwise. *Post* takes a value of one from September 2018 and zero otherwise. Δ*NBFC_Share* is the change in NBFC allocation between $t-2$ and $t-1$. We include the fund's performance, size, and flow, as well as the fund category's size and flow as control variables. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	*Flows*	
	(1)	(2)
High_NBFC_Alloc × Post	-0.038***	-0.049***
	(0.013)	(0.013)
High_NBFC_Alloc × Post × ΔNBFC_Share	-0.503*	-0.602**
	(0.269)	(0.245)
Post × ΔNBFC_Share	0.103	0.212
	(0.209)	(0.190)
High_NBFC_Alloc × ΔNBFC_Share	0.266	0.195
	(0.195)	(0.176)
ΔNBFC_Share	0.035	0.002
	(0.137)	(0.127)
Observations	1,494	1,493
R^2	0.328	0.384
Fund FE	Yes	Yes
Month FE	Yes	Yes
Fund Controls		Yes

Table 6: CLOSED-END MUTUAL FUNDS' ALLOCATION TO NBFCS

This table demonstrates how closed-end mutual funds altered their allocation towards NBFCs. Our data are organized at the fund-NBFC-month level. Panel A and Panel B report the results from Linear and Poisson regressions, respectively. In Panel A, the dependent variable is the logarithm of one plus the value of commercial paper investment in columns (1)-(2), the logarithm of one plus the value of bond investment in columns (3)-(4), the logarithm of one plus the value of total investment in columns (5)-(6). In Panel B, the dependent variables are commercial paper investment in columns (1)-(2), bond investment in columns (3)-(4), and total investment in columns (5)-(6). Across both the panels, odd-numbered columns include fund, NBFC, month fixed effects and even-numbered columns include Fund × Month, Fund × NBFC fixed effects. Aff_NBFC is an indicator variable identifying affected NBFCs. *Post* is an indicator variable that takes the value of one from September 2018 and zero otherwise. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Panel A	*log(1+CP Invst.)*		*log(1+Bond Invst.)*		*log(1+Tot Invst.)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Unaff_NBFC × Post	0.010***	0.002	0.006	0.008**	0.016***	0.010**
	(0.002)	(0.002)	(0.006)	(0.004)	(0.006)	(0.004)
Observations	812,046	800,074	812,046	800,074	812,046	800,074
R^2	0.037	0.724	0.298	0.947	0.293	0.942
Fund FE	Yes		Yes		Yes	
NBFC FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Fund × Month FE		Yes		Yes		Yes
Fund × NBFC FE		Yes		Yes		Yes

Panel B	*CP Invst.*		*Bond Invst.*		*Tot Invst.*	
	(1)	(2)	(3)	(4)	(5)	(6)
Unaff_NBFC × Post	0.682	0.853	0.118***	0.087***	0.145***	0.103***
	(0.440)	(0.656)	(0.023)	(0.012)	(0.029)	(0.021)
Observations	38,550	1,508	527,016	49,100	612,864	50,942
Fund FE	Yes		Yes		Yes	
NBFC FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Fund × Month FE		Yes		Yes		Yes
Fund × NBFC FE		Yes		Yes		Yes

Table 7: EVIDENCE OF MITIGATING INEFFICIENT LIQUIDATION

This table examines whether mutual funds exit from NBFCs has real effects on NBFCs' borrowers (in Panel-A) and whether liquidation cost is different for IL&FS Industries versus Other Industries (in Panel-B). Our data are organized at the firm-quarter level for Panel A and the firm-date level for Panel B. In Panel-A, the dependent variable is an indicator variable that is set to one if at least one of the firm's projects stalled during the quarter and zero otherwise. Aff_NBFC_Dep ($Unaff\_NBFC\_Dep$) indicates borrowers dependent on affected (unaffected) NBFCs, as defined in Section 8. *Post* is an indicator variable that takes the value of one from September 2018 and zero otherwise. All columns include firm and quarter fixed effects. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively. In Panel-B, we present the average one-week return around project stalling for firms belonging to IL&FS (other) industries. Pre-period contains events from 1st April 2015 to 31st March 2018. Post-period contains events from 1st April 2019 to 31st March 2020. In Panel-C, we conduct the same analysis as in Panel-B, but after considering the subset of firms with high FII presence (i.e., more than 10% at the end of the previous financial year)

Panel-A		*Stalled*	
	(1)	(2)	(3)
Aff_NBFC_Dep × Post	0.023*		0.024*
	(0.014)		(0.014)
Unaff_NBFC_Dep × Post		-0.002	-0.004
		(0.018)	(0.017)
Observations	9,693	9,693	9,693
Firm FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes

Panel-B	Pre (1)	Post (2)
IL&FS Industries (a)	0.68%	0.32%
Other Industries (b)	0.24%	-2.50%
Difference (a-b)	0.44%	2.82%
t-stat	0.57	2.20

Panel-C	Pre (1)	Post (2)
IL&FS Industries (a)	-0.09%	1.16%
Other Industries (b)	0.64%	-3.54%
Difference (a-b)	-0.73%	4.69%
t-stat	-0.68	2.63

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Online Appendix

Table A1: VARIABLE DEFINITION

Variable	Definition	Data Source
Aff_NBFC	Indicator variable set to one if NBFC has above-median exposure to the infrastructure sector and zero otherwise	MCA
Unaff_NBFC	Indicator variable set to one if NBFC has below-median exposure to the infrastructure sector and zero otherwise	MCA
$\mathbb{1}_{FreshLoan}$	Indicator variable set if the lender issued a loan to the firm during the quarter	MCA
FreshLoan	Amount of fresh loan issued by the lender to a firm during the quarter	MCA
Flow	Net inflow into the mutual fund	Morningstar
High_NBFC_Alloc	Indicator variable set to one if mutual fund has above-median allocation towards NBFCs and zero otherwise	Morningstar
High_Aff_NBFC_Alloc	Indicator variable set to one if mutual fund has above-median allocation towards affected NBFCs and zero otherwise	Morningstar
Reduced	Indicator variable set to one if mutual fund reduced NBFC allocation between $t-2$ and $t-1$ and zero otherwise	Morningstar
ΔNBFC_Share	Change in allocation towards NBFCs between $t-2$ and $t-1$. A negative value indicates a reduction in exposure	Morningstar
Tot_Loans	Total loans issued by an NBFC	Prowess
Post	Indicator variable set to one from September 2018 and zero otherwise	
Fund Size	Total assets under management (AUM) with a mutual fund	Morningstar
Return	Monthly return of a mutual fund	Morningstar
ExcessReturn	Return of a mutual fund over and above the average category's return	Morningstar
NBFC Share	Fraction of mutual funds' AUM invested in debt securities of NBFCs	Morningstar
Loan Outstanding	Total outstanding amount between a lender-firm pair at the end of the corresponding quarter	MCA
ILFS_Ind	An indicator set to one if the firm belongs to any of the three IL&FS industries identified in Section A2	Prowess
CP Investment	Total investment by mutual fund in commercial papers of an NBFC	Morningstar
Bond Investment	Total investment by mutual fund in bonds of an NBFC	Morningstar
Total Investment	Total investment by mutual fund in an NBFC	Morningstar

Table A2: Events Corresponding to Stalled Projects

	Project Events
Stalled Projects	Bids opening deferred Implementation stalled on Shelved on Stalled upto Announced and stalled on Contract cancelled Abandoned on Land acquisition problem Land allotment cancelled Rejected by central government Power purchase agreement (PPA) cancelled Bids cancelled Memorandum of Understanding (MoU) cancelled Acquired land returned

A1 Debt Mutual Funds Classification in India

The Indian mutual fund regulator, Securities and Exchange Board of India (SEBI), classifies debt funds into 16 categories.[1] Note that the regulator provides explicit investment guidelines for each category. For instance, debt funds belonging to the 'Government Bond' category must invest at least 80% of their AUM in government securities. Similarly, funds belonging to the 'Banking & PSU' category must invest at least 80% of their AUM in debt securities of banks and public sector undertakings (PSUs). Table A3 illustrates the classification of debt mutual funds in India. For our analysis, we exclude funds belonging to the 'Gilt Fund' and 'Gilt Fund with 10-year Duration' categories.

Furthermore, each fund comprises several share classes (investment plans). For instance, the investor can choose between regular and direct plans. Under a regular plan, the investor invests in funds through the help of an intermediary; however, in the case of a direct plan, the investor purchases the fund directly from the mutual fund. Mutual funds also provide investors with several dividend payout options, such as weekly payout, annual payout, and no payout (growth).

[1] https://www.sebi.gov.in/legal/circulars/oct-2017/categorization-and-rationalization-of-mutual-fund-schemes_36199.html

Table A3: SEBI's Debt MF Categorization

Sr. No	Scheme Type	Definition
1	Overnight Fund	Overnight securities having maturity of 1 day
2	Liquid Fund	Securities with maturity of upto 91 days only
3	Ultra Short Duration Fund	Securities with Macaulay duration of the portfolio between 3 months - 6 months
4	Low Duration Fund	Securities with Macaulay duration portfolio between 6 months- 12 months
5	Money Market Fund	Securities having maturity upto 1 Year
6	Short Duration Fund	Securities instruments with Macaulay duration of the portfolio between 1 year - 3 years
7	Medium Duration Fund	Securities with Macaulay duration of portfolio between 3 years - 4 years
8	Medium to Long Duration Fund	Securities with Macaulay duration of the portfolio between 4 - 7 years
9	Long Duration Fund	Securities with Macaulay duration of the portfolio greater than 7 years
10	Dynamic Bond	Investment across duration
11	Floater Fund	Minimum 65% in floating rate instruments
12	Gilt Fund	Minimum 80% in G-secs, across maturity
13	Gilt Fund with 10-year Duration	Minimum 80% in G-secs, such that the Macaulay duration of the portfolio is equal to 10 years
14	Banking and PSU Fund	Minimum 80% in securities of banks, PSUs, PFIs and Municipal Bonds
15	Corporate Bond Fund	Minimum 80% investment in corporate bonds only in AA+ and above rated corporate bonds
16	Credit Risk Fund	Minimum 65% investment in corporate bonds, only in AA and below rated corporate bonds

A2 Health of IL&FS Industries

We use the MCA dataset to identify the industries to which the IL&FS group had high exposure. We obtain the list of IL&FS group companies using the CMIE Prowess database and compute their outstanding loans using the approach described in Section 4.1. Note that we do not have the industry mapping in the MCA dataset. Hence, we infer the borrower's industry using the Corporate Identification Number (CIN). As per the CIN format, characters two and three identify the industry, i.e., the two-digit National Industrial Classification (NIC) code, to which the company belongs.

We compute the fraction of IL&FS group loans outstanding with the top three industries. These top three industries are 'Construction,' 'Real estate activities,' and 'Electricity.' Firms belonging to these three industries accounted for approximately 75% of IL&FS group's loan book. Henceforth, we refer to these industries collectively as 'IL&FS Industries.' We examine how firms belonging to these industries performed during 1st April 2017-31st March 2018, i.e., the last financial year before the collapse of IL&FS. We evaluate these firms on several dimensions of financial health, including profitability, solvency, and leverage.

We obtain the financial information of all firms that appear in the Prowess database at the end of 31st March 2018. Specifically, we obtain the interest coverage ratio (ICR), net worth, EBITDA, and debt-assets ratio. We define the indicator variables, low_icr, neg_nw, and neg_ebitda, identifying firms with ICR less than one, negative net worth, and negative EBITDA, respectively. $high\_debt$ identifies firms with debt to assets ratio falling in the top quartile among all the firms. To examine the health of IL&FS industries vis-à-vis others, we use the following specification.

$$Y_i = \beta_0 + \beta_1 ILFS\_Ind_i + X_i + \varepsilon_i \tag{8}$$

The dependent variable represents different aspects of firm health: short-term solvency, long-term solvency, profitability, and leverage. Our first measure, low_icr, represents short-term solvency. The second measure, neg_nw, represents long-term solvency. Our third measure, neg_ebitda, represents profitability. The final measure, $high\_debt$, represents leverage. $ILFS\_Ind_i$ is set to one if the firm belongs to any of the three IL&FS industries. X denotes a vector of control variables. We include firm size and age as controls to account for financial constraints. The standard errors are clustered at the industry level.

Table A4 presents the results. Consider the first column; the coefficient of *ILFS_Ind* is 0.16, implying that firms belonging to IL&FS industries were 16 percentage points (pp) more likely to have an ICR of less than one. Similarly, when we consider *neg_nw*, *neg_ebitda*, and *high_debt* as dependent variables in the remaining columns, firms in the IL&FS industries were 6.3pp more likely to have a negative net worth, 7.2pp more likely to have a negative EBITDA, and 20pp more likely to have high debt-assets ratio. These results indicate that firms belonging to IL&FS industries fared worse on several dimensions of financial health.

Table A4: HEALTH OF IL&FS INDUSTRIES

This table examines the health of IL&FS industries vis-à-vis others as of 31st March 2018. *low_icr* is an indicator variable set to one if the firm has an ICR less than one and zero otherwise. *neg_nw* is an indicator variable set to one if the firm has a negative net worth and zero otherwise. *neg_ebitda* is an indicator variable set to one if the firm has a negative EBITDA and zero otherwise. *high_debt* is an indicator variable set to one if the firm's debt to assets ratio falls in the top quartile and zero otherwise. *ILFS_Ind* identifies if the firm belongs to any of the three IL&FS industries, as defined in Section A2. We include the firm's size and age as controls. The standard errors are clustered at the industry level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	*low_icr*	*neg_nw*	*neg_ebitda*	*high_debt*
	(1)	(2)	(3)	(4)
ILFS_Ind	0.160***	0.063***	0.072***	0.200***
	(0.028)	(0.013)	(0.017)	(0.026)
Observations	20,050	27,919	26,629	22,536
Firm Controls	Yes	Yes	Yes	Yes

Table A5: MUTUAL FUNDS' EXIT FROM NBFCS - PRE VS POST

This table demonstrates how mutual funds responded to the redemption pressure on average. Our data are organized at the fund-NBFC-month level. The dependent variable is the logarithm of one plus the value of commercial paper investment in columns (1)-(2), the logarithm of one plus the value of bond investment in columns (3)-(4), the logarithm of one plus the value of total investment in columns (5)-(6). Across both the panels, odd-numbered columns include fund and NBFC fixed effects and even-numbered columns include Fund × NBFC fixed effects. *Post* is an indicator variable that takes the value of one from September 2018 and zero otherwise. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Panel A	*log(1+CP Invst.)*		*log(1+Bond Invst.)*		*log(1+Tot Invst.)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.040***	-0.040***	-0.056***	-0.056***	-0.090***	-0.090***
	(0.012)	(0.012)	(0.011)	(0.011)	(0.014)	(0.014)
Observations	282,818	282,654	282,818	282,654	282,818	282,654
R^2	0.168	0.521	0.251	0.797	0.262	0.714
Fund FE	Yes		Yes		Yes	
NBFC FE	Yes		Yes		Yes	
Fund × NBFC FE		Yes		Yes		Yes

Table A6: Mutual Funds' Exit from NBFCs - Impact on Primary Issuance

This table demonstrates the impact on primary issuance of NBFCs. Since we do not have a direct approach to identify primary issuance, we assume that the mutual fund participated in the primary issuance if the debt instrument's issuance date falls during that month. The month-end value of the invested amount is deemed as the fresh funding raised by NBFC during that month. We estimate equation (4) using Poisson regression and the value of fresh issuance as the dependent variable. For example, if a security's issuance date is 16th October 2018 and investment by the mutual fund in this security is INR 10 million as of 31st October 2018, we assume that mutual participated in the primary issuance and provided a fresh funding of INR 10 million. Our data are organized at the fund-NBFC-month level. The dependent variables are commercial paper investment in columns (1)-(2), bond investment in columns (3)-(4), and total investment in columns (5)-(6). Across both the panels, odd-numbered columns include fund, NBFC, month fixed effects and even-numbered columns include Fund × Month, Fund × NBFC fixed effects. Aff_NBFC is an indicator variable identifying affected NBFCs. *Post* is an indicator variable that takes the value of one from September 2018 and zero otherwise. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable	*CP Invst.*		*Bond Invst.*		*Tot Invst.*	
	(1)	(2)	(3)	(4)	(5)	(6)
Aff_NBFC × Post	-0.223**	-0.272***	1.279***	1.503***	-0.092	-0.190*
	(0.095)	(0.099)	(0.232)	(0.341)	(0.096)	(0.098)
Observations	154,922	14,958	84,720	2,501	223,161	18,229
Fund FE	Yes		Yes		Yes	
NBFC FE	Yes		Yes		Yes	
Month FE	Yes		Yes		Yes	
Fund × Month FE		Yes		Yes		Yes
Fund × NBFC FE		Yes		Yes		Yes

Table A7: MUTUAL FUNDS' EXIT FROM NBFCS - PORTFOLIO SHARE

This table demonstrates how mutual funds responded to the redemption pressure. Our data are organized at the fund-NBFC type-month level. The dependent variable is the fraction of the fund's AUM invested in affected or unaffected NBFCs. Aff_NBFC takes a value of one if the NBFC type is affected and zero otherwise. *Post* is an indicator variable that takes the value of one from September 2018 and zero otherwise. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Dependent Variable		*Share*	
	(1)	(2)	(3)
Aff_NBFC × Post	-0.021***	-0.021***	-0.021***
	(0.005)	(0.005)	(0.005)
Aff_NBFC	0.103***	0.103***	0.103***
	(0.006)	(0.006)	(0.006)
Post	0.006**		
	(0.003)		
Observations	6,898	6,898	6,898
R^2	0.602	0.603	0.699
Fund FE	Yes	Yes	
Month FE		Yes	
Fund × Month FE			Yes

Table A8: CLOSED-END MUTUAL FUNDS' ALLOCATION TO NBFCS - PRE VS POST

This table demonstrates how closed-end mutual funds altered their allocation towards NBFCs on average. Our data are organized at the fund-NBFC-month level. The dependent variable is the logarithm of one plus the value of commercial paper investment in columns (1)-(2), the logarithm of one plus the value of bond investment in columns (3)-(4), the logarithm of one plus the value of total investment in columns (5)-(6). Across both the panels, odd-numbered columns include fund and NBFC fixed effects and even-numbered columns include Fund $\times$ NBFC fixed effects. *Post* is an indicator variable that takes the value of one from September 2018 and zero otherwise. The standard errors are clustered at the fund level. Standard errors are reported in parentheses. ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

Panel A	*log(1+CP Invst.)*		*log(1+Bond Invst.)*		*log(1+Tot Invst.)*	
	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.001	-0.001	0.014***	0.014***	0.013***	0.013***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)
Observations	812,046	800,074	812,046	800,074	812,046	800,074
R^2	0.037	0.718	0.298	0.945	0.293	0.940
Fund FE	Yes		Yes		Yes	
NBFC FE	Yes		Yes		Yes	
Fund $\times$ NBFC FE		Yes		Yes		Yes