Nonbank Fragility in Credit Markets:

Evidence from a Two-Layer Asset Demand System[*]

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June 29, 2023

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

1 Introduction

Market fragility is often at the center of economic crises, featuring 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 (shadow) 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 on the fundamental value 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 decrease.

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[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.

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 includes thousands of investor-specific parameters. The model guides us to construct an asset fragility 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. A similar fragility measure can be constructed for each financial institution in an analogous manner.[2] These two measures can help policymakers evaluate the source of systemic 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 exploits rigidities in institutions' investment mandates (Koijen and Yogo, 2019; Bretscher 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.

We estimate asset fragility in the cross-section of corporate bonds. The least fragile asset class is long-term investment-grade (IG) bonds with a fragility of 1.49, which means that a 1% shock to the long-term IG bond prices would decrease the aggregate bond index

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[2]Falato et al. (2021) provide strong empirical evidence of fire-sales spillovers across funds.

by 1.49% multiplied by the market value share of these bonds. Fragility also varies across different duration of bonds. In particular, short-term IG bonds (less than five years) are more fragile: they face a level of amplification approaching that of long-term HY bonds and a fragility of 1.64. Our framework allows us to unpack these differences: these IG bonds are more likely to be held by mutual funds than longer-term IG bonds, particularly by mutual funds with a high flow sensitivity. This is intuitive: funds anticipating potentially large flows prefer to hold liquid IG bonds as a precautionary measure. In principle, differences in investor price elasticity also matter in explaining differences in fragility, but quantitatively the effect of flow sensitivities dominates. Across institutions, we find a significant fraction of mutual funds that are extremely fragile.

We use our estimates 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.[3] In each counterfactual, we feed in two weeks of price shocks implied by CDS spreads and evaluate the impact of an intervention two days (early) or 14 days (late) 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 with the highest fragility, as measured above, per unit of price elasticity.

First, we find that a rate cut improves prices and restores some of the loss in fund value.

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[3]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).

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. Interestingly, the timing of the intervention matters for the short-term path of prices and AUM, but the eventual rebound is similar when intervening early or late. Second, we evaluate a policy where the central bank purchases 3% of outstanding short-term (five years or less) IG bonds. While these asset purchases target IG bonds, there is nevertheless a small price benefit 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 following good performance but remain significantly below pre-crisis levels. A policy of announcing future purchases works similarly: there is an immediate rebound at the announcement, followed by a small drift until purchases start. The timing of the intervention also matters relatively little for the size of the eventual rebound.

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.[4] We find that this policy is effective at supporting prices and limiting out-flows, but the magnitude of the effect is constrained by how significant a share of the market mutual funds hold. 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 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.

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[4]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.

We then compare how well-targeted these policies are in addressing fragility. Perhaps surprisingly, even though they only focus on IG bonds, asset purchases are the best-targeted intervention. This is because they target short-term IG bonds, which are significantly fragile due to being held by especially flow-sensitive investors. This gives support to the policy choice of the Federal Reserve in Spring 2020 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 considerations other than addressing the bond market turmoil specifically. Direct lending to the mutual fund sector is better targeted, although quantitatively, the effect is perhaps not as large as could be expected.

Finally, we also provide a counterfactual to gauge the effects of implementing swing pricing, a preventive policy measure that requires funds to adjust their NAV to pass trading costs to redeeming shareholders. We model this policy through a reduction in flow-to-performance sensitivities, informed by the empirical finding of Jin, Kacperczyk, Kahraman, and Suntheim (2021). Swing pricing helps reduce outflows and further price declines. Naturally however, the policy does not fully prevent the effect of a negative shock, and the effect is relatively small. Our quantitative result nevertheless supports the recent regulatory proposal to mandate swing pricing for mutual funds. [5]

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-

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[5]See the SEC swing pricing proposal at `https://www.sec.gov/rules/proposed/2022/33-11130.pdf`.

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

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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).[6] 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 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. For instance, 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

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[6]See Coval and Stafford (2007); Frazzini and Lamont (2008); Greenwood and Thesmar (2011) for earlier work on stock markets.

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.[7] 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

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

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.[8]

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. We complement the CRSP dataset using the daily fund flows and net asset value (NAV) of open-end fixed-income mutual funds from the Morningstar database. The daily sample focuses on the COVID-19 crisis period from January 1, 2020, to April 30, 2020, covering a total of 1,199 funds. The daily sample allows us to zoom in on the high-frequency variations in the flow and returns in a distressed period.

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

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[8]Because we focus on two classes of investors in the model, insurers and mutual funds, we group fund types as follows: money market, balanced, unit investment trusts, funds of funds, and variable annuity funds are classified as mutual funds, and property and casualty insurance, life insurance, and reinsurance companies are classified as insurers.

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 $X_t(i)$, 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.

$$\max_{h \in \mathcal{H}} u_{h,t}(i) = \kappa_h X_t(i) + \epsilon_{h,t}(i), \tag{1}$$

where κ_h are sensitivities to the characteristics of household type h; $\epsilon_{h,t}(i)$ captures horizontal differentiation across each investment option. The weight of institution i in household h's portfolio is given by the following logit form:[9]

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

The demand for institution liability by household h is then given by the portfolio shares multiplied by the household's wealth $A_{h,t}$, then divided by the net asset value (NAV) $P_t(i)$:

$$Q_{h,t}^D(i) = \frac{\theta_{h,t}(i) A_{h,t}}{P_t(i)}, \tag{3}$$

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 $X_t(n)$,

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

which includes risk and return, rating, maturity, and so on. Each institution chooses the best option to maximize its indirect utility, i.e.

$$\max_{i\in\mathcal{I}} u_{i,t}(n) = \kappa_i X_t(n) + \epsilon_{i,t}(n), \tag{4}$$

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

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

The NAV of an institution can be calculated using its asset portfolio weights,[10]

$$P_t(i) = \sum_{n=0}^{N} \theta_{i,t}(n) P_t(n). \tag{6}$$

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

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

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:

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

where $P_t^*(n)$ 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. This assumption assumes that managers do not aggressively change their portfolio in response to temporary price deviation. Section 4.1

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[10]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.

provides some evidence that this assumption seems verified for fixed income, including index funds.[11]

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

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

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

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

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

for all assets $n = 0, 1, ..., N$.[12]

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

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[11]This is nevertheless different from the model of equity funds of Gabaix and Koijen (2020) which assumes $Q_{i,t}^{D}(n) = \frac{\theta_{i,t}(n)W_{i,t}}{P_t(n)}$ and thus more aggressive re-balancing by passive investors.

[12]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.

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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 after the first difference is the return of the institutions. Therefore, we can specify $x_{i,t} = p_{i,t}$ for the household demand for institution liabilities, equation (3). Note $p_{i,t}$ is the percentage deviation of the NAV from its steady state. Therefore, it can be interpreted as a cumulative excess return of the fund. In that case, the aggregate inflow into institution i follows a familiar flow-to-performance relationship:

$$f_{i,t} \simeq \beta_i p_{i,t}. \tag{11}$$

The key coefficient is the institution's *flow sensitivity* β_i which reflects the return sensitivity of its households investors (κ_h).[13]

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.

Layer 2: Institutions' asset demand To derive institutions' asset demand, we follow the same steps of log-linearizing demand (equation (8)):

$$q_{i,n,t} = \kappa_i x_{n,t} - \sum_{m=0}^{N} \theta_{i,m} \kappa_{i,m} x_{m,t} + f_{i,t}. \tag{12}$$

We assume the main time-varying asset characteristic that affects institutions' asset demand

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[13]The full derivation is in Appendix A.

is the asset's expected return:

$$X_{n,t} = \frac{E_t\left[\Delta P_{n,t+1} + D_{n,t+1}\right]}{P_{n,t}}, \tag{13}$$

where $D_{n,t+1}$ is the coupon payment of a perpetual bond. One can think about this security as a CDS contract with infinity maturity. This allows us to simplify the algebra as we abstract from explicit rollovers. Following Gabaix and Koijen (2021), we use the Taylor expansion of the total return formula such that deviations from expected returns are given by:

$$x_{n,t} = \delta_n(d_{n,t} - p_{n,t}) + E\left[\Delta p_{n,t+1}\right], \tag{14}$$

where $\delta_n = E_t[D_{t+1}^*(n)]/P_t(n)$ is the income yield, $d_{n,t} = (E_t[D_{t+1}(n)] - E_t[D_{t+1}^*(n)])/E_t[D_{t+1}^*(n)]$ is the deviation of expected coupon payment from its steady state, $p_{n,t}$ is the deviation of the asset price from its steady state, and $E\left[\Delta p_{n,t+1}\right]$ is the expected price change in the future. The variation in expected coupon payment is driven by default risk.

Substituting equation (14) in the above characteristic to the log linearized equation implies:

$$q_{i,n,t} = \sum_{m=0}^{N} \left(\mathbb{1}_{m=n} - \theta_{i,m}\right)\left(-\zeta_{i,m}p_{m,t} + \kappa_{i,m}\delta_m d_{m,t} + \kappa_{i,m}E\left[\Delta p_{m,t+1}\right]\right) + f_{i,t} \tag{15}$$

The key coefficient is the *price elasticity* $\zeta_{i,n} = \kappa_{i,n}\delta_n$ of institution i for asset n. Importantly, inflows $f_{i,t}$ also impact demand because they determine the overall institutional wealth (AUM) to be invested. The expression also includes cross-price elasticities: when the price of another asset m increases, the demand for asset n increases via a traditional substitution effect.[14]

Matrix notation We can aggregate across assets and institutions using matrix nota-

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[14]The derivation is in Appendix B.

tion. Aggregating the demand for assets across institutions weighted by their holding shares of each bond implies:

$$q_t = -\zeta p_t + f_t + \kappa \delta d_t + \kappa E\left[\Delta p_{t+1}\right]. \tag{16}$$

κ is a $N \times N$ matrix of the holding-share-weighted demand sensitivity to the expected return

$$\kappa = \text{diag}(\mathbb{1}'(S' \odot \hat{\kappa})) - S(\theta \odot \hat{\kappa}).$$

where $\hat{\kappa}$ is an $I \times N$ matrix of the demand sensitivity of institution i into the expected return of asset n, $\kappa_{i,n}$.

S_t is a $N \times I$ matrix of each investor's share of holding for each bond: the (n,i) element is thus equal to $s_{i,t}(n) = Q_{i,t}(n)/\sum_{i=0}^{I} Q_{i,t}(n)$. One row of S_t thus reports every fund's holdings of one asset normalized by the size of that asset, and adds up to one. θ is an $I \times N$ matrix of portfolio weights for each institution. One row of θ represents one fund's portfolio weights across all assets and adds up to one. $\mathbb{1}$ is an $I \times 1$ vector of ones.

ζ is an $N \times N$ matrix

$$\zeta = \text{diag}(\mathbb{1}'(S' \odot \hat{\zeta})) - S(\theta \odot \hat{\zeta}), \tag{17}$$

where $\hat{\zeta}$ is an $I \times N$ matrix of the demand elasticity of institution i to the price of asset n, $\zeta_{i,n}$.

δ is an $N \times N$ diagonal matrix with the nth diagonal element being δ_n, the income yield of asset n.

f_t is the cumulative flow at the asset level

$$f_t = S\hat{f}_t = S\beta\theta p_t, \tag{18}$$

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where $\hat{f}_t = \beta\theta p_t$ is the vector of flow at the fund level.

To derive the equilibrium price dynamics, we impose market clearing, i.e., $q = 0$. (for simplicity, we assume fixed supply and drop the expectation sign.) After some manipulation, we obtain

$$p_t = (I + \kappa^{-1}(\zeta - S\beta\theta))^{-1}(\delta d_t + p_{t+1}) \tag{19}$$

Define the *amplification matrix* $A = \kappa^{-1}(\zeta - S\beta\theta)$. The pricing equation can be simplified to $p_t = (I + A)^{-1}(\delta d_t + p_{t+1})$. Iterating forward:

$$p_t = \sum_{\tau=t}^{\infty}(I + A)^{-(\tau-t+1)}\delta d_\tau. \tag{20}$$

One special case of equation (20) obtains if the cash flow shock is a permanent shock, i.e. $d_\tau = d$ for all τ after t:

$$p_t = A^{-1}\delta d. \tag{21}$$

To provide intuition, suppose there is only one asset and one fund. In that case, the amplification matrix is $A^{-1} = \kappa/(\zeta - \beta\theta)$. Following negative news that the expected cash flows permanently drop by d, the demand for this asset would fall by $\kappa\delta d$. The demand drop leads to a first round of price drop of $(\kappa/\zeta)\delta d$. However, this is not the end because the deterioration in fund performance leads to an outflow of $(\kappa/\zeta)\beta\theta\delta d$. The outflow leads to a second round of price impact $(\kappa/\zeta)(\beta\theta/\zeta)\delta d$. This process continues and the nth round is $\kappa/\zeta(\beta\theta/\zeta)^{n-1}\delta d$. The cumulative impact is thus $\kappa/(\zeta - \beta\theta)\delta d$, following the geometric series formula, which is exactly what equation (21) gives us.

Under the special case of one asset and one fund, if the market were perfectly elastic $(\kappa \to \infty)$, the amplification matrix would reduce to $A \to \delta$. Equation (20) becomes a

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variation of the NPV formula:

$$p_t = \sum_{\tau=t}^{\infty}(1+\delta)^{-(\tau-t+1)}\delta d_\tau, \tag{22}$$

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. In other words, the amplification is zero in the benchmark case of a perfectly elastic market. This example makes clear the amplification of flows depends crucially on how elastic the market is.

Figure 1 shows an example of the model dynamics. We consider an economy with two sectors: mutual funds and insurance companies investing in four asset classes: IG-long term (over five years), IG-short term, HY-long term, and HY-short term. 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 average flow-to-performance sensitivity β of 0.63 while insurance companies face a sensitivity of 0 because insurance companies' liabilities are not demandable as mutual funds. The weighted average demand elasticities are 1.5 and 1.0 for active mutual funds and insurance companies, respectively. The assets under management W and the portfolios θ for each sector are calibrated to the 2019Q4 level. We simulate the dynamics following a sequence of permanent negative shocks to both HY bond categories. We assume that cumulative negative cash flow shocks grow over time in a smooth concave function, following $(1 - \exp(-\frac{t}{2}))$.

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.

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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' investment mandates; funds need to maintain certain portfolio weights, so they will sell IG bonds to rebalance their portfolios.

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 Figure 2. This setting assumes 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 below includes thousands of investor-specific parameters.

4 Estimation

In this section, we describe the estimation of key parameters of the model. Specifically, we estimate for each fund: (1) asset-specific demand elasticities and (2) flow-to-performance sensitivities. This rich set of 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.

4.1 Demand estimates

To estimate the price elasticity of demand, we implement a method similar to Bretscher et al. (2022) and Koijen et al. (2021). Specifically, we take the investment universe of other funds as exogenous to a given fund's demand for an asset, and use other fund investment universes as an exogenous price shifter to pin down demand elasticities.[15] Based on the empirically tractable model derived in Koijen and Yogo (2019), we can write log demand $\delta_{i,t}(n)$[16] as a function of credit spreads and bond characteristics $x_t(n)$:

$$\ln \delta_{i,t}(n) \equiv \alpha_i s_t(n) + \beta_i x_t(n) + u_{i,t}(n). \tag{23}$$

We include the following bond characteristics in $x_t(n)$ to capture potential risk sources that could affect both credit spread and investor demand: duration-matched U.S. Treasury yield, issuer credit rating, time to maturity, initial offering amount (logged), and the bid-ask spread.

To address the endogeneity concerns discussed above, we instrument the credit spread by

$$\widehat{z}_{i,t}(k) = \ln \left(\sum_{j \neq i} A_{j,t} \frac{\mathbb{1}_{j,t}(k)}{1 + \sum_m^N \mathbb{1}_{j,t}(m)} \right), \tag{24}$$

where k indexes the bond category, as defined by the credit rating-tenor-industry of the issuer and $\mathbb{1}_{j,t}(k)$ indicates that fund j includes bonds in category k in its investment universe in period t. This definition of the instrument prevents a fund's investment universe from being affected by the frequent issuance and maturity of bonds. It accounts for the findings of Li

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[15]A growing literature explores other methodological advances, including incorporating the competitive interaction among investor demand elasticities (Haddad et al. (2021)), and identifying off of fund flows rather than holdings (van der Beck (2021)). While we adjust the instrument to reflect the idea that investors have preferred habitats (Vayanos and Vila (2021)), the goal is not to deviate significantly from the existing demand estimation literature.

[16]Note that $\delta_{i,t}(n) = \frac{w_{i,t}(n)}{w_{i,t}(0)}$ represents the portfolio weight fund i invests in asset n at time t relative to the portfolio weight of the fund's outside option

et al. (2022) that individual bonds can be very good substitutes: inelastic demand tends to arise across types of bonds instead.[17] The intuition behind the instrument is that it affects prices because the more funds (and the larger those funds) include a bond in category k in their investment universe, the larger the exogenous component of demand, holding fixed other bond characteristics. The instrument satisfies the exclusion restriction as long as other funds' investment universes are exogenous to one fund's demand for individual bonds.

We construct the instrument by defining a security as part of a fund's investment universe in a given quarter if the fund has held that type of the security at least once in the prior 12 quarters. Bonds are categorized into 460 "bond categories" based on tenor-rating-industry.[18] Tables 2 reports summary statistics of the categories. The median bond category is held by 204 unique funds and has 11 unique bonds. In Table IA.1, we report the bond categories k that have the highest exogenous component of demand, as measured by the value of $\hat{z}_t(k)$. The top bond categories include 7-15 year bonds issued by manufacturing companies or information companies rated A and above or BBB. Table IA.2 reports the top bond categories by time period. While popular issuer industries and tenor categories have not changed significantly, lower rated, in particular BBB bonds, have become more popular in the post-crisis period.

We find the instrument is relevant: i.e., a higher $\hat{z}(k)$ corresponds to lower (higher) credit spreads (prices). Table 3 reports the results for the first stage, within fund-quarter. A higher value for the instrument corresponds to higher prices and thus lower yields, and the relationship is statistically significant. Because the value of z is unlikely to be correlated with an individual fund's demand for a given bond category, we consider this a reasonable instrument for price.

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[17]Concretely, an insurer might be close to indifferent between two BBB bonds of similar maturity, but might display very inelastic demand for a similar HY bond. See Table 13 of Siani (2021) for a summary of the persistence of fund class holdings.

[18]There are six tenor categories (up to and including 1, 3, 5, 7, 15, 100 years), five rating categories (up to and including CCC+, B+, BB+, BBB+, and AAA), and 16 industry categories (2-digit NAICS codes). Not all tenor-rating-industry triplets have bonds outstanding in the category in each quarter.

We run IV regressions for each investor for its IG and HY holdings. The baseline specification uses observations from 2010-2019.[19] We include all observations in which the institution holds at least 20 unique bonds in that year. We aggregate the data to the fund–bond category–quarter level, computing amount-outstanding weighted bond characteristics for each bond-category at each point in time. On the left-hand side, we use the total market value of bonds in each bond category held by a fund divided by fund size. We absorb market conditions that may affect all funds as well as time-varying fund characteristics, including the fund's investment in the outside option, by absorbing quarter fixed effects. We construct the right-hand-side variable as the last traded credit spread as of quarter end, scaled by the time to maturity remaining on the bond in years so that we can map it easily to prices.[20] We construct a "residual" sector, which we treat as one fund holding the remainder of amount outstanding for bonds in our sample.[21]

Table 4 reports the distribution of estimated demand elasticities used in the estimation.[22] While demand curves are downward sloping (i.e., funds allocate towards lower-priced securities, all else equal), funds are relatively inelastic, as documented in prior papers including Bretscher et al. (2022). On average, holders of HY bonds are more elastic than holders of IG bonds. Across investors, active mutual funds are more price elastic than insurers,

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[19]While we use the parameter estimates from 2010-2019 for our primary model simulation and counterfactual analysis, we also run the estimation for 2002-2007, 2008-2009, and 2020-2022 to see how parameters vary across different time periods. We report these results in the second panel of Table 4. We find little time-series variation in the demand elasticity estimates across time periods, giving us confidence that these parameters are reasonably policy invariant.

[20]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.

[21]That is, the residual sector holds for each bond the total bond outstanding minus the amount held by mutual funds and insurance companies. The residual sector includes hedge funds, pension funds, foreign entities, governments, and households. Because we do not observe the equivalent of fund size for the residual sector, we take the largest market value of its bond portfolio across the time period as a proxy for its AUM. Note we also do not observe the outside option invested by the residual sector; this is absorbed by the time fixed effect.

[22]We convert estimated coefficients to demand elasticities as per Koijen et al. (2021). where $-\frac{\partial q_{it}(n)}{\partial p_t(n)} = 1 + \frac{\beta}{m_t(n)}(1 - w_{it}(n))$, where $m_t(n)$ is the remaining maturity of the asset n. Because we estimate directly the elasticity on credit spread times remaining maturity, our coefficients map to $\frac{\beta}{m_t(n)}$, and we approximate the weight of the asset n to be zero, as the weight of each individual asset is negligible relative to the full fund.

consistent with findings in Bretscher et al. (2022). These fund-asset-specific elasticities will be used in simulating the model to run policy counterfactuals. Because the fund-asset-level estimates are noisy, we bound the estimates at 0 and 10 in the counterfactuals. We estimate a weighted average demand elasticity of 1.0 for insurers and 1.5 for active mutual funds in 2010-2019. Within mutual funds, index funds have a mean elasticity very close to 1, as expected.

We apply the estimated demand elasticities for IG and HY bonds to the four asset classes in our model simulation: long IG, short IG, long HY, and short HY. To run counterfactuals, we also need the distribution of the parameter $\hat{\kappa}$, which determines how sensitive institutions' demand is to expected returns. $\hat{\kappa}$ is a function of elasticity and can be recovered via the formula: $dqdp = -\delta\hat{\kappa}$, where δ is approximated with the bond yield. Specifically, we compute δ for each asset class as the time-series mean of the yield-to-maturity for bonds in each asset class.[23] Recall that this formula assumes that fixed-income investors do not aggressively re-balance after temporary price pressure. Table IA.3 in the Internet Appendix provides supporting evidence for this assumption. Very few funds sell bonds that improved in value within a quarter, or buy bonds that have lost value. These numbers should be much larger if funds were constantly re-balancing.

4.2 Flow to performance estimates

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

$$\text{Flow}_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t})}{TNA_{i,t-1}}, \tag{25}$$

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[23]The values for δ across the four asset classes are 4.5%, 2.8%, 8.8%, and 9.8%, for long IG, short IG, long HY, and short HY, respectively.

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:

$$f_{i,t} = \beta r_{i,t} + \gamma X_{i,t} + \tau_i + \tau_t + \epsilon_{i,t} \tag{26}$$

$X_{i,t}$ 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.

Columns 1–4 of Table 5 show that fund flows are highly responsive to returns, a relation well documented in prior literature (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). In the monthly sample, one percentage point reduction in monthly fund return leads to a net outflow in the magnitude of 0.34%–0.37% of the fund's assets under management. The magnitudes are robust to the inclusion of fund and time fixed effects. Because we are mostly interested in the pattern of fund outflows, in Column 5 we separate negative and positive returns. We find the flows are more sensitive to negative returns, consistent with Chen, Goldstein, and Jiang (2010). A one percentage point reduction in monthly fund return leads to a net outflow in the magnitude of 0.48% of the fund's assets under management.

We next estimate equation (26) fund by fund and report details on the heterogeneity in flow sensitivity estimates across fund groups in Table 6. Because the fund-level estimates are noisy, we bound the estimates at 0 and 2. These fund-specific sensitivities will be used in simulating the model to run policy counterfactuals. The weighted average β in 2010-2019 across all active mutual funds was 0.63, indicating that a 1pp decline in returns leads to a

net outflow of 0.63% of the fund's assets under management. The coefficient is significantly smaller on average for index funds, although there is significant heterogeneity. We assume flow sensitivity is zero for insurers and the residual sector for simplicity.

5 Measures of fragility

Using the model dynamics derived in Section 3.2, we can construct two measures of fragility in the model. *Asset fragility* measures fragility in the cross-section of bonds, while *fund fragility* measures fragility in the cross-section of mutual funds. It is worth noting that both fragility measures are macro-prudential in nature. They measure the contribution of a specific asset or a specific financial institution to the aggregate market fragility but do not measure the risk of the individual asset or institution by itself.

5.1 Fragility in the cross-section of bonds

The first measure is defined at the asset level. 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, fragility 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 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

$$\textbf{Asset fragility} \equiv \alpha' A^{-1} \delta. / \alpha' \tag{27}$$

where α is an $N \times 1$ vector of the market share of each bond, A is the amplification matrix, and δ is the matrix of income yields. 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 fragility measures the contribution an asset makes to aggregate fragility. It is not a measure of the risk of the asset itself. As we will see in the empirical analysis, safe bonds can score high on this fragility metric.[24]

Numerical example: To see more clearly what contributes to an asset's fragility, we consider a simple numerical example with three funds of equal size that invest in two equally-valued assets, A and B, as well as in an outside asset. One fund invests in equal weights in each asset A and B, another is a specialist in asset A and holds twice as much of asset A as asset B, and the third specializes in asset B and holds twice as much of asset B as asset A. We fix the flow sensitivity of the equal-weighted fund to 0.1 and the flow sensitivity of Specialist A to 0.6. See Table 1 for a summary of the parameters in the numerical example.

We plot how the fragility of the two assets varies with different parameter values in Figure 3. In the first panel of Figure 3, we hold all fund demand elasticities fixed at 1 (i.e., a 1% drop in prices corresponds to a 1% increase in quantity) to mimic a value-weighted portfolio target and demonstrate how variation in the flow sensitivity of Specialist B impacts the fragility of the assets in its portfolio. As the flow sensitivity for Specialist B increases, asset B fragility increases as a convex function of the flow sensitivity. Asset A fragility increases as well because all funds hold both assets, but not as much because Specialist B holds a smaller share of Asset A.

In the second panel of Figure 3, we hold the flow sensitivity of Specialist B fixed at one and instead vary the demand elasticity of Specialist B over asset B. As Specialist B becomes more price elastic over asset B, reducing the price impact of a given sale, the asset fragility of asset B declines. The fragility of asset A also declines as a smaller price

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[24]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).

impact on sales of asset B will also reduce asset A fragility. However, the effect is not as dramatic as adjusting flow sensitivities. The asset pricing literature has emphasized the role of demand elasticity (Bretscher et al., 2022) while works on mutual funds have emphasized flow sensitivities (Falato et al., 2021). We argue that both perspectives are important to understand the cross-section of bond fragility, but that neither is sufficient on its own.

Asset fragility estimates: We can use the fund-level flow sensitivity estimates, the fund-asset-level demand estimates, and observed holdings shares and fund values to compute this asset fragility measure in the cross-section of bonds. 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.

Across asset classes, asset fragility is between 1.4 and 2.4. Interestingly, while IG bonds are generally less fragile than HY bonds, the difference in fragility between short IG and long HY is smaller than the difference between long and short IG. Within rating categories, short-term bonds are more fragile than long-term bonds. In terms of economic magnitudes, the least fragile asset class are long-term IG bonds, with a fragility of 1.49. This corresponds to some moderate, albeit not insignificant, amount of amplification. Short-term IG bonds are more fragile: with a fragility of 1.64, they face an amount of amplification close to that of long-term HY bonds (fragility of 1.74) but less than that of short-term HY bonds (fragility of 2.3).

Our framework allows us to unpack these differences. First, being held by investors facing a stronger flow sensitivity β increases fragility. For instance, the third row of Table 7 shows that long-term IG bonds have a very low mutual fund market share, while short-term HY bonds have the highest share. The fact that insurers and pensions are large investors in that segment plays an important stabilizing role that is reflected in our low fragility estimate (Coppola, 2021). In addition, the fourth row shows that heterogeneity in mutual funds' flow sensitivities β is also important for fragility: short-term bonds in both IG and HY tend to be

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held by mutual funds that have particularly high β. IG bonds tend to have lower β overall.

In principle, differences in investor price elasticity also matter in explaining differences in fragility, as illustrated in the numerical example above. For example, long-term IG bonds are still fragile in spite of low investors' flow sensitivities in part because they are held by the most inelastic investors (elasticity of 1). However, quantitatively the effect of flow sensitivities dominates. Mutual funds are more elastic than insurers, but the asset classes they hold tend to nevertheless be more fragile.

5.2 Fragility in the cross-section of mutual funds

We next define a fund-level fragility measure, which tells us the impact of the aggregate bond price index if fund i experiences a shock to its return:

$$\text{Fund fragility} \equiv \alpha' A^{-1} \kappa^{-1} (S\beta)./\alpha'_f \tag{28}$$

where α_f is a $I \times 1$ vector of the market share of each fund. We normalize each fund i's effect on the market by its market share so that the overall impact on the bond index is expressed on the basis of per dollar AUM.

Numerical example: To clarify what contributes to a fund's fragility, we return to the numerical example above and plot fund fragilities in Figure 4. In the first panel of Figure 4, we hold all fund demand elasticities fixed at one and demonstrate how variation in the flow sensitivity of Specialist B impacts the fragility of all funds. As the flow sensitivity for Specialist B increases, its fund fragility increases. Importantly, the fragility of the other funds increases as well, given the increased fragility in the underlying assets. In the second panel of Figure 4, as the demand elasticity of Specialist B over asset B increases, the price impact of a given shock decline, and thus the fragility of the fund declines. The decline in

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the price impact for Specialist B's holding of asset B will also reduce the fund fragility of the other funds that hold asset B. In both panels, the fund fragility of the equal-weighted fund is lower than the fund fragility of the other two funds, given its low flow-to-performance sensitivity.

Intuitively, the fund fragility is driven by two categories of characteristics: (1) its own characteristics as well as (2) the characteristics of its holdings. In the first category, the fund's elasticity, flow to performance, and its portfolio share in each asset affect its fragility. Importantly, in the second category, we find fragility can also arise from the characteristics of a fund's holdings. If a fund holds more assets that are also held by funds with high flow sensitivities or low demand elasticities and are thus more fragile, its fragility increases. This fund fragility measure thus demonstrates the importance of considering the interaction between fund- and asset-level holdings and characteristics.

Fund fragility estimates: Across mutual funds, we find a significant fraction of mutual funds that are extremely fragile. Figure 5 presents a histogram of our fund fragility estimates at year-end 2019. Many funds have a fragility between 1 and 5, but many are substantially more fragile. To understand the economic magnitudes, a fund having a fragility of 10 means that a 1pp decline in its return would lead to a 10% decline in aggregate bond market values if that fund held the entire market portfolio (taking the matrix A that captures amplification as given).

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. 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, ζ) documented above to capture cross-sectional differences in flow sensitivities and elasticities across institutions. Specifically, we consider an economy with two sectors: mutual funds and insurance companies. Mutual funds face a fund-specific flow-to-performance sensitivity β as summarized in Table 6, while insurance companies and the residual sector face a sensitivity of 0.[25] The estimated demand elasticities vary by fund-asset class and are reported in Table 4.[26] The assets under management W and the portfolios θ for each institution are calibrated to the 2019Q4 levels.[27] Our framework

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[25]O'Hara et al. (2021) document how insurers' stable funding allows the sector to become buyers in periods of market distress; see Figure 7 of Coppola (2021).

[26]To ensure our counterfactual results are not driven by outliers, we focus on the 83% (89%) of IG (HY) elasticities that are between 0 and 10, and the 89% of positive flow sensitivity funds with flow sensitivity between 0 and 2. We then transform estimated elasticities into the parameter ζ_i using equation 17.

[27]For the outside share for mutual funds, we use the share each fund has invested in cash at 2019Q4; for the outside share for insurers, we use the share of financial assets held in cash and cash-like assets including treasuries, agencies, and money-market funds by the insurance sector in 2019Q4. The outside option for mutual funds is computed using CRSP Mutual Fund Holdings; the outside option for insurers is computed using the Flow of Funds Financial Accounts Data.

is tractable enough to account for thousands of parameters capturing the rich investor heterogeneity of the data. In particular, we include 1,674 institutions for which we can estimate both ζ and β in 2019.

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 estimate $(\lambda_{IG}, \lambda_{HY})$ using panel regressions of bond holdings on fund-level outflows. Table IA.4 in the Internet Appendix confirms 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).[28]

The estimated model can match some key moments of price and flow dynamics of the March 2020 turmoil. Figure 6 shows the dynamics of bond prices and flows in our model simulation. We see an average cumulative mutual fund outflow of 10% of AUM in line with Falato et al. (2021). We see a large drop in HY bond prices (Haddad et al., 2021b), although the drop in IG bond prices is smaller than in the data.

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[28]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. Accordingly, we use $\lambda_{IG} = 0.6, \lambda_{HY} = -0.7$ in the model 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 (both actual and expected), direct lending to funds, and redemption restrictions on mutual fund shares. For each intervention, we compare how much the timing, early versus late, matters. We can also use the model to measure how well "targeted" an intervention is, given the large heterogeneity in fragility documented above. Finally, we study the impact of swing pricing, an important type of ex-ante intervention.

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, there is a concern that policies might change the underlying parameters. This concern is especially salient for fund-to-performance sensitivities β. For this reason, we deliberately include specific policies that affect β directly, such as redemption restrictions or swing pricing, and allow β to vary within the policy counterfactual.

6.2.1 Conventional monetary policy

First, in Figure 7, 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 7 shows that there is also a rebound in the AUM of both mutual funds and insurers.

Interestingly, the timing of the intervention matters for the short-term path of the recovery, but not for the eventual size of the rebound. The bottom panel shows the effect of cutting interest rates two days after the start of the crisis ($T = 2$). Eventually, bond prices and institutions' AUM reach similar values as the case of a late intervention.[29]

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[29]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):

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.[30]

Figure 8 considers a policy of outright purchase of 3% of outstanding short-term (below 5 years) IG assets. The top panel shows a sizeable market rebound. Naturally, short-term IG bonds benefit from these asset purchases, as they are directly targeted; however, there is a small rebound for HY bonds. This is due to the rebound of fund wealth as well as the investment mandate increasing demand for HY assets. Mutual fund values rebound by more than insurers due to the amplifying effect of inflows following the positive performance. As with conventional monetary policy, the timing of the intervention also matters little for the size of the eventual rebound.

Figure 9 consider a policy of expected purchases of 5% of short-term IG bonds. The policy is announced either at $T = 2$ or $T = 14$, but purchases actually start at $T = 20$. There is an immediate rebound at the announcement, followed by a small drift upward 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)).

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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.

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

6.2.3 Direct lending to mutual funds

In Figure 10, 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 central bank. The intervention helps to support prices and reduce outflows, although the timing matters little for the eventual rebound. 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 11 displays the effects. This type of intervention is naturally particularly effective at preventing the mutual fund sector from shrinking considerably, as long as it is implemented early. Early onset of such a policy 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 is virtually ineffective, because much of the performance induced outflow would already have occurred.

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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 price impact of these purchases is $A^{-1}\kappa^{-1}g$. The impact on the market index is $\alpha' A^{-1}\kappa g$, 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:

$$\text{Policy multiplier}(g) = \frac{\alpha' A^{-1}\kappa^{-1}g}{\alpha'g} \tag{29}$$

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

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the cumulative impact on the aggregate bond market index for a given budget. A formal derivation can be found in Appendix C. 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 out-flows 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 interven-tions studied above were in addressing fragility in March 2020. Figure 12 compares these four interventions using our model estimates. It also reports the maximum-price-impact benchmark. Perhaps surprisingly, this reveals that asset purchases ("AP" and "E[AP]") are the best-targeted intervention. This is because purchases targeted short-term IG bonds, which are more fragile than long-term IG bonds due to being held by especially flow-sensitive investors. This gives support to the policy choice of the Federal Reserve in Spring 2020, at least if the goal was to maximize price impact under a limited budget. On the other hand, conventional monetary policy ("MP") is the least well-targeted because it has the biggest price effect on less fragile 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 consid-erations other than addressing the bond market turmoil specifically. Direct lending to the mutual fund sector is better targeted than the conventional rate cut by focusing on the more fragile fund sector.

6.4 Preventative policy: swing pricing

We can also use our framework to evaluate preventative policies that could mitigate a negative feedback loop in the first place. For example, in November 2022, the SEC proposed a policy to avoid selling pressure of open-ended mutual funds called swing pricing.[31] This policy would require funds to adjust their NAV to pass trading costs to shareholders who are redeeming (or purchasing) shares in the fund. Jin et al. (2021) show that implementation of this policy in the UK led to a significant reduction in flow-to-performance sensitivity.

Motivated by this policy proposal, we test how swing pricing would affect the propagation of the negative shock via a reduction in flow-to-performance sensitivities. To implement this, we refer to Jin et al. (2021) Table 3, Panel B, which reports the reduction in flow sensitivity estimates due to swing pricing across different magnitudes of fund outflows. We adjust each fund's flow-to-performance sensitivity according to their estimates and see how prices and fund valuations respond to the same negative shocks to bond prices in March 2020. Figure 13 shows that swing pricing help reduce outflows and further price declines. Naturally, however, the policy does not fully prevent the effect of a negative shock, and the effect is relatively small. Our quantitative result nevertheless supports the recent regulatory proposal to mandate swing pricing for mutual funds.

This exercise comes with important caveats. Implementation of swing pricing would likely have equilibrium effects on fund investment decisions, as documented by Jin et al. (2021) and Ma et al. (2023). In this counterfactual, we hold asset characteristics fixed. Estimating a counterfactual that endogenizes holding characteristics would be useful but outside the scope of this paper.

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[31]See, for example, "SEC proposes mutual fund-pricing rule to protect long-term investors", *Financial Times*, November 2, 2022.

7   Conclusion

This paper develops a two-layer asset pricing 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
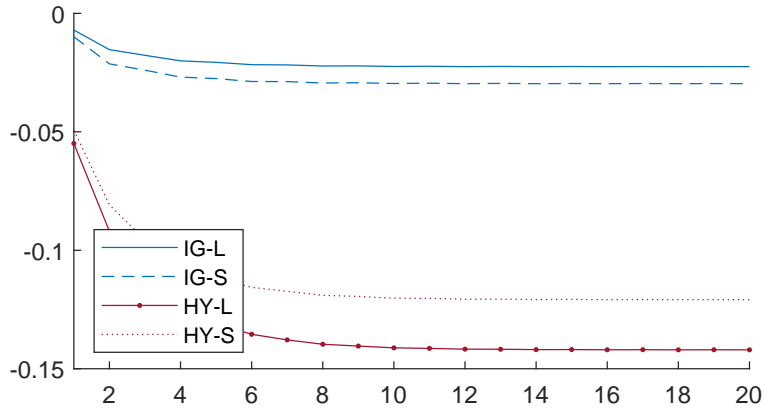
(a) Prices
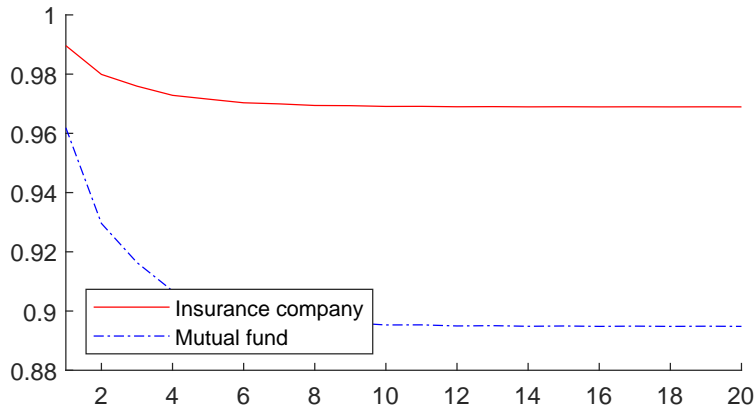
(b) AUM

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.

Figure 2: Beta equals 0
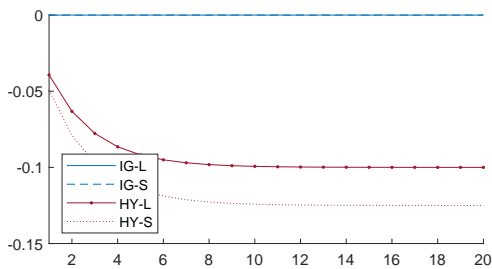
(a) Prices
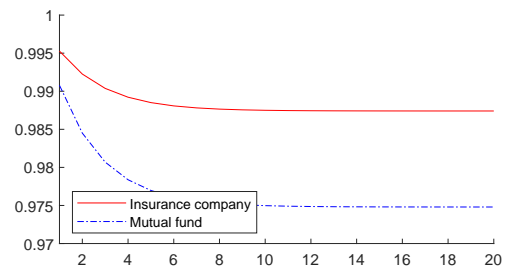
(b) AUM

Note: This graph shows the counterfactual AUM and asset prices given a series of smooth negative shocks. $\beta = 0$, meaning funds do not experience outflows in response to poor returns.
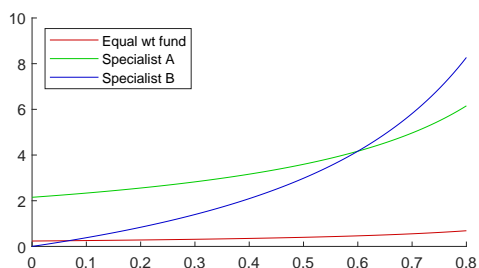
Figure 3: Asset fragility: numerical example
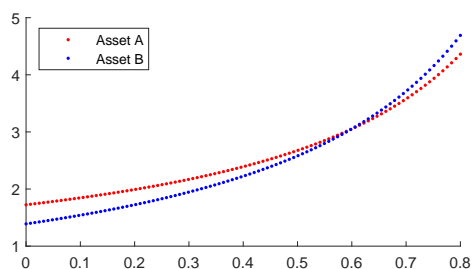
(a) Flow sensitivity of Specialist B
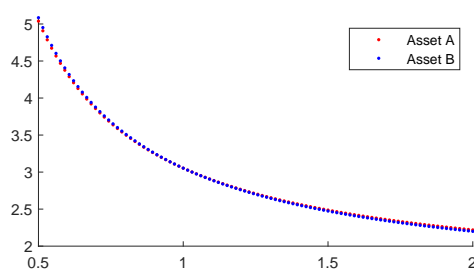
(b) Demand elasticity over B: Specialist B

Note: Reports on the y-axis the asset fragility of two assets in an illustrative numerical example. The left panel holds fixed the demand elasticities of all funds and varies only the flow sensitivity (beta) of Specialist B. The right panel holds fixed the flow sensitivities of all funds and varies only the demand elasticity of Specialist B for asset B.

Figure 4: Fund fragility: numerical example

(a) Flow sensitivity of Specialist B
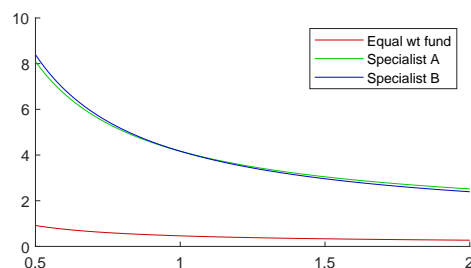
(b) Demand elasticity over B: Specialist B

Note: Reports on the y-axis the fund fragility of three funds in an illustrative numerical example. The left panel holds fixed the demand elasticities of all funds and varies only the flow sensitivity (beta) of Specialist B. The right panel holds fixed the flow sensitivities of all funds and varies only the demand elasticity of Specialist B for asset B.

Figure 5: Fund fragility distribution: all mutual funds
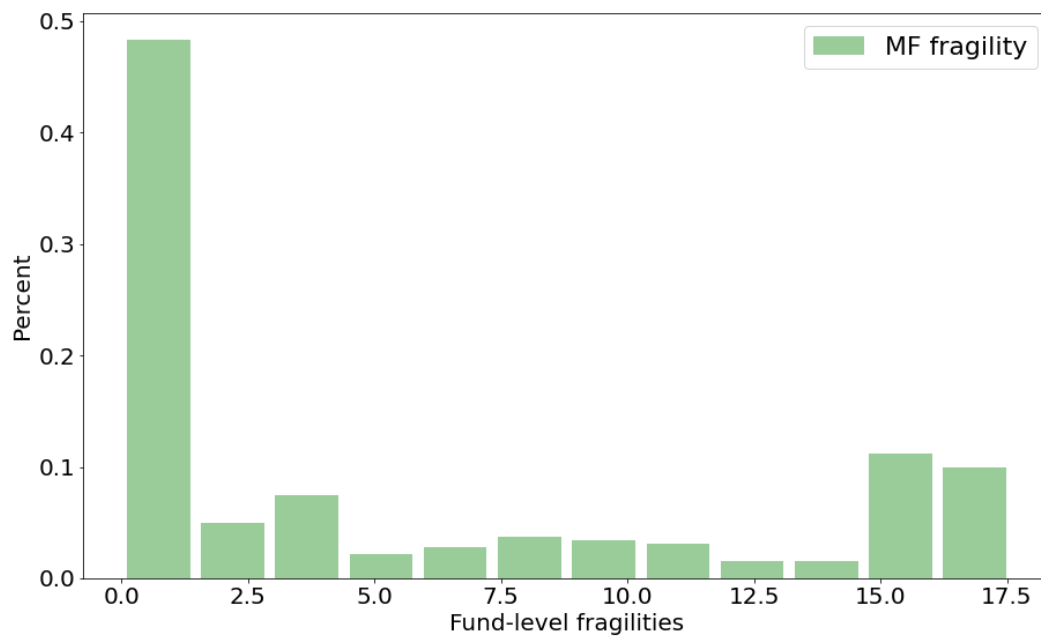
Note: This table summarizes the fund fragilities estimated across our sample of mutual funds for year-end 2019.

Figure 6: March 2020: Model-implied dynamics
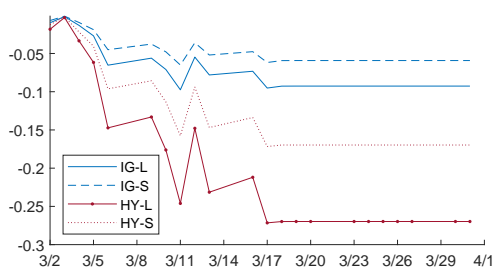
(a) Asset prices
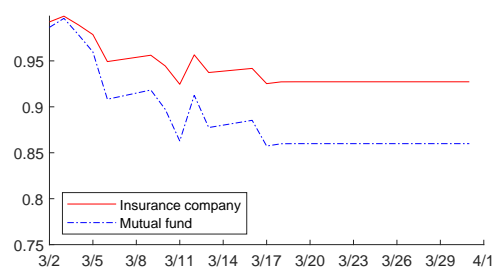
(b) Fund AUM

Note: This graph shows the counterfactual AUM and asset prices with fundamental shocks to asset prices in line with the corporate bond CDS changes from March 2-19. There is no policy intervention in this simulation.
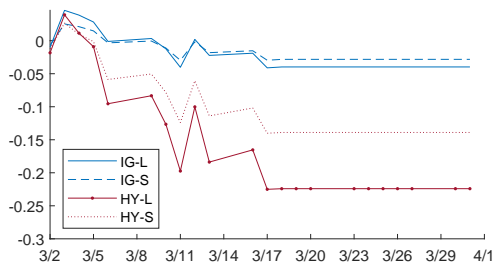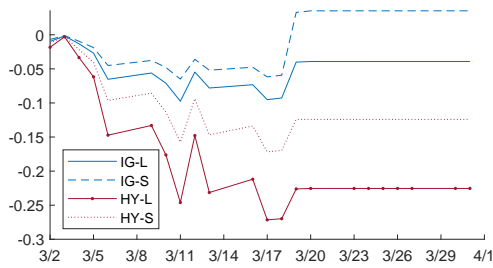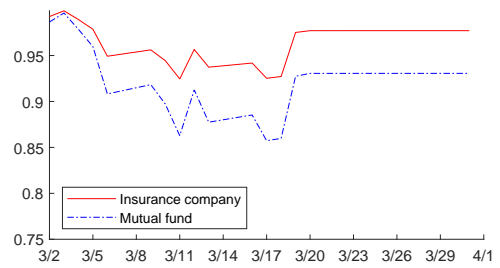
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Figure 7: Counterfactual simulation: rate cut
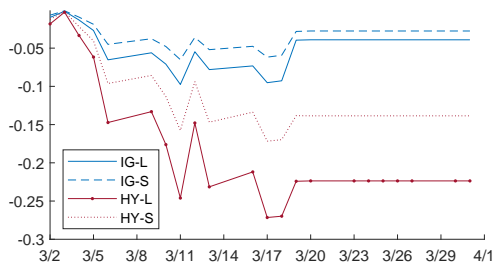
(a) Prices with $T = 14$
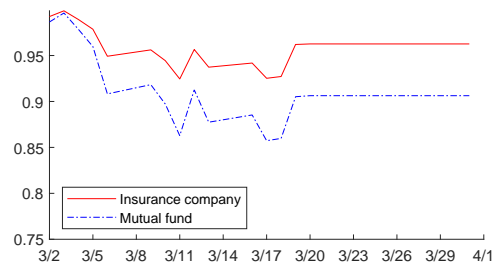
(b) AUM with $T = 14$
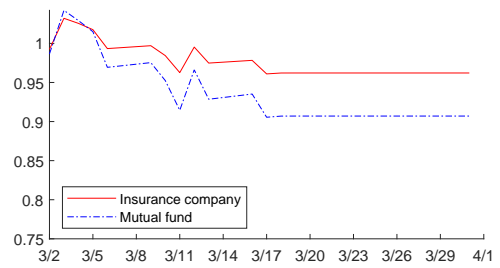
(c) Prices with $T = 2$

(d) AUM with $T = 2$

Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices in line with CDS yields. The central bank cut the policy rate by 50 basis points on day 14 and day 2 for the upper and lower panels, respectively.
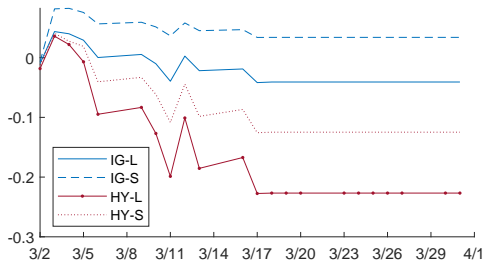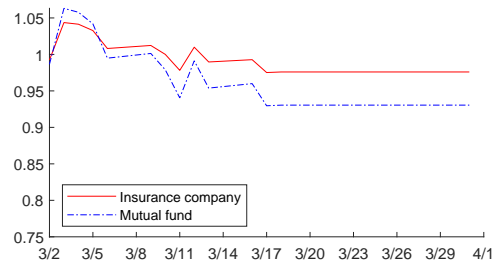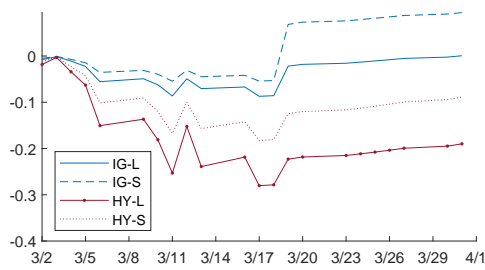
48

Figure 8: Counterfactual simulation: asset purchases

(a) Prices with $T = 14$

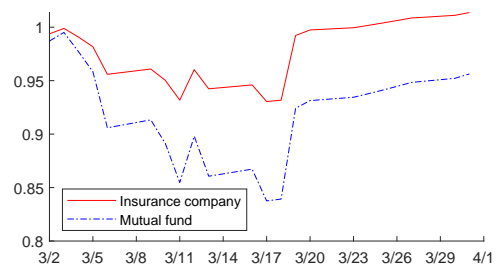(b) AUM with $T = 14$

(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 in line with CDS yields. The central bank conducts asset purchases of 3% of short-term IG bonds on day 14 and day 2 for the upper and lower panels, respectively.
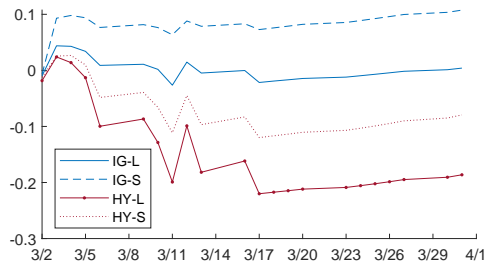
49

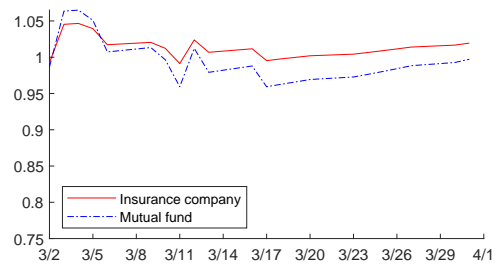Figure 9: Counterfactual simulation: expected asset purchases

(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 in line with CDS yields. The central bank plans asset purchases of 5% of short-term IG bonds at time $T = 20$, and announces the plan on day 14 and day 2 for the upper and lower panels, respectively.

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Figure 10: Counterfactual simulation: central bank lending to mutual funds

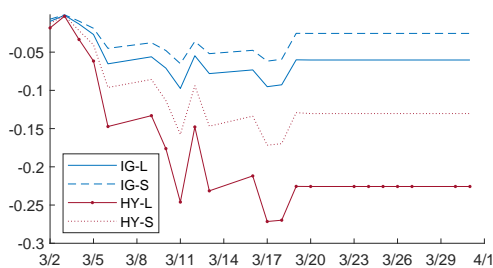

(a) Prices with $T = 14$

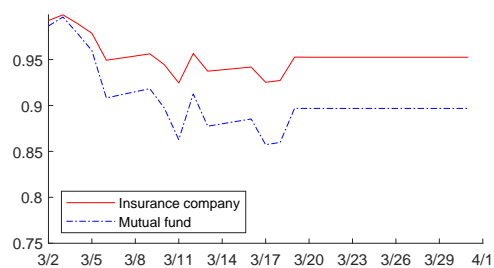(b) AUM with $T = 14$

(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 in line with CDS yields. The central bank allows all mutual funds to borrow 10% of the value of their IG holdings on day 14 and day 2 for the upper and lower panels, respectively.
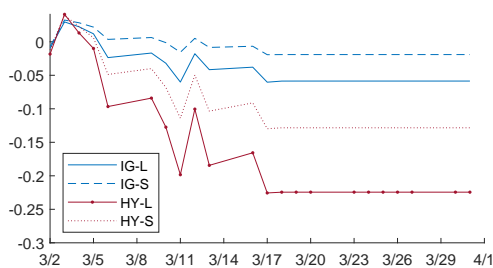
51

Figure 11: Counterfactual simulation: limits to redemption for mutual funds
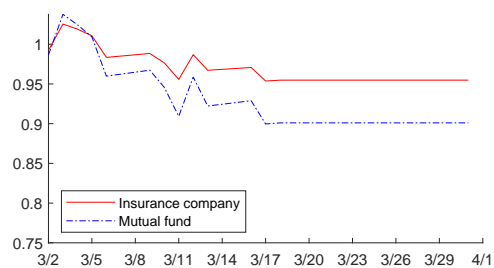

(a) Prices with $T = 14$
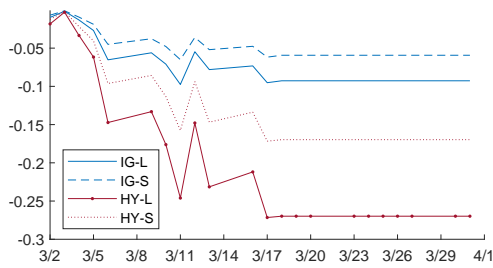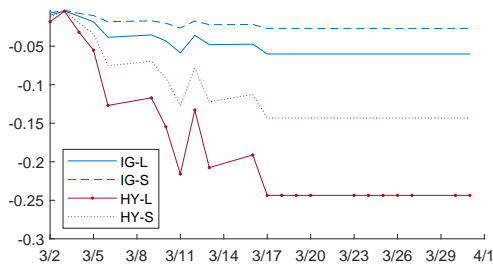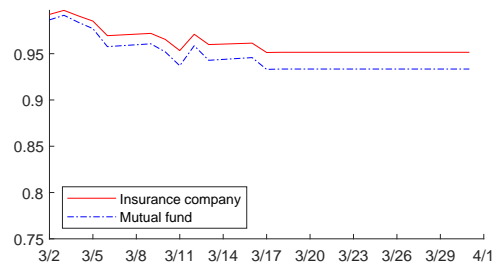

(b) AUM with $T = 14$
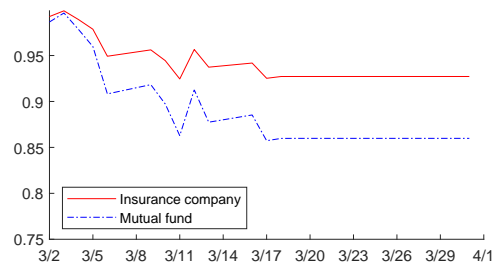

(c) Prices with $T = 2$

(d) AUM with $T = 2$

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

Figure 12: Price impact multipliers of various interventions
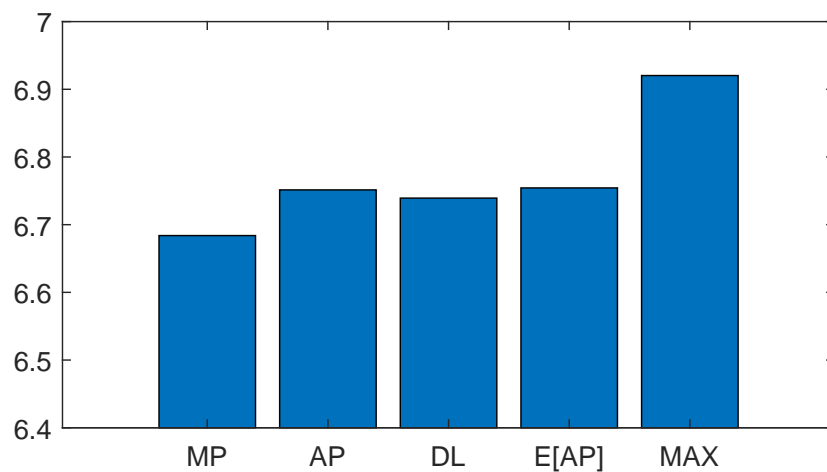
Note: This graph shows the policy targeting multipliers of various interventions at $T = 2$ as described in Section 6.2. "MP" stands for conventional monetary policy. "AP" stands for asset purchases. "DL" stands for direct lending. "E[AP]" stands for expected asset purchases. "MAX" stands for the maximum-price-impact.

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Figure 13: Counterfactual simulation: swing pricing
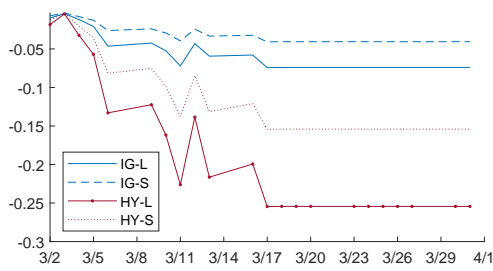
(a) Prices
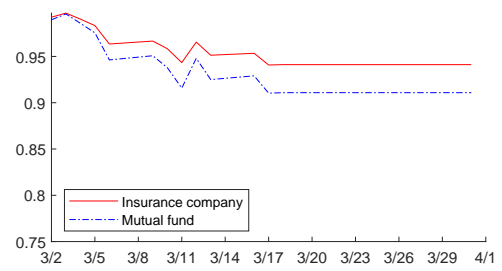
(b) AUM

Note: This graph shows the counterfactual AUM and asset prices with swing pricing implemented in day 1

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Table 1: Numerical example: parameters

	Equal weighted fund	Specialist A	Specialist B
Asset A share held by each fund	0.25	0.50	0.25
Asset B share held by each fund	0.25	0.25	0.5
Total wealth	1.00	1.00	1.00
Flow sensitivity	0.10	0.60	X1
Demand elasticity over Asset A	1.00	1.00	1.00
Demand elasticity over Asset B	1.00	1.00	X2

Note: This table summarizes parameters in the numerical example illustrating asset and fund fragility metrics. The X1 and X2 values take on various values in Figures 3 and 4 to demonstrate how fragility metrics respond to variations in flow sensitivities and demand elasticities.

Table 2: Summary of bond categories

	min	25%	50%	75%	max
Avg categories per quarter	293	332	342	360	379
Unique bonds per category-quarter	1	2	5	14	234
Unique bonds per category	1	4	11	33	374
Avg num funds holding each category	2	82	204	486	2,718

Note: This table summarizes the distribution of statistics aggregated to the bond category-quarter and bond-category level from 2010-2021. A bond category is defined as a 2-digit NAIC industry category, a tenor at issuance, and the credit rating of the bond. Data source: Thomson Reuters eMAXX and CRSP Mutual Fund Holdings.

Table 3: First stage test for instrument

	(1) All	(2) Ins	(3) MF	(4) Resid
Z_icq	-0.0112***	-0.0136***	-0.00769***	-0.0221***
	(0.00137)	(0.00108)	(0.00200)	(0.00278)
UST x yrs	-0.0776	-0.119***	0.0404	-0.188***
	(0.0599)	(0.0406)	(0.111)	(0.0571)
Bidask	3.431***	2.656***	6.952***	2.073***
	(0.779)	(0.739)	(0.968)	(0.519)
Yrs remaining	0.0208***	0.0207***	0.0182***	0.0289***
	(0.00198)	(0.00168)	(0.00326)	(0.00218)
Amount issued (log)	0.00145**	0.00181***	0.00197**	0.00490***
	(0.000618)	(0.000554)	(0.000938)	(0.00167)
Issuer rating	0.101***	0.0842***	0.134***	0.144***
	(0.00385)	(0.00347)	(0.00597)	(0.00590)
Constant	-0.0552**	0.0261	-0.200***	-0.00182
	(0.0229)	(0.0161)	(0.0359)	(0.0364)
Quarter FE				✓
Fund x Quarter FE	✓	✓	✓	
Observations	4798242	2986687	1799802	11753
R-squared	0.720	0.723	0.721	0.695

Note: This table shows the first stage estimates of the instrument on term-adjusted credit spreads within fund-asset-quarter. The instrument is constructed from equation (24) as described in subsection 4.1. 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 2000 to 2021 with quarterly observations. The first column reports the first-stage results for all funds; the second column reports results for insurers, the third column reports results for mutual funds, and the last column reports results for the residual investor. Includes fund–quarter fixed effects, except for the last regression, which includes quarter fixed effects because their residual demand is treated as one fund. Standard errors are clustered at the fund and quarter levels.

Table 4: Summary of demand elasticity estimates

	25%	Weighted mean	75%
2010-2019 estimates			
Active mutual funds	1.277	1.492	1.301
Index funds	0.956	1.030	1.023
Insurers	1.003	1.018	1.027
Residual funds	1.005	1.026	1.037
HY holdings	0.992	1.104	1.051
IG holdings	0.950	1.084	1.229
	25%	Weighted mean	75%
Time periods			
Pre-2008	1.011	1.017	1.032
2008 financial crisis	0.994	1.109	1.012
2020-2022	1.001	1.034	1.033

Note: This table summarizes the distribution of demand elasticities used in the estimation. The top panel summarizes estimates for different asset and fund categories in 2010-2019. Weighted averages are weighted by the fund size. The bottom panel summarizes estimates for mutual funds in different time periods: respecetively, 2002-2007, 2008-2009, and 2020-2022. Data source: Thomson Reuters eMAXX and CRSP Mutual Fund Holdings.

Table 5: Flow to return sensitivity

	(1) Flow	(2) Flow	(3) Flow	(4) Flow	(5) Flow
Return	0.348***	0.344***	0.373***	0.347***	
	[0.013]	[0.013]	[0.016]	[0.016]	
L.Flow	0.349***	0.274***	0.339***	0.238***	0.241***
	[0.003]	[0.003]	[0.003]	[0.003]	[0.004]
Positive return					0.165***
					[0.029]
Negative return					0.477***
					[0.028]
Fund F.E.	No	Yes	No	Yes	Yes
Time F.E.					
Observations	171,655	171,637	171,655	171,637	153,257
Adj. R-squared	0.130	0.168	0.138	0.192	0.191

Note: This table shows the relationship between fund flows and returns. The sample period is from 1992 to 2021 with monthly observations. "Return" is the net monthly return of the fund in percentage points. "Flow" is measured by the percentage change in the asset under management from the previous month. The dependent variable is the fund flow. Data source: CRSP Mutual Fund Database.

Table 6: Summary of flow to performance estimates

	25%	Weighted mean	75%
2010-2019 estimates			
Active mutual funds	0.000	0.634	1.464
Index funds	0.000	0.220	0.496
Insurers	0.000	0.000	0.000
Residual funds	0.000	0.000	0.000

Note: This table summarizes the distribution of flow to performance elasticities used in the estimation for different fund categories in 2010-2019. Weighted averages are weighted by the fund size. Data source: CRSP Mutual Fund Database.

Table 7: Asset fragility measure

	IG		HY	
	Long	Short	Long	Short
Asset fragility 2019	1.488	1.637	1.742	2.318
Market share of asset	0.629	0.270	0.058	0.043
Mutual fund holding share of asset	0.114	0.147	0.292	0.311
Holdings-weighted average beta	0.081	0.106	0.123	0.212
Holdings-weighted average elasticity	1.002	1.155	1.168	1.334

Note: This table summarizes the asset fragilities and key inputs 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. Reported flow sensitivities (beta) and demand elasticities are holdings weighted averages across funds for each asset.

Appendix: derivations and proofs

A   Log-linearization of household demand

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

$$q_{h,i,t} = \kappa_h x_{i,t} - \sum_{i=0}^{I} \kappa_h x_{i,t} + a_t - p_{i,t}. \tag{30}$$

Note that $p_{i,t}$ can be interpreted as a cumulative return of the fund relative to the baseline.

Plugging in the special case $x_{i,t} = p_{i,t}$, we obtain the flow-to-performance relationship for each household:

$$q_{h,i,t} = (\kappa_h - 1)p_{i,t} - \kappa_h \sum_{i=0}^{I} \theta_{h,i,t} p_{i,t} + a_{h,t}. \tag{31}$$

Finally, we aggregate this flow-to-performance relationship across households by multiplying equation (31) by the wealth share of each household $s_{h,t} = A_{h,t} / \sum_{h=0}^{H} A_{h,t}$ and summing them up, which gives rise to the equation in the main text:

$$f_{i,t} \simeq \beta_i p_{i,t} - \omega_i \bar{p}_t + \bar{a}_t,$$

where $f_{i,t} = \sum_{h=0}^{H} s_{h,t} q_{h,i,t}$ is the aggregate cumulative inflow into institution i, $\beta_i = \sum_{h=0}^{H} s_{h,i,t}(\kappa_h - 1)$ is the weighted sensitivity to the returns for households who invest in institution i, $\bar{p}_t = \sum_{i=0}^{I} \bar{\theta}_{i,t} p_{i,t}$ is the weighted average cumulative return of all institutions. The approximation is exact when the portfolio weights of the households are the same, $\bar{\theta}_{i,t} = \theta_{h,i,t}$. $\omega_i = \sum_{h=0}^{H} s_{h,i,t} \kappa_h$ is the sensitivity to the average returns. $\bar{a}_t = \sum_{h=0}^{H} s_{h,t} a_{h,t}$ is the average household wealth change.

For tractability, the benchmark model makes one additional assumption. We study shocks that affect the corporate bond market but not other assets in the household portfolio. This implies that the shock a has a negligible impact on the average return of household portfolio ($\bar{p} \approx 0$) and induces a negligible change in total household wealth ($\bar{a} \approx 0$). In the model, this assumption corresponds to the outside option being large enough relative to corporate bond investments. Consistent with this assumption, in practice, the majority of household wealth is invested in other asset classes, such as housing, stocks, deposits, and government bonds. We study shocks that are orthogonal to shocks to these assets. Therefore, we can get

$$f_{i,t} \simeq \beta_i p_{i,t}.$$

These assumptions can be relaxed. Assuming that household wealth falls following a negative shock to bond values would only amplify the feedback loop between flows and asset values we emphasize. Our main mechanism also applies if the shock affects other asset classes as long as it affects corporate bonds relatively more. In Section **??**, we include time and fund fixed effects to absorb this term, $\omega_i \bar{p}_t + \bar{a}_t$.

B   Log-linearization of institution demand

We convert equation (8) to the percentage deviation from the steady state: $x = (X - X^*)/X$:

$$q_{i,n,t} = \kappa_{i,n} x_t - \sum_{m=0}^{N} \kappa_i x_{m,t} + w_{i,t}^* - p_{i,n,t}^*, \tag{32}$$

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

Note that

$$w_{i,t}^* = p_{i,t}^* + q_{i,t} = \sum_{m=0}^{N} \theta_{m,t} p_{m,t}^* + f_{i,t} = f_{i,t}. \tag{33}$$

Therefore, we have

$$q_{i,t}(n) = \kappa_i x_t(n) - \sum_{m=0}^{N} \kappa_i x_t(m) + f_{i,t}. \tag{34}$$

Plug in the special case $x_{n,t} = \delta_n (d_{n,t} - p_{n,t}) + E[\Delta p_{n,t+1}]$, we get equation (15).

C   The maximum-price-impact benchmark

The policy-maker's problem is

$$\max_{0 \leq g \leq \bar{g}} \alpha' A^{-1} \kappa^{-1} g, \tag{35}$$

$$\text{subject to: } \alpha' g \leq b,$$

The Lagrangian function is

$$\mathcal{L}(g, \lambda) = \alpha' A^{-1} \kappa^{-1} g + \lambda(b - \alpha' g) + \bar{\mu}'(\bar{g} - g) + \underline{\mu}' g, \tag{36}$$

We have

$$\frac{\partial \mathcal{L}}{\partial g_n} = \alpha' A^{-1} \kappa^{-1} e_n - \alpha_n - \bar{\mu}_n + \underline{\mu}_n, \tag{37}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = b - \alpha' g, \tag{38}$$

$$\frac{\partial \mathcal{L}}{\partial \bar{\mu}_n} = \bar{g}_n - g_n, \tag{39}$$

$$\frac{\partial \mathcal{L}}{\partial \underline{\mu}_n} = g_n, \tag{40}$$

Sorting the N assets by $\alpha' A^{-1} \kappa^{-1} e_n / \alpha_n$ in descending order, define the marginal asset N^* such that

$$\sum_{n=1}^{N^*} \alpha_n g_n \leq b, \tag{41}$$

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$$\sum_{n=1}^{N^*+1} \alpha_n g_n \geq b. \tag{42}$$

The optimal solution is $g_n = \bar{g}_n$ 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: Top bond categories

Bond category	Avg number of funds holding	Avg number of bonds in the category
33-15.0-Aaa	2,018.0	105.0
32-15.0-Baa1	1,758.5	102.4
51-15.0-Aaa	1,636.0	38.8
51-15.0-Baa1	1,802.9	67.9
48-15.0-Baa1	1,637.4	82.9
33-15.0-Baa1	1,621.0	105.8
33-5.0-Aaa	1,320.6	40.5
21-15.0-Baa1	1,533.9	68.2
31-15.0-Aaa	1,359.8	39.0
33-5.0-Baa1	1,114.0	37.9

Note: This table summarizes the top 10 categories by the value of the instrument z across the full sample. A bond category is defined as a 2-digit NAIC industry category, a tenor at issuance, and the credit rating of the bond. The tenor at issuance listed in each bond category is the upper end of a range; for example, 15 indicates bonds 7-15 years at issuance, and 5 indicates bonds 3-5 years at issuance. The rating listed in each category is the upper end of a range; for example, Aaa indicates bonds rated A- and above; Baa1 indicates bonds rated Baa3-Baa1 based on the median rating across rating agencies. The avg number of funds reports the average number of funds that hold any bond in this category each quarter. The avg number of bonds in the category is the number of bonds, on average, that is considered within that category. Data source: Mergent FISD, Thomson Reuters eMAXX, and CRSP Mutual Fund Database.

Table IA.2: Top bond categories by year

Time period	Top bond categories
2000-2007	[51-15.0-Aaa, 33-15.0-Aaa, 33-5.0-Aaa]
2008-2009	[33-5.0-Baa1, 33-15.0-Aaa, 32-15.0-Aaa]
2010-2019	[33-5.0-Baa1, 33-15.0-Aaa, 33-15.0-Baa1]
2020-2022	[33-15.0-Baa1, 48-5.0-Baa1, 33-5.0-Caa1]

Note: This table summarizes the top 3 categories by the value of the instrument z for each time period, in descending order of z. A bond category is defined as a 2-digit NAIC industry category, a tenor at issuance, and the credit rating of the bond. The tenor at issuance listed in each bond category is the upper end of a range; for example, 15 indicates bonds 7-15 years at issuance, and 5 indicates bonds 3-5 years at issuance. The rating listed in each category is the upper end of a range; for example, Aaa indicates bonds rated A3 and above; Baa1 indicates bonds rated Baa3-Baa1 based on the median rating across rating agencies. Data source: Mergent FISD, Thomson Reuters eMAXX, and CRSP Mutual Fund Database.

Table IA.3: Fund portfolio rebalancing

	Pct poor performers that are purchased		Pct good performers that are sold	
	mean	50%	mean	50%
Non-index fund	6.28%	0.00%	6.02%	0.00%
Index-based fund	14.90%	1.43%	11.56%	0.88%
Pure index fund	16.59%	2.17%	7.69%	0.28%

Note: Reports mean and median percentages of various portfolio rebalancing by fund-month within all CRSP mutual funds that hold corporate bonds. Observations in the first (second) column are conditional on fund-months with positive holdings of bonds with negative (positive) monthly returns. For example, "pct poor performers that are purchased" is the number of bonds that the fund purchased in a month when the bond had a negative return divided by the number of bonds in the fund's portfolio that had a negative return that month. Summarizes fund-month observations from 2002 - 2022 for holdings of corporate bonds in the FISD dataset. Data source: WRDS Bond returns, CRSP Mutual Fund Holdings and Mergent FISD.

Table IA.4: Lambda estimation

	(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.