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

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January 30, 2023

**Abstract**

We develop a two-layer asset pricing framework to analyze fragility in the corporate bond market. Households allocate wealth to institutions, which allocate funds to specific assets. The framework generates tractable joint dynamics of flows and asset values, featuring amplification and contagion, by combining a flow-performance relationship for fund flows with a logit model of institutional asset demand. The framework can be estimated using micro-data on bond prices, investors holdings, and fund flows, allowing for rich parameter heterogeneity across assets and institutions. We use the estimated model to quantify the equilibrium effects of unconventional monetary and liquidity policies on bond prices.

*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

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# 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. 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). An important driver of this turmoil was nonbank fragility and in particular historical levels of outflows suffered by bond mutual funds (Falato, Goldstein, and Hortaçsu, 2021; Ma, Xiao, and Zeng, 2022b). Forced sales by shrinking funds significantly contributed to the sharp increase in credit spreads. This episode, as well as prior ones, suggests 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, how to quantify these equilibrium effects and what is the appropriate policy response is largely an open question.

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, which allocate funds to specific assets. Equilibrium asset prices reflect the demand of both households and institutional investors. Fragility arises when negative returns lead to investor redemptions, forcing managers to sell assets and further depress bond prices. The model features dynamic feedback loops between investor outflows and asset prices, as well as contagion across assets and institutions. We show how the model can be estimated using micro-data on bond prices, institutional investors holding, and fund flows. We use the estimated model to quantify the equilibrium effects of unconventional monetary and liquidity policies on bond prices.

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 leads to inflows into a fund, while poor returns lead to outflows. In the second layer, institutional investors then allocate funds to specific assets. Asset demand is driven by asset returns as well as the institutions' investment mandates. Equilibrium asset prices reflect the demand of both households and institutional investors: AUM determine asset demand through mandates, while asset holdings affect fund returns and drive changes in AUM going forward.

The model yields rich yet tractable equilibrium dynamics characterized by a difference-equation system of fund flows and asset prices. First, the model displays feedback loop between prices and flows. A negative shock to asset prices reduces fund returns, which leads to outflows from institutions that have demandable liabilities, such as mutual funds. Outflows then lead to asset sales by these institutions, which further depresses asset prices. The cumulative effect could be several times greater than the initial shock. Second, the model displays contagion across assets. Shocks on fundamental value of one asset can spillover to other assets through investor outflows. Because institutions are constrained by mandate, they have to buy and sell assets that are not directly affected by the fundamental shock to maintain certain portfolio weights. Third, the model displays contagion across institutions. Institutions that do not issue demandable liabilities, such as insurance companies, are affected by outflows from institutions that issue demandable liabilities such as mutual funds. Because asset prices are depressed by the outflow-induced asset sales, the asset values of insurance companies can decrease.

Although these amplifications and contagions have been documented in the prior literature, our framework has a unique advantage to characterize them as simple sufficient statistics of parameters 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 in the presence of 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 indirect spillovers through other assets or institutions. A similar fragility measure can be constructed for each financial institution in an analogous manner. These two measures can help policy makers evaluate the source of fragility in credit markets and the systemic importance of financial institutions.

Importantly, we show how to estimate the model parameters using micro data. The first layer uses flow-performance regressions to determine how much outflows 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 exploit rigidities in institutions' investment mandates (Koijen and Yogo, 2019; Bretscher et al., 2020). 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 Merget FISD.

We use our estimates to study the effects of policy interventions aimed at stabilizing the market. The Federal Reserve responded swiftly in Spring 2020 by lowering its interest rate targeting and announcing corporate bond purchases for the first time ever. Other potential interventions have been discussed, but quantifying their effects has largely been an open question. We study four types of ex-post interventions: (i) conventional monetary policy, (ii) asset purchases, (iii) direct lending to mutual funds, and (iv) restricting redemption on mutual fund shares.[1] In each counterfactual, we begin with a negative 10% shock to high yield bond prices, consistent with the initial shock of COVID crisis in early March 2020, and

[1]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).

evaluate the impact of an intervention two or ten days after the shock. Moreover, we also study how well targeted these interventions are in addressing fragility. In particular, our framework allows us to compute the benchmark of a maximum-price-impact intervention. We show that to maximize the price impact on the market subject to a resource constraint, the policy-maker should target the assets with the highest fragility, as measured above, per unit of resource.

First, we find that a rate cut of 25 basis points improves prices and restores some of the loss in fund value. Investment grade bonds rebound more quickly because they are longer duration, and HY bonds value remain significantly below their pre-shock level. There is also a significant drop in institutional investors assets under management due to permanent outflows, especially for mutual funds.

Second, we evaluate a policy where the central bank purchases 1% of outstanding investment grade bonds. While asset purchases typically target IG bonds, there is nevertheless a small price benefit for high yield bonds because of the rebound in fund AUM as well as fixed investment mandates increasing demand for high yield assets. Mutual fund values rebound relatively more than insurers due to the amplifying effect of inflows following good performance.

Next, we study two types of intervention that were not implemented in 2020. We consider the effects of lending directly to funds, using a fraction of their bond portfolio as collateral of 1% of IG assets.[2] As soon as this policy is implemented, the decline in prices stops. Despite targeting mutual funds directly, insurers indirectly benefit as outflows reverse and allow asset prices recover somewhat. Intervening early is particularly valuable in this case: waiting an additional week would lead to as much as an additional 10% drop in asset

[2]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.

values relative to pre-shock levels.

We then consider a policy of freezing mutual fund redemptions. Regulators did not mandate this policy in Spring 2020, but a significant number of funds facing severe liquidity issues suspended redemptions (Grill, Vivar, and Wedow, 2021). Unlike the other policies, the implementation of a redemption restriction on mutual funds does not allow prices and fund values to rebound at all. Moreover, it can only mitigate the drop in fund values and prices when it occurs sufficiently quickly.

Finally, we compare these policies to the maximum-price-impact benchmark derived in the theoretical framework. While no policy proposed reaches the theoretical benchmark, comparing the efficacy of each policy is informative. An asset purchase policy has a higher price impact multiplier than conventional monetary policy (risk-free rate cut). This is because asset purchases more directly affect prices on all IG bonds, while a rate cut has a disproportionate impact on the least fragile asset class, long-term IG bonds. Moreover, asset purchases are also more effective than IG-collateralized lending, given they target prices rather than flows. This result gives an empirical justification for the choice made by the Federal Reserve to introduce corporate bond purchases in the early days of the 2020 crisis. 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 (Jin et al., 2021), which inhibits significant outflows and further price declines, thereby avoiding the onset of a negative feedback loop.

Our paper contributes to the debate on 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 objective: (i) linking transparently to the economic forces that have been documented in prior theoretical and empirical work, (ii) being estimable with micro-data, (iii) conducting counterfactual analysis of unconventional monetary and liquidity policies within a unified setting. We show how to combine a flow-performance relationships 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 first relate to the literature studies 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 externality (Coval and Stafford, 2007; Frazzini and Lamont, 2008; Falato, Hortacsu, Li, and Shin, 2021). We contribute to this literature by providing a two-layer asset demand model that connects both strands of the literature, in which the equilibrium dynamics of fund flows and asset returns are jointly characterized. This framework allows us to assess various policy interventions that the policy-maker has adopted in serious stress events. Our structural approach complements the existing empirical studies of the stress events in the credit markets (Falato, Goldstein, and Hortaçsu, 2021; Haddad, Moreira, and Muir, 2021b; Ma, Xiao, and Zeng, 2022b).

Our paper is closely related to the literature that measure the systemic risks of the financial system (Adrian and Brunnermeier, 2016; Acharya, Pedersen, Philippon, and Richardson, 2017; Greenwood, Landier, and Thesmar, 2015; Duarte and Eisenbach, 2021). We contribute to this literature in two dimensions. First, the existing literature often focuses on levered financial intuitions such as traditional banks and shadow banks, where the key amplification mechanism is through deleveraging and firesale. In contrast, we focus on unlevered nonbanks such as open-end mutual funds, where the key amplification mechanism is through the feedback through outflows and asset prices. Second, we bring in the new insights and methods from the recent literature on demand system asset pricing, which allows us to more tightly map the model to the data.

From a methodological standpoint, we contribute to the growing literature on applying a demand system approach to asset pricing (Koijen and Yogo, 2019, 2020; Koijen et al., 2021; Bretscher et al., 2020) by endogenizing institutional investors' AUM, incorporating a second layer into our model. In this way, we are also able to capture asset price dynamics 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 markets in equity markets (Gabaix and Koijen, 2021).

This paper also contributes to our understanding of intermediary asset pricing (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Haddad and Muir, 2021). This literature has shown the importance of financial intermediaries for the dynamics of asset prices during crises, with a focus on net worth and equity capital constraints. We argue that this insight is more general and focus on unlevered non-bank intermediaries, whose fund sizes fluctuate over time even absent a capital constraint. We also incorporate techniques from the industrial organization literature to estimate the model using micro-data.[3] Finally, we connect to the extensive literature studying how central banks affect asset prices through a variety of channels (Cieslak and Vissing-Jorgensen, 2021; Cieslak and Pang, 2021; Cieslak et al., 2019; Caballero and Simsek, 2022b,a), although our specific focus is on non-bank fragility.

[3]However, one limitation of our framework relative to this work is that, while it generates asset price dynamics, it does not explicitly model institutions' portfolio choice as a fully dynamic optimization problem.

## 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.[4] We exclude bonds that are issued in exchange of 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 all fund-quarters in which the fund holds at least 20 unique corporate bonds in our sample in the year. Following Bretscher et al. (2020), we use the last recorded price and yield for each quarter in the WRDS Bond Returns dataset. We back out the credit spread for each bond-quarter using an interpolated U.S. Treasury yield curve as per Gürkaynak et al. (2007). We include holdings from 2010-2021 to capture the post-2008 financial crisis period up through the COVID crisis of 2020. The estimation sample includes 2,306 mutual funds, 987 insurers, and 10,942 unique corporate bonds.[5]

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 the high frequency variations in the flow and returns in a distress period.

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

[5]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 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.

## 3.1 Household demand for institutions

In general, households invest in various financial institutions. Given our focus on nonbank fragility in credit markets, we however emphasize flows in and out of the mutual fund sector which played a central role in the 2020 turmoil (Falato et al., 2021; Haddad et al., 2021b; Ma et al., 2022b). In particular, we model the well-know flow-to-performance relationship linking fund size (AUM) to past fund returns (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Berk and Green, 2004).

We model fund flows into fund $i$ between time $t-1$ and $t$ as the canonical relation:

$$f_{i,t} = \beta r_{i,t-1} + v_{i,t}, \tag{1}$$

where $r_{i,t-1}$ is the fund return in the previous period and $v_{i,t}$ represents the residual flow shocks. In that setting, the key coefficient is $\beta$: the sensitivity of flows to fund returns, which we take as a fund-level summary statistic that captures various potential micro-foundations.[6]

Our specific focus is justified by how important this economic channel is for nonbank

[6] A number of non-exclusive forces have been suggested in prior work, including learning about fund managers' skill, first-mover advantage in redemptions, or portfolio re-balancing in the face of risk.

fragility, both conceptually and practically. Nevertheless, in principle the first layer could be modeled in a much richer way. To illustrate this point, we sketch a logit model of household asset allocation and show it nests our simpler model. Each household unit is endowed with a dollar that can be invested in a set of institutions including mutual funds, insurance companies, and pension funds indexed by $\mathcal{I} = \{0, 1, ..., I\}$, with option 0 representing the outside option of managing the wealth by themselves. Each option is described a vector of characteristics $U_t(i)$ and each household chooses the best option to maximize its utility, i.e. $\max_{i \in \mathcal{I}} u_h(i) = \beta U_t(i) + \epsilon_h(i)$. Coefficients $\beta$ are sensitivities to the characteristics of each option, while $\epsilon_h(i)$ captures horizontal differentiation across each investment option. Under standard assumptions,[7] the market share of each institutions takes a familiar logit form $s_t(i) = \frac{\exp(\beta U_t(i))}{\sum_{i=1}^{I} \exp(\beta U_t(i))}$.[8] Investors' flows to each institutions at $t$ is thus given by:

$$f_{i,t} = \Delta \ln \left( s_t(i) H \right) = \beta \Delta U_t(i) - \Delta \ln \left( \sum_{i=1}^{I} \exp \left( \beta U_t(i) \right) \right). \tag{2}$$

which is a generalized version of equation above. While this general model is conceptually straightforward, the practical difficulty is accurately modeling demand shifts across a wide array of institutions. A realistic model should (at the very least) account for demand for insurance and savings over the cycle, which is outside the scope of our paper. Instead, we make the simplifying assumption that in the short-term flows into the insurance and pension sector are largely stable around crisis events (see Coppola (2021) for suggestive evidence).

## 3.2 Institution demand for assets

Financial institutions manage households' assets and invest in a set of assets. We index institution investors by $i = 1, 2, ..., I$, assets by $n = 0, 1, ..., N$, where $n = 0$ corresponds to

[7] Namely, that $\epsilon_h(i)$ follows a generalized extreme-value distribution with a cumulative distribution function given by $F(\epsilon) = \exp(-\exp(-\epsilon))$.

[8] The assets-under-management of institution $i$ is then given by the market share multiplied by total household assets, $s_t(i)H$, where $H$ is total household wealth invested.

the outside asset and, time by $t$. Each institution has wealth $W_{i,t}$ to invest. Each bond has its own expected return $\Pi_t(n)$.[9] Institutions have a mandate: the fraction invested in each asset, $\frac{P_t(n)Q_{i,t}(n)}{W_{i,t}}$ is given by

$$\theta_{i,t}(n) := \frac{P_{i,t}(n)Q_{i,t}(n)}{W_{i,t}} = \frac{\delta_{i,t}(n)}{1 + \Sigma_m \delta_{i,t}(m)} \tag{3}$$

The variable $\delta_{i,t}(n)$ determines how much fund $i$ "wants" to hold asset $n$ at time $t$. We normalize $\delta_{i,t}(0) = 1$ for the outside asset, so that $\delta_{i,t}(n)$ can be interpreted as the ratio of the fraction invested in asset $n$ at time $t$ relative to that invested in the outside asset $(\theta_{i,t}(n)/\theta_{i,t}(0))$. We model the economic determinants of $\delta_{i,t}(n)$ as follows:

$$\delta_{i,t}(n) = \bar{\delta}_i(n) \exp\left(\kappa_i(\Pi_t(n) - \bar{\Pi}(n))\right) E_{i,t}(n) \tag{4}$$

This expression highlights the three drivers of asset holding: (i) a bond-institution-specific "mandate parameter" $\bar{\delta}_i(n)$ which is time-invariant; (ii) the current deviation from the asset expected return $\kappa_i(\Pi_t(n) - \bar{\Pi}(n))$; and (iii) a temporary institution demand shock for an asset $E_{i,t}(n)$. Note that if $\Pi_t(n) = \bar{\Pi}(n)$ (no return shock) and $E_{i,t}(n) = 1$ (no demand shock), realized portfolio shares are equal to "target" portfolio shares $\theta$, i.e $\theta_{i,t}(n) = \theta_i(n) := \frac{\bar{\delta}_i(n)}{1+\Sigma_m \bar{\delta}_i(m)}$

A great advantage of this modeling is that asset demand follows a logit specification (Koijen and Yogo, 2019; Bretscher et al., 2020), which can be estimated using instrumental variables, as described in detail below.

We assume the changes in expected return premium is negatively related to the price change:

$$\pi_t(n) = \Delta \ln \Pi_t(n) = \rho(n)\left(d_t^e(n) - p_t(n)\right), \tag{5}$$

[9] Appendix A.1 shows how to extend the model to include other bond characteristics $x(n)$.

where $d_t^e = \Delta E_t[\ln D_{t+1}]$ and $p_t = \Delta \ln P_t$. $D_t$ is the cash flow from the asset. $\rho = \frac{D}{P}$ is the yield of the asset. The intuition is the following: an increase in expected cash flow leads to an increase in the expected return, while an increase in price implies that the expected return going forward is likely to be low (the intuition is similar to dividend price ratio or earning price ratio being a return predictor).[10]

## 3.3 Linking flows and asset demand

In this section, we show how flows map to demand and equilibrium prices. First, define $F_{i,t}$ as the cumulative inflow from time 0 to time $t$ into investor $i$. The inflow in period $t$ is then $\Delta F_{i,t}$. The percent flow $f_{i,t}$ is then given by $f_{i,t} \equiv \Delta F_{i,t}/W_{i,t-1}$, where $W$ is investor $i$ Asset Under Management (AUM). The dynamics of assets under management of the fund is given by

$$w_{i,t} \equiv \frac{\Delta W_{i,t}}{W_{i,t-1}} = \frac{\Sigma_n Q_{i,t-1}(n)\Delta P_t(n)}{W_{i,t-1}} + \frac{\Delta F_{i,t}}{W_{i,t-1}} = \Sigma_n \theta_{i,t-1}(n) p_t(n) + f_{i,t} \tag{6}$$

To solve for equilibrium, start by taking logs of the logit demand of a fund $i$'s for an asset $n$:

$$q_{i,t}(n) = w_{i,t} - p_t(n) + \Delta \log \delta_{i,t}(n) - \Delta \log(1 + \Sigma_m \delta_{i,t}(m)) \tag{7}$$

We linearize the last term using a first-order approximation for $\Pi_t(n) \approx \bar{\Pi}(n)$ and $E_{i,t} \approx 1 : \ln(1 + \Sigma_m \delta_{i,t}(m)) \approx \kappa_i \Sigma_m \theta_i(m) \left(\Pi_t(m) - \bar{\Pi}\right) + \text{constant}$. Here, $\theta_i(m)$ is the target portfolio share of bond $m$. This implies that $\Delta \log(1 + \Sigma_m \delta_{i,t}(m)) = \kappa_i \Sigma_m \theta_i(m) \Delta \Pi_t(m)$. The change in demand is thus given by:

$$q_{i,t}(n) = w_{i,t} - p_t(n) + \kappa_i \Delta \Pi_t(n) + e_{i,t}(n) - \kappa_i \Sigma_m \theta_i(m) \Delta \Pi_t(m) \tag{8}$$

[10]Formally, consider a perpetuity bond that pays an expected cash flow $D$ (adjusting for inflation and default). The discount rate is $\rho$. Using the perpetuity formula, the price of this asset is given by $P = \frac{D}{\rho}$, where $\rho$ is the expected return of this asset. Take the first difference, $\pi = \Delta\rho = \Delta\frac{D}{P} = \Delta\frac{D}{P} / \left(\frac{D}{P}\right) \times \frac{D}{P} = (d - p) \times \rho$.

where $e_{i,t}(n) := \Delta \log E_{i,t}(n)$. Using our expression for $w_{i,t}$ and $\Delta\Pi_t(n) = \rho(n)\left(d_t^e(n) - p_t(n)\right)$, we obtain the following intuitive decomposition for what drives changes in fund $i$'s demand for asset $n$:

$$
\begin{aligned}
q_{i,t}(n) = & \underbrace{-\zeta_{i,t}(n,n)p_t(n) + d_t^e(n)\kappa_i\rho(n)[1-\theta_i(n)]}_{\text{Own-asset effects}} \\
& + \underbrace{f_{i,t} + e_{i,t}(n)}_{\text{Flow and demand shocks}} \\
& \underbrace{-\left(\sum_{n' \neq n} \zeta_{i,t}(n,n')p_t(n') + d_t^e(n')\kappa_i\rho(n')\theta_i(n')\right)}_{\text{Cross-asset effects}}
\end{aligned}
\tag{9}
$$

where own-price and cross-price elasticities are respectively given by:

$$
\begin{aligned}
\zeta_{i,t}(n,n) = & \quad 1 - \theta_{i,t-1}(n) + \kappa_i\rho(n)[1-\theta_i(n)] \\
\zeta_{i,t}(n,n') = & \quad -\theta_{i,t-1}(n') - \kappa_i\rho(n')\theta_i(n')
\end{aligned}
\tag{10}
$$

which is an adaptation of the model of inelastic markets of Gabaix and Koijen (2021). Importantly, all demand coefficients can be estimated using standard IV techniques. In matrix notation, the elasticity of investor $i$ can be written as $\zeta_{i,t}$, which is of dimension $N \times N$. The diagonal entries are $\zeta_{i,t}(n,n)$, and only depend on the row $n$. Similarly, the off diagonal entries $\zeta_{i,t}(n,n')$ only depend on the column $n'$.[11]

Next, we aggregate demand elasticities for each asset using bond holding shares. To represent aggregation as in matrix notation, define $\boldsymbol{S_t}$ as an $N \times I$ vector of each investor' share of holding for each bond: the $(n,i)$ element is thus equal to $S_{i,t}(n) = Q_{i,t}(n)/\Sigma_j Q_{j,t}(n)$. One row of $\boldsymbol{S}_t$ thus reports every fund's holdings of one asset normalized by the size of that asset, and adds up to one. The aggregate elasticity for each asset market is $\text{diag}(\boldsymbol{S}_t \times \boldsymbol{\zeta}_t)$, where $\boldsymbol{\zeta}_t$ is an $I \times N$ matrix with the $(n,i)$ element representing the demand elasticity of institution $i$ for asset $n$. The aggregate elasticity for each asset market depends on the holding shares of each investor. A bond mostly held by an inelastic investor has a lower

[11] This is a well-known property of logit demand.

aggregate demand elasticity.

Similarly, we can write an expression for aggregate flows at the asset level as $\boldsymbol{S}_t \times \boldsymbol{f}_t$, where $\boldsymbol{f}_t$ is a $I \times 1$ vector of the flow for each institution. Importantly, note that $\boldsymbol{S}_t \times \boldsymbol{f}_t$ represents how flows affect *each* bond, depending on how much the investor subject to this flow was holding of the bond. Aggregate asset-level flows thus depend on the distribution of bond holdings interacted with individual fund outflows.

We can now write down an expression for asset prices based on aggregated flows and demand. Note first that assuming no fundamental or demand shock ($d^e = e = 0$), aggregate demand is (using matrix notation): $\boldsymbol{q}_t = \boldsymbol{S}_t \times \boldsymbol{f}_t - \text{diag}\left(\boldsymbol{S}_t \times \boldsymbol{\zeta}_t\right) \times \boldsymbol{p_t}$. Market clearing with no net issuance implies that $\boldsymbol{q}_t = \boldsymbol{0}$, thus

$$\boldsymbol{p}_t = \text{diag}^{-1}\left(\boldsymbol{S}_t \times \boldsymbol{\zeta}\right) \times \boldsymbol{S}_t \times \boldsymbol{f}_t, \tag{11}$$

where $\boldsymbol{p}_t$ is an $N \times 1$ vector of the log price for each asset. Finally, we map fund flows to asset prices. First, note that asset prices determine the returns of institution based on the portfolio holdings:

$$\boldsymbol{r}_t = \boldsymbol{\theta}_t \times \boldsymbol{p}_t, \tag{12}$$

where $\boldsymbol{\theta}_t$ is a $I \times N$ matrix of portfolio weights for each institution. One row of $\boldsymbol{\theta}_t$ thus represents one fund's portfolio weights across all assets, and adds up to one. Combined with the flow-to-performance equation (3.1), the next period fund flows are given by

$$\boldsymbol{f}_{t+1} = \text{diag}\left(\boldsymbol{\beta}\right) \times \boldsymbol{r}_t = \text{diag}\left(\boldsymbol{\beta}\right) \times \boldsymbol{\theta}_t \times \boldsymbol{p}_t, \tag{13}$$

where $\boldsymbol{\beta}$ is $I \times 1$ vector with the $i$'th element being $\beta_i$, the flow-to-performance sensitivity of institution $i$.

### 3.4 Model dynamics

We summarize equilibrium dynamics of asset prices and fund flows with the following difference equation system:

$$
\begin{aligned}
\boldsymbol{f}_t &= \operatorname{diag}(\boldsymbol{\beta}) \times \boldsymbol{\theta}_{t-1} \times \boldsymbol{p}_{t-1} \\
\boldsymbol{p}_t &= \operatorname{diag}^{-1}(\boldsymbol{S}_t \times \boldsymbol{\zeta}) \times \boldsymbol{S}_t \times \boldsymbol{f}_t
\end{aligned} \tag{14}
$$

Previous period asset log prices $\boldsymbol{p}_{t-1}$ affect current period fund flows $\boldsymbol{f}_t$ by a price-to-flow multiplier $\boldsymbol{\Phi} \equiv \operatorname{diag}(\boldsymbol{\beta}) \times \boldsymbol{\theta}$, which depends on fund flow to performance sensitivity and the portfolio weights of each fund. Current period fund flows $\boldsymbol{f}_t$ in turn affect current period prices $\boldsymbol{p}_t$ by a price impact matrix $\boldsymbol{\Psi} \equiv \operatorname{diag}^{-1}(\boldsymbol{S}_t \times \boldsymbol{\zeta}) \times \boldsymbol{S}_t$, which depends on fund demand elasticities and fund shares.

What is the cumulative effect of a given price shock? We can use the equation system to derive a closed form expression for how a primitive shock $\boldsymbol{v}$ to asset prices propagates through the system. The first round impact on asset prices is $\boldsymbol{v}$. The second round impact is $(\boldsymbol{\Psi\Phi})\boldsymbol{v}$. The $n$'th round impact is $(\boldsymbol{\Psi\Phi})^{n-1}\boldsymbol{v}$. The cumulative impact is thus $\left(\boldsymbol{I} + \boldsymbol{\Psi\Phi} + (\boldsymbol{\Psi\Phi})^2 + ...\right)\boldsymbol{v} = (\boldsymbol{I} - \boldsymbol{\Psi\Phi})^{-1}\boldsymbol{v}$.

Figure 1 shows an example of the model dynamics. We consider an economy with two sectors: mutual funds and insurance companies. 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 $\beta$ of 1.1 while insurance companies face a sensitivity of 0 because insurance companies' liabilities are not demandable as mutual funds. The demand elasticities $\zeta$ are 1.4 and 0.9 for mutual funds and insurance companies, respectively. The assets under management $W$ and the portfolios $\theta$ for each sector are calibrated to the 2019Q4 level. We simulate the dynamics following a 10% shock on the asset prices of high-yield bonds at time 1.

The example shows three interesting dynamics in equilibrium. First, there is a feedback loop between prices and flows. A negative shock reduces the high-yield bond price by 10%, as shown by the intercept of the red solid line of Figure 1a. However, this 10% is not the full impact. The price drop reduces fund returns, which leads to outflows. Outflows then lead to asset sales by mutual funds, which further depresses asset prices. The cumulative effect on the high yield bond prices is over 20% in this example, or two times the initial shock.

Second, the model displays contagion across assets. Although there is no fundamental shock on investment-grade bonds, their prices also drop in the equilibrium because institutions' demand for these assets fall. The cause of the cross-asset contagion is due to institutions' investment mandates; funds need to maintain certain portfolio weights, so they will sell investment-grade 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.

Note that while this example assumes away most of 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.

## 3.5 Measures of fragility

**Asset Fragility.** Using the model dynamics derived in Section 3.4, we can construct two measures of fragility in the model. The first measure is defined at the asset level. We ask: what is the impact of 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

$$\textbf{Asset fragility} \equiv \boldsymbol{\alpha}'(\boldsymbol{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}./\boldsymbol{\alpha}, \tag{15}$$

where $\boldsymbol{\alpha}$ is an $N \times 1$ vector of the market share of each bond and $\boldsymbol{\Psi}$ and $\boldsymbol{\Phi}$ are the price impact matrix of flows and the price-to-flow multiplier, respectively. We normalize each asset's effect on the market by the total market share of this asset $\alpha_n$ so that the shock is on a per dollar basis. The asset fragility measures the contribution an asset makes to the 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 larger on that fragility metric.

To understand the intuition behind this formula, it is useful to define a new variable $m_{n,k} = (\boldsymbol{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}_{n,k}$ as the cumulative spillover from asset $n$ to asset $k$.[12] This parameter measures the cumulative price impact on asset $k$ due to a shock on asset $n$ through all the flow-return linkages. The aggregate impact on the aggregate asset market index is then $\sum_{k=1}^{N} \alpha_k m_{n,k}$.

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. One fund invests in equal weights in each asset, 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 one. See Table 1 for a summary of the parameters in

[12] Recall from the example in the previous section that this formula for the cumulative impact comes from $\big(\boldsymbol{I} + \boldsymbol{\Psi}\boldsymbol{\Phi} + (\boldsymbol{\Psi}\boldsymbol{\Phi})^2 + ...\big) = (\boldsymbol{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}$, summing up indirect effects across all "rounds".

the numerical example.

We plot how fragility of the two assets varies with different parameter values in Figure 2. In the first panel of Figure 2, 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 2, 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 impact on sales of asset B will also reduce asset A fragility. However, the effect is not as dramatic as adjusting flow sensitivities.

**Fund Fragility.** 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:

$$\textbf{Fund fragility} \equiv [\boldsymbol{\alpha}'(\boldsymbol{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}\boldsymbol{\Psi}] \odot [\boldsymbol{\beta}./\boldsymbol{\alpha}^f]', \tag{16}$$

We normalize each fund $i$'s effect on the market by its market share $\alpha_i^f$, so that the overall impact to bond index is not mechanically driven by fund size.

To clarify what contributes to a fund's fragility, we return to the numerical example above and plot fund fragilities in Figure 3. In the first panel of Figure 3, 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. The equal-weighted fund is more negatively affected by the increase in Specialist B's flow sensitivity than Specialist A is, given Specialist A holds a smaller share of asset B.

In the second panel of Figure 3, as the demand elasticity of Specialist B over asset B increases, the price impact of a given shock declines and thus the fragility of the fund declines. The decline in 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.

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. In other words, an asset or an institution that has a high fragility measure does not necessarily do poorly in a crisis. Instead, the high fragility suggests that they contribute more to the aggregate fragility through their position in the contagion network. In other words, the fragility measures should be interpreted as "macro fragility" rather than "micro fragility". This distinction will be more apparent in the following section when we discuss policy targeting.

### 3.6 Policy intervention: maximum-price-impact benchmark

The model can help assess the effects of policy interventions in credit markets during crises. Specifically, our framework can identify which specific assets or institutions to target in order to maximize the price impact on the market, given a maximum amount of resources that can be spent.[13]

We can define such a *maximum-price-impact benchmark* for policy targeting as follows. The choice variable of the policy-maker is a vector $\boldsymbol{g}$ of price shocks for the different existing assets. This is more general that it seems at first. Policy interventions can take many forms: some intervention such as interest rate policy directly change the prices of bonds, but others operate through quantities such as quantitative easing and asset purchases. However, note that quantity-based and price-based policies can be mapped to each other using demand elasticities. Therefore, modeling the intervention as a vector of price shocks encompasses a wide range of interventions. In this section, we focus on a abstract intervention, but Section 5 shows how to apply this benchmark to different monetary and liquidity policies.

Formally, the maximum-price-impact intervention maximizes the cumulative impact on the aggregate bond market index for a given resource constraint:

$$\begin{aligned} &\max_{\boldsymbol{0}\leq\boldsymbol{g}\leq\overline{\boldsymbol{g}}} \boldsymbol{\alpha}'(\boldsymbol{I}-\boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}\boldsymbol{g}, \\ &\text{subject to: } \boldsymbol{\gamma}'\boldsymbol{g} \leq b, \end{aligned} \tag{17}$$

[13]This is not to say that this problem characterizes the fully optimal intervention. In practice, there are various other objective and constraints central banks take into account when deciding on policies, such as limiting credit risk, signalling information to investors and consumers, or fostering their credibility. Nevertheless, understanding the maximum-price-impact benchmark should be a useful input to optimal policy design.

$\boldsymbol{g}$ is an $N \times 1$ vector of the price shock due to the policy intervention: each asset is potentially affected differentially. For tractability, we abstract away from the many potential reasons why a resource constraint might exist, and simply model it as a linear constraint: $\boldsymbol{\gamma}$ is an $N \times 1$ vector of the cost to generate one percent of price change for each asset, $b$ is a scalar indicating the total resources that the policy-maker has.

For example, in the context of asset purchases, $\boldsymbol{\gamma}$ can be interpreted as the dollar value of an asset to be purchased to move the price by 1% (normalized by the size of the total asset market):

$$\boldsymbol{\gamma} = \boldsymbol{\alpha} \odot \text{diag}\left(\boldsymbol{S} \times \boldsymbol{\zeta}\right), \tag{18}$$

where $\boldsymbol{\alpha}$ normalizes the quantity of purchases by the total market size of all the assets, $\odot$ indicates element-wise product of two vectors. $b$ can be interpreted as the total dollar value of the asset purchase committed by the Federal Reserve normalized by the the total market size. $\boldsymbol{g}$ is bounded by zero because the policy-maker would not short assets to relax the budget constraint. $\boldsymbol{g}$ is also bounded from above by a vector $\overline{\boldsymbol{g}}$, the maximum price change that policy-maker intervention can create for each asset (e.g., buying up the entire stock of the asset). Section 5 considers types of intervention other than asset purchases.

The maximum-price-impact benchmark turns out to be a function of the asset fragility measure constructed in section 3.5. Specifically, we sort assets in descending order by the ratio of the asset fragility over the resources needed to move the asset price, weighted by the respective asset's market share:

$$\frac{\text{Asset fragility}_1 \times \alpha_1}{\gamma_1} \geq \frac{\text{Asset fragility}_2 \times \alpha_2}{\gamma_2} \geq ... \geq \frac{\text{Asset fragility}_N \times \alpha_N}{\gamma_N}. \tag{19}$$

Targeting follows a pecking-order: the policy-maker should first raise the price of the asset with the highest asset fragility per unit of resource. After the maximum price change is reached, the policy-maker then should move to the asset with the next highest asset fragility per unit of resource until the budget is exhausted.[14]

This result suggests that simply supporting the most beaten-up assets or assisting the institutions that suffer the most outflows or value loss in a crisis might not have the highest "bang-for-the-buck". Instead, to maximize price impact from a macro-prudential perspective it is best to target the assets or institutions that are central in the network that propagate and amplify the shock.

We can also compare different policy interventions by constructing *price impact multipliers*, defined as the average asset fragility per unit of resource of a given policy, $\boldsymbol{g}$:

$$\text{Price impact multiplier}(\boldsymbol{g}) = \frac{\textbf{Asset fragility}\boldsymbol{\alpha}'\boldsymbol{g}}{\boldsymbol{\gamma}'\boldsymbol{g}}, \tag{22}$$

where **Asset fragility** is a vector of asset fragility of each asset, as defined in equation (19).

It is worth noting that this multiplier can be constructed for an intervention that does not have an explicit resource constraint. For instance, an interest rate cut that raises bond prices can be mapped to an equivalent hypothetical asset purchase that generates the same price appreciation. The price impact multiplier of hypothetical asset purchase then can be interpreted as the multiplier of the interest rate cut. Doing so allows us to study the distance between conventional monetary policy and other more targeted asset purchase in terms of the degree of amplifications that is achieved by different types of policies.

[14] Formally, we define the marginal asset $N^*$ such that

$$\sum_{n=1}^{N^*} \gamma_n g_n \leq b, \tag{20}$$

$$\sum_{n=1}^{N^*+1} \gamma_n g_n \geq b. \tag{21}$$

The maximum-price-impact benchmark is $g_n = \overline{g}_n$ when $n < N^*$, $g_n = b - \sum_{n=1}^{N^*} \gamma_n g_n$ when $n = N^*$, and $g_n = 0$ when $n > N^*$. The detailed derivation can be found in Appendix B.2.

# 4 Estimation

In this section, we describe the estimation of key parameters of the model. Specifically, we estimate for each fund-year: (1) asset-specific demand elasticities and (2) flow to performance elasticities. 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 $\zeta$, the demand elasticity of price, we implement a method similar to Bretscher et al. (2020) and Koijen et al. (2021). Specifically, we take the investment universe of other funds as exogenous to a given fund's demand for a security, 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 $x_t(n)$:

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

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 tenor, initial offering amount (logged), and the bid ask spread.

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

To address 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 class of a bond, as defined by the credit rating-tenor-industry of issuer and $\mathbb{1}_{j,t}(k)$ indicates that fund $j$ includes class $k$ 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.[17] The intuition behind the instrument is that it affects prices because the more funds (and the larger those funds) include class $k$ 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 class of security at least once in the prior 12 quarters. Bonds are categorized into 460 "classes" based on tenor-rating-industry.[18] Tables 2 and 10 reports summary statistics of the classes and Table 11 reports summary statistics on investor holdings data. 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-asset. A higher value for the instrument corresponds to higher prices and thus lower yields, and the relationship is statistically significant.

We run IV regressions for each investor, asset class, and year from 2010-2021 in which the fund holds at least 20 unique bonds and at least 20% of its holdings in corporate bonds in the period. On the left hand side we use the total market value of bonds relative to the total value invested in the outside asset. We construct the right-hand-side variable as the

[17] 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 ratings 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 in the category.

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. We include quarter fixed effects to absorb within-year variation in market conditions that may affect all funds.

Table 4 reports the distribution of estimated demand elasticites.[19] 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. (2020). On average, holders of HY bonds are more elastic than holders of IG bonds. Across investors, mutual funds are more price elastic than non-mutual funds (in this case, insurers), consistent with findings in Bretscher et al. (2020). We estimate an average demand elasticity of 0.9 for insurers and 1.4 for mutual funds. Within mutual funds, ETFs are the most demand elastic on average, followed by index funds. Over time, funds have become more price elastic overall, with average elasticities increasing from 0.8 before the 2008 financial crisis to 2.3 in the 2020-2022 period, likely driven by the increase in mutual fund share.

## 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,

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

[19] 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.

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 conduct the following regression at the fund-month panel and report the results in Table 5:

$$Flow_{i,t+1} = \beta Return_{i,t} + \gamma X_{i,t} + v_{i,t}, \tag{26}$$

where $X_{i,t}$ is a vector of control variables including flows at time $t$, fund fixed effects, and time fixed effects.

Columns 1–4 of Table 5 show that fund flows are highly responsive to past 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 0.26%–0.29% of the fund's assets under management. The magnitude 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).

We next consider the daily sample during the COVID-19 crisis. Using the daily sample allows us to calibrate the model to daily frequency during a major distress event in the bond market, which helps to study financial stability implications. We run similar regressions as equation (26) and report the results in Table 6. In the daily sample, a one percentage point reduction in daily fund return leads to a net outflow in the magnitude of 0.06%–0.14% of the fund's assets under management, as shown in Columns 1–4. We find the flows are more sensitive to negative returns in the daily sample in Column 5. A one percentage point reduction in daily fund return leads to a net outflow in the magnitude of 0.17% of the fund's assets under management.

We report further cross-sectional and time-series variation in flow to performance estimates in Table 7. These fund-specific elasticities will be used in simulating the model to run policy counterfactuals. Average flow to performance estimates in 2019 across all mutual funds was 0.38, indicating a 1% decline in returns leads to a net outflow of 0.38% of the fund's assets under management.

### 4.3 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 the fragility measures derived in Section 3.5. First, Table 8 shows the asset fragility estimates for different asset classes, 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 and 1.2. IG bonds are less fragile than HY bonds. Within rating categories, short-term bonds are more fragile than long-term bonds. In terms of economic magnitudes, an IG bonds' fragility of 1.02-1.06 implies little amplification, of the order of a few basis points. HY bonds are more fragile, especially short-term HY bonds, with a fragility measure of 1.16. Our framework allows us to unpack these differences. First, being held by investors facing a stronger flow sensitivity $\beta$ increases fragility. For instance, the third row of Table 8 show that more fragile assets tend to have a larger mutual fund holding share. However, fragility cannot be reduced to flow sensitivity alone: it is key to also consider the role of demand elasticity $\zeta$. For example, short-term IG bonds have a higher flow sensitivity than long-term HY bonds but are less fragile because they have a larger demand elasticity to compensate. In a similar vein, long-term IG bonds have very low flow sensitivity (low $\beta$) but are still fragile because they are held by very inelastic investors (low $\zeta$).

Next, Table 9 shows the fund fragility estimates and for different categories of funds. For insurers and pension funds, to which we assign flow-to-performance sensitivities of zero, fund fragility is mechanically equal to zero. Mutual funds and ETF have fund fragility ranging from 0.7 to 2.7. Passive mutual funds and index ETF have the highest fragility, driven by high flow sensitivities $\beta$. The fragility of passive mutual funds is particularly large in economic terms: a fund fragility of 2.7 implies significant amplification of any shock to the returns of these funds.

# 5 Counterfactuals

We have developed and estimated a model of the corporate bond market, incorporating household choice of funds and fund demand for bonds. The model simulates dynamics of feedback effects between price changes and flows, as well as contagion effects across asset classes and institutions. Equipped with this framework, we can run counterfactuals to evaluate different policies that attempt to mitigate a large negative shock to the corporate bond market.

We consider an economy with two sectors: mutual funds and insurance companies. Mutual funds face a fund-specific flow-to-performance sensitivity $\beta$ as reported in Table 7, while insurance companies, which we aggregate into one fund, face a sensitivity of 0.[20] The estimated demand elasticities $\zeta$ vary by fund-year-asset and are reported in Table 4.[21] The assets under management $W$ and the portfolios $\theta$ for each sector are calibrated to the 2019Q4 levels. We simulate the dynamics following a 10% shock on the asset prices of high-yield bonds at time 1, consistent with the magnitude of the initial shock of the COVID crisis in early March, 2020.[22] We evaluate the impact of responding to the negative shock to corporate bond markets with conventional monetary policy, asset purchases, direct lending

[20] In fact, insurers may even experience net inflows when credit conditions worsen and prices drop; see Figure 7 of Coppola (2021).

[21] To ensure our counterfactual results are not driven by outliers, we focus on the 95% (96%) of IG (HY) elasticities that are between 0 and 5, the 89% of positive flow sensitivity funds with flow sensitivity below 5, and the 83% of funds with $1 billion or less in AUM.

[22] See Figure 2 of Haddad et al. (2021b), Returns during the COVID-19 crisis across asset classes.

to funds, and finally by restricting redemption on mutual funds.

For each policy, we simulate the impact on asset prices and fund values of intervention immediately following the negative shock (at $T = 2$) and of intervention later on (at $T = 10$). We consider the estimated demand elasticities and flow to performance coefficients for the year 2019 to best simulate the economy entering the spring 2020 market crash.

Our framework is tractable enough to account for thousands of parameters capturing the rich investor heterogeneity of the data. In the following counterfactuals, we include the 264 unique mutual funds for which we can estimate both $\zeta$ and $\beta$ in 2019, and we aggregate insurers into one fund, assigning it the average $\zeta$ computed across all insurers in 2019 and a $\beta = 0$. We account for all fund holdings across 2 assets (IG and HY bonds) and show how the price of each asset changes after the shock.[23]

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 $\beta$. For this reason, we deliberately include specific policies that affect $\beta$ directly, such as redemption restrictions or swing pricing, and allow $\beta$ to vary within the policy counterfactual.

[23] For simplicity, the counterfactual plots show prices of these two asset classes. In principle, the framework allows us to account for many more assets. In section 5.5, we describe a policy price impact comparison that simulates policy-specific counterfactual price dynamics across four assets.

## 5.1 Conventional monetary policy

First, in Figure 4, we simulate a conventional policy rate cut of 25 basis points implemented after the negative shock to bond markets. Specifically, we allow the price of each asset to increase by $0.25\% \times m(n)$ at implementation of the policy, where $m(n)$ equals the average remaining maturity for each asset. In 2019, the average remaining maturity was 6.76 for IG bonds and 4.75 for high yield bonds.

As in the baseline example in Figure 1, asset prices continue dropping after the initial shock due to the feedback loop of lower returns encouraging outflows and further depressing prices. Immediately following the rate cut, the fall in asset prices is mitigated, although high yield bond prices remain at below pre-shock value in the long run (see the left panel of Figure 4). The right panel of Figure 4 shows that the total value of insurers and mutual funds stops dropping immediately after the intervention and recovers somewhat, but similarly remains below pre-shock value.

We compare the effects of early and late policy intervention. In the upper panel, we simulate policy intervention at $T = 2$ and compare the outcomes for asset prices and fund values to the same intervention at $t = 10$ in the bottom panel. However, the early policy intervention reduces the magnitude of the trough and allows prices and values to rebound more quickly in contrast to intervening at $T = 10$.

## 5.2 Central bank asset purchases

Next, in Figure 5, we evaluate a policy where the central bank purchases 1% of outstanding investment grade assets. 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 investment grade 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.[24]

With our model, we can trace the effect of actual purchases on the different asset classes and investor sectors. Even though the purchases are targeted towards investment grade, there is also a small price benefit for high yield because (1) the rebound of fund wealth and (2) the fixed investment mandate increase demand for high yield assets. Mutual fund values rebound by more than insurers due to the amplifying effect of flows following positive performance.

Intervening quickly, as before, dampens the decline in both price and value, with investment grade bonds benefiting slightly more. Earlier intervention improves slightly the post-intervention steady state fund values and prices, but the effect is small (less than 1% of pre-fund value).

## 5.3 Direct lending

In Figure 6, we consider the effects of a policy that lends directly to mutual funds up to 1% of IG assets. Specifically, we allow the inflow of funds into mutual funds to increase by 1% of their IG. As soon as this policy is implemented, the decline in prices stops, however unlike the previous two policy counterfactuals, there is no significant rebound in prices or fund values post-intervention.

Early intervention makes a big difference in this policy counterfactual. By implementing a lending facility immediately, the price drop for IG (HY) assets is limited to less than 1% (12%) of pre-shock values, versus a price drop of 7% (17%) in the case of slow intervention. Similarly, the drop in mutual fund and insurer values is significantly worse in slow intervention compared to the case of immediate implementation.

[24]At year end 2019, there was over $9.5 trillion in outstanding corporate bonds across investment. Source: SIFMA 2021 Capital Markets Factbook).

## 5.4 Redemption restrictions

We next consider a policy of freezing mutual fund redemptions. At implementation of the policy, we set the net flow for each fund to be bounded below by zero. Figure 7 displays the effects, assuming that the intervention is implemented either two days after the shock ($T = 2$) or ten days later ($T = 10$). Unlike the other policies, the implementation of a redemption restriction on mutual funds does not allow prices and fund values to rebound at all. Moreover, it can only mitigate the drop in fund values and prices when it occurs sufficiently quickly. In the counterfactual with $T = 10$, a restriction on redemptions is implemented too late to create significant improvements in steady-state prices or values compared to the baseline in Figure 1.

## 5.5 Policy price impact: comparison

Finally, we compare these policies to the maximum-price-impact benchmark derived in the theoretical framework. Figure 8 compares the different type of interventions, taking into consideration the variation in prices across four assets classes (long IG, short IG, long HY, and short HY).[25] Conventional monetary policy (risk-free rate cut) is the least effective, because it has the biggest price effect on less fragile long-term IG assets, which have a median time to maturity of 13 years. Direct lending to mutual funds is marginally more effective because assets held by mutual funds are more fragile than assets held primarily by insurers, but because they target fund flows rather than prices directly, they are less effective than asset purchases. Asset purchases are more effective because they target IG bonds more broadly, but given IG bonds are not the most fragile, this is still not optimal. Redemption restrictions are more effective because they target mutual funds overall. However, no policy counterfactual reaches the maximum price efficacy because each still targets assets or funds

[25] Long assets are corporate bonds that are at least 5 years in remaining maturity; short assets have less than 5 years in remaining maturity.

that are not the most fragile.[26]

### 5.6 Preventative policies: 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.[27] 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 10% negative shock in HY asset prices. See Figure 9 for the results. The implementation of swing pricing inhibits significant outflows and further price declines, thereby avoiding the onset of a negative feedback loop.

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. (2022a). In this counterfactual, we hold fund holding characteristics fixed. Estimating a counterfactual that endogenizes holding characteristics would be useful but outside the scope of this paper.

[26]Note that the policy impact comparison is based on an initial negative price shock. Optimal policy may be different if the initial shock arises from exogenous fund outflows.

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

# 6 Conclusion

This paper develops a two-layer asset pricing framework to theoretically and empirically analyze the fragility of the corporate bond market. Equilibrium asset prices reflect the demand of both households and institutional investors. The model features dynamic feedback loops between investor outflows and asset prices, as well as contagion across assets and institutions. Importantly, we show how the key 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' underlying economics are general enough and its estimation methodology 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 instance 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 markets disruptions and policy interventions on real activity using an integrated framework and structural estimation.

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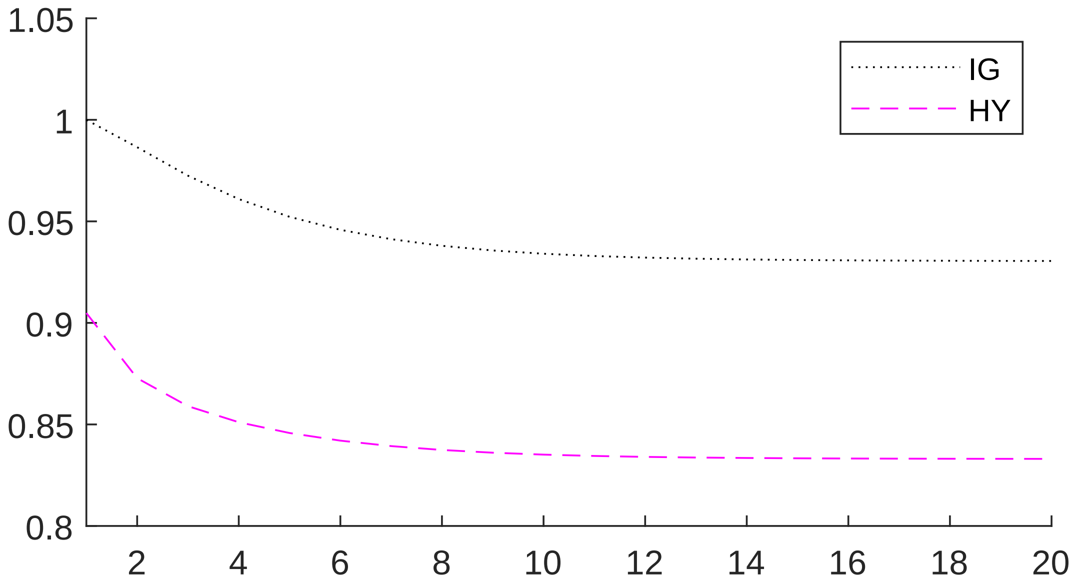
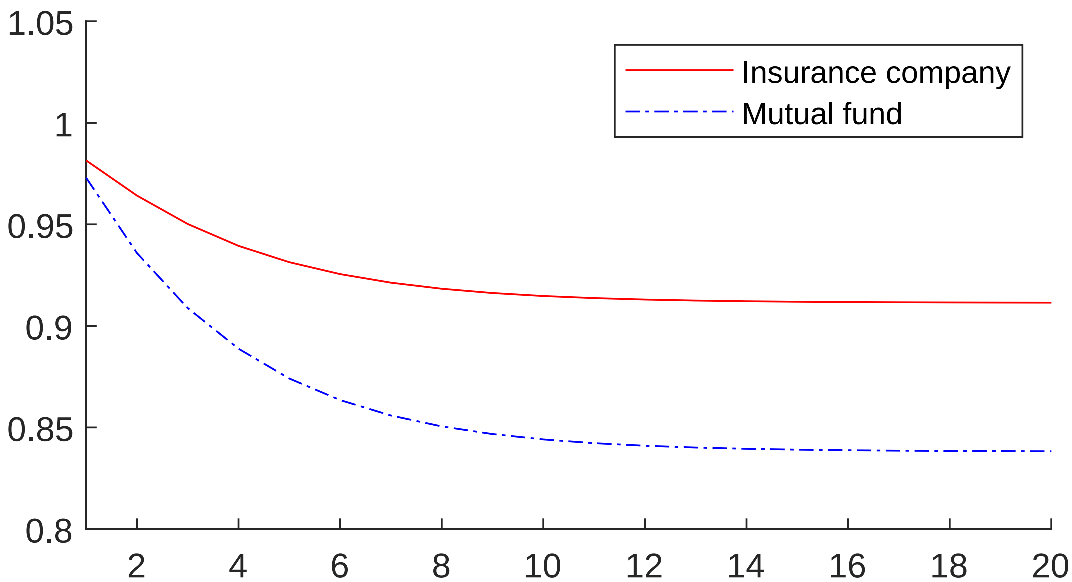
Figure 1: Model dynamics: example



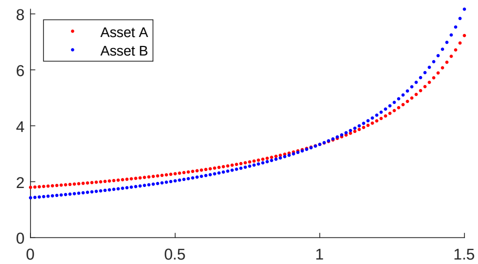

(a) Prices



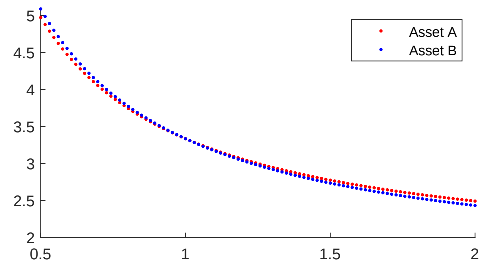

(b) AUM

*Note:* This graph shows simulated paths of AUM and asset prices for a two-sector-two-asset model. Parameters values described in Section 3.4.

Figure 2: Asset fragility: numerical example



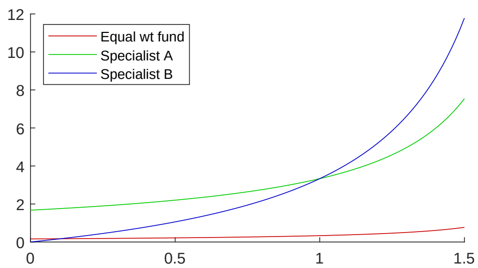

(a) Flow sensitivity of Specialist B



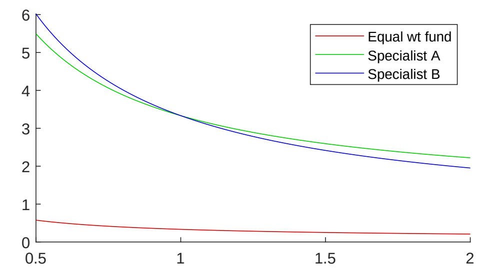

(b) Demand elasticity over B: Specialist B

*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 3: Fund fragility: numerical example



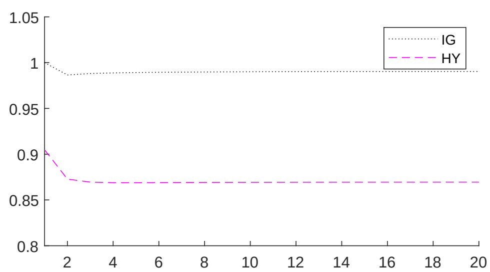

(a) Flow sensitivity of Specialist B



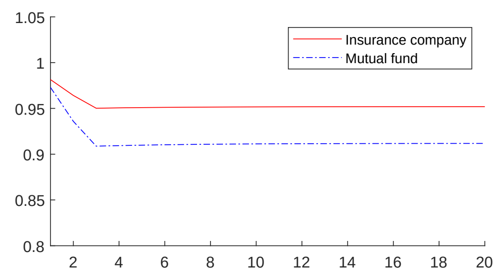

(b) Demand elasticity over B: Specialist B

*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.

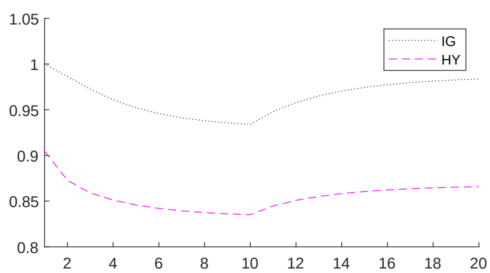
Figure 4: Counterfactual simulation: rate cut



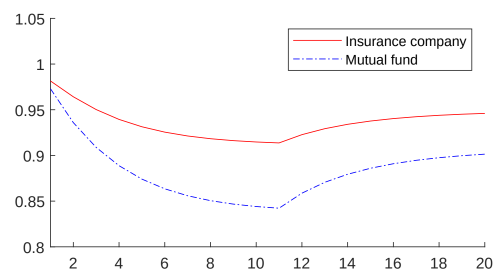

(a) Prices with $T = 2$




(b) AUM with $T = 2$



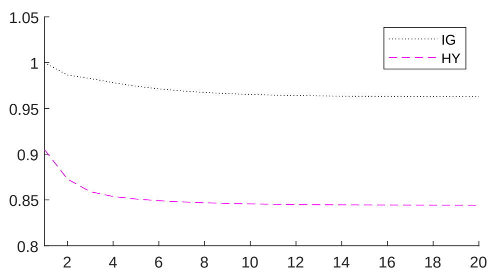

(c) Prices with $T = 10$



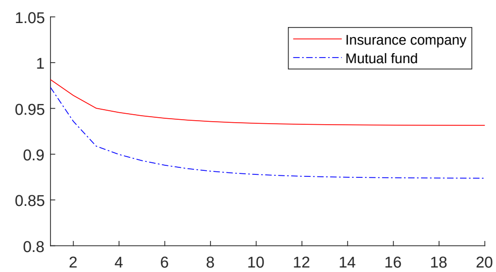

(d) AUM with $T = 10$

*Note:* This graph shows the counterfactual AUM and asset prices following a 10% shock on investment-grade and high-yield bond prices at time 1. The central bank cut the policy rate by 25 basis points at time 2 and time 10 for the upper and lower panels, respectively.

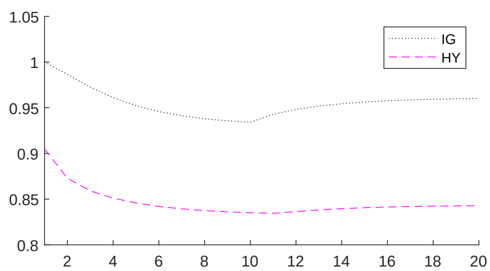
Figure 5: Counterfactual simulation: asset purchases



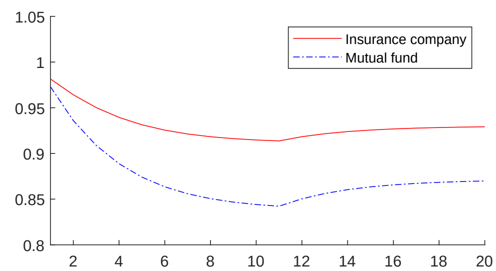

(a) Prices with $T = 2$




(b) AUM with $T = 2$



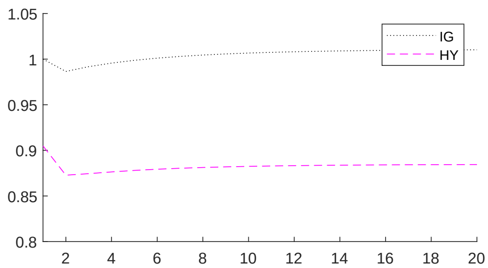

(c) Prices with $T = 10$



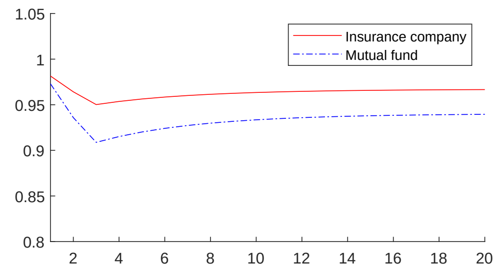

(d) AUM with $T = 10$

*Note:* This graph shows the counterfactual AUM and asset prices following a 10% shock on investment-grade and high-yield bond prices at time 1. The central bank conducts asset purchases of 1% of the investment-grade bond market at time 2 and time 10 for the upper and lower panels, respectively.

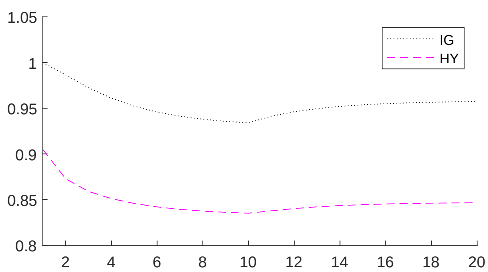
Figure 6: Counterfactual simulation: central bank lending to mutual funds



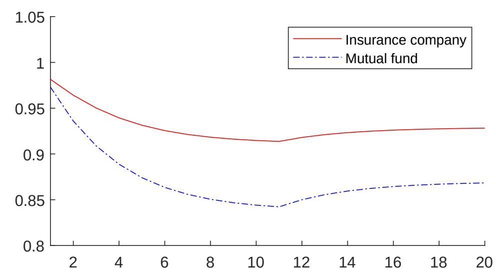

(a) Prices with $T = 2$




(b) AUM with $T = 2$



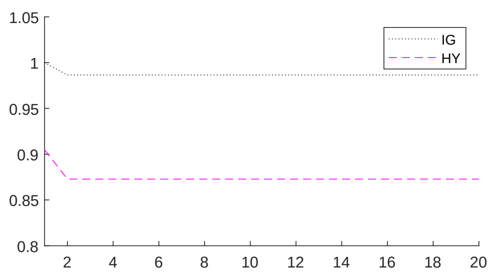

(c) Prices with $T = 10$



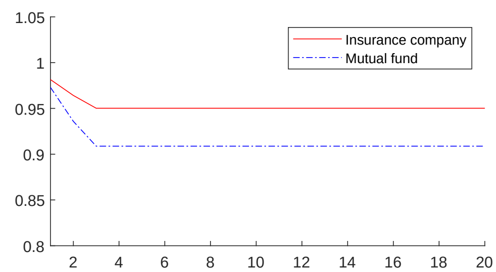

(d) AUM with $T = 10$

*Note:* This graph shows the counterfactual AUM and asset prices following a 10% shock on investment-grade and high-yield bond prices at time 1. The central bank allows all mutual funds to borrow up to 5% of their IG holdings and 1% of their high-yield holdings at time 2 and time 10 for the upper and lower panels, respectively.

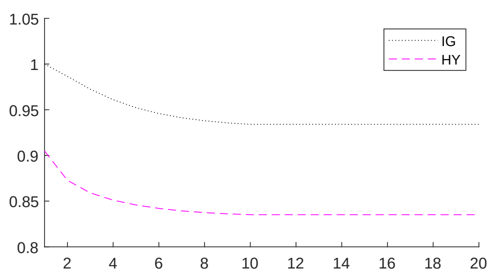
Figure 7: Counterfactual simulation: limits to redemptions for mutual funds



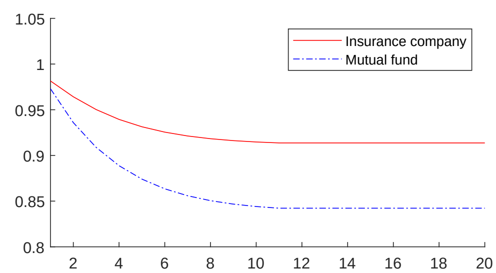

(a) Prices with $T = 2$




(b) AUM with $T = 2$



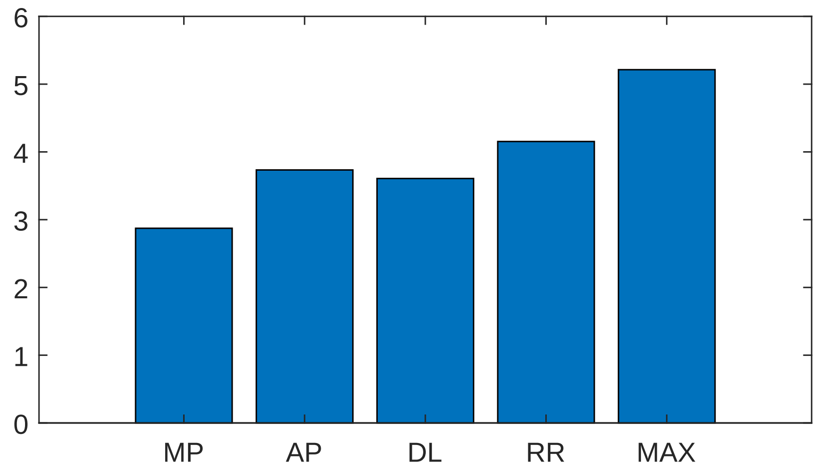

(c) Prices with $T = 10$




(d) AUM with $T = 10$

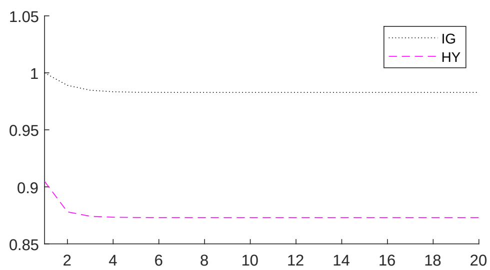
*Note:* This graph shows the counterfactual AUM and asset prices following a 10% shock on investment-grade and high-yield bond prices at time 1. Mutual funds restrict suspend redemptions at time 2 and time 10 for the upper and lower panels, respectively.

Figure 8: Price impact multipliers of various interventions

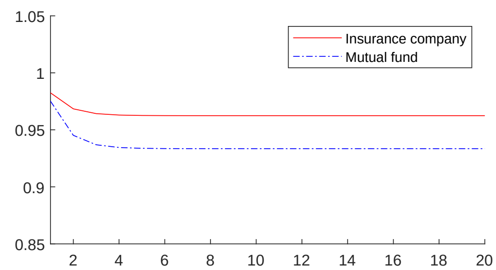



*Note:* This graph shows the policy targeting multipliers of various interventions at $T = 10$, as described in Section 5. "MP" stands for conventional monetary policy. "AP" stands for asset purchases. "DL" stands for direct lending. "RR" stands for redemption restrictions. "MAX" stands for the maximum-price-impact. The price impact multiplier is defined in equation (22).

Figure 9: Counterfactual simulation: swing pricing for mutual funds




(a) Asset prices




(b) Fund AUM

*Note:* This graph shows the counterfactual AUM and asset prices following a 10% shock on investment-grade and high-yield bond prices at time 1. Mutual fund flow sensitivity to performance is adjusted according to Jin et al. (2021) Table 3 in period 1.

Table 1: Numerical example: parameters

| | Equal weighted fund | Specialist A | Specialist B |
|---|---|---|---|
| Asset A share | 0.50 | 0.66 | 0.33 |
| Asset B share | 0.50 | 0.33 | 0.66 |
| Total wealth | 1.00 | 1.00 | 1.00 |
| Flow sensitivity | 0.10 | 1.00 | 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 2 and 3 to demonstrate how fragility metrics respond to variation in flow sensitivities and demand elasticities.

Table 2: Summary of classes

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| Funds per class-quarter | 26055 | 7.9 | 11.6 | 1 | 2.0 | 3.0 | 9.0 | 125 |
| Holdings per class-quarter | 26055 | 29207.0 | 87878.5 | 0 | 1148.5 | 5900.0 | 22984.5 | 3657773 |
| Unique bonds per class-quarter | 26055 | 11.1 | 20.5 | 1 | 2.0 | 4.0 | 11.0 | 233 |
| TS avg num funds per class | 460 | 5.8 | 8.2 | 1 | 1.3 | 2.8 | 6.5 | 60 |
| TS avg holdings per class | 460 | 21841.3 | 47502.0 | 0 | 2780.8 | 6844.5 | 17619.4 | 437881 |
| TS avg num bonds per class | 460 | 8.0 | 14.2 | 1 | 1.4 | 3.0 | 8.0 | 105 |
| Avg classes per quarter | 88 | 296.1 | 66.6 | 59 | 274.8 | 308.0 | 342.2 | 375 |

*Note:* This table summarizes the distribution of statistics aggregated to the class-quarter and class level. A bond class is defined as a 2-digit NAIC industry category, a tenor at issuance, and the credit rating of the bond.

Table 3: First stage test for instrument

| | (1)<br>All funds | (2)<br>Insurers | (3)<br>Mutual funds |
|---|---|---|---|
| Z_icq | -0.00512*** | -0.00622*** | -0.00455** |
| | (0.00142) | (0.00154) | (0.00150) |
| U.S. Treasury | -3.807** | -4.224*** | -2.959* |
| | (1.339) | (1.304) | (1.523) |
| Bidask | 6.183*** | 5.953*** | 6.891*** |
| | (1.550) | (1.545) | (1.552) |
| Original tenor (log) | 0.0457*** | 0.0538*** | 0.0356*** |
| | (0.00619) | (0.00713) | (0.00669) |
| Years remaining | 0.0163*** | 0.0158*** | 0.0163*** |
| | (0.00112) | (0.00110) | (0.00126) |
| Amount issued (log) | -0.00401* | -0.00347 | -0.00196 |
| | (0.00193) | (0.00210) | (0.00190) |
| Issuer rating | -0.245*** | -0.261*** | -0.236*** |
| | (0.0181) | (0.0185) | (0.0232) |
| Constant | 0.683*** | 0.729*** | 0.647*** |
| | (0.0540) | (0.0543) | (0.0614) |
| Fund x IG x Quarter FE | ✓ | ✓ | ✓ |
| Observations | 1809233 | 1059467 | 709888 |
| R-squared | 0.697 | 0.696 | 0.703 |

*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 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, the bid–ask spread as reported by WRDS, the tenor at issuance (logged), number of years remaining,the initial amount issued (logged), the issuer credit rating. The sample period is 2010 to 2019 with quarterly observations. The first column reports the first stage results for all funds; the second column reports results for insurers, and the last column reports results for mutual funds. Includes fund–IG dummy–quarter fixed effects. Standard errors are clustered at the fund and quarter level.

Table 4: Summary of demand elasticity estimates

| 2010-2019 estimates | 10% | mean | 90% |
|---|---|---|---|
| All fund-bonds | 0.782 | 0.988 | 1.203 |
| IG holdings | 0.765 | 0.916 | 1.234 |
| HY holdings | 0.798 | 1.059 | 1.181 |
| Non-mutual funds | 0.807 | 0.884 | 1.179 |
| Mutual funds | 0.639 | 1.445 | 1.349 |
| ETFs | 0.823 | 1.615 | 1.215 |
| Index funds | 0.814 | 1.515 | 1.230 |
| Other MF | 0.542 | 1.363 | 1.424 |

| Time periods | 10% | mean | 90% |
|---|---|---|---|
| Pre-2008 | 0.543 | 0.805 | 0.983 |
| 2008 financial crisis | 0.865 | 1.148 | 1.343 |
| 2010-2019 | 0.542 | 1.363 | 1.424 |
| 2020-2022 | 0.421 | 2.312 | 1.500 |

*Note:* This table summarizes the distribution of demand elasticities. The top panel summarizes estimates for different asset and fund categories in 2010-2019. The bottom panel summarizes estimates for mutual funds in different time periods, excluding ETFs and index funds.

Table 5: Flow to return sensitivity: monthly

| | (1)<br>F.Flow | (2)<br>F.Flow | (3)<br>F.Flow | (4)<br>F.Flow | (5)<br>F.Flow |
|---|---|---|---|---|---|
| Return | $0.288^{***}$ | $0.294^{***}$ | $0.274^{***}$ | $0.259^{***}$ | |
| | [0.021] | [0.021] | [0.029] | [0.029] | |
| Flow | $0.193^{***}$ | $0.165^{***}$ | $0.185^{***}$ | $0.140^{***}$ | $0.140^{***}$ |
| | [0.004] | [0.004] | [0.004] | [0.004] | [0.004] |
| Positive return | | | | | $0.209^{***}$ |
| | | | | | [0.051] |
| Negative return | | | | | $0.309^{***}$ |
| | | | | | [0.046] |
| Fund F.E. | No | Yes | No | Yes | Yes |
| Time F.E. | No | No | Yes | Yes | Yes |
| Observations | 242,046 | 242,033 | 242,033 | 242,020 | 242,020 |
| Adj. R-squared | 0.043 | 0.058 | 0.051 | 0.080 | 0.080 |

*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 managements from the previous month. The dependent variable is one-month forward fund flow. Data source: CRSP Mutual Fund Database.

Table 6: Flow to return sensitivity: daily

| | (1) F.Flow | (2) F.Flow | (3) F.Flow | (4) F.Flow | (5) F.Flow |
|---|---|---|---|---|---|
| Return | 0.137*** | 0.058 | 0.171*** | 0.067* | |
| | [0.038] | [0.036] | [0.063] | [0.037] | |
| Flow | 0.292* | 0.292* | -0.010 | -0.011 | -0.011 |
| | [0.163] | [0.163] | [0.037] | [0.037] | [0.037] |
| Positive return | | | | | -0.120 |
| | | | | | [0.175] |
| Negative return | | | | | 0.167 |
| | | | | | [0.137] |
| Time fixed effects | No | Yes | No | Yes | Yes |
| Fund fixed effects | No | No | Yes | Yes | Yes |
| Observations | 45,614 | 45,614 | 45,613 | 45,613 | 45,613 |
| Adj. R-squared | 0.084 | 0.084 | 0.288 | 0.288 | 0.288 |

*Note:* This table shows the relationship between fund flows and returns. The sample period is 2020Q1 with daily observations. "Return" is the net daily return of the fund in percentage points. "Flow" is measured by the percentage change in the asset under managements from the previous day. The dependent variable is one-day forward fund flow. Data source: Morningstar Mutual Fund Database.

Table 7: Summary of flow to performance estimates

| 2010-2019 estimates | 10% | mean | 90% |
|---|---|---|---|
| All fund-bonds | -3.078 | 0.584 | 4.677 |
| ETFs | -2.729 | 0.788 | 4.870 |
| Index funds | -2.437 | 0.926 | 4.810 |
| Other MF | -3.125 | 0.482 | 4.514 |

| Time periods | 10% | mean | 90% |
|---|---|---|---|
| Pre-2008 | -2.392 | 0.120 | 2.632 |
| 2008 financial crisis | -0.699 | 0.104 | 1.453 |
| 2010-2019 | -3.125 | 0.482 | 4.514 |
| 2020-2022 | -1.107 | 0.186 | 1.601 |

*Note:* This table summarizes the distribution of flow to performance elasticities. The top panel summarizes estimates for different asset and fund categories in 2010-2019. The bottom panel summarizes estimates for mutual funds in different time periods, excluding ETFs and index funds.

Table 8: Asset fragility measure

| | IG | | HY | |
|---|---|---|---|---|
| | Long | Short | Long | Short |
| Asset fragility 2019 | 1.022 | 1.055 | 1.085 | 1.161 |
| Market share of asset | 0.507 | 0.237 | 0.165 | 0.091 |
| Mutual fund holding share of asset | 0.347 | 0.506 | 0.766 | 0.783 |
| Holdings-weighted average beta | 0.040 | 0.160 | 0.125 | 0.249 |
| Holdings-weighted average zeta | 1.049 | 1.683 | 1.138 | 1.239 |

*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 (zeta) are holdings weighted averages across funds for each asset.

Table 9: Fund fragility estimates by subsample: 2019

| 2019 | IG Elasticity | HY Elasticity | Flow-to-performance | IG share | Fund fragility |
|---|---|---|---|---|---|
| Life Insurers | 0.915 | 0.960 | 0.000 | 0.876 | 0.000 |
| Pension Funds | 1.086 | 1.006 | 0.000 | 0.923 | 0.000 |
| Active MF | 1.089 | 1.002 | 0.885 | 0.700 | 0.834 |
| Passive MF | 1.300 | 1.008 | 2.852 | 0.955 | 2.659 |
| ETF | 5.285 | 1.063 | 0.742 | 0.655 | 0.698 |
| Index ETF | 1.130 | 0.947 | 1.324 | 0.683 | 1.248 |

*Note:* This table summarizes the fund value weighted average elasticities, flow-to-performance sensitivities, and fund fragilities estimated across different subsamples of funds. Reports the distribution for 2019.

# Appendix: derivations and proofs

## A.1 Adding bond characteristics

Adding $K$ time-invariant bond characteristics $\{X^k\}$ is straightforward. They only enter the definition of the target portfolio share $\theta_i(n) := \frac{\bar{\delta}_i(n)}{1+\Sigma_m \bar{\delta}_i(m)}$, with $\bar{\delta}_i(n) = \exp\left(\Sigma_k \beta_i^k X^k(n)\right)$, instead of being just an asset-specific fixed effect. Nothing else changes.

Time-varying characteristics enter the model like the cash-flow shock $d_t^e(n)$. Denote by $x_t^k(n) = \Delta X_t^k(n)$ the change in characteristic $k$ for asset $n$. The change in demand is now (including the cash-flow shock in characteristics $X^k$ to consolidate notation):

$$
\begin{aligned}
q_{i,t}(n) = & \underbrace{-\zeta_{i,t}(n,n)p_t(n) + [1-\theta_i(n)]\Sigma_k \beta_i^k x_t^k(n)}_{\text{Own-asset effects}} \\
& + \underbrace{f_{i,t} + e_{i,t}(n)}_{\text{Flow and demand shocks}} \\
& \underbrace{-\left(\sum_{n' \neq n} \zeta_{i,t}(n,n')p_t(n') + \theta_i(n')\Sigma_k \beta_i^k x_t^k(n')\right)}_{\text{Cross-asset effects}}
\end{aligned} \tag{27}
$$

where own-price and cross-price elasticities are the same as before.

## B.2 Derivations of maximum-price-impact benchmark

The policy-maker's problem is

$$
\begin{aligned}
& \max_{\mathbf{0} \leq \boldsymbol{g} \leq \bar{\boldsymbol{g}}} \boldsymbol{\alpha}'(\boldsymbol{I} - \boldsymbol{\Psi\Phi})^{-1}\boldsymbol{g}, \\
& \text{subject to: } \boldsymbol{\gamma}'\boldsymbol{g} \leq b,
\end{aligned} \tag{28}
$$

The Lagrangian function is

$$\mathcal{L}(\boldsymbol{g}, \lambda) = \boldsymbol{\alpha}'(\boldsymbol{I} - \boldsymbol{\Psi\Phi})^{-1}\boldsymbol{g} + \lambda(b - \boldsymbol{\gamma}'\boldsymbol{g}) + \overline{\boldsymbol{\mu}}'(\overline{\boldsymbol{g}} - \boldsymbol{g}) + \underline{\boldsymbol{\mu}}'\boldsymbol{g}, \tag{29}$$

We have

$$\frac{\partial \mathcal{L}}{\partial g_n} = \boldsymbol{\alpha}'(\boldsymbol{I} - \boldsymbol{\Psi\Phi})^{-1}\boldsymbol{e}_n - \gamma_n - \overline{\mu}_n + \underline{\mu}_n, \tag{30}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = b - \boldsymbol{\gamma}'\boldsymbol{g}, \tag{31}$$

$$\frac{\partial \mathcal{L}}{\partial \overline{\mu}_n} = \overline{g}_n - g_n, \tag{32}$$

$$\frac{\partial \mathcal{L}}{\partial \underline{\mu}_n} = g_n, \tag{33}$$

Sorting the $N$ assets by $\boldsymbol{\alpha}'(\boldsymbol{I} - \boldsymbol{\Psi\Phi})^{-1}\boldsymbol{e}_n/\gamma_n$ in descending order, define the marginal asset $N^*$ such that

$$\sum_{n=1}^{N^*} \gamma_n g_n \leq b, \tag{34}$$

$$\sum_{n=1}^{N^*+1} \gamma_n g_n \geq b. \tag{35}$$

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

# Appendix: Additional Tables and Figures

Table 10: Top classes

| Classifier | TS avg num funds | TS avg holdings | TS avg num bonds |
|---|---|---|---|
| 33-15.0-Aaa | 57.6 | 297,430.8 | 104.5 |
| 33-15.0-Baa1 | 53.7 | 232,133.4 | 102.2 |
| 32-15.0-Baa1 | 60.4 | 254,196.1 | 101.2 |
| 53-15.0-Baa1 | 49.0 | 251,800.6 | 90.5 |
| 48-15.0-Baa1 | 45.9 | 196,145.1 | 80.3 |
| 32-15.0-Aaa | 43.0 | 184,862.9 | 77.4 |
| 21-15.0-Baa1 | 41.7 | 149,029.1 | 67.7 |
| 51-15.0-Baa1 | 39.2 | 159,900.0 | 67.0 |
| 33-100.0-Aaa | 27.9 | 332,493.3 | 65.1 |
| 48-100.0-Baa1 | 29.4 | 173,449.4 | 56.1 |

*Note:* This table summarizes the top 10 classes by the number of bonds within the class. A classifier is defined as a 2-digit NAIC industry category, a tenor at issuance, and the credit rating of the bond. The TS avg num funds reports the average number of funds that hold this class of bond each quarter. The TS average holdings is the average quarterly volume of each class that is reported. The TS avg num bonds is the number of bonds, on average, that is considered within each classifier.

Table 11: Summary of investor holdings

| | 2002 mean | 2002 median | 2010 mean | 2010 median | 2019 mean | 2019 median |
|---|---|---|---|---|---|---|
| Avg AUM | 804,708 | 95,095 | 1,016,236 | 100,204 | 1,386,188 | 118,482 |
| Num classes per fund-qtr | 12 | 7 | 23 | 15 | 35 | 24 |
| Num bonds per fund-qtr | 17 | 8 | 49 | 21 | 98 | 36 |
| Avg holding | 1,965 | 700 | 1,542 | 513 | 2,614 | 441 |
| Std_holding | 1,335 | 388 | 1,221 | 319 | 1,925 | 324 |

*Note:* This table summarizes the distribution of fund characteristics statistics aggregated to the fund-quarter level.