Nonbank Fragility in Credit Markets: Evidence from a Two-Layer Asset Demand System*

Olivier Darmouni
Columbia Business School

Kerry Y. Siani
MIT Sloan

Kairong Xiao
Columbia Business School

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Abstract

We develop a two-layer asset demand framework to analyze fragility in the corporate bond market. Households allocate wealth to institutions, and institutions then allocate funds to specific assets. The framework generates tractable joint dynamics of flows and asset values, featuring amplification and contagion. The framework can be estimated using micro-data on bond prices, investor holdings, and fund flows, allowing for rich parameter heterogeneity across assets and institutions. We match the model to the March 2020 turmoil and quantify the equilibrium effects of unconventional monetary and liquidity policies on asset prices and institutions.

Keywords: Nonbanks, financial fragility, corporate bond markets, mutual fund flows, illiquidity, demand system asset pricing, unconventional monetary policy
JEL codes: G23, G01, G12, E43, E44, E52

*Olivier Darmouni (omd2109@columbia.edu) and Kairong Xiao (kx2139@columbia.edu) are at Columbia Business School, New York, NY. Kerry Y. Siani (ksiani@mit.edu) is at MIT Sloan, Cambridge, MA. For helpful comments, we thank Valentin Haddad, Gregor Matvos, Alan Moreira, Tyler Muir, Sam Hanson (discussant), Zheng Sun (discussant), Adi Sunderam, Moto Yogo (discussant), as well as participants at the 2023 NBER Risks of Financial Institutions, 2023 NBER Long Term Asset Management, 2023 Short-Term Funding Markets Conference, 2023 SITE Financial Regulation, European Central Bank, Bank of England, UCLA, UCSD, Toulouse School of Economics, Federal Reserve of Atlanta, Federal Reserve Board, CU Boulder, Columbia Business School, and Baruch College. Ruiquan Chang and Vincent Philipp Marohl provided excellent research assistance.

1 Introduction

"Financial fragility" is often at the center of economic crises: the notion that intermediaries can amplify fundamental shocks through their balance sheets. Fragility leads to spirals of depressed asset prices and illiquidity, with potentially devastating consequences for the economy. Traditionally, the focus has been on deleveraging and capital shortages in the banking sector, exemplified by the 2008 Global Financial Crisis. However, in recent decades nonbanks have been growing rapidly and now perform a large share of intermediation in the economy. This growth is, however, not without systemic risk. The COVID-19 episode was a clear example, with bond markets entering severe turmoil in March 2020, prompting a large-scale intervention by the Federal Reserve (Haddad, Moreira, and Muir, 2021a). Nonbank fragility was an important driver of this turmoil, with historical levels of outflows suffered by bond mutual funds (Falato, Goldstein, and Hortaçsu, 2021). Forced sales by shrinking funds significantly contributed to the sharp increase in credit spreads, as shifts in institutional demand can lead to substantial disruptions in corporate bond prices (Ma, Xiao, and Zeng, 2022). This episode, as well as prior ones, suggest that asset prices and flows are jointly determined in equilibrium and that their interaction is a key driver of market fluctuations (Gabaix and Koijen, 2021). Nevertheless, the quantitative magnitude of the equilibrium effects and the appropriate policy response still remain open questions.

This paper aims to fill this gap by developing a framework to analyze the fragility of the corporate bond market. The model features a two-layer asset demand system: households allocate wealth to institutions; institutions then allocate funds to specific assets. The framework generates tractable joint dynamics of flows and asset values. It captures the dynamics of crisis episodes by featuring the amplification between asset prices and fund flows, as well as the contagion across assets and institutions. We show how the model can be estimated using micro-data on bond prices, institutional investors' holdings, and fund flows. We match the model to the March 2020 turmoil and quantify the equilibrium effects of unconventional monetary and liquidity policies on asset prices and institutions.

We first develop equilibrium conditions for the two-layer asset demand model. In the first layer, households allocate wealth to institutional investors. Our key focus is on the flow-performance relationship in the mutual fund sector, which affects the size of funds' Assets under Management (AUM): high returns lead to inflows into a fund, while poor returns lead to outflows. In the second layer, institutional investors then allocate funds to specific assets. We build on the framework of Koijen and Yogo (2019) in which asset demand is driven by asset returns and the institutions' investment mandates. Equilibrium asset prices reflect the demand of both households and institutional investors: AUM determines asset demand through mandates, while asset holdings affect fund returns and drive changes in AUM. The framework can account for large heterogeneity across institutions in terms of their flow sensitivities or asset demand elasticities.

The model yields rich yet tractable equilibrium dynamics. First, the model displays a feedback loop between prices and flows. A negative shock to asset prices reduces fund returns, which leads to outflows from mutual funds. Outflows then lead to asset sales by these institutions, further depressing asset prices. The cumulative effect could be significantly greater than the initial shock.[1] Second, the model displays contagion across assets. Shocks to the cash-flows of one asset can spill over to other assets through investor outflows. Because institutions prefer to maintain certain portfolio weights, they tend to buy and sell assets that are not directly affected by the fundamental shock. Third, the model displays contagion across institutions. Institutions that themselves do not face significant outflows, such as insurance companies, are affected by outflows from other institutions. Because asset prices are depressed by outflow-induced asset sales, the asset values of insurance companies can

[1]Most of the paper focuses on an initial shock to bond values. However, the model is equally well suited to studying *flow* shocks in the mutual fund sector. For example, households might decide to massively re-balance away from bond funds towards money market funds at the start of a crisis, even before fund performance deteriorates significantly. Because flows and asset prices are tightly linked in our framework, price and flow shocks are amplified in relatively similar ways. We thus mainly focus on only one type of shock for readability.

decrease.

Although these amplifications and contagions have been documented in the prior literature, our framework has the unique advantage of characterizing them with simple sufficient statistics that can be estimated, such as institution demand elasticities, flow-to-return sensitivities, and the distribution of assets across institutions. This tractability makes the model highly scalable despite heterogeneity: our empirical implementation incorporates variation in elasticities and flow sensitivities across investor groups. The model also guides us to construct an asset systemic risk measure, which measures how much aggregate asset prices would decline for a given shock to the value of one asset, taking into account both the direct contribution of the asset and the amplification through other assets or institutions. This type of measure can help policymakers evaluate the source of fragility in credit markets and better target any ex-post interventions.

We estimate the model parameters using microdata. The first layer uses flow-performance regressions to determine how much outflow an institution would suffer if it experienced negative returns (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). The second layer uses an instrumental variables technique to estimate the asset demand system that leverages idisoyncratic flow-driven demand by bond holders (van der Beck et al., 2022). For the first layer, we construct a monthly panel of fixed-income funds from January 1992 to December 2021 from the CRSP Mutual Fund Database and complement it with daily fund flow and net asset value data for open-end funds from Morningstar. For the second layer, we use a comprehensive dataset that merges holdings data from eMAXX and CRSP, pricing data from WRDS Bond Returns, and bond details from Mergent FISD. In the cross-section, funds with higher flow-performance sensitivity invest in assets with higher demand elasticities.

We estimate how systemic different assets are in the cross-section of corporate bonds. We find that all asset classes can be the source of non-trivial amplification to the rest of the market. IG bonds are somewhat less systemic than HY bonds, because they are more likely to be held by insurers and pensions as opposed to mutual funds. Interestingly, within rating categories, short-term bonds are more systemic than long-term bonds. This is the reverse of conventional liquidity measures, that typically rank short-term bonds as more liquid. The key aspect here is that our measure includes investors' propensity to sell in bad times. In particular, mutual funds are more likely to hold short-term bonds, relative to insurers that typically prefer long-term bonds.

We then use our estimated model to study the effects of policy interventions to stabilize the market. The Federal Reserve responded swiftly in the Spring of 2020 by lowering interest rates and purchasing corporate bonds for the first time. Other potential interventions, such as direct lending to mutual funds and redemption restrictions, have been discussed, but quantifying their effects has largely been an open question. We match the model to the key moments of the flows and price dynamics of March 2020 and study four types of ex-post interventions: conventional monetary policy (risk-free rate cut), asset purchases, direct lending to mutual funds, and restricting redemption on mutual fund shares.[2] In each counterfactual, we feed in two weeks of price shocks implied by CDS spreads and evaluate the impact of an intervention 14 days after the initial shocks. Moreover, we also study how well targeted these interventions are in addressing fragility, in the sense of maximizing price impact while limiting the size of the intervention. Our framework allows us to compute the benchmark of a maximum-price-impact intervention, in which the policy-maker targets the assets responsible for the most amplification.

First, we find that a rate cut improves prices and restores some of the loss in fund value. IG bonds rebound more than HY bonds because they have a longer duration. There is also a significant rebound in institutional investors' assets under management. Second, we evaluate a policy where the central bank announces purchases 5% of outstanding short-term (five years or less) IG bonds. While these asset purchases target IG bonds, there is nevertheless a price

[2] Nevertheless, there are some important dimensions of policy that are outside the current scope of our framework, such as promises (Haddad et al., 2021a) or signaling (Cieslak et al., 2019).

impact for HY bonds because of the rebound in fund AUM as well as investment mandates increasing demand for HY assets. Mutual fund values rebound relatively more than insurers due to the amplifying effect of inflows. There is an immediate rebound at the announcement, followed by a small drift until purchases start.

Next, we study two types of intervention targeting the mutual fund sector specifically. We consider the effects of lending directly to mutual funds against 10% of their IG bonds as collateral.[3] We find that this policy is effective at supporting prices and limiting outflows. Despite not being targeted directly, insurers also benefit from the market rebound. This evidence suggests that a "lender of last resort" towards nonbanks can potentially be effective, particularly if the mutual fund presence is large. We then consider a policy of freezing mutual fund redemption. Regulators did not mandate this policy in Spring 2020, but a significant number of funds facing severe liquidity issues suspended redemption (Grill, Vivar, and Wedow, 2021). This policy is very effective at preventing the mutual fund sector from shrinking, but only when it occurs sufficiently quickly. Redemption restrictions, a classical tool of bank regulation, might thus also be a consideration for nonbanks.

We then compare how well-targeted these policies are in addressing fragility. Direct lending to mutual funds is the best-targeted intervention. This is because mutual funds are especially fragile due to their holding of highly-fragile HY bonds and their high flow-to-performance sensitivity. It is in fact close to the maximum-price-impact benchmark. This gives support to some of the proposals to extend lender-of-last-resort policies to non-banks, at least if the goal was to maximize price impact under a limited budget. On the other hand, conventional monetary policy (risk-free rate cut) is the least well-targeted because it has the biggest price effect on less fragile long-term IG assets due to their high duration. This is not necessarily surprising: the return to the zero lower bound was dictated by many

[3]On March 18, 2020, broadens program of support for the flow of credit to households and businesses by establishing a Money Market Mutual Fund Liquidity Facility (MMLF). See "Money Market Mutual Fund Liquidity Facility", `https://www.federalreserve.gov/monetarypolicy/mmlf.htm`. However, this facility does not cover bond mutual funds.

considerations other than addressing the bond market turmoil specifically. Asset purchases stand between these two other interventions.

Our paper contributes to the debate on the financial stability implications of non-bank financial institutions. Our main contribution is to provide a framework to quantify the joint dynamics of financial flows and asset values, with three objectives: (i) linking transparently to the economic forces that have been documented in prior theoretical and empirical work, (ii) being estimable with micro-data, (iii) conducting counterfactual analysis of unconventional monetary and liquidity policies within a unified setting. We show how to combine a flow-performance relationship for fund flows with a logit model of institutional asset demand to generate *tractable* dynamics, amplification, and contagion. Moreover, key parameters can be estimated with standard regression techniques, which allows for rich heterogeneity across assets and institutions. To achieve this tractability, some dimensions are admittedly left outside the scope of our modeling assumptions. Generalizing the framework further is an important area for future research.

Related literature: We mainly relate to two growing areas of research: the literature applying a demand system approach to asset pricing and the literature on mutual funds fragility. While the first area has focused on the limited price elasticity of institutions' demand and the second on the flow sensitivity of bond mutual funds, we focus on how the combination of these two forces is key to generating the large amplification generally seen in crises.

From a methodological standpoint, relative to existing work applying a demand system approach to asset pricing (Koijen and Yogo, 2019, 2020; Koijen et al., 2021; Bretscher et al., 2022) we endogenize institutional investors' AUM, incorporating a second layer into our model. In this way, we are able to capture strong dynamic feedback loops between flows and asset prices that are particularly important in crisis episodes. Our focus on fund outflows is also directly related to work on the role of flows and inelastic investors in equity markets

(Gabaix and Koijen, 2021). Our paper supports the view of Bretscher et al. (2022) that argue that institutional investors' demand is crucial for the pricing of corporate bonds. We build on their result that the main investors in the corporate bond market exhibit different demand elasticities and that investor composition matters greatly for corporate bond pricing. We add that institutions' flow sensitivity is a key driver of fragility in crisis times. In a different application, Fang (2022) quantifies monetary policy amplification through bond fund flows by estimating a nested logit demand system with flexible investor elasticity both within and across asset classes. Similar in spirit, Azarmsa and Davis (2022) develop and estimate a two-layer demand system in equity markets to study whether asset demand elasticity is set at the household or intermediary level. For an alternative approach, Kargar et al. (2020) develop a theory of asset pricing and portfolio flows in OTC markets emphasizing search frictions and capacity-constrained dealers. Their model's quantitative implications for asset prices and liquidity conditions in response to a large adverse shock are consistent with the evidence from March 2020.

This paper is also closely related to works studying the risks imposed by investor redemption for institutions that issue demandable liabilities, such as open-end mutual funds (Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017; Zeng, 2017). Another strand of the literature focuses on the illiquidity of the bond market and the fire-sale spillovers (Ellul et al., 2011).[4] Falato, Hortacsu, Li, and Shin (2021) in particular provide compelling evidence of how flow shocks to some funds affect other funds, asset values, and ultimately financial stability. Importantly, the impact of forced sales on prices depends on the market price elasticity, i.e., the ability of other investors to absorb the selling pressure. Our two-layer framework explicitly connects both strands of this literature and accounts for the interaction between flows and limited price elasticity. Our structural approach complements the existing empirical studies of the stress events in the credit markets by nesting an explicit

[4]See Coval and Stafford (2007); Frazzini and Lamont (2008); Greenwood and Thesmar (2011); Jotikasthira, Lundblad, and Ramadorai (2012) for earlier work on stock markets.

equilibrium asset pricing model (Falato, Goldstein, and Hortaçsu, 2021; Haddad, Moreira, and Muir, 2021b; Ma, Xiao, and Zeng, 2022; Jiang, Li, Sun, and Wang, 2022). For instance, our framework allows us to run counterfactuals to study various policy interventions that have been implemented or discussed in serious stress events. We can shed light on the "bond-fund fragility channel" of Falato, Goldstein, and Hortaçsu (2021) whereby the Fed liquidity backstop transmits to the real economy via funds.

More generally, this paper also contributes to our understanding of the role of intermediaries for asset valuation during crisis episodes, and thus the mechanisms behind different policy responses. A large body of work measures the systemic risk in the financial system, with a particular focus on banks (Adrian and Brunnermeier, 2016; Acharya, Pedersen, Philippon, and Richardson, 2017; Greenwood, Landier, and Thesmar, 2015; Duarte and Eisenbach, 2021; Hanson, Kashyap, and Stein, 2011). Other papers have popularized the idea of intermediary asset pricing (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Haddad and Muir, 2021). We contribute to this line of work in two dimensions. First, the existing literature often focuses on levered financial intuitions such as traditional banks and shadow banks such that the key amplification mechanism is through deleveraging and capital constraints. In contrast, we focus on unlevered nonbanks such as open-end mutual funds whose fund sizes fluctuate over time even absent a leverage constraint. Second, we bring in new insights and methods from the recent literature on demand system asset pricing, which allows us to tightly map the model to micro-data on investor holdings and evaluate potential policy interventions.

2 Data

For demand estimation, we construct a comprehensive dataset of corporate bonds using bond issuance details from Mergent FISD, fund holdings from Thomson Reuters eMAXX and CRSP Mutual Fund holdings, and trading information from WRDS Bond Returns. From Mergent FISD, we include all USD corporate bonds issued by non-financial, non-utility, non-sovereign firms that are over $100 million at issuance.[5] We exclude bonds that are issued in exchange for an identical existing bond, or that do not report at least one credit rating, tenor, credit spread, or size at issuance. We further exclude convertible bonds, capital impact bonds, community investment bonds, and PIK securities. We restrict the holdings sample to fund-quarters in which the fund holds at least 20 unique corporate bonds in our sample in the year. Following Bretscher et al. (2022), we use the last recorded price and yield for each quarter in the WRDS Bond Returns dataset. We back out the credit spread for each bond-quarter using an interpolated U.S. Treasury yield curve as per Gürkaynak et al. (2007). We include holdings from 2010-2021 to capture the post-2008 financial crisis period up through the COVID crisis of 2020. The estimation sample includes 2,306 mutual funds, 987 insurers, and 10,942 unique corporate bonds.

For estimating flow-to-performance parameters, we use the CRSP Mutual Fund Database to create a monthly panel of fixed-income funds from January 1992 to December 2021, covering a total of 2,967 funds.

3 Framework

This section presents a two-layer asset demand model of institutional investors' size, portfolio holdings, and asset prices. The first layer consists of household demand for institutions (mutual funds flows), i.e., savings allocation, which determines the dynamics of fund size (Assets Under Management, or AUM). The second layer consists of institutional portfolio allocation across assets. The combination of AUM and portfolio allocation across institutions determines asset prices through market clearing. We first present a general setup and then a

[5] Issuers with NAICS codes beginning with 52, 92, and 22 are excluded.

more specific version to focus on the joint dynamics of fund flows and asset prices in a crisis.

3.1 General setup

Layer 1: Household demand for institutions. Each household is endowed with a dollar that can be invested in a set of institutions, including mutual funds and insurance companies indexed by $\mathcal{I} = \{0, 1, ..., I\}$, with option 0 representing the outside option of managing the wealth by themselves. Each option is described as a vector of characteristics $X_{i,t}$, which includes the return of the institution, the fee paid to the management, and so on. Each household chooses the best option to maximize its indirect utility, i.e.

$$\max_{i \in \mathcal{I}} u_{h,i,t} = \beta_{h,i} X_{i,t} + \epsilon_{h,i,t}, \tag{1}$$

where $\beta_{h,i}$ are sensitivities to the characteristics of household type h; $\epsilon_{h,i,t}$ captures horizontal differentiation across each investment option. The weight of institution i in household h's portfolio is given by the following logit form:[6]

$$\theta_{h,i,t} \equiv \frac{\exp\left(\beta_{h,i} X_{i,t}\right)}{\sum_{i=0}^{I} \exp\left(\beta_{h,i} X_{i,t}\right)}, \tag{2}$$

The demand for institution liability by household h is then given by the portfolio shares multiplied by the household's wealth, then divided by the net asset value (NAV):

$$Q_{h,i,t}^{D} \equiv \frac{\theta_{h,i,t} W_{h,t}^{*}}{V_{i,t}^{*}}, \tag{3}$$

where $V_{i,t}^{*}$ is the net asset value in the steady state, and $W_{i,t}^{*}$ is the household wealth calculated using steady-state net asset value. We define the household demand for institution liabilities as a function of the steady state NAV and wealth because changes in NAVs would

[6]This follows from the standard assumption that $\epsilon_{h,i,t}$ follows a generalized extreme-value distribution with a cumulative distribution function given by $F(\epsilon) = \exp(-\exp(-\epsilon))$.

not mechanically lead to changes in quantity demand. Under this assumption, a passive household ($\beta_{h,i} = 0$) would not trade when the NAVs change. Alternatively, one could define the demand as $Q^D_{h,i,t} \equiv \frac{\theta_{h,i,t} W_{h,t}}{V_{i,t}}$, then a passive investor would increase the demand for institution i proportionally if the NAV of an institution drops, which does not seem to be consistent with the usual behavior of a passive household.

Layer 2: Institution demand for assets. Financial institutions allocate households' investments to a set of assets. We index assets by $n = 0, 1, ..., N$, where $n = 0$ corresponds to the outside asset and, time by t. Each institution has wealth $W_{i,t}$ to invest (its assets under management, or AUM). Each asset is described by a vector of characteristics $X_t(n)$, which includes risk and return, rating, maturity, and so on. Each institution chooses the best option to maximize its indirect utility, i.e.

$$\max_{n \in \mathcal{N}} u_{i,t}(n) = \kappa_{i,n} X_{n,t} + \epsilon_{i,n,t}, \tag{4}$$

where $\kappa_{i,n}$ are institution i's sensitivities to asset n's characteristics, which reflects the mandates of different institutions; $\epsilon_{i,n,t}$ captures the idiosyncratic preference over different assets. Assuming that $\epsilon_{i,n,t}$ are extreme-value distributed, the weight of asset n in institution i's portfolio also takes a logit form:

$$\theta_{i,n,t} = \frac{\exp\left(\kappa_{i,n} X_{n,t}\right)}{\sum_{n=0}^{N} \exp\left(\kappa_{i,n} X_{n,t}\right)}, \tag{5}$$

The NAV of an institution can be calculated using its asset portfolio weights,[7]

$$V_{i,t} = \sum_{n=0}^{N} \theta_{i,n,t} P_{n,t}. \tag{6}$$

The quantity of institution liability supplied is given by the asset under management divided

[7]Note that we can incorporate a management fee when calculating NAV. Because our focus is short-run in which the management fee is mostly fixed, we abstract away the management fee.

by the NAV,

$$Q_t^S(i) = \frac{W_{i,t}}{V_{i,t}}. \tag{7}$$

The demand for asset n of institution i is given by the institution's asset portfolio weights multiplied by its assets under management, then divided by the steady-state price of the asset:

$$Q_{i,n,t}^D = \frac{\theta_{i,n,t} W_{i,t}^*}{P_{n,t}^*}, \tag{8}$$

where $P_{n,t}^*$ is the price of asset n at time t in the steady state, and $W_{i,t}^*$ is the fund wealth calculated using steady-state asset prices. Again, this assumption ensures that a passive fund ($\kappa_i = 0$) would not trade in the absence of when asset prices fluctuate.

Market clearing The market for institution liabilities clears when the households' demand for institution i's liabilities equals its supply:

$$\sum_{h=0}^{H} Q_{h,i,t}^D = Q_{i,t}^S \tag{9}$$

for all institutions $i = 0, 1, ..., I$.

The asset market clears the demand for asset n equals its supply:

$$\sum_{i=0}^{I} Q_{i,n,t}^D = Q_{n,t}^S \tag{10}$$

for all assets $n = 0, 1, ..., N$.

Note that the two markets clear in different manners. The price of institution liabilities is the NAV, which is mechanically determined by the underlying assets according to the accounting rule, equation (6). Therefore, the market of institution liabilities clears mostly through quantity adjustment: mutual funds elastically create and destroy shares given investors' purchase and redemption. In comparison, the asset market clears mainly through prices, at least in the short run, because the quantity of outstanding assets is mostly fixed.

3.2 Joint dynamics of flows and asset prices

In this section, we focus on the joint dynamics of flows and asset prices after a shock. To this end, for any variable X_t we define $x_t = (X_t - X^*)/X^*$ as the percentage deviation of the level of that variable from its steady state.

Layer 1: Flow-to-performance relationship: We derive the equilibrium dynamics following a shock to asset values. Specifically, we log-linearize the household demand for institution liabilities, equation (3). Note that time-invariant characteristics would drop out as their deviation from the steady state is zero. The main time-varying characteristic that remains is the net asset value of the institutions. Note that the deviation of the net asset value from the steady state also equals the cumulative return, $v_{i,t} = \frac{V_{i,t} - V_{i,t}^*}{V_{i,t}^*}$, and the deviation of the household holding from the steady state also equals the cumulative fund flows, $f_{h,i,t} = \frac{Q_{h,i,t} - Q_{h,i,t}^*}{Q_{h,i,t}^*}$. We obtain the flow-to-performance relationship for each household:[8]

$$f_{h,i,t} = \beta_{h,i}(v_{i,t} - \overline{v}_{h,t}), \tag{11}$$

where $\overline{v}_{h,t} = \sum_i \theta_{h,i,t} v_{i,t}$ is the weighted average cumulative return of all institutions and outside options for household h.

Next, we aggregate this flow-to-performance relationship across households by multiplying equation (29) by the share of each household of a given institution $s_{h,i,t} = Q_{h,i,t}/\sum_h Q_{h,i,t}$ and summing them up, which gives rise to the following matrix form:

$$f_t = B_t(\beta) v_t, \tag{12}$$

[8]The full derivation is in Appendix A.

where $B_t(\beta)$ is the flow-to-performance matrix that depends on households' preference and holdings:

$$B_t(\beta) = \text{diag}(\mathbb{1}^\top(S_{H,t} \odot \beta)) - S_{H,t}(\theta_{H,t} \odot \beta), \tag{13}$$

where $S_{H,t}$ is a $H \times I$ matrix with elements $s_{h,i,t}$, the share of each household of a given institution, β is a $H \times I$ matrix with elements $\beta_{h,i}$, the sensitivity to returns for households, $\theta_{H,t}$ is a $H \times I$ matrix with elements $\theta_{h,i,t}$, representing the portfolio weights for each institution for each household, v_t is a $I \times 1$ column vector with elements $v_{i,t}$, the returns for each institution, $\mathbb{1}$ is the $H \times 1$ vector of 1.

However, in our application below, we will use only flow data aggregated at the fund level, implying a simpler expression: the $H \times I$ flow to performance matrix, β, collapses to a $1 \times I$ vector with the ith element being the flow-sensitivity β_i of each institution. Data on household asset holdings could be used to estimate a richer version of the first layer.

Given our focus on nonbank fragility in credit markets, we emphasize this well-known flow-to-performance relationship linking fund size (AUM) to past fund returns (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Berk and Green, 2004). Flows in and out of the mutual fund sector also played a central role in the 2020 turmoil (Falato et al., 2021; Haddad et al., 2021b; Ma et al., 2022). Our focus on this particular version of the model is justified by how important this economic channel is for nonbank fragility, both conceptually and practically. Note that conceptually we want to capture the total effect of returns on flows, which means the parameter β should capture (at least) two effects. The first is the effect of a fundamental shock to returns, the second is potential strategic complementarities across investors (Chen et al., 2010).[9] They both contribute to price-flow dynamics and our goal is not necessarily to distinguish between these two forces. Our empirical approach will thus focus on estimating "total" flow-sensitivity. In addition, our baseline model assumes households react to recent

[9]In a global games framework, they are naturally linked: strategic complementarities amplify fundamental shocks.

changes in fund returns rather that to anticipation of future expected returns. This is in line with recent empirical evidence including Ben-David et al. (2022).[10]

Layer 2: Institutions' asset demand: To derive institutions' asset demand, we follow the same steps of log-linearizing demand (equation (8)). We assume the main time-varying asset characteristic that affects institutions' asset demand is the asset's expected return, $r^e_{n,t}$. Each institution's demand function is given by:

$$q_{i,n,t} = \kappa_{i,n}(r^e_{n,t} - \overline{r}^e_{i,t}) + f_{i,t}, \tag{14}$$

where $\kappa_{i,n}$ is institution i's sensitivity to the expected return of asset n, $r^e_{n,t}$ is the expected return of asset n, $\overline{r}^e_{i,t} = \sum_n \theta_{i,n,t} r^e_{n,t}$ is average expected return of institution i's portfolio with $\theta_{i,n,t}$ being the portfolio weight, and $f_{i,t}$ is the fund flow of institution i.

Next, we aggregate each institution's demand function by multiplying equation (14) by the share of each institution of a given asset $s_{i,n,t} = Q_{i,n,t}/\sum_i Q_{i,n,t}$ and summing them up, which gives rise to the following matrix form:

$$q_t = K_t(\kappa) r^e_t + S_t^\top f_t, \tag{15}$$

where $K_t(\kappa)$ is the institution sensitivity matrix that depends on institutions' preference and asset holdings:

$$K_t(\kappa) = \mathrm{diag}(\mathbb{1}^\top (S_t \odot \kappa)) - S_t(\theta_t \odot \kappa), \tag{16}$$

where S_t is a $I \times N$ matrix with elements $s_{i,n,t}$, the holding share for asset n of institution i, κ is a $I \times N$ matrix with elements $\kappa_{i,n}$, θ_t is a $I \times N$ matrix with elements $\theta_{i,n,t}$, r^e_t is a $N \times 1$ column vector with elements $r^e_{n,t}$, $\mathbb{1}$ is the $I \times 1$ vector of 1, and f_t is a $I \times 1$ column vector with elements $f_{i,t}$.

[10]A version of the model with fully forward-looking households is nevertheless sketched in Appendix B.

Following Gabaix and Koijen (2021), we use the Taylor expansion of the expected return formula such that deviations from expected returns are given by: $r_t^e = \delta(d_t - p_t) + E\left[\Delta p_{t+1}\right]$, where δ is the income yield, d_t is the deviation of expected coupon payment from its steady state, p_t is the deviation of the asset price from its steady state, and $E\left[\Delta p_{t+1}\right]$ is the expected price change in the future. We also note that the returns of institutions equal the underlying asset returns multiplying the portfolio weights: $r_t = \theta_t p_t$. Substitute these two expressions into equation (15):

$$q_t = K_t(\kappa)\delta(d_t - p_t) + K_t(\kappa)E\left[\Delta p_{t+1}\right] + S_t^\top B_t(\beta)\theta_t p_t, \tag{17}$$

where δ is a $N \times N$ diagonal matrix with the nth diagonal element being $\delta_{n,n}$. Note $K_t(\kappa)\delta$ is the sensitivity of the quantity to the price, so it can be interpreted as the demand elasticity matrix of the institutions.

Equilibrium price dynamics: To derive the equilibrium price dynamics, we impose market clearing. For simplicity, we assume a fixed supply $q = 0$ and drop the expectation sign and the time subscript for the sensitivity matrices. The pricing equation can be simplified to $p_t = (I + \delta(I - (K\delta)^{-1}S^\top B\theta))^{-1}(\delta d_t + p_{t+1})$. Iterating forward:

$$p_t = \sum_{\tau=t}^{\infty}(I + \delta(I - (K\delta)^{-1}S^\top B\theta))^{-(\tau-t+1)}\delta d_\tau. \tag{18}$$

To provide intuition, suppose there is only one asset and one fund. Suppose there is negative news and that the expected cash flows permanently drop by d. This news leads to a first round of price drop of d. However, this is not the end because the deterioration in fund performance leads to an endogenous outflow of $S^\top B\theta d$. The outflow leads to a second round of price impact $(K\delta)^{-1}S^\top B\theta d$. This process continues and the nth round is $((K\delta)^{-1}S^\top B)^{n-1}\theta d$. The cumulative impact is thus $d + (K\delta)^{-1}S^\top B\theta d + ... + ((K\delta)^{-1}S^\top B\theta)^{n-1}d = (1 - (K\delta)^{-1}S^\top B\theta)^{-1}d$, following the geometric series formula, which is exactly what equation (18) gives us if we plug in $d_\tau = d$.

To understand the economics behind amplification, it is useful to consider two special cases. We illustrate them in the context of the one-asset-one-fund example. First, if the market were perfectly elastic ($\zeta \to \infty$), equation (18) becomes a variation of the NPV formula:

$$p_t = \sum_{\tau=t}^{\infty} (1+\delta)^{-(\tau-t+1)} \delta d_\tau, \tag{19}$$

which implies the deviation of price equals the discounted deviations of cash flows from the steady state. The asset price would drop by one percentage point for a one percentage point permanent drop in the expected cash flow $p_t = \sum_{\tau=t}^{\infty}(1+\delta)^{-(\tau-t+1)}\delta d = d$. In other words, the amplification is zero in the benchmark case of a perfectly elastic market. This makes clear the amplification of flows depends crucially on how elastic the market is. Second, note that if there is no flow-sensitivity ($B = 0$), the price change similarly reduces to $p_t = \sum_{\tau=t}^{\infty}(1 + \delta)^{-(\tau-t+1)}\delta d = d$. There is thus no amplification if there is no flow-sensitivity in our model. The combination of the two is necessary: when $\zeta < \infty$ and $B > 0$, $(1 - (K\delta)^{-1} S^\top B\theta) d > d$.

We now consider the multi-asset, multi-sector case, which we illustrate using a numerical example. Figure 1 shows an example of the model dynamics. We consider an economy with two sectors: mutual funds and insurance companies investing in two asset classes: IG and HY bonds. For the sake of illustration, we provide an example with parameters that are in line with the data, although we defer the details of estimation to the next section. Mutual funds face an positive flow-to-performance sensitivity β of 0.5 while insurance companies face a sensitivity of 0 because insurance companies' liabilities are not demandable as mutual funds. Both sectors do not perfectly elastic asset demand. The assets under management W and the distribution of bond holdings for each sector are calibrated to the 2019Q4 level. We simulate the dynamics following a sequence of permanent negative shocks to HY bonds. We assume that cumulative negative cash flow shocks grow over time in a smooth concave function, following $(1 - \exp\left(-\frac{t}{2}\right))$.

The example shows three interesting dynamics in equilibrium. First, there is a feedback loop between prices and flows. Negative shocks are amplified: they reduce HY bonds prices above and beyond what the magnitude of the shocks implies in a perfectly elastic market. Intuitively, the price drop reduces fund returns, which leads to outflows. Outflows then lead to asset sales by mutual funds, which further depresses asset prices.

Second, the model displays contagion across assets. Although there is no fundamental shock on IG bonds, their prices also drop in the equilibrium because institutions' demand for these assets falls. The cause of the cross-asset contagion is due to institutions' selling both IG bonds and HY bonds to meet redemptions.

Third, the model displays contagion across institutions. Although insurance companies are not directly affected by the outflows, their asset values decrease subsequently due to the falling asset prices. The magnitude of the reduction is smaller than mutual funds, which suffer from outflows on top of decreasing asset prices.

Importantly, the flow effects embodied in the first layer of the model are crucial to generate these dynamics. This is most easily seen when looking at the dotted lines in Figure 1. These lines correspond to the equilibrium under the assumption that institutions' wealth is exogenous, i.e. that outflows do not respond to fund performance ($\beta = 0$). In that case, there is neither amplification nor contagion.

Note also that while this example assumes away most of the investor heterogeneity for the sake of illustration, the framework's tractability makes it highly scalable: our empirical implementation incorporates variation in elasticities and flow sensitivities across investor groups.

3.3 Where are the "arbitrageurs"?

The previous discussion made clear that significant amplification coming from flows occurs when markets are inelastic at an aggregate level. This contrasts with the textbook view that "arbitrageurs" stand ready to trade aggressively on expected returns, rendering markets very elastic. An appealing aspect of our framework is that it focuses on institutions' trading behavior and asset demand directly, we can thus nest the existence of arbitrageurs explicitly without appealing to more abstract concepts like a "no arbitrage" condition. We discuss it from the perspective of three sets of agents: insurers, hedge funds, and the entry of new arbitrage capital.

Insurers are a natural first set of agents to consider since their funding is more stable than mutual funds in bad times (Coppola, 2021; Chodorow-Reich et al., 2021). In fact, there is evidence of insurers increasing their corporate bond positions during the Spring of 2020, particularly in bonds facing fire sales by mutual funds (O'Hara et al., 2021). We include insurers explicitly within our set of institutions and estimate their asset demand directly.

Other institutions might of course try to take advantage of price dislocations. Our empirical approach allows us to estimate the elasticity of a "residual investors" sector that hold all corporate bonds not held by mutual funds and insurers for which we have micro-data. The data will thus be directly informative about how elastic this residual sector is.

Concretely, hedge funds for instance are part of our residual sector. Hedge funds are often thought to perform important arbitrage activity. It is important to note however that the hedge fund sector tend to hold a small share of total corporate bonds outstanding. Moreover, hedge funds did not appear to increase significantly their positions in bad times: their corporate bond holdings fell by 2% in the first quarter of 2020.[11] These fact tend to

[11] Aggregate data on hedge funds holdings is available from the Enhanced Financial Accounts. Holdings of corporate and foreign bonds amounted to \$1.72B in 2019Q4 and \$1.69B in 2020Q1. In comparison, there was about \$6T of corporate bonds outstanding for U.S. non-financial firms at this time. Link:

mirror evidence from equity markets (Ben-David et al., 2012) and treasury markets (Kruttli et al., 2021). Interestingly, redemptions appeared to be a primary driver of selloffs, reminding us of the fact that hedge funds are intermediaries that do not have stable capital.

Our baseline counterfactuals take the size and elasticity of residual sector as fixed, equal to their estimated values. Nevertheless, we can study the equilibrium effect of the entry of new "arbitrage" capital within our framework. For example, within the context of the previous numerical example, Figure 2 shows that the entry of elastic arbitrage capital after a few days indeed bring prices closer to no-amplification benchmark. Section 6.1 below provides a calibration to the COVID crisis to size the potential effects of impact of slow-moving capital in the U.S. corporate bond market. Intuitively, in the presence of other large inelastic investors, new entrants must be both large and elastic enough to impact the market-clearing price. That calibration will inform us about the quantitative magnitudes.

4 Estimation

In this section, we describe the estimation of key parameters of the model. Specifically, we estimate for different investor groups: (1) flow-to-performance sensitivities and (2) demand elasticities. This heterogeneity in parameter estimates is important to realistically quantify the contagion of shocks through financial markets. Our framework is tractable enough to handle these multiple dimensions of heterogeneity. We report estimates for five investor groups: life insurers, P&C insurers, index-based funds, mutual funds, and a residual sector. In principle, the model can be estimated at lower level of aggregation given its tractability[12]

https://www.federalreserve.gov/releases/efa/efa-hedge-funds.htm

[12]In principle the model can handle a separate set of parameters for each individual fund, but the fund-level estimation can yield noisy results.

4.1 Flow to performance estimates

A key input to our model is the flow to performance sensitivities. We first use the CRSP data to construct a monthly panel of flows and returns for mutual funds. Since the flow data are at the fund level rather than at the fund-household level, we cannot estimate household-specific flow to performance sensitivities. Instead, we assume a representative household. As a result, the $H \times I$ flow to performance matrix, β, collapses to a $1 \times I$ vector with the ith element being β_i, and the $H \times I$ holding share matrix $S_{H,t}$ collapses to a $1 \times I$ vector of ones.

We define net flow as the net growth in fund assets adjusted for price changes. Formally,

$$\text{Flow}_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t})}{TNA_{i,t-1}}, \tag{20}$$

where $TNA_{i,t}$ is fund i's total net assets at time t, $R_{i,t}$ is the fund's return over the prior month.

We estimate flow sensitivity β in the cross-section of mutual funds using the following regression, allowing for:

$$f_{i,t} = \beta^+ r^+_{i,t} + \beta^- r^-_{i,t} + \gamma X_{i,t} + \tau_i + \tau_t + \epsilon_{i,t} \tag{21}$$

In line with prior work, we allow for different effects of positive $(r^+_{i,t})$ and negative returns $(r^-_{i,t})$. We thus estimate two betas for each mutual fund group. $X_{i,t}$ is a vector of control variables, including lagged flows, and we also include fund and time-fixed effects. A potential identification concern is that an exogenous flow shock drives asset prices and fund returns. Then, we will have a reverse causality issue. Note, however, that once we include time fixed effect, the only remaining flow shock in $\epsilon_{i,t}$ is idiosyncratic to a specific fund. If the fund is small enough, the idiosyncratic flow shock would have a negligible impact on the asset prices and hence fund returns.

Table 4 shows that across mutual fund groups fund flows are highly responsive to returns, a relation well documented in prior literature (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). We find that flows are more sensitive to negative returns, consistent with Chen, Goldstein, and Jiang (2010). A one percentage point negative monthly fund return leads to a net outflow in the magnitude of 31% of the fund's assets under management. Positive returns have significant effects, but the magnitudes are considerably smaller.

For insurers, we assume that their flow sensitivity is zero. This is largely in line with the data. Indeed, Table 5 shows that flow sensitivity in the insurance sector is considerably smaller than in the mutual fund sector and generally not significantly different from zero.[13] We run regressions in a similar spirit to the mutual fund sector. We use panel data from Capital IQ on direct premiums written to measure flows from households to insurers. We regress premiums growth on quarterly corporate bond portfolio returns. We assume a flow sensitivity of zero for the residual sector since we cannot observe their balance sheet.

4.2 Demand estimates

To simulate the model, we also need estimates of price elasticities of demand. Based on the empirically tractable model derived in Koijen and Yogo (2019), we can write log demand as a function of prices and bond characteristics. We build on this by estimating how *changes* in holdings respond to (exogenous) price changes, similar in spirit to van der Beck et al. (2022). We subtract out the change in holdings relative to an index bond fund to identify

[13] Using the estimated β instead of zero for insurers does not materially affect any results.

how institutional investors deviate from the market index portfolio.[14] The model is thus:

$$\Delta \tilde{q}_{it}(n) = \gamma_{0i}\Delta p_t(n) + \gamma_{1i}x_t(n) + \alpha_{i,t} + \alpha_n + \nu_{it}(n) \tag{22}$$

where $\Delta p_t(n) = s_t(n) \times m_t(n) - s_{t-1}(n) \times m_{t-1}(n)$ represents changes in prices based on credit spreads. Fund-time fixed effects absorb variation in fund size and allocation to the outside option, while security fixed effects absorb time-invariant characteristics of the asset that may be correlated with latent demand.

One challenge with estimating elasticities from security-level data (as per the literature) for corporate bonds is that there are many more unique bonds than equities.[15] The sheer number of bonds outstanding would lead to many zero holdings. To overcome this challenge, we aggregate the data using bond types rather than unique securities, similar in spirit to what is proposed by Chaudhary et al. (2023), using the method proposed in Mota and Siani (2023). Bonds are categorized into 72 unique "bond types" based on five dimensions of bond characteristics, including rating, size, and time to maturity.[16] Tables IA.1 reports summary statistics of the types. The median bond type is held by 2,410 unique funds and has 454 unique bonds.[17]

[14]To proxy for the index bond fun, we use the largest index fund in the data (Vanguard Total Bond Market Index Fund), so that the left hand side variable is $\Delta \tilde{q}_{it}(n) = \Delta q_{it}(n) - \Delta q_{It}(n)$, where $\Delta q_{it}(n) = \ln\left(\frac{Q_{it}(n)}{A_{i,t}}\right) - \ln\left(\frac{Q_{it-1}(n)}{A_{i,t-1}}\right)$ represents changes in investor i's holdings of asset n (absent valuation changes) in quarter t, normalized by its assets under management (AUM). If the index fund does not hold a given bond type in that quarter, then we set $\Delta \tilde{q}_{it}(n) = \Delta q_{it}(n)$. Normalizing by AUM ensures that we are not incorporating changes in quantities held arising from the fluctuating size of the institution. However, because AUM is mechanically affected by prices, we will adjust the estimated coefficient by portfolio weights to map to the price elasticity.

[15]Bonds have finite maturities of 7-8 years on average, and thus are often replaced with new bonds at redemption; moreover one firm may issue bonds with many different characteristics. See Mota and Siani (2023) for a discussion.

[16]Following Mota and Siani (2023), we unique bond type based on five dimensions: credit rating (A-rated, BBB-rated, and high yield), time to maturity (up to three years, three to ten years, and ten years or more), issuance size (up to 500 million and 500 million or more), covenants (covenant lite or not, where covenant lite bonds have fewer than the median number of covenants across all bonds within a period), and redemption option (redemption option or not).

[17]In Table IA.2, we report the bond types k that have the highest total amount of outstanding in that bond type across the full sample from 2007Q1 to 2021Q4. The top bond type across the sample by amount

Next, we tackle the classic endogeneity problem when estimating elasticities of demand. We exploit exogenous net flows into institutions that hold the bond type in the previous period. Exogenous flow-based price changes have been used to identify the slope of investor demand curves going back to Shleifer (1986). Here, we recover the exogenous component of flows by residualizing any fund-specific characteristics and contemporaneous fund returns, in the spirit of van der Beck et al. (2022), $f_t^i = \beta ret_t^i + \alpha_i + f_t^{\perp,i}$. We aggregate the orthogonalized component of flows $\hat{f}_t^{\perp,i}$, to the bond type level in each period using the prior period holdings distribution. We take out the own-fund contribution to the residual, and compute an instrument at the fund, bond type, and quarter level:

$$z_{it}(k)^{flow} = \frac{\sum_{j \neq i} \hat{f}_{j,t}^{\perp} \times AUM_{j,t-1} \times w_{j,t-1}(k)}{mc_{k,t-1}} \tag{23}$$

where $w_{it}(k) = \frac{\sum_{b \in K} MV_{bit}}{AUM_{it}}$ is the portfolio weight investor i holds of bond type k's in period t, and $mc_{k,t-1} = \sum_{b \in k} P_{t-1}(b) amt_{t-1}(b)$ is the market cap (total market value) across all bonds in bond type k.[18]

We run IV regressions for each investor group using fund-bondtype-quarter level data from 2007-2021.[19] We control for duration-matched U.S. Treasury yield, issuer credit rating, time to maturity, initial offering amount (logged), and the bid-ask spread.[20] We include fund-time fixed effects to absorb time-variation in fund characteristics such as investment strategies or allocations to the outside option. The outcome variable is the total par value held of each bond type normalized by fund size.[21] The endogenous variable is the change

outstanding encompasses BBB-rated bonds that are 3-10 years remaining, over 500 million in size, are not covenant-lite and have a redemption option. Table IA.3 reports the top bond types by time period. While popular tenor types have not changed significantly, lower rated, in particular BBB bonds, have become more popular in the post-crisis period.

[18]For institutions without flow information, we assign the instrument at the bond type quarter level.

[19]We include all funds that have AUM of over \$10 million between 2007-2021, and only when the portfolio weights are between 0 and 1.

[20]We aggregate bond characteristics for each bond type at the quarter level by computing averages of characteristics weighted by amount outstanding of each bond. To avoid undue influence of outliers, we winsorize all characteristics at the 1% level before aggregating them to the bond type - quarter level.

[21]We drop observations where portfolio weights are greater than one.

in the credit spread, scaled by the time to maturity to map to prices.[22] In an important addition to the existing literature, we construct a "residual" sector, which we treat as the combination of non-insurer and non-mutual funds that are observed in the data, in addition to one last fund that holds the remainder of amount outstanding for bonds in our sample.[23]

We show in Table 1 that the instrument is relevant: the coefficient estimates are negative and significant, indicating that credit spreads decline when there are more net flows into institutions holding that bond type. Table 2 reports the second stage coefficient estimates which are positive and significant, indicating downward sloping demand. We can translate coefficient estimates into a price elasticity of demand, summarized in Table 3.[24] Net of the benchmark index holdings, insurers are more responsive to prices, with elasticities between 1.3-1.9, while index funds are virtually inelastic, with an elasticity of 0. Active mutual funds have an elasticity of 0.9. Finally, the residual sector has an elasticity of 1.2, far lower than is implied by the infinitely elastic, deep-pocketed risk-neutral arbitrageur characterized in standard asset pricing models.[25] This is consistent with a view that markets are far more inelastic than implied by standard models (e.g., Gabaix and Koijen (2021)), and demonstrates

[22]We use the log approximation of $\log(P) \approx -ny$, where n is the number of years remaining, and y is the yield to maturity.

[23]That is, the last residual fund holds for each bond the total bond outstanding minus the amount held by funds observed in the data. The residual sector includes hedge funds and pension funds; the last fund in the residual sector includes unreported hedge funds, pension funds, governments, foreign entities, and households. We do not observe the equivalent of fund size or outside share for the last fund in the residual sector. In the estimation, we deal with this by assuming a constant fund value for the last fund in the residual sector, which is then absorbed with the fund-time fixed effect. In the model simulation, we assume the residual sector has the same outside share as the average of other investors and use this to back out the fund size.

[24]Note that since $\Delta q_{it}(k) = \ln \frac{Q_{it}(k)}{A_{it}} - \ln \frac{Q_{it-1}(k)}{A_{it-1}}$,

$$\gamma_i = \frac{\partial \Delta q_{it}(k)}{\partial (s_t(k) \times m_t(k))} = -\frac{\partial \ln \frac{Q_{it}(k)}{A_{it}}}{\partial p_t(k)} = -\left[\frac{\partial q_{it}(k)}{\partial p_t(k)} - \frac{Q_{it}(k)P_t(k)}{A_{it}}\right] \implies -\frac{\partial q_{it}(k)}{\partial p_t(k)} = \gamma_i - \omega_{it}(k) \tag{24}$$

where $\omega_{it}(k) = \frac{Q_{it}(k)P_t(k)}{A_{it}}$.

[25]Our estimates are lower than those in Bretscher et al. (2022), which estimate elasticities for individual bonds of between one and 14. The difference likely reflects our less granular securities grouping (intuitively, the more granular the security group, the more substitutable the securities are for each other and thus the higher the elasticities). Consistent with this intuition, splitting the bonds into less granular security groups (48 instead of 72) reduces the elasticities somewhat.

the importance of estimating elasticities when quantifying the aggregate effects of fireselling in crises.[26] In a final step, we transform these coefficients into the appropriate vector of model parameters κ.[27]

4.3 Cross-fund variation in parameters

We can relate the fund-level flow-to-performance sensitivities to portfolio allocations and overall elasticities. Theory suggests that more flighty investors would encourage managers to invest in more liquid assets that are easier to sell in a crisis. We test this in two ways. First, we run cross-sectional regressions of fund-level portfolio allocations on the fund-specific flow-to-performance sensitivity estimate β_i.

$$\omega_{it}(n) = \gamma_1 \hat{\beta}_i + \gamma_2 Retail_{it} + \gamma_3 \ln(TNA)_{it} + \alpha_t + \epsilon_{it}, \tag{25}$$

where $\hat{\beta}_i$ is recovered using negative shocks from the time series of fund flows for fund i, $Retail_{it}$ is the fund-level share of retail investors that varies over time, and $\ln(TNA)_{it}$ is the fund's total net assets. We include year fixed effects to absorb macro trends. Table 6 reports the results among mutual funds. We find that indeed, funds with higher estimated betas are more likely to invest their bond portfolios in shorter duration assets and less so in long duration bonds. Funds with higher shares of retail investors invest less in IG bonds and more in long HY bonds. Index funds are more likely to buy IG bonds, and long IG bonds

[26] In the baseline simulation, we use one pooled elasticity for each fund class. However, our framework is flexible enough to incorporate different levels of aggregation for parameter estimates, with the caveat that more granular estimation yields noisier values. That being said, we can estimate an asset class-specific elasticity for each fund class. See Table IA.5 in the Internet Appendix for a summary of these elasticities, with standard errors in parentheses below each estimate. Consistent with findings in Bretscher et al. (2022), funds are generally more elastic over IG bonds.

[27] As a robustness, we run the baseline specification across different time periods and report the results in Table IA.4 in the Internet Appendix. There is not a significant variation across time periods in elasticities for insurers and the residual investor. Mutual funds have higher elasticities in the post-GFC period, but they decline in the 2019-2021 period. The variation in inelasticities over time likely arises from variation in portfolio allocations.

in particular.[28]

Second, we consider fund-level correlations between flow-to-performance sensitivity and demand elasticity.[29]. Figure 5 shows a binned scatter plot of flow-performance sensitivities and demand elasticities for the cross-section of funds. We find that within the subset of funds in our sample that have positive flow-to-performance estimates and well-behaved (downward sloping) demand curves, there is a positive relationship between the beta estimate and the elasticity estimates, consistent with fund managers holding assets with lower price impacts (higher price elasticities) if they have flightier investors.

5 Systemic risk across assets

Using the model dynamics derived in Section 3.2 and the estimated parameters, we can construct a new measure of the systemic importance of different *assets*. This contrasts with conventional measures focusing on large institutions. It is worth noting that this measure is macro-prudential in nature. It captures the contribution of a specific asset to the aggregate market fragility but do not measure the risk of the individual asset or institution by itself.

We ask: what is the impact on the *aggregate* bond price index if asset n experiences an exogenous shock to its price? For each asset, the size of the impact depends on how prices affect flows and how flows then affect prices. As described in the previous section, these objects are functions of the asset's share of the overall market and the characteristics of the

[28]Given how noisy the beta estimates are, we run a robustness where we rerun the analysis conditional on non-negative betas. The results, which are qualitatively similar, are reported in Table IA.6 in the Internet Appendix. The coefficients are larger in absolute magnitude, except for the coefficient on HY short share, which is closer to 0 and not statistically significant.

[29]Fund-level elasticity estimates are noisy, but we can verify that fund-level estimates aggregate roughly to the investment category estimates used in the baseline estimation. We run the baseline regression at the fund level, replacing fund-year fixed effects with fund fixed effects. The AUM-weighted average second-stage IV coefficient is 2.65, 0.81, and 1.38 for life insurers, active mutual funds, and property and casualty insurers, respectively, after winsorizing at the 5% to remove the influence of significant outliers; the AUM-weighted average flow to performance sensitivity across active mutual funds is 0.4. This is roughly in line with estimates reported in Tables 2 and 4.

funds that hold the asset, including portfolio weights, the flow to return sensitivity, demand elasticities, and other asset holdings. Building on this intuition, the asset fragility measure is given by

$$\textbf{Asset systemic measure} \equiv \alpha'(I - (K\delta)^{-1}S^{\top}B\theta)^{-1}./\alpha' \tag{26}$$

We normalize each asset's effect on the market by the total market share of this asset α_n so that the shock is on a per-dollar basis. In other words, we normalize asset fragility to 1 in the absence of amplification (i.e., when $\beta = 0$ or $\kappa \to \infty$). Asset systemic importance measures the contribution an asset makes to aggregate fragility. It is not a measure of the risk of the asset itself.[30]

Using our estimates of flow sensitivity and demand elasticities, as well as observed holdings shares and fund values to compute this measure in the cross-section of bonds. This constrast with typical measure of systemic risk that focuses on large institutions. Table 7 shows the asset fragility estimates for different asset classes as of 2019, splitting our sample of bonds into four categories based on IG vs. HY and long-term (5 or more years remaining) vs. short-term. We call these four categories "asset classes", to distinguish them from the 72 "bond types" we use as the unit of observation in the demand estimation described above.

Across asset classes, estimates are between 1.2 and 1.9. IG bonds are somewhat less systemic than HY bonds. In terms of economic magnitudes, the least systemic asset class are long-term IG bonds, with a fragility of 1.23. This corresponds to some non-trivial amount of amplification, about 20% above no-amplification benchmark of 1. Short-term IG bonds are more systemic, with a fragility of 1.9.

Interestingly, within rating categories, short-term bonds are more systemic than long-term bonds. This is the reverse of conventional liquidity measures, that typically rank short-

[30]This formula shares some elements with the fire-sales spillover measure of Falato et al. (2021), the fragility measure of Jiang et al. (2022), or the stock price fragility measure of Greenwood and Thesmar (2011).

term bonds as more liquid. The key aspect here is that our measure includes investors' price elasticity for these bonds and their propensity to sell them in bad times. Our framework allows us to rationalize these differences across bonds. In particular, mutual funds are more likely to hold HY and short-term bonds. In contrasts, insurers and pensions are large investors for IG and long-term bonds, playing an important stabilizing role that is reflected in our lower estimates for these assets (Coppola, 2021).

6 The March 2020 turmoil and intervention

The onset of the COVID-19 crisis saw significant disruptions in the corporate bond market, including sudden spikes in spreads and outflows from bond mutual funds as liquidity dried up in a matter of days in March 2020 (Haddad et al., 2021b; Falato et al., 2021; Kargar et al., 2021; O'Hara et al., 2021). Our framework is designed to understand such an episode and can capture feedback loops between price changes and flows, as well as contagion effects across asset classes and institutions. In this section, we first match our model to the March 2020 turmoil and then we run counterfactuals to evaluate different policies that attempt to mitigate this large negative shock to the corporate bond market.

6.1 Matching the model to the March 2020 turmoil

We match our model using three ingredients. First, we feed a sequence of daily price shocks to IG and HY bonds separately for the first 13 days of the crisis in March. The magnitudes of these shocks are implied by the rise of CDS spreads from March 2-19 and capture a sudden deterioration in fundamental credit risk. At their peak, the shock to IG bonds amounted to 120 basis points, and to HY bonds to 420 basis points, in line with Haddad et al. (2021b). We however feed no initial flow shock to the mutual fund sector, such that the dynamics of outflows will be entirely endogenous to our equilibrium model.

Second, we use estimates of (β, κ) documented above to capture cross-sectional differences in flow sensitivities and elasticities across institutions, as described above. Specifically, we consider an economy with four investor sector sectors: life insurers, P&C insurers, mutual funds, and a residual sector. The assets under management W and the portfolios θ for each institution are calibrated to the 2019Q4 levels.[31] Our framework is tractable enough to account for this rich investor heterogeneity of the data.

Third, we add an additional economic force to institutions' asset demand: the tendency to potentially sell certain assets first to meet redemption given outflows. In our baseline model, a mutual fund sells assets proportionally when faced with outflows holding future expected returns constant. However, empirically it is now well understood that institutions have a tendency to sell more liquid assets first (Ma, Xiao, and Zeng, 2022). Formally, the demand for assets depends also on the level of outflows f_t faced by the fund: $\Delta X_t = (\pi_t, f_t)$. The loading on outflows for a specific asset, which we refer to as $\lambda(n)$, has a natural interpretation in terms of (relative) transaction costs: an asset with $\lambda > 0$ will be sold more than proportionally after an outflow, while an asset with $\lambda < 0$ will be sold less than proportionally (for the same news about their expected returns). We allow two values of λ, one for each of IG and HY bonds, and choose $(\lambda_{IG}, \lambda_{HY}) = (1.8, -1.8)$ in order to help match some important moments of the data, as explained below. Table IA.7 in the Internet Appendix uses panel regressions to confirm that mutual funds have a tendency to sell IG bonds first when facing outflows, in line with the evidence in Ma, Xiao, and Zeng (2022).[32]

The estimated model can match three key moments of price and flow dynamics of the

[31] In the simulation, we set the outside share for each fund group to 25%.

[32] Specifically, on fund-bond category-quarter level data, we regress the log quantity held of a given bond category by a fund on the percent of outflows in that quarter interacted with dummy variables for the bond category falling within IG or HY, respectively. We include quarter fixed effects and IG fixed effects, and estimate a coefficient of 0.6 for IG interacted with outflows and -0.7 for HY interacted with outflows, consistent with demand for IG bonds falling more than demand for HY bonds for every given unit of outflow.

March 2020 turmoil. Figure 3 shows the dynamics of bond prices and AUM in our model simulation. First, there is an average cumulative mutual fund outflow of approximately 5% of in line with Falato et al. (2021).[33] Second, we see a large bond price decline of 13 to 17%, even for safer IG bonds with moderate credit risk (Haddad et al., 2021b). Finally, we see that a large share of the IG price decline is due to amplification, while amplification is much lower for HY bonds. This asymmetry is one of the most important facts in Haddad et al. (2021b), which document in particular the widening of the CDS-bond basis (its empirical equivalent). Our model is able to capture some of these key dynamics in spite of being parsimonious and using parameters estimates from pre-2020. Note however that our simple model underestimates the decline in bond prices and the widening of the IG CDS-bond basis relative to the data, in line with not being the only force at play during these times.

Slow-Moving Arbitrage Capital: As a way to size how inelastic the corporate bond market was during that episode, it is helpful to consider the potential effects of arbitrage capital on market prices. How large and elastic must new entrants be to move asset prices closer to the no-amplification benchmark?

Figure 4 illustrates the entry of elastic arbitrageurs of different size. They enter at $t = 8$ and we assume their elasticity is equal to 10, approximately five times more than insurers. Panel (b) assumes that their initial AUM is $400B and grows at 10% daily. These are very large numbers, but strikingly the top panel shows their impact on market prices is almost negligible, as compared to the no entry benchmark displayed in Panel (a). Intuitively, in the presence of other large inelastic investors, new entrants might make profits but might not be large enough to impact the market-clearing price.

Panel (c) shows that new entrants must be implausibly large to have significant price effects. If we assume that that their initial size is five times larger ($2T), prices would now

[33]Note that not all the decline of AUM in the figure is driven by flows, the rest is driven by declining prices.

be significantly closer to the no-amplification benchmark. We want to emphasize how large these figures are relative to real-world institutions. For example, actual hedge funds holdings were close to \$2B, which is only about 0.1% of the last simulation.

6.2 Policy intervention

Policy-makers often choose to intervene in the face of market turmoil, and March 2020 was no exception. Intervention can involve some form of unconventional monetary or liquidity policy, where the typical rationale is to stop feedback loops between declining asset prices and asset sales. How to design/conduct these interventions is still largely an open question. In practice, vastly different policies have been implemented or discussed. For instance, the interventions carried out by the Federal Reserve in the Spring of 2020 were pretty broad: a large interest rate cut and a program of corporate bond purchases. On the other hand, other proposals have suggested more focus on the fragile mutual fund sector specifically. While traditional banks are often subject to such targeted interventions in crises, similar policies were not implemented for non-banks intermediaries such as bond mutual funds, despite being at the center of the 2020 turmoil.

In this section, we use our model to study the equilibrium effects of ex-post interventions on corporate bond prices and institutional investors. Our framework is well suited to compare different interventions within a unifying framework. We run counterfactuals related to four types of ex-post interventions: conventional monetary policy, asset purchases, direct lending to funds, and redemption restrictions on mutual fund shares. We can also use the model to measure how well "targeted" an intervention is, given the large heterogeneity in fragility documented above.

While our model can simulate the effects of these policies on prices and fund value, we note from the outset that any counterfactual analysis is subject to potential caveats. First, we can only study interventions that can be clearly mapped to variables in our framework. Certain dimensions of policy are thus outside the current scope of our analysis, such as conditional policy promises (Haddad et al., 2021a) or signaling (Cieslak et al., 2019). Second, the counterfactual exercise takes estimated parameters as invariant and re-calculates equilibrium prices and flows across assets and institutions. Nevertheless, we cannot fully rule out the concern that policies might change the underlying parameters.

6.2.1 Conventional monetary policy

First, in Figure 6, we simulate a conventional policy rate cut of 50 basis points implemented after the negative shock to bond markets. Specifically, we allow the price of each asset to increase by $0.50\% \times m(n)$ at the implementation of the policy, where $m(n)$ equals the average remaining maturity for each asset. In 2019, the average remaining maturity for long-term IG, short-term IG, long-term HY, and short-term HY bonds is 7.2, 2.9, 6.6, and 3.8 years, respectively.

The top panels show the effects of intervening two weeks after the start of the crisis ($T = 14$). We see a broad market rebound. The left panel shows that the fall in asset prices is reversed immediately following the rate cut. Because IG bonds are longer duration, their prices rebound nevertheless more relative to HY bonds. The right panel of Figure 6 shows that there is also a rebound in the AUM of both mutual funds and insurers.[34]

[34]Note that we focus on the short-term effect of an emergency rate cut during a crisis. Changes in the policy rate can have other effects on the size of the mutual fund sector, as shown by Bretscher et al. (2022): the sector tends to shrink in a rising rate environment for example. See also Fang (2022) for an analysis of monetary transmission through mutual fund flows.

6.2.2 Corporate bond purchases

Next, we evaluate a policy where the central bank purchases corporate bonds directly. In March 2020, in response to the market turmoil brought upon by the COVID-19 pandemic, the Federal Reserve announced its intention to purchase up to $750 billion in primarily IG corporate bonds. While the actual purchases were much smaller, the announcement effect was significant (Haddad et al., 2021a; Boyarchenko et al., 2022) and the potential purchase size was over 7% of the corporate bond market.[35]

Figure 7 considers a policy of expected purchases of 5% of short-term IG bonds. The policy is announced at $T = 14$, but purchases actually start at $T = 20$. There is an immediate rebound at the announcement, followed by a small upward drift in prices until purchases begin. This dynamic of announcement-date effect is in line with what we observed in March 2023 upon the Fed's announcement of the corporate bond purchase program (Boyarchenko et al., 2022; Haddad et al., 2021a). Naturally, short-term IG bonds benefit from these asset purchases, as they are directly targeted; however, there is also a visible rebound for HY bonds. This is due to the rebound of fund wealth as well as the investment mandate increasing demand for HY assets. Both mutual fund and insurers AUM rebound.

6.2.3 Direct lending to mutual funds

In Figure 8, we consider the effects of a policy that lends directly to bond mutual funds. While such a policy currently has not been implemented for such nonbank intermediaries, such direct lending (or "lender of last resort") is a classical policy tool for traditional banks. In the counterfactual, we assume funds can borrow against up to 10% of their IG assets. Specifically, net outflows from mutual funds decrease by the amount borrowed from the

[35] At the end of 2019, there was over $9.5 trillion in outstanding corporate bonds. Source: SIFMA 2021 Capital Markets Factbook).

central bank. The intervention helps to support prices and reduce outflows, although the timing matters little for the eventual rebound. The effect on HY bond prices is large, given that they are predominantly held by mutual funds. Note that the size of the mutual fund sector in holding corporate bonds is an important driver of the magnitude of this effect. At the end of 2019, mutual funds and ETFs made up around 20% of corporate bond holdings, and this share has been increasing over time (see for example Li et al. (2022)). This evidence suggests that acting as a "lender of last resort" towards nonbanks could potentially be effective, particularly if mutual funds are a large share of holders.

6.2.4 Redemption restrictions

We next consider a policy of freezing mutual fund redemption. This is also a policy tool that has been repeatedly implemented in the banking sector. At the implementation of the policy, we set the net flow for each fund to be bounded below at zero. Figure 9 displays the effects. This type of intervention is naturally particularly effective at preventing the mutual fund sector from shrinking considerably, but that the timing is crucial. Intervening early ($T = 2$, bottom panel) mitigates significant drops in fund values and asset prices, particularly IG bonds given funds are more likely to sell IG bonds first in the event of large outflows. Late intervention ($T = 14$, top panel) is virtually ineffective, because much of the performance induced outflow would already have occurred.

6.3 Policy targeting and price impact

In practice, policymakers often prefer to limit the "size" of intervention. For example, they might explicitly want to limit the increase in the central bank's balance sheet when designing an asset purchases program. We can use our model to construct a measure of a policy's "bang for the buck." In order to have a measure that can be used to compare very different types of interventions, it is useful to introduce some notation in order to define a unifying framework.

For illustration, consider first the case of asset purchases. Let g be a $N \times 1$ vector of permanent government purchase of bonds (permanent in the sense that they do not revert within our horizon), with the nth element being the quantity of asset n being purchased as a percentage of the total outstanding for this asset. The impact on the market index is $\alpha'(I - (K\delta)^{-1}S^{\top}B\theta)^{-1}K^{-1}g$, where α is the market share of each asset. The total value of the purchase as a fraction of the bond market value is $\alpha' g$.

The policy multiplier of g, or its "bang for the buck" is simply the ratio of the two:

$$\text{Policy multiplier}(g) = \frac{\alpha'(I - (K\delta)^{-1}S^{\top}B\theta)^{-1}K^{-1}g}{\alpha' g} \tag{27}$$

If a policy intervention is not a direct purchase, say, an interest rate cut, we can convert such an intervention into an asset purchase that generates an equivalent price impact. For instance, for an interest rate cut, we can solve the equivalent asset purchase g_{MP} using the following relationship: $\delta d^{MP} = \delta(0.25\% \times M) = \kappa^{-1}g_{MP}$. The implied incremental government purchase is $g_{MP} = \kappa\delta \cdot (0.25\% \times M)$. The direct lending is straightforward, $\kappa^{-1}g_{DL} = \kappa^{-1}(S(\theta L))$. Note we cannot calculate the asset purchase equivalent of redemption restriction or swing pricing because they are about changing β.

We can also compute a benchmark for the best-targeted intervention that maximizes the cumulative impact on the aggregate bond market index for a given budget. A formal derivation can be found in Appendix D. The maximum-price-impact benchmark turns out to be a function of the amplification matrix A. Targeting follows a pecking order: the policy-maker should first target the asset with the highest price impact on the market, accounting for amplification through flows. The policy-maker then should move to the asset with the next highest price impact until the budget is exhausted. This result suggests that simply supporting the most beaten-up assets or assisting the institutions that suffer the most outflows or value loss in a crisis might not have the highest "bang-for-the-buck". Instead, to maximize price impact from a macro-prudential perspective it is best to target the assets or institutions that are central in the network that propagates and amplify the shock.

We can use these concepts to compare how well targeted the different types of interventions studied above were in addressing fragility in March 2020. Figure 10 compares these four interventions using our model estimates. It also reports the maximum-price-impact benchmark. This reveals that direct lending ("DL") to mutual funds is the best-targeted intervention. This is because it targets especially flow-sensitive investors. This gives support to some of the proposal to extend lender of last resort policies to nonbanks, at least if the goal was to maximize price impact under a limited budget. This policy is actually close to the maximum-price-impact benchmark. On the other hand, conventional monetary policy ("MP") is the least well-targeted because it has the biggest price effect on less systemic long-term IG assets, which have the highest duration. This is not necessarily surprising: the return to the zero lower bound was dictated by many considerations other than addressing the bond market turmoil specifically. Asset purchases ("E[AP]") are better targeted than the conventional rate cut but not as much as direct lending to mutual funds.

7 Conclusion

This paper develops a two-layer asset demand framework to analyze the fragility of the corporate bond market. Equilibrium asset prices reflect the demand of both households and institutional investors. The model features a feedback loop between investor outflows and asset prices, as well as contagion across assets and institutions. The model parameters can be estimated using micro-data on bond prices, institutional investors' holdings, and fund flows. We use our estimated model to evaluate the equilibrium impact on asset prices of policies designed to mitigate market fragility, including unconventional monetary and liquidity policies.

Our framework's underlying economics are general enough and its estimation methodology is flexible enough to be applied to other settings. While we focus on corporate bond markets, similar equilibrium dynamics are at play in equity, government bonds, or currency markets. Moreover, the heterogeneity in institutions could be enriched, accounting for differences between active and passive mutual funds or between different types of insurers and pensions. Finally, the model could be extended to incorporate a third layer of debt issuance and firm investment. This would allow for quantifying the effects of financial market disruptions and policy interventions on real activity using an integrated framework and structural estimation.

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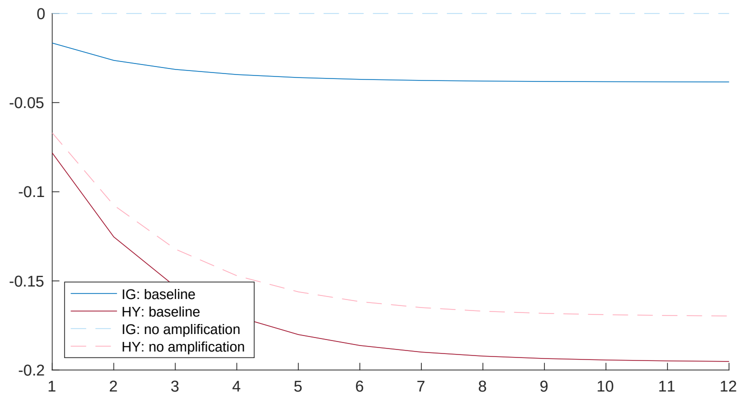
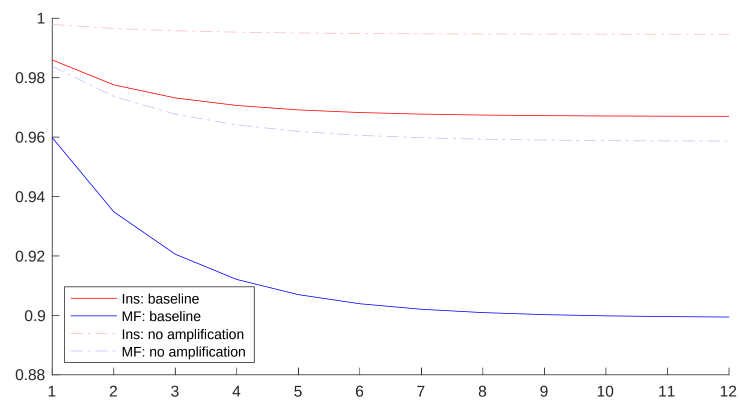
Figure 1: Model dynamics: example



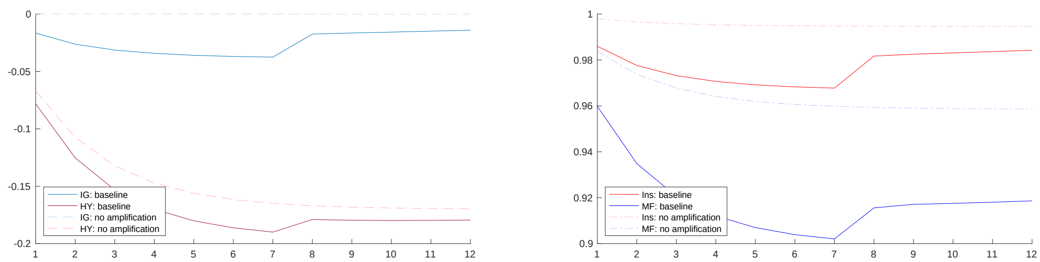
(a) Prices



(b) AUM

Note: This graph shows simulated paths of AUM and asset prices given a series of smooth negative shocks. Parameters values are described in Section 3.2. “No amplification” refers to the case in which $\beta = 0$, meaning funds do not experience outflows in response to poor returns.

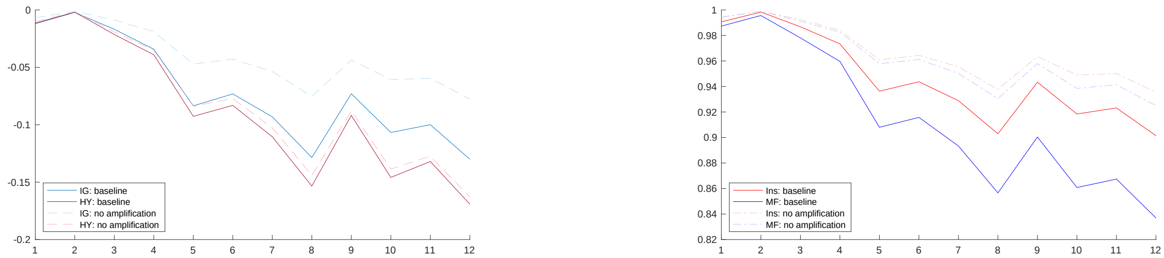
Figure 2: Slow-Moving Arbitrage Capital: Example



Bond prices | Institutions' AUM

Note: This graph shows simulated paths of AUM and asset prices given a series of smooth negative shocks similar to Figure 1. Elastic arbitrageur enters at t=8 and raise capital progressively.

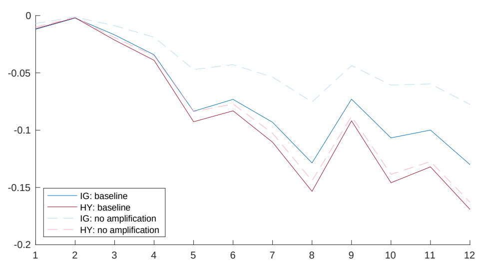
Figure 3: Model-implied dynamics



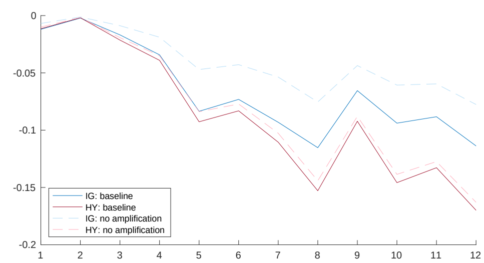
(a) Asset prices

(b) Fund AUM

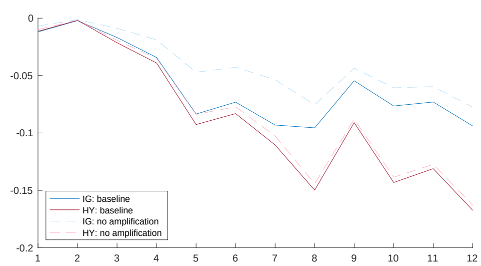
Note: This graph shows the counterfactual AUM and asset prices with fundamental shocks to asset prices. There is no policy intervention in this simulation.



(a) No entry baseline



(b) Entry: $\text{AUM}_0 = \$400B$, $g = 10\%$



(c) Entry: $\text{AUM}_0 = \$2T$, $g = 10\%$

Figure 4: Slow-moving Arbitrage Capital: COVID crisis simulation

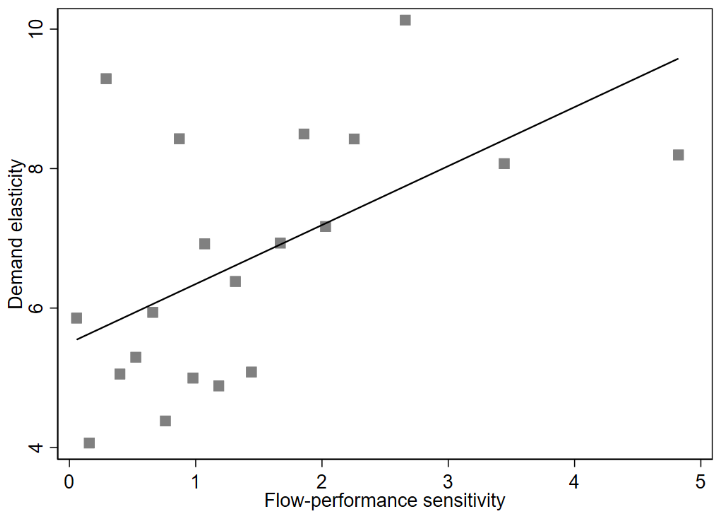
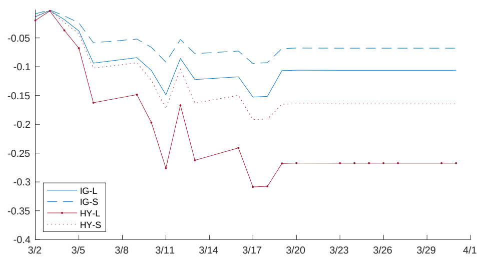


Figure 5: Funds with higher betas have higher elasticities

Figure 6: Counterfactual simulation: rate cut

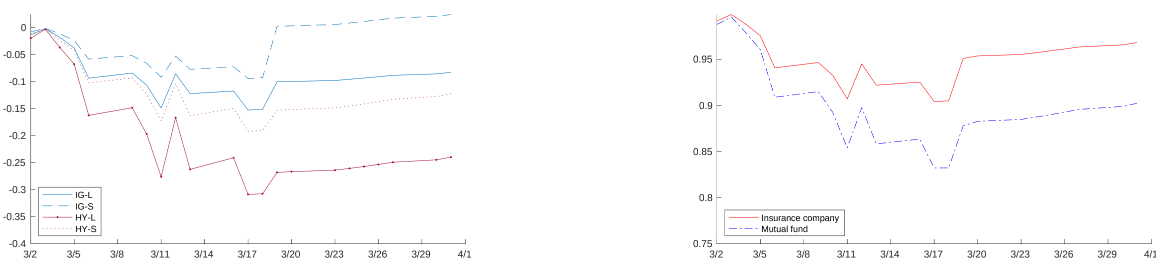


(a) Prices with $T = 14$

(b) AUM with $T = 14$

Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices. The central bank cut the policy rate by 50 basis points on day 14.

Figure 7: Counterfactual simulation: expected asset purchases

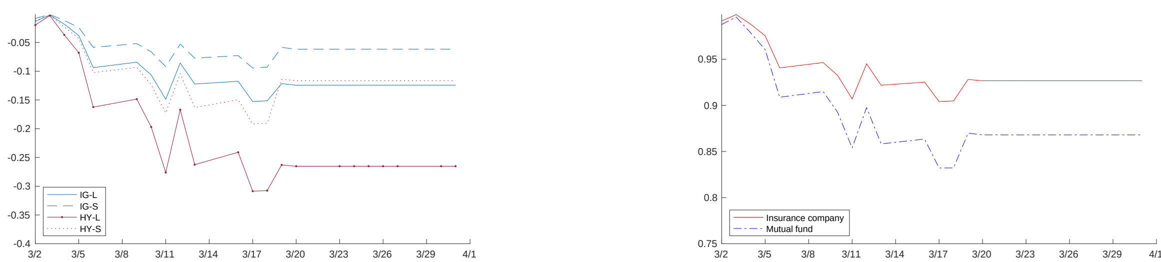


(a) Prices with $T = 14$

(b) AUM with $T = 14$

Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices. The central bank plans asset purchases of 5% of short-term IG bonds at time $T = 20$, and announces the plan on day 14.

Figure 8: Counterfactual simulation: central bank lending to mutual funds

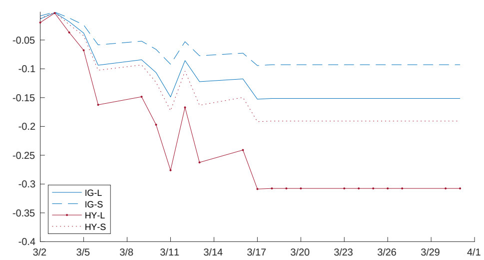


(a) Prices with $T = 14$

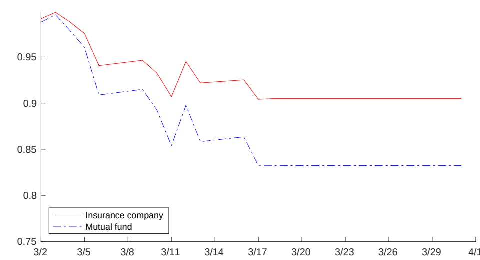
(b) AUM with $T = 14$

Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices. The central bank allows all mutual funds to borrow 10% of the value of their IG holdings on day 14.

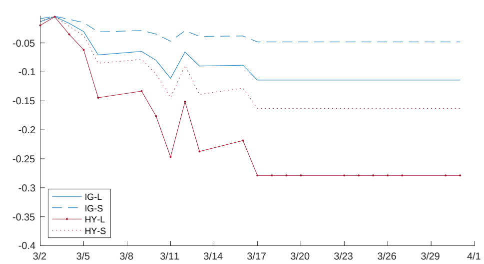
Figure 9: Counterfactual simulation: limits to redemption for mutual funds



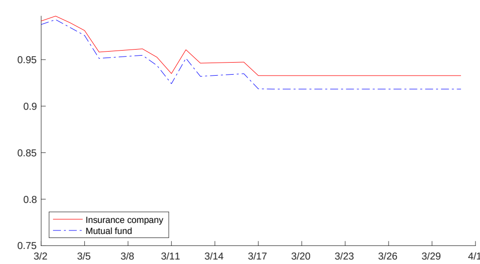
(a) Prices with $T = 14$



(b) AUM with $T = 14$



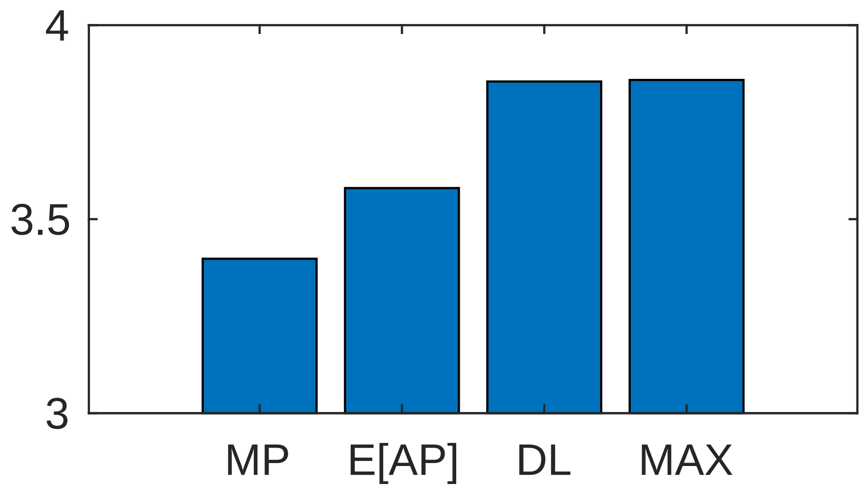
(c) Prices with $T = 2$



(d) AUM with $T = 2$

Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices. Mutual funds restrict suspend redemption on day 14 and day 2 for the upper and lower panels, respectively.

Figure 10: Price impact multipliers of various interventions



Note: This graph shows the policy targeting multipliers of various interventions at $T = 14$ as described in Section 6.2. “MP” stands for conventional monetary policy. “E[AP]” stands for expected asset purchases. “DL” stands for direct lending. “MAX” stands for the maximum-price-impact benchmark.

Table 1: First stage test for flow-based instrument

	(1) Life ins	(2) PC Ins	(3) Index funds	(4) Active MFs	(5) Residual
z_it^{flow}	-1.186***	-1.082***	-1.125***	-1.269***	-1.359***
	(0.00957)	(0.00879)	(0.0367)	(0.0109)	(0.0654)
UST x yrs	-0.0796***	-0.0677***	-0.0861***	-0.0878***	-0.158***
	(0.000991)	(0.00117)	(0.00524)	(0.00135)	(0.0100)
Bidask	9.312***	8.628***	13.85***	11.62***	6.475***
	(0.0656)	(0.0637)	(0.364)	(0.0894)	(0.195)
Yrs remaining	0.00741***	0.00741***	0.00254***	0.00204***	0.0154***
	(0.000145)	(0.000247)	(0.000418)	(0.000155)	(0.00109)
Amount issued (log)	0.000156	-0.000296***	-0.00230***	-0.00103***	-0.000513
	(0.000100)	(0.000103)	(0.000281)	(0.000127)	(0.000483)
Issuer rating	0.00239***	0.00115***	-0.000338	0.000653***	0.00228***
	(0.000127)	(0.000134)	(0.000448)	(0.000111)	(0.000459)
Constant	-0.111***	-0.0768***	-0.0339***	-0.0455***	-0.132***
	(0.00197)	(0.00202)	(0.00517)	(0.00239)	(0.00841)
Bond type FE	✓	✓	✓	✓	✓
Fund x Year FE	✓	✓	✓	✓	✓
Observations	1472179	1268754	119489	1416318	138487
R-squared	0.298	0.313	0.285	0.259	0.396

Note: This table shows the first stage estimates of the instrument on term-adjusted credit spreads within fund-bond type-quarter. The instrument is constructed from equation (23). The outcome variable in the first stage regressions is credit spread multiplied by the number of years remaining on the asset. Credit spreads are from the WRDS Bond Returns month-end transactions data, reported at the bond-quarter level. Controls include duration-matched US Treasury yield multiplied by the number of years remaining on the bond, the bid–ask spread as reported by WRDS, the number of years remaining, the initial amount issued (logged), and the issuer credit rating as reported in WRDS. The sample period is from 2007 to 2021. The first column reports the first-stage results for all life insurers, the second column reports results for property and casualty insurers, the third column reports results for all index funds, the fourth column reports all active mutual funds, and the last column reports results for the residual investor. Index funds include only pure index funds whose objective is to match the investment performance of a specific securities market index. Includes bond type and fund–year fixed effects. Standard errors are clustered at the fund level.

Table 2: Demand elasticity estimates: flow-based

	(1) Life ins	(2) PC Ins	(3) Index funds	(4) Active MFs	(5) Residual
Delta CS x yrs	1.945***	1.342***	-0.00710	0.856***	1.199*
	(0.238)	(0.250)	(0.344)	(0.101)	(0.618)
UST x yrs	0.153***	0.104***	-0.00628	-0.0365***	0.00624
	(0.0228)	(0.0207)	(0.0350)	(0.0119)	(0.108)
Bidask	-21.22***	-18.75***	2.288	-0.328	-11.86***
	(2.076)	(1.947)	(5.079)	(1.273)	(4.318)
Yrs remaining	-0.0129***	-0.0157***	-0.00943***	-0.00952***	-0.00702
	(0.00211)	(0.00273)	(0.00361)	(0.000909)	(0.00959)
Amount issued (log)	-0.00641***	-0.00906***	0.00360	0.0133***	0.00174
	(0.000989)	(0.00117)	(0.00307)	(0.00132)	(0.00399)
Issuer rating	0.00650***	-0.00113	0.0196***	0.0311***	0.0201***
	(0.00126)	(0.00124)	(0.00301)	(0.00115)	(0.00380)
Bond type FE	✓	✓	✓	✓	✓
Fund x Year FE	✓	✓	✓	✓	✓
Observations	1472179	1268754	119489	1416318	138487
R-squared	-0.0223	-0.00551	0.000560	0.00141	-0.00919

Note: This table shows the second stage estimates of demand on instrumented term-adjusted credit spreads. The instrument is constructed from equation (23). The outcome variable is the change in holdings relative to the index fund, normalized by the fund AUM: $\Delta\tilde{q}_{it}(n) = \Delta q_{it}(n) - \Delta q_{It}(n)$, where $\Delta q_{it}(n) = \ln\left(\frac{Q_{it}(n)}{A_{i,t}}\right) - \ln\left(\frac{Q_{it-1}(n)}{A_{i,t-1}}\right)$ and I is the largest index fund. Credit spreads are from the WRDS Bond Returns month-end transactions data, reported at the bond-quarter level. Controls include duration-matched US Treasury yield multiplied by the number of years remaining on the bond, the bid–ask spread as reported by WRDS, the number of years remaining, the initial amount issued (logged), and the issuer credit rating as reported in WRDS. The sample period is from 2007 to 2021. The first column reports the first-stage results for all life insurers, the second column reports results for property and casualty insurers, the third column reports results for index funds, the fourth column reports all active mutual funds, and the last column reports results for the residual investor. Index funds include only pure index funds whose objective is to match the investment performance of a specific securities market index. Includes bond type and fund–year fixed effects. Standard errors are clustered at the fund level.

Table 3: Flow-based demand estimates

Fund type	Coefficient estimate	Portfolio weight	Implied demand elasticity
Life insurers	1.945	0.092%	-1.945
Active mutual funds	0.856	0.079%	-0.856
Index funds	-0.007	0.081%	0.008
PC insurers	1.342	0.085%	-1.341
Residual fund	1.199	0.084%	-1.198

Note: This table summarizes the demand estimates implied by the flow-based estimation. Index funds include only pure index funds whose objective is to match the investment performance of a specific securities market index. All parameters are based on estimating from 2007-2021 data. Portfolio weights reported are the median across all bond types held by the institutions in each investor category as of end of 2019.

Table 4: Flow to performance estimates across mutual funds groups

	(1) Flow	(2) Flow	(3) Flow
Positive return	0.148***	0.250***	0.128***
	[0.018]	[0.048]	[0.019]
Negative return	0.312***	0.203***	0.342***
	[0.018]	[0.049]	[0.020]
L.Flow	0.265***	0.200***	0.278***
	[0.003]	[0.007]	[0.003]
Sample	All funds	Index	Active
Fund F.E.	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes
Observations	255,809	34,750	221,059
Adj. R-squared	0.187	0.143	0.194

Note: This table shows the relationship between fund flows and returns. The sample period is from 2008 to 2022 with monthly observations. “Return” is the monthly return of the fund in percentage points. The dependent variable is the fund flow, measured by the percentage change in the asset under management from the previous month. Data source: CRSP Mutual Fund Database.

Table 5: Flow to performance estimates across insurer groups

	(1) All insurers	(2) Life insurers	(3) Property & casualty insurers
Positive return	0.049**	0.080*	0.037
	[0.022]	[0.047]	[0.026]
Negative return	-0.023	0.002	-0.049
	[0.054]	[0.121]	[0.062]
L.Premium growth	0.470***	0.467***	0.471***
	[0.006]	[0.010]	[0.007]
Fund F.E.	Yes	Yes	Yes
Time F.E.	Yes	Yes	Yes
Observations	77795	20648	57147
Adj. R-squared	0.375	0.350	0.386

Note: This table shows the relationship between fund flows and returns. The sample period is from 2010 to 2019 with quarterly observations. "Return" is the net quarterly return of the bond portion of the insurer's fund in percentage points. The dependent variable is the growth in direct premiums, measured by the growth in direct premiums from the previous quarter. Data source: Capital IQ NAICS Insurer Data and WRDS Bond Returns.

Table 6: Portfolio shares regressed on flow-performance sensitivities

	(1) IG long share	(2) IG short share	(3) HY long share	(4) HY short share
β	-0.0255***	0.0370***	-0.0146***	0.00310***
	(0.00255)	(0.00193)	(0.00279)	(0.000910)
Retail share	-0.0258**	-0.0163*	0.0431***	-0.00104
	(0.0121)	(0.00917)	(0.0133)	(0.00433)
Log AUM	0.000119	0.00283*	-0.00417*	0.00121
	(0.00222)	(0.00168)	(0.00243)	(0.000793)
Index MF indicator	0.333***	0.0374*	-0.312***	-0.0584***
	(0.0274)	(0.0207)	(0.0301)	(0.00979)
Constant	0.429***	0.130***	0.388***	0.0531***
	(0.0156)	(0.0118)	(0.0171)	(0.00556)
Year FE	✓	✓	✓	✓
Observations	6772	6772	6772	6772
R-squared	0.0402	0.0597	0.0311	0.0124

Note: This table shows results of regressing the market value of holdings for an asset class normalized by the total reported corporate bond holdings for each fund on fund characteristics. β is the fund-specific flow to performance sensitivity estimated using equation (21). Fund data is from CRSP Mutual Fund Holdings. Index funds include only pure index funds whose objective is to match the investment performance of a specific securities market index. Includes year fixed effects.

Table 7: Systemic risk across assets

	IG		HY	
	Long	Short	Long	Short
Asset systemic measure 2019	1.23	1.34	1.40	1.91

Note: This table summarizes our measure of systemic importance of assets for year-end 2019. “IG” indicates bonds with credit rating of BBB- and above; “HY” indicates bonds with credit rating below BBB-. “Long” assets are those with five or more years remaining and “short” assets have fewer than 5 years remaining.

Appendix: derivations and proofs

A Log-linearization of household demand

We convert equation (3) to the percentage deviation from the steady state: $x = (X - X^*)/X$:

$$f_{h,i,t} = \kappa_{h,i} x_{i,t} - \sum_{i=0}^{I} \kappa_{h,i} \theta_{h,i,t} x_{i,t} + w^*_{h,t} - v^*_{i,t}. \tag{28}$$

Note $v^*_{i,t} = 0$ as the deviation of steady state NAV from itself is 0. The same applies to $w^*_{h,t}$.

Plugging in the special case $x_{i,t} = r_{i,t}$, where $r_{i,t}$ is the cumulative return of the fund relative to the baseline, we obtain the flow-to-performance relationship for each household:

$$q_{h,i,t} = \kappa_{h,i} v_{i,t} - \kappa_{h,i} \sum_{i} \theta_{h,i,t} v_{i,t}. \tag{29}$$

B Forward-looking household demand

The flow-to-performance relationship for each household depends on both the current period return and the expected return of the future period:

$$q_{h,i,t} = \beta_{h,i}(v_{i,t} - \sum_{i} \theta_{h,i,t} v_{i,t}) + \gamma_{h,i}(v^e_{i,t} - \sum_{i} \theta_{h,i,t} v^e_{i,t}). \tag{30}$$

Next, we aggregate this flow-to-performance relationship across households by multiplying equation (30) by the share of each household of a given institution $s_{h,i,t} = Q_{h,i,t} / \sum_h Q_{h,i,t}$ and summing them up, which gives rise to the following matrix form:

$$f_t = B_t(\beta) v_t + G_t(\gamma) v^e_t, \tag{31}$$

where $B_t(\beta)$ is the flow-to-performance matrix that is defined in equation (13), $G_t(\gamma)$ is the households' sensitivity to expected returns:

$$G_t(\gamma) = \text{diag}(\mathbb{1}^\top(S_{H,t} \odot \gamma)) - S_{H,t}(\theta_{H,t} \odot \gamma), \tag{32}$$

where $S_{H,t}$ is a $H \times I$ matrix with elements $s_{h,i,t}$, the share of each household of a given institution, γ is a $H \times I$ matrix with elements $\gamma_{h,i}$, the sensitivity to expected returns for households, $\theta_{H,t}$ is a $H \times I$ matrix with elements $\theta_{h,i,t}$, representing the portfolio weights for each institution for each household, v_t is a $I \times 1$ column vector with elements $v_{i,t}$, the returns for each institution, v_t^e is a $I \times 1$ column vector with elements $v_{i,t}^e$, the expected returns for each institution, $\mathbb{1}$ is the $H \times 1$ vector of 1.

C Log-linearization of institution demand

To derive institutions' asset demand, we convert equation (8) to the percentage deviation from the steady state: $x = (X - X^*)/X$:

$$q_{i,n,t} = \kappa_{i,n} x_t - \sum_{m=0}^{N} \theta_{i,m} \kappa_{i,m} x_{m,t} + w_{i,t}^* - p_{i,n,t}^*, \tag{33}$$

where $p_{i,n,t}^* = 0$ as the deviation of steady state price from itself is 0.

Note that the wealth of the institution depends on the fund inflows from households:

$$w_{i,t}^* = p_{i,t}^* + q_{i,t} = \sum_m \theta_{m,t} p_{m,t}^* + f_{i,t} = f_{i,t}. \tag{34}$$

Therefore, we have

$$q_{i,n,t} = \kappa_i x_{n,t} - \sum_m \theta_{i,m} \kappa_{i,m} x_{m,t} + f_{i,t}. \tag{35}$$

D The maximum-price-impact benchmark

The policy-maker's problem is

$$\max_{0\leq g\leq \overline{g}} \alpha'(I-(K\delta)^{-1}S^{\top}B\theta)^{-1}K^{-1}g, \qquad \text{subject to: } \alpha' g \leq b, \tag{36}$$

The Lagrangian function is

$$\mathcal{L}(g,\lambda) = \alpha'(I-(K\delta)^{-1}S^{\top}B\theta)^{-1}K^{-1}g + \lambda(b-\alpha' g) + \overline{\mu}'(\overline{g}-g) + \underline{\mu}' g, \tag{37}$$

We have

$$\frac{\partial \mathcal{L}}{\partial g_n} = \alpha'(I-(K\delta)^{-1}S^{\top}B\theta)^{-1}\kappa^{-1}e_n - \alpha_n - \overline{\mu}_n + \underline{\mu}_n, \tag{38}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = b - \alpha' g, \tag{39}$$

$$\frac{\partial \mathcal{L}}{\partial \overline{\mu}_n} = \overline{g}_n - g_n, \tag{40}$$

$$\frac{\partial \mathcal{L}}{\partial \underline{\mu}_n} = g_n, \tag{41}$$

Sorting the N assets by $\alpha'(I-(K\delta)^{-1}S^{\top}B\theta)^{-1}\kappa^{-1}e_n/\alpha_n$ in descending order, define the marginal asset N^* such that

$$\sum_{n=1}^{N^*} \alpha_n g_n \leq b, \tag{42}$$

$$\sum_{n=1}^{N^*+1} \alpha_n g_n \geq b. \tag{43}$$

The optimal solution is $g_n = \overline{g}_n$ when $n < N^*$, $g_n = b - \sum_{n=1}^{N^*} \alpha_n g_n$ when $n = N^*$, and $g_n = 0$ when $n > N^*$.

Appendix: Additional Tables and Figures

Table IA.1: Summary of bond types

	min	25%	50%	75%	max
Unique bonds per type-quarter	1	189	355	596	1,151
Avg num bonds in the type	4	193	454	555	731
Unique bonds per type	32	1,298	2,338	2,900	4,618
Unique funds per type-quarter	7	1,842	2,490	3,375	4,299
Avg num funds holding the type	198	1,858	2,410	3,209	3,901
Unique funds per type	996	5,376	6,066	6,720	7,475

Note: This table summarizes the distribution of statistics aggregated to the bond type-quarter and bond-type level from 2007Q1 - 2021Q4. A bond type is defined based on five dimensions: the credit rating (A-rated, BBB-rated, and high yield (lower than BBB- rating)), the time to maturity (up to three years, three to ten years, and ten years or more), the size grouped based on total amount of outstanding (up to 500 million and 500 million or more), covenants (covenants lite when the number of covenants of a bond is below the median number of covenants across all bonds within a period), and redemption option. *Avg num bonds in the type* is the number of unique bonds, on average, that is considered within the bond type each quarter. *Avg num funds holding the type* reports the average number of funds that hold any bond in that bond type each quarter. Data source: Thomson Reuters eMAXX and CRSP Mutual Fund Holdings.

Table IA.2: Top bond types, sorted by average amt_{kt}

Bond type	Avg amount outstanding	Avg num funds holding	Avg num bonds in the type
BBB-rated, 3-10y, $\geq$ 500mm, not cov-lite w/ redemption	677,447.3	3,900.7	730.9
A-rated, 3-10y, $\geq$ 500mm, not cov-lite w/ redemption	508,648.7	3,719.4	485.6
BBB-rated, $\geq$ 10y, $\geq$ 500mm, not cov-lite w/ redemption	494,498.0	2,409.9	454.1
High yield, 3-10y, $\geq$ 500mm, not cov-lite w/ redemption	473,127.5	2,251.4	555.1
A-rated, $\geq$ 10y, $\geq$ 500mm, not cov-lite w/ redemption	469,532.3	2,185.1	455.0
BBB-rated, $<$ 3y, $\geq$ 500mm, not cov-lite w/ redemption	251,797.9	3,208.6	275.5
A-rated, $<$ 3y, $\geq$ 500mm, not cov-lite w/ redemption	245,525.5	3,177.4	241.0
High yield, 3-10y, $<$ 500mm, not cov-lite w/ redemption	227,074.2	1,857.6	730.6
BBB-rated, 3-10y, $<$ 500mm, not cov-lite w/ redemption	223,383.6	3,120.4	647.9
A-rated, $<$ 3y, $\geq$ 500mm, cov-lite without redemption	212,159.2	2,702.6	202.7

Note: This table summarizes the top 10 bond types by the value of average total amount of outstanding in that bond type each quarter across the full sample from 2007Q1 - 2021Q4. A bond type is defined based on five dimensions: the credit rating (A-rated, BBB-rated, and high yield (lower than BBB- rating)), the time to maturity (up to three years, three to ten years, and ten years or more), the size grouped based on total amount of outstanding (up to 500 million and 500 million or more), covenants (covenants lite when the number of covenants of a bond is below the median number of covenants across all bonds within a period), and redemption option. *Avg amount outstanding* is the total amount of outstanding in millions across the bond type. *Avg num funds holding* reports the average number of funds that hold any bond in the bond type each quarter. *Avg num bonds in the type* is the number of unique bonds, on average, that is considered within that bond type each quarter. Data source: Mergent FISD, WRDS Bond Returns, Thomson Reuters eMAXX, and CRSP Mutual Fund Database.

Table IA.3: Top bond types by year, sorted by average amt_{kt}

Time period	Top bond types
2007-2009	A-rated, 3-10y, $\geq$ 500mm, not cov-lite w/ redemption; High yield, 3-10y, $<$ 500mm, not cov-lite w/ redemption; A-rated, $<$ 3y, $\geq$ 500mm, cov-lite without redemption
2009-2019	BBB-rated, 3-10y, $\geq$ 500mm, not cov-lite w/ redemption; A-rated, 3-10y, $\geq$ 500mm, not cov-lite w/ redemption; High yield, 3-10y, $\geq$ 500mm, not cov-lite w/ redemption
2019-2022	BBB-rated, 3-10y, $\geq$ 500mm, not cov-lite w/ redemption; BBB-rated, $\geq$ 10y, $\geq$ 500mm, not cov-lite w/ redemption; A-rated, $\geq$ 10y, $\geq$ 500mm, not cov-lite w/ redemption

Note: This table summarizes the top 3 bond types by the value of average total amount of outstanding in that bond type per quarter across each time period specified. A bond type is defined based on five dimensions: the credit rating (A-rated, BBB-rated, and high yield (lower than BBB- rating)), the time to maturity (up to three years, three to ten years, and ten years or more), the size grouped based on total amount of outstanding (up to 500 million and 500 million or more), covenants (covenants lite when the number of covenants of a bond is below the median number of covenants across all bonds within a period), and redemption option. Data source: Mergent FISD, WRDS Bond Returns, Thomson Reuters eMAXX, and CRSP Mutual Fund Database.

Table IA.6: Portfolio shares regressed on flow-performance sensitivities (non-negative betas)

	(1) IG long share	(2) IG short share	(3) HY long share	(4) HY short share
β	-0.0442***	0.0892***	-0.0464***	0.00147
	(0.00379)	(0.00278)	(0.00415)	(0.00140)
Retail share	-0.0334**	-0.0197*	0.0566***	-0.00359
	(0.0141)	(0.0103)	(0.0154)	(0.00518)
Log AUM	0.00862***	0.00457**	-0.0131***	-0.0000732
	(0.00263)	(0.00192)	(0.00287)	(0.000966)
Index MF indicator	0.345***	0.00995	-0.296***	-0.0588***
	(0.0323)	(0.0237)	(0.0353)	(0.0119)
Constant	0.409***	0.0251*	0.500***	0.0657***
	(0.0192)	(0.0141)	(0.0210)	(0.00706)
Year FE	✓	✓	✓	✓
Observations	5124	5124	5124	5124
R-squared	0.0558	0.176	0.0537	0.0121

Note: This table shows results of regressing the market value of holdings for an asset class normalized by the total reported corporate bond holdings for each fund on fund characteristics. β is the fund-specific flow to performance sensitivity estimated using equation (21). Fund data is from CRSP Mutual Fund Holdings. Index funds include only pure index funds whose objective is to match the investment performance of a specific securities market index. Includes only funds for which the estimated $\beta >= 0$. Includes year fixed effects.

Table IA.4: Demand elasticities over different time periods

	Time period		
	2007-2012	2013-2018	2019-2021
Life Insurers	2.936	2.484	1.789
	(0.337)	(0.477)	(0.702)
Active MFs	1.603	3.583	-3.932
	(0.109)	(0.279)	(0.213)
Index MFs	0.734	1.993	-2.205
	(0.414)	(1.004)	(0.648)
PC Insurers	2.574	1.401	3.093
	(0.446)	(0.45)	(1.028)
Residual	1.672	2.012	1.318
	(0.486)	(1.951)	(3.388)

Note: This table shows the second stage estimates of demand on instrumented term-adjusted credit spreads. The instrument is constructed from equation (23). The outcome variable is the change in holdings relative to the index fund, normalized by the fund AUM: $\Delta\tilde{q}_{it}(n) = \Delta q_{it}(n) - \Delta q_{It}(n)$, where $\Delta q_{it}(n) = \ln\left(\frac{Q_{it}(n)}{A_{i,t}}\right) - \ln\left(\frac{Q_{it-1}(n)}{A_{i,t-1}}\right)$ and I is the largest index fund. Credit spreads are from the WRDS Bond Returns month-end transactions data, reported at the bond-quarter level. Controls include duration-matched US Treasury yield multiplied by the number of years remaining on the bond, the bid–ask spread as reported by WRDS, the number of years remaining, the initial amount issued (logged), and the issuer credit rating as reported in WRDS. Includes bond type and fund–year fixed effects. Standard errors are clustered at the fund level.

Table IA.5: Elasticity by asset class

	Asset class	
	HY	IG
Life Insurers	1.386	2.214
	(0.318)	(0.262)
Active MFs	-0.947	2.198
	(0.144)	(0.128)
Index MFs	-2.372	0.862
	(0.667)	(0.337)
PC Insurers	1.061	1.52
	(0.474)	(0.248)
Residual	1.467	1.083
	(0.579)	(0.784)

Note: This table shows the second stage estimates of demand on instrumented term-adjusted credit spreads. The instrument is constructed from equation (23). The outcome variable is the change in holdings relative to the index fund, normalized by the fund AUM: $\Delta\tilde{q}_{it}(n) = \Delta q_{it}(n) - \Delta q_{It}(n)$, where $\Delta q_{it}(n) = \ln\left(\frac{Q_{it}(n)}{A_{i,t}}\right) - \ln\left(\frac{Q_{it-1}(n)}{A_{i,t-1}}\right)$ and I is the largest index fund. Credit spreads are from the WRDS Bond Returns month-end transactions data, reported at the bond-quarter level. Controls include duration-matched US Treasury yield multiplied by the number of years remaining on the bond, the bid–ask spread as reported by WRDS, the number of years remaining, the initial amount issued (logged), and the issuer credit rating as reported in WRDS. Includes bond type and fund–year fixed effects. Standard errors are clustered at the fund level.

Table IA.7: Propensity to sell IG bonds first

	(1) Q demand (log)	(2) Q demand (log)
IG holding×Outflow percent	0.599***	0.814***
	(0.210)	(0.111)
HY holding×Outflow percent	-0.686***	-1.093***
	(0.117)	(0.0721)
Constant	6.928***	6.925***
	(0.00447)	(0.00297)
Quarter FE	✓	
IG HY FE	✓	✓
Quarter x Fund FE		✓
Observations	350945	350104
R-squared	0.00263	0.693

Note: Observations are at the fund-bond category-quarter level. Outcome variable is the logged par amount of the fund-quarter's holdings of a given bond-portfolio. IG HY FE are fixed effects for investment grade (credit rating of BBB- and above) versus high yield (credit rating of below BBB-). Includes all mutual funds, 2010-2022. Standard errors clustered at the quarter level. Data source: WRDS Bond returns, Thomson Reuters eMAXX, CRSP Mutual Fund Holdings and Mergent FISD.