

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

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Abstract

We develop a two-layer asset demand framework to analyze fragility in the corporate bond market. Households allocate wealth to institutions, 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, investor holdings, and fund flows, allowing for rich parameter heterogeneity across assets and institutions. We match the model to the March 2020 turmoil and quantify the equilibrium effects of unconventional monetary and liquidity policies on asset prices and institutions.

Keywords: Nonbanks, financial fragility, corporate bond markets, mutual fund flows, illiquidity, demand system asset pricing, unconventional monetary policy

JEL codes: G23, G01, G12, E43, E44, E52

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

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

We first develop equilibrium conditions for the two-layer asset demand model. In the first layer, households allocate wealth to institutional investors. Our key focus is on the flow-performance relationship in the mutual fund sector, which affects the size of funds' Assets under Management (AUM): high returns lead to inflows into a fund, while poor returns lead to outflows. In the second layer, institutional investors then allocate funds to specific assets. We build on the framework of Bretscher et al. (2022) in which asset demand is driven by asset returns and the institutions' investment mandates. Equilibrium asset prices reflect the demand of both households and institutional investors: AUM determines asset demand through mandates, while asset holdings affect fund returns and drive changes in AUM going forward. The framework can account for large heterogeneity across institutions in terms of their flow sensitivities or asset demand elasticities.

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

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

decrease.

Although these amplifications and contagions have been documented in the prior literature, our framework has the unique advantage of characterizing them as simple sufficient statistics that can be estimated, such as institution demand elasticities, flow-to-return sensitivities, and the distribution of assets across institutions. This tractability makes the model highly scalable despite heterogeneity: our empirical implementation includes thousands of investor-specific parameters. The model guides us to construct an asset fragility measure, which measures how much aggregate asset prices would decline for a given shock to the value of one asset, taking into account both the direct contribution of the asset and the amplification through other assets or institutions. A similar fragility measure can be constructed for each financial institution in an analogous manner.² These two measures can help policymakers evaluate the source of systemic fragility in credit markets and better target any ex-post interventions.

We estimate the model parameters using microdata. The first layer uses flow-performance regressions to determine how much outflow an institution would suffer if it experienced negative returns (Chevalier and Ellison, 1997; Sirri and Tufano, 1998). The second layer uses an instrumental variables technique to estimate the asset demand system that exploits rigidities in institutions' investment mandates (Kojien and Yogo, 2019; Bretscher et al., 2022). For the first layer, we construct a monthly panel of fixed-income funds from January 1992 to December 2021 from the CRSP Mutual Fund Database and complement it with daily fund flow and net asset value data for open-end funds from Morningstar. For the second layer, we use a comprehensive dataset that merges holdings data from eMAXX and CRSP, pricing data from WRDS Bond Returns, and bond details from Mergent FISD.

We estimate asset fragility in the cross-section of corporate bonds. The least fragile asset class is long-term investment-grade (IG) bonds with a fragility of 1.3, which means

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

that a 1% shock to the long-term IG bond prices would decrease the aggregate bond index by 1.3% multiplied by the market value share of these bonds. Interestingly, IG bonds are not always less fragile than high-yield (HY) bonds. In particular, short-term IG bonds (less than five years) are surprisingly fragile: they face a level of amplification similar to short-term HY bonds and a fragility of 2. Our framework allows us to unpack these differences: these IG bonds are much more likely to be held by mutual funds than longer-term IG bonds, particularly by mutual funds with a high flow sensitivity. This is intuitive: funds anticipating potentially large inflows prefer to hold liquid IG bonds as a precautionary measure. In principle, differences in investor price elasticity also matter in explaining differences in fragility, but quantitatively the effect of flow sensitivities dominates. Across institutions, we find a significant fraction of mutual funds that are extremely fragile.

We use our estimates to study the effects of policy interventions to stabilize the market. The Federal Reserve responded swiftly in the Spring of 2020 by lowering its interest rate targeting and announcing corporate bond purchases for the first time. Other potential interventions have been discussed, but quantifying their effects has largely been an open question. We match the model to the key moments of the flows and price dynamics of March 2020 and study four types of ex-post interventions: First, conventional monetary policy (risk-free rate cut) and asset purchases, which are broad measures that were implemented in 2020. Then we study two interventions focused on the fragile mutual fund sector, specifically: direct lending to mutual funds and restricting redemption on mutual fund shares, which have not been implemented but are related to interventions that have been implemented for the banking sector.³ In each counterfactual, we feed in two weeks of price shocks implied by CDS spreads and evaluate the impact of an intervention two days (early) or 14 days (late) after the initial shocks. Moreover, we also study how well targeted these interventions are in addressing fragility, in the sense of maximizing price impact while limiting the size of

³Nevertheless, 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).

the intervention. Our framework allows us to compute the benchmark of a maximum-price-impact intervention, in which the policy-maker targets the assets with the highest fragility, as measured above, per unit of price elasticity.

First, we find that a rate cut improves prices and restores some of the loss in fund value. IG bonds rebound significantly more than HY bonds because they have a longer duration. There is also a significant rebound in institutional investors' assets under management. Interestingly, the timing of the intervention matters for the short-term path of prices and AUM, but the eventual rebound is similar when intervening early or late. Second, we evaluate a policy where the central bank purchases 5% of outstanding short-term (five years or less) IG bonds. While these asset purchases target IG bonds, there is nevertheless a small price benefit for HY bonds because of the rebound in fund AUM as well as investment mandates increasing demand for HY assets. Mutual fund values rebound relatively more than insurers due to the amplifying effect of inflows following a good performance but remain significantly below pre-crisis levels. The timing of the intervention also matters relatively little for the size of the eventual rebound.

Next, we study two types of intervention targeting the mutual fund sector specifically. We consider the effects of lending directly to mutual funds against 2% of their IG bond portfolio as collateral.⁴ We find that this policy is extremely effective at supporting prices and limiting outflows, but only if it is implemented early. Despite not being targeted directly, insurers also benefit from the market rebound. Intervening late, however, is almost entirely ineffective. This evidence suggests that a “lender of last resort” towards nonbanks can potentially be effective, but only if implemented sufficiently quickly. We then consider a policy of freezing mutual fund redemption. Regulators did not mandate this policy in Spring 2020, but a significant number of funds facing severe liquidity issues suspended redemption

⁴On 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.

(Grill, Vivar, and Wedow, 2021). Similar to direct lending, this policy is very effective, but only when it occurs sufficiently quickly. Redemption restrictions, a classical tool of bank regulation, might thus also be a consideration for nonbanks.

We then compare how well-targeted these policies are in addressing fragility. Perhaps surprisingly, even though they only focus on IG bonds, asset purchases are the best-targeted intervention and in fact close to the theoretical maximum-price-impact benchmark. This is because they target short-term IG bonds which are significantly fragile due to being held by especially flow-sensitive investors. This gives support to the policy choice of the Federal Reserve in Spring 2020 if the goal was to maximize price impact under a limited budget. On the other hand, conventional monetary policy (risk-free rate cut) is the least well-targeted because it has the biggest price effect on less fragile long-term IG assets due to their high duration. This is not necessarily surprising: the return to the zero lower bound was dictated by many considerations other than addressing the bond market turmoil specifically. The two other interventions targeting the mutual fund sector are better targeted, although quantitatively, the effect is perhaps not as large as could be expected.

Finally, we also provide a counterfactual to gauge the effects of implementing swing pricing, a preventive policy measure that requires funds to adjust their NAV to pass trading costs to redeeming shareholders. We model this policy through a reduction in flow-to-performance sensitivities, informed by the empirical finding of Jin, Kacperczyk, Kahraman, and Suntheim (2021). We find that this policy is effective in avoiding the onset of a negative feedback loop. It reduces by about 10 percentage points the decline in bond prices as well as in the size of the mutual sector, even if naturally the policy does not fully prevent the effect of a negative shock. Our quantitative result thus supports the recent regulatory proposal to mandate swing pricing for mutual funds.⁵

Our paper contributes to the debate on the financial stability implications of non-bank

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

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

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

From a methodological standpoint, relative to existing work applying a demand system approach to asset pricing (Kojen and Yogo, 2019, 2020; Kojen et al., 2021; Bretscher et al., 2022) we endogenize institutional investors' AUM, incorporating a second layer into our model. In this way, we are able to capture strong dynamic feedback loops between flows and asset prices that are particularly important in crisis episodes. Our focus on fund outflows is also directly related to work on the role of flows and inelastic investors in equity markets (Gabaix and Kojen, 2021). Our paper supports the view of Bretscher et al. (2022) that argue that institutional investors' demand is crucial for the pricing of corporate bonds. We build on their result that the main investors in the corporate bond market exhibit vastly different

demand elasticities and that investor composition matters greatly for corporate bond pricing. We add that institutions’ flow sensitivity is a key driver of fragility in crisis times. In a different application, Fang (2022) quantifies monetary policy amplification through bond fund flows by estimating a nested logit demand system with flexible investor elasticity both within and across asset classes. Similar in spirit, Azarmlsa and Davis (2022) develop and estimate a two-layer demand system in equity markets in which households allocate funds among heterogeneous intermediaries.

This paper is also closely related to works studying the risks imposed by investor redemption for institutions that issue demandable liabilities, such as open-end mutual funds (Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017; Zeng, 2017). Another strand of the literature focuses on the illiquidity of the bond market and the fire-sale spillovers.⁶ Falato, Hortacsu, Li, and Shin (2021) in particular provide compelling evidence of how flow shocks to some funds affect other funds, asset values, and ultimately financial stability. Importantly, the impact of forced sales on prices depends on the market price elasticity, i.e. the ability of other investors to absorb the selling pressure. Our two-layer framework explicitly connects both strands of this literature and accounts for the interaction between flows and limited price elasticity. Our structural approach complements the existing empirical studies of the stress events in the credit markets by nesting an explicit equilibrium asset pricing model (Falato, Goldstein, and Hortacsu, 2021; Haddad, Moreira, and Muir, 2021b; Ma, Xiao, and Zeng, 2022; Jiang, Li, Sun, and Wang, 2022). For instance, our framework allows us to run counterfactuals to study various policy interventions that have been implemented or discussed in serious stress events. For instance, we can shed light on the “bond-fund fragility channel” of Falato, Goldstein, and Hortacsu (2021) whereby the Fed liquidity backstop transmits to the real economy via funds.

More generally, this paper also contributes to our understanding of the role of inter-

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

mediaries for asset valuation during crisis episodes. A large body of work measures the systemic risk in the financial system, with a particular focus on banks (Adrian and Brunnermeier, 2016; Acharya, Pedersen, Philippon, and Richardson, 2017; Greenwood, Landier, and Thesmar, 2015; Duarte and Eisenbach, 2021). Other papers have popularized the idea of intermediary asset pricing (He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Haddad and Muir, 2021). We contribute to this line of work in two dimensions. First, the existing literature often focuses on levered financial intuitions such as traditional banks and shadow banks such that the key amplification mechanism is through deleveraging and capital constraints. In contrast, we focus on unlevered nonbanks such as open-end mutual funds whose fund sizes fluctuate over time even absent a leverage constraint. Second, we bring in new insights and methods from the recent literature on demand system asset pricing, which allows us to tightly map the model to micro-data on investor holdings.⁷

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.⁸ We exclude bonds that are issued in exchange for an identical existing bond, or that do not report at least one credit rating, tenor, credit spread, or size at issuance. We further exclude convertible bonds, capital impact bonds, community investment bonds, and PIK securities. We restrict the holdings sample to fund-quarters in which the fund holds at least 20 unique corporate bonds in our sample in

⁷However, one limitation of our framework relative to existing models of intermediary asset pricing is that, while it generates asset price dynamics, it does not explicitly model institutions' portfolio choice as a fully dynamic optimization problem.

⁸Issuers with NAICS codes beginning with 52, 92, and 22 are excluded.

the year. Following Bretscher et al. (2022), we use the last recorded price and yield for each quarter in the WRDS Bond Returns dataset. We back out the credit spread for each bond-quarter using an interpolated U.S. Treasury yield curve as per Gürkaynak et al. (2007). We include holdings from 2010-2021 to capture the post-2008 financial crisis period up through the COVID crisis of 2020. The estimation sample includes 2,306 mutual funds, 987 insurers, and 10,942 unique corporate bonds.⁹

For estimating flow-to-performance parameters, we use the CRSP Mutual Fund Database to create a monthly panel of fixed-income funds from January 1992 to December 2021, covering a total of 2,967 funds. We complement the CRSP dataset using the daily fund flows and net asset value (NAV) of open-end fixed-income mutual funds from the Morningstar database. The daily sample focuses on the COVID-19 crisis period from January 1, 2020, to April 30, 2020, covering a total of 1,199 funds. The daily sample allows us to zoom in on the high-frequency variations in the flow and returns in a distressed period.

3 Framework

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

⁹Because we focus on two classes of investors in the model, insurers and mutual funds, we group fund types as follows: money market, balanced, unit investment trusts, funds of funds, and variable annuity funds are classified as mutual funds, and property and casualty insurance, life insurance, and reinsurance companies are classified as insurers.

3.1 General setup

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

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

where κ_h are sensitivities to the characteristics of household type h ; $\epsilon_{h,t}(i)$ captures horizontal differentiation across each investment option. The weight of institution i in household h 's portfolio is given by the following logit form:¹⁰

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

The demand for institution liability by household h is then given by the portfolio shares multiplied by the household's wealth $A_{h,t}$, then divided by the net asset value (NAV) $P_{t-1}(i)$:¹¹

$$Q_{h,t}^D(i) = \frac{\theta_{h,t}(i) A_{h,t}}{P_{t-1}(i)}, \quad (3)$$

Layer 2: Institution demand for assets Financial institutions allocate households' investments to a set of assets. We index assets by $n = 0, 1, \dots, N$, where $n = 0$ corresponds

¹⁰This follows from the standard assumption that $\epsilon_{h,t}(i)$ follows a generalized extreme-value distribution with a cumulative distribution function given by $F(\epsilon) = \exp(-\exp(-\epsilon))$.

¹¹The assumption that household demand depends on $P_{t-1}(i)$ is motivated by the fact the NAV is calculated at the end of the date, so households only know the last period's NAV when they invest. In our application, the time between periods is small and equal to one day. The main result remains robust if we use a different timing convention.

to the outside asset and, time by t . Each institution has wealth $W_{i,t}$ to invest (its assets under management, or AUM). Each asset is described by a vector of characteristics $X_t(n)$, which includes risk and return, rating, maturity, and so on. Each institution chooses the best option to maximize its indirect utility, i.e.

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

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

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

The NAV of an institution can be calculated using its asset portfolio weights,¹²

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

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

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

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

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

where $P_t(n)$ is the price of asset n .

¹²Note that we can incorporate a management fee when calculating NAV. Because our focus is short-run in which the management fee is mostly fixed, we abstract away the management fee.

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

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

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

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

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

for all assets $n = 0, 1, \dots, N$.¹³

3.2 Joint dynamics of flows and asset prices

Layer 1: Flow-to-performance relationship We derive the equilibrium dynamics following a shock to asset values. Specifically, we log-linearize the household demand for institution liabilities, equation (3), and then take a first difference. Note that time-invariant characteristics would drop out after taking the first difference. The main time-varying characteristic that remains after the first difference is the lagged return of the institutions. Therefore, we can specify $\Delta X_{i,t} = r_{i,t-1}$ for the household demand for institution liabilities, equation (3). In that case, the aggregate inflow into institution i follows a familiar flow-to-performance relationship:

$$f_{i,t} \simeq \beta_i r_{i,t-1} - \kappa_i \bar{r}_{t-1} + \bar{a}_t, \quad (11)$$

¹³Note that the two markets clear in different manners. The price of institution liabilities is the NAV, which is mechanically determined by the underlying assets according to the accounting rule, equation (6). Therefore, the market of institution liabilities clears mostly through quantity adjustment: mutual funds elastically create and destroy shares given investors' purchase and redemption. In comparison, the asset market clears mainly through prices, at least in the short run, because the quantity of outstanding assets is mostly fixed.

The key coefficient is the institution’s *flow sensitivity* β_i which reflects the return sensitivity of its households investors (κ_h). \bar{r}_{t-1} is the weighted average return of all institutions, while \bar{a}_t is the average change in household wealth.¹⁴

Given our focus on nonbank fragility in credit markets, we emphasize this well-known flow-to-performance relationship linking fund size (AUM) to past fund returns (Chevalier and Ellison, 1997; Sirri and Tufano, 1998; Berk and Green, 2004). Flows in and out of the mutual fund sector also played a central role in the 2020 turmoil (Falato et al., 2021; Haddad et al., 2021b; Ma et al., 2022). Our focus on this particular version of the model is justified by how important this economic channel is for nonbank fragility, both conceptually and practically.

Layer 2: Institutions’ asset demand To derive institutions’ asset demand, we follow the same steps of log-linearizing demand (equation (8)) before taking a first difference. We assume the main time-varying asset characteristic that remains after the first difference is the asset’s expected return. Furthermore, we assume changes in expected return are negatively related to the price change according to the following relationship: $\Delta X_t(n) = \pi(n) = \rho(n) (d_t(n) - p_t(n))$, where $d_t(n) = \Delta \mathbb{E}_t [\ln D_{t+1}(n)]$ is the expected change in the cash flow from the asset, in the spirit of Gabaix and Koijen (2021). $\rho = \frac{D}{P}$ is the yield of the asset.¹⁵ Therefore, the log-linearized equation (8) can be written as

$$q_{i,t}(n) = -\zeta_i(n)p_t(n) + \kappa_i\rho(n)d_t(n) + f_{i,t} + \sum_{m=0}^N \theta_i(m) (\zeta_i(m)p_t(m) - \kappa_i\rho(m)d_t(m)), \quad (12)$$

The key coefficient is the *price elasticity* $\zeta_i(n) = 1 + \kappa_i\rho(n)$ of institution i for asset n .¹⁶

¹⁴The full derivation is in Appendix A.

¹⁵Formally, consider a perpetuity bond that pays an expected cash flow D (adjusting for inflation and default). The discount rate is ρ . Using the perpetuity formula, the price of this asset is given by $P = \frac{D}{\rho}$, where ρ is the expected return of this asset. Take the first difference, $\pi = \Delta\rho = \Delta\frac{D}{P} = \Delta\frac{D}{P} / \left(\frac{D}{P}\right) \times \frac{D}{P} = (d-p) \times \rho$. 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.

¹⁶Technically, the price elasticity is $\partial q_{i,t}(n) / \partial p_t(n) = -\zeta_i(n)(1 - \theta_i(n))$. It is however more convenient for the algebra to keep track of the parameter ζ . Empirically, we recover ζ from elasticity estimates by dividing

Importantly, inflows $f_{i,t}$ also impact demand because they determine the overall institutional wealth (AUM) to be invested. The last term captures cross-price elasticities: when the price of another asset m increases, the demand for asset n increases via a traditional substitution effect.¹⁷

Matrix notation We can represent the model dynamics around a shock to asset values using matrix notation. For simplicity, we ignore changes in immediate cash flows, i.e. $d = 0$, so that the shock can thus for example be thought as a shock to the asset’s risk or its long-term cash-flows. Note that the framework is equally well suited to study other types of shocks such as flow shocks on the mutual fund sector.¹⁸

For tractability, the benchmark model makes one additional assumption. We study shocks that affect the corporate bond market but not other assets in the household portfolio. This implies that the shock a has negligible impact on the average return of household portfolio ($\bar{r} \approx 0$) and induces a negligible change in total household wealth ($\bar{a} \approx 0$). In the model, this assumption corresponds to the outside option being large enough relative to corporate bond investments. Consistent with this assumption, in practice, the majority of household wealth is invested in other asset classes, such as housing, stocks, deposits, and government bonds. We study shocks that are orthogonal to shocks to these assets.¹⁹

Now, we can express the model dynamics using matrix notation. Note that asset prices

by $(1 - \theta_i(n))$.

¹⁷Technically, the last term also includes one term related to own-price elasticity (when $m = n$). The derivation is in Appendix B.

¹⁸For example, households might decide to massively re-balance away from bond funds towards money market funds at the start of a crisis even before fund performance deteriorates significantly. Because flows and asset prices are tightly linked in our framework, price and flow shocks are amplified in relatively similar ways. Internet Appendix C provide an illustration. We thus mainly focus on one type of shock for readability.

¹⁹These assumptions can be relaxed. Assuming that household wealth falls following a negative shock to bond values would only amplify the feedback loop between flows and asset values we emphasize. Our main mechanism also applies if the shock affects other asset classes as long as it affects corporate bonds relatively more.

determine the returns of institution based on the portfolio holdings:

$$\mathbf{r}_{t-1} = \boldsymbol{\theta}_{t-1} \times \mathbf{p}_{t-1}, \quad (13)$$

where $\boldsymbol{\theta}_{t-1}$ is a $I \times N$ matrix of portfolio weights for each institution. One row of $\boldsymbol{\theta}_{t-1}$ represents one fund's portfolio weights across all assets, and adds up to one. Combined with the flow-to-performance equation (11), the next period fund flows are given by

$$\mathbf{f}_t = \boldsymbol{\beta} \times \mathbf{r}_{t-1} = \boldsymbol{\beta} \times \boldsymbol{\theta}_{t-1} \times \mathbf{p}_{t-1}, \quad (14)$$

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

Next, we map fund flows to asset prices. Define \mathbf{S}_t as an $N \times I$ matrix of each investor's share of holding for each bond: the (n, i) element is thus equal to $s_{i,t}(n) = Q_{i,t}(n) / \sum_{i=0}^I Q_{i,t}(n)$. One row of \mathbf{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 $\text{diag}(\mathbf{S}_t \times \boldsymbol{\zeta})$, where $\boldsymbol{\zeta}$ is an $I \times N$ matrix with the (n, i) element representing the demand elasticity of institution i for asset n , $\zeta_i(n)$. 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 aggregate demand elasticity. This captures the key idea in Bretscher et al. (2022) that investor composition matters greatly for market-level elasticity.

Similarly, we can write an expression for aggregate flows at the asset level as $\mathbf{S}_t \times \mathbf{f}_t$, where \mathbf{f}_t is a $I \times 1$ vector of the flow for each institution. Importantly, note that $\mathbf{S}_t \times \mathbf{f}_t$ 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.

Now we can write down an expression for asset prices based on aggregated flows and demand: $\mathbf{q}_t = -\text{diag}(\mathbf{S}_t \times \boldsymbol{\zeta}) \times \mathbf{p}_t + \mathbf{S}_t \times \mathbf{f}_t + \mathbf{S}_t \times (\boldsymbol{\theta}_t \odot \boldsymbol{\zeta}) \mathbf{p}_t$, which is obtained by multiplying equation (12) with $s_{i,t}(n)$ and summing across i . Intuitively, the three terms capture the three drivers of demand described above (1) own-price elasticity; (2) flows; and (3) cross-price elasticities.²⁰ Market clearing with no net issuance implies that $\mathbf{q}_t = \mathbf{0}$, thus we can recover equilibrium prices. To simplify notation, define the price impact matrix of flows as $\boldsymbol{\Psi}_t \equiv (\text{diag}(\mathbf{S}_t \times \boldsymbol{\zeta}) - \mathbf{S}_t \times (\boldsymbol{\theta}_t \odot \boldsymbol{\zeta}))^{-1} \times \mathbf{S}_t$, which depends on fund demand elasticities and fund shares. Equilibrium prices are given by

$$\mathbf{p}_t = \boldsymbol{\Psi}_t \times \mathbf{f}_t \quad (15)$$

where \mathbf{p}_t is an $N \times 1$ vector of the change in log price for each asset.

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

$$\begin{aligned} \mathbf{f}_t &= \boldsymbol{\Phi}_t \times \mathbf{p}_{t-1} \\ \mathbf{p}_t &= \boldsymbol{\Psi}_t \times \mathbf{f}_t \end{aligned} \quad (16)$$

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

What is the cumulative effect of a given price shock? To build intuition, we can use the equation system to derive a closed-form expression for how a primitive shock \mathbf{v} to asset

²⁰Technically, the last term also includes some terms related to own-price elasticity (the diagonal elements). The main effect nevertheless comes from the off-diagonal elements capturing cross-price elasticities.

prices propagates through the system by making the simplifying assumption that Ψ and Φ are constant over time. In that case, the first round impact on asset prices is \mathbf{v} . The second round impact is $(\Psi\Phi)\mathbf{v}$. The n 'th round impact is $(\Psi\Phi)^{n-1}\mathbf{v}$. The cumulative impact is thus $(\mathbf{I} + \Psi\Phi + (\Psi\Phi)^2 + \dots)\mathbf{v} = (\mathbf{I} - \Psi\Phi)^{-1}\mathbf{v}$.

Figure 1 shows an example of the model dynamics. We consider an economy with two sectors: mutual funds and insurance companies investing in two assets: IG and HY. For the sake of illustration, we provide an example with parameters that are in line with the data, although we defer the details of estimation to the next section. Mutual funds face an average flow-to-performance sensitivity β of 0.6 while insurance companies face a sensitivity of 0 because insurance companies' liabilities are not demandable as mutual funds. The demand elasticities ζ are 1.1 and 0.97 for mutual funds and insurance companies, respectively. The assets under management W and the portfolios θ for each sector are calibrated to the 2019Q4 level. We simulate the dynamics following a 10% shock on the asset prices of HY 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 HY 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 HY bond prices is over 13% in this example, well over the initial 10% shock.

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

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

Importantly, the flow effects embodied in the first layer of the model are crucial to generate these dynamics. Figure IA.1 in the Internet Appendix shows that there is no dynamic amplification nor contagion when institutions' wealth is exogenous. Note also that while this example assumes away most of the investor heterogeneity for the sake of illustration, the framework's tractability makes it highly scalable: our empirical implementation below includes thousands of investor-specific parameters.

4 Estimation

In this section, we describe the estimation of key parameters of the model. Specifically, we estimate for each fund-year: (1) asset-specific demand elasticities and (2) flow-to-performance sensitivities. This rich set of parameter estimates is important to realistically quantify the contagion of shocks through financial markets. Our framework is tractable enough to handle these multiple dimensions of heterogeneity.

4.1 Demand estimates

To estimate the price elasticity of demand, we implement a method similar to Bretscher et al. (2022) and Kojien et al. (2021). Specifically, we take the investment universe of other funds as exogenous to a given fund's demand for an asset, and use other fund investment universes

as an exogenous price shifter to pin down demand elasticities.²¹ Based on the empirically tractable model derived in Kojien and Yogo (2019), we can write log demand $\delta_{i,t}(n)$ ²² as a function of credit spreads and bond characteristics $x_t(n)$:

$$\ln \delta_{i,t}(n) \equiv \alpha_{i,t} s_t(n) + \beta_{i,t} x_t(n) + u_{i,t}(n). \quad (17)$$

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.

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

$$\widehat{z}_{i,t}(k) = \ln \left(\sum_{j \neq i} A_{j,t} \frac{\mathbb{1}_{j,t}(k)}{1 + \sum_m^N \mathbb{1}_{j,t}(m)} \right), \quad (18)$$

where k indexes the class of a bond, as defined by the credit rating-tenor-industry of the 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. It accounts for the findings of Li et al. (2022) that individual bonds can be very good substitutes: inelastic demand tend to arise across classes of bonds instead.²³ 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

²¹A 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.

²²Note that $\delta_{i,t}(n) = \frac{w_{i,t}(n)}{w_{i,t}(0)}$ represents the portfolio weight fund i invests in asset n at time t relative to the portfolio weight of the fund's outside option

²³Concretely, an insurer might be close to indifferent between two BBB bonds of similar maturity, but might display very inelastic demand for a similar HY bond. See Table 13 of Siani (2021) for a summary of the persistence of fund class holdings.

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.²⁴ Tables 2 and IA.1 reports summary statistics of the classes and Table IA.2 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 a fund-asset combination. 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 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 variations in market conditions that may affect all funds.

Table 4 reports the distribution of estimated demand elasticities.²⁵ 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

²⁴There are six tenor categories (up to and including 1, 3, 5, 7, 15, 100 years), five rating categories (up to and including CCC+, B+, BB+, BBB+, and AAA), and 16 industry categories (2-digit NAICS codes). Not all tenor-rating-industry triplets have bonds in the category.

²⁵We convert estimated coefficients to demand elasticities as per Kojien 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.

et al. (2022). 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. (2022). We estimate an average demand elasticity of 0.97 for insurers and 1.1 for mutual funds. Within mutual funds, ETFs are the most demand elastic on average, followed by index funds. Index funds have a mean elasticity very close to 1, as expected. Over time, funds have become more price elastic overall, with average elasticities increasing from 0.8 before the 2008 financial crisis to 1.5 in the 2020-2022 period, likely driven by the increase in mutual fund shares.

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,

$$\text{Flow}_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1} \times (1 + R_{i,t})}{TNA_{i,t-1}}, \quad (19)$$

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:

$$\text{Flow}_{i,t+1} = \beta \text{Return}_{i,t} + \gamma X_{i,t} + v_{i,t}, \quad (20)$$

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 magnitudes are robust to the inclusion of fund and time fixed effects. Because we are mostly interested in the pattern of fund outflows, in Column 5 we separate negative and positive returns. We find the flows are more sensitive to negative returns, consistent with Chen, Goldstein, and Jiang (2010).

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 (20) 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. The average flow to performance estimates in 2010-2019 across all mutual funds was 0.6, indicating that a 1pp decline in returns leads to a net outflow of 0.6% of the fund’s assets under management.

5 Measures of fragility

Using the model dynamics derived in Section 3.2, we can construct two measures of fragility in the model. *Asset fragility* measures fragility in the cross-section of bonds, while *fund fragility* measures fragility in the cross-section of mutual funds. It is worth noting that

both fragility measures are macro-prudential in nature. They measure the contribution of a specific asset or a specific financial institution to the aggregate market fragility but do not measure the risk of the individual asset or institution by itself.

5.1 Fragility in the cross-section of bonds

The first measure is defined at the asset level. We ask: what is the impact on the aggregate bond price index if asset n experiences an exogenous shock to its price? For each asset, fragility depends on how prices affect flows and how flows then affect prices. As described in the previous section, these objects are functions of the asset’s share of the overall market and the characteristics of the funds that hold the asset, including portfolio weights, the flow to return sensitivity, demand elasticities, and other asset holdings. Building on this intuition, the asset fragility measure is given by

$$\text{Asset fragility} \equiv \boldsymbol{\alpha}'(\mathbf{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}./\boldsymbol{\alpha}', \quad (21)$$

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 α_n so that the shock is on a per-dollar basis. Asset fragility measures the contribution an asset makes to aggregate fragility. It is not a measure of the risk of the asset itself. As we will see in the empirical analysis, safe bonds can score larger on that fragility metric.²⁶

²⁶This formula shares some elements with the fire-sales spillover measure of Falato et al. (2021), the fragility measure of Jiang et al. (2022), or the stock price fragility measure of Greenwood and Thesmar (2011). To understand the intuition behind this formula, it is useful to define a new variable $m_{n,k} = (\mathbf{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})_{n,k}^{-1}$ as the cumulative spillover from asset n to asset k . Recall from the example in the previous section that this formula for the cumulative impact comes from $(\mathbf{I} + \boldsymbol{\Psi}\boldsymbol{\Phi} + (\boldsymbol{\Psi}\boldsymbol{\Phi})^2 + \dots) = (\mathbf{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}$, summing up indirect effects across all “rounds”. 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 $\sum_{k=1}^N \alpha_k m_{n,k}$. For simplicity, the measure assumes that $\boldsymbol{\Psi}$ and $\boldsymbol{\Phi}$ are constant. We however use time-varying $\boldsymbol{\Psi}$ and $\boldsymbol{\Phi}$ in our policy counterfactuals below.

Numerical example: To see more clearly what contributes to an asset’s fragility, we consider a simple numerical example with three funds of equal size that invest in two equally-valued assets, A and B, and 30% in an outside asset. One fund invests in equal weights in each asset A and B, another is a specialist in asset A and holds twice as much of asset A as asset B, and the third specializes in asset B and holds twice as much of asset B as asset A. We fix the flow sensitivity of the equal-weighted fund to 0.1 and the flow sensitivity of Specialist A to 0.6. See Table 1 for a summary of the parameters in the numerical example.

We plot how the fragility of the two assets varies with different parameter values in Figure 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. The asset pricing literature has emphasized the role of demand elasticity (Bretscher et al., 2022) while works on mutual funds have emphasized flow sensitivities (Falato et al., 2021). We argue that both perspectives are important to understand the cross-section of bond fragility, but that neither is sufficient on its own.

Asset fragility estimates: We can use the fund-level flow sensitivity estimates, the fund-asset-level demand estimates, and observed holdings shares and fund values to compute

this asset fragility measure in the cross-section of bonds. Table 8 shows the asset fragility estimates for different asset classes as of 2019, splitting our sample of bonds into four categories based on IG vs. HY and long-term (5 or more years remaining) vs. short-term.

Across asset classes, asset fragility is between 1.3 and 2.1. Interestingly, IG bonds are not generally less fragile than HY bonds. Moreover, within rating categories, short-term bonds are more fragile than long-term bonds. In terms of economic magnitudes, the least fragile asset class are long-term IG bonds, with a fragility of 1.3. This corresponds to some moderate, albeit not insignificant, amount of amplification. Strikingly, short-term IG bonds are significantly more fragile: with a fragility of 2, they face an amount of amplification between that of long-term HY bonds (fragility of 1.9) and that of short-term HY bonds (fragility of 2.1).

Our framework allows us to unpack these differences. First, being held by investors facing a stronger flow sensitivity β increases fragility. For instance, the third row of Table 8 shows that long-term IG bonds have a very low mutual fund market share, while short-term HY bonds have the highest share. The fact that insurers and pensions are large investors in that segment plays an important stabilizing role that is reflected in our low fragility estimate (Coppola, 2021). However, fragility cannot be reduced to mutual funds' market share alone. Short-term IG bonds are more fragile than long-term HY bonds in spite of not having a higher mutual fund market share. The fourth row shows that heterogeneity in mutual funds' flow sensitivities β is key: short-term IG bonds are held by mutual funds that have particularly high β . This is intuitive: funds that anticipate potentially large inflows prefer to hold liquid IG bonds as a precautionary measure.

In principle, differences in investor price elasticity also matter in explaining differences in fragility, as illustrated in the numerical example above. For example, long-term IG bonds are still fragile in spite of low investors' flow sensitivities in part because they are held by the most inelastic investors (elasticity of 1). However, quantitatively the effect of flow

sensitivities dominates. Mutual funds are more elastic than insurers, but the asset classes they hold tend to nevertheless be more fragile.

5.2 Fragility in the cross-section of mutual funds

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

$$\text{Fund fragility} \equiv \boldsymbol{\alpha}'(\mathbf{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}\boldsymbol{\Psi} \times \boldsymbol{\beta}./\boldsymbol{\alpha}_f', \quad (22)$$

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

Numerical example: To clarify what contributes to a fund's fragility, we return to the numerical example above and plot fund fragilities in Figure 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 of 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 decline, 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.

Fund fragility estimates: Across mutual funds, we find a significant fraction of mutual funds that are extremely fragile. Figure 4 presents a histogram of our fund fragility estimates at year-end 2019. Many funds have a fragility between 1 and 5, but many are substantially more fragile. To understand the economic magnitudes, a fund having a fragility of 10 means that a 1pp decline in its return would lead to a 10% decline in aggregate bond market values if that fund held the entire market portfolio (taking the matrices Ψ and Ψ that capture amplification as given).²⁷

6 The March 2020 turmoil and intervention

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

²⁷In this picture, we exclude fund with an estimated fragility larger than 25 as they are likely driven by estimation noise.

large negative shock to the corporate bond market.

6.1 Matching the model to the March 2020 turmoil

We match our model using three ingredients. First, we feed a sequence of daily price shocks to IG and HY bonds separately for the first 10 days of the crisis in March. The magnitudes of these shocks are implied by the rise of CDS spreads from March 4-18 and capture a sudden deterioration in fundamental credit risk. We however feed no initial flow shock to the mutual fund sector, such that the dynamics of outflows will be entirely endogenous to our equilibrium model.

Second, we use estimates of (β, ζ) documented above to capture cross-sectional differences in flow sensitivities and elasticities across institutions. Specifically, we consider an economy with two sectors: mutual funds and insurance companies. Mutual funds face a fund-specific flow-to-performance sensitivity β as summarized in Table 7, while insurance companies, which we aggregate into one fund, face a sensitivity of 0.²⁸ The estimated demand elasticities vary by fund-year-asset and are reported in Table 4.²⁹ The assets under management W and the portfolios θ for each institution are calibrated to the 2019Q4 levels. Our framework is tractable enough to account for thousands of parameters capturing the rich investor heterogeneity of the data. In particular, we include the 264 unique mutual funds for which we can estimate both ζ and β in 2019.

Third, we add an additional economic force to institutions' asset demand: the tendency to potentially sell certain assets first to meet redemption given outflows. In our baseline model, a mutual fund sells assets proportionally when faced with outflows holding future

²⁸O'Hara et al. (2021) document how insurers' stable funding allow the sector to become buyers in periods of market distress. In fact, insurers may even experience net inflows when credit conditions worsen and prices drop; see Figure 7 of Coppola (2021), although these are probably small at the horizon of a week or two.

²⁹To 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, and the 89% of positive flow sensitivity funds with flow sensitivity below 5. We then transform estimated elasticities into the parameter ζ_i by dividing by $1 - \theta_i$.

expected returns constant. However, empirically it is now well understood that institutions have a tendency to sell more liquid assets first (Ma, Xiao, and Zeng, 2022). Formally, the demand for assets depends also on the level of outflows f_t faced by the fund: $\Delta X_t = (\pi_t, f_t)$. The loading on outflows for a specific asset, which we refer to as $\lambda(n)$, has a natural interpretation in terms of (relative) transaction costs: an asset with $\lambda < 0$ will be sold more than proportionally after an outflow, while an asset with $\lambda > 0$ will be sold less than proportionally (for the same news about their expected returns). We will assume two values of λ , one for each of IG and HY bonds, and calibrate $(\lambda_{IG}, \lambda_{HY})$ to match the data given our other parameter estimates.

Specifically, we match key moments of price and flow dynamics of the March 2020 turmoil. We target a 20% price decline for IG bonds (Haddad et al., 2021b), as well as cumulative mutual fund outflows of 10% of AUM (Falato et al., 2021). Figure 5 shows the dynamics of bond prices and flows in our model simulation. It matches the data well, except that the model-implied cumulative outflows are a little larger than in the data. We also recover that $\lambda_{IG} < 0$ and $\lambda_{HY} > 0$, which is consistent with IG bonds having a tendency to be sold first. This was by assumption but is a by-product of our calibration that lines up with the evidence in Ma, Xiao, and Zeng (2022).

6.2 Policy intervention

Policy-makers often choose to intervene in the face of market turmoil, and March 2020 was no exception. Intervention can involve some form of unconventional monetary or liquidity policy, where the typical rationale is to stop feedback loops between declining asset prices and asset sales. How to design/conduct these interventions is still largely an open question. In practice, vastly different policies have been implemented or discussed. For instance, the interventions carried out by the Federal Reserve in the Spring of 2020 were pretty broad: a

large interest rate cut and a program of corporate bond purchases. On the other hand, other proposals have suggested more focus on the fragile mutual fund sector specifically. While traditional banks are often subject to such targeted interventions in crises, similar policies were not implemented for non-banks intermediaries such as bond mutual funds, despite being at the center of the 2020 turmoil.

In this section, we use our model to study the equilibrium effects of ex-post interventions on corporate bond prices and institutional investors. Our framework is well suited to compare different interventions within a unifying framework. We run counterfactuals related to four types of ex-post interventions: conventional monetary policy, asset purchases, direct lending to funds, and redemption restrictions on mutual fund shares. For each intervention, we can also study how much the timing, early versus late, matters. We can also use the model to measure how well “targeted” an intervention is, given the large heterogeneity in fragility documented above. Finally, we study the impact of swing pricing, an important type of ex-ante intervention.

While our model can simulate the effects of these policies on prices and fund value, we note from the outset that any counterfactual analysis is subject to potential caveats. First, we can only study interventions that can be clearly mapped to variables in our framework. Certain dimensions of policy are thus outside the current scope of our analysis, such as conditional policy promises (Haddad et al., 2021a) or signaling (Cieslak et al., 2019). Second, the counterfactual exercise takes estimated parameters as invariant and re-calculates equilibrium prices and flows across assets and institutions. Nevertheless, there is a concern that policies might change the underlying parameters. This concern is especially salient for fund-to-performance sensitivities β . For this reason, we deliberately include specific policies that affect β directly, such as redemption restrictions or swing pricing, and allow β to vary within the policy counterfactual.

6.2.1 Conventional monetary policy

First, in Figure 6, we simulate a conventional policy rate cut of 100 basis points implemented after the negative shock to bond markets. Specifically, we allow the price of each asset to increase by $1.00\% \times m(n)$ at the implementation of the policy, where $m(n)$ equals the average remaining maturity for each asset. In 2019, the average remaining maturity for long-term IG, short-term IG, long-term HY, and short-term HY bonds is 13.5, 2.4, 6.7, and 3.1 years, respectively.

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

Interestingly, the timing of the intervention matters for the short-term path of the recovery, but not for the eventual size of the rebound. The bottom panel shows the effect of cutting interest rates two days after the start of the crisis ($T = 2$). Eventually, bond prices and institutions' AUM reach similar values as the case of a late intervention.³⁰

6.2.2 Corporate bond purchases

Next, in Figure 7, we evaluate a policy where the central bank purchases 5% of outstanding short-term (below 5 years) IG 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 IG corporate bonds. While the actual purchases were

³⁰Note that we focus on the short-term effect of an emergency rate cut during a crisis. Changes in the policy rate can have other effects on the size of the mutual fund sector, as shown by Bretscher et al. (2022): the sector tends to shrink in a rising rate environment for example. See also Fang (2022) for an analysis of monetary transmission through mutual fund flows.

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.³¹

The top panel shows a smaller market rebound. This is to be expected given that short-term IG bonds only constitute a fraction of the overall market. Naturally, IG bonds benefit from these asset purchases, as they are directly targeted; however, there is a small rebound for HY bonds. This is due to the rebound of fund wealth as well as the investment mandate increasing demand for HY assets. Mutual fund values rebound by more than insurers due to the amplifying effect of inflows following the positive performance. As with conventional monetary policy, the timing of the intervention also matters little for the size of the eventual rebound.

6.2.3 Direct lending to mutual funds

In Figure 8, we consider the effects of a policy that lends directly to bond mutual funds. While such a policy currently has not been implemented for such nonbank intermediaries, such direct lending (or “lender of last resort”) is a classical policy tool for traditional banks. In the counterfactual, we assume funds can borrow against up to 2% of their IG assets. Specifically, net outflows from mutual funds decrease by the amount borrowed from the central bank. The key finding is that such a policy is extremely effective, but only if it is implemented early. Comparing the top and bottom panels reveals that a late intervention ($T = 14$) leads to virtually no rebound in contrast to an early intervention ($T = 2$) which has large effects in equilibrium. Intuitively, intervening early stops spirals of feedback loops in their tracks. This evidence suggests that acting as a “lender of last resort” towards nonbanks could potentially be effective.

³¹At the end of 2019, there was over \$9.5 trillion in outstanding corporate bonds. Source: SIFMA 2021 Capital Markets Factbook).

6.2.4 Redemption restrictions

We next consider a policy of freezing mutual fund redemption. This is also a classical policy tool that has been repeatedly implemented in the banking sector. Figure 9 displays the effects. At the implementation of the policy, we set the net flow for each fund to be bounded below zero. Like the previous intervention, acting early is critical: a late intervention has no effects while an early intervention has dramatic positive effects in stopping amplification. This type of intervention is naturally particularly effective at preventing the mutual fund sector from shrinking considerably.

6.3 Policy targeting and price impact

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

Any policy can be mapped to a vector \mathbf{g} of price shocks for the different existing assets. This is more general than it seems at first. Policy interventions can take many forms: some interventions 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. We also need to model the “cost” of a policy. For tractability, we abstract away from the many potential reasons why a resource constraint might exist and simply model it as a linear constraint $\boldsymbol{\gamma}'\mathbf{g} \leq b$. $\boldsymbol{\gamma}$ is an $N \times 1$ vector of the cost to generate one percent of price change for each asset, and 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) $\boldsymbol{\gamma} = \boldsymbol{\alpha} \odot \text{diag}(\mathbf{S} \times \boldsymbol{\zeta})$, where $\boldsymbol{\alpha}$ normalizes the quantity of purchases by the total market size of all the assets. The n th element of $\text{diag}(\mathbf{S} \times \boldsymbol{\zeta})$ is simply the aggregate (market) elasticity for asset n , which we also denote by ζ_n . b can be interpreted as the total dollar value of the asset purchase committed by the Federal Reserve normalized by the total market size.

We define a policy *price impact multiplier* as the average asset fragility per unit of resource of a given policy, \mathbf{g} :

$$\text{Price impact multiplier}(\mathbf{g}) = \frac{(\mathbf{Asset\ fragility} \odot \boldsymbol{\alpha}) \mathbf{g}}{\boldsymbol{\gamma}' \mathbf{g}}, \quad (23)$$

where **Asset fragility** is a vector of asset fragility of each asset, as defined in equation (21). Importantly, targeting matters for price impact given the significant amount of heterogeneity in fragility documented above. It is worth repeating that this multiplier can be constructed for an intervention that does not have an explicit resource constraint. Doing so allows us to study the distance between conventional monetary policy and other more targeted asset purchases in terms of the degree of amplifications that is achieved by different types of policies.

We can also compute a benchmark for the best-targeted intervention that maximizes the cumulative impact on the aggregate bond market index for a given resource constraint. Such a maximum-price-impact intervention solves the following program:

$$\begin{aligned} \max_{\mathbf{0} \leq \mathbf{g} \leq \bar{\mathbf{g}}} \boldsymbol{\alpha}' (\mathbf{I} - \boldsymbol{\Psi} \boldsymbol{\Phi})^{-1} \mathbf{g}, \\ \text{subject to: } \boldsymbol{\gamma}' \mathbf{g} \leq b, \end{aligned} \quad (24)$$

The maximum-price-impact benchmark turns out to be a function of the asset fragility

measure constructed in section 5. Specifically, we sort assets in descending order by the ratio of their asset fragility over their aggregate elasticity: $\frac{\text{Asset fragility}_1}{\zeta_1} \geq \frac{\text{Asset fragility}_2}{\zeta_2} \geq \dots \geq \frac{\text{Asset fragility}_N}{\zeta_N}$. Targeting follows a pecking order: the policymaker should first raise the price of the asset with the highest asset fragility per unit of price elasticity. Assets with higher fragility lead to higher price impact, but assets with higher elasticity require more resources to raise their price. 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 elasticity until the budget is exhausted.³² 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 macroprudential perspective it is best to target the assets or institutions that are central in the network that propagates and amplifies the shock.

We can use these concepts to compare how well targeted the different types of interventions studied above were in addressing fragility in March 2020. Figure 10 compares these four interventions using our model estimates. It also reports the maximum-price-impact benchmark. Perhaps surprisingly, this reveals that asset purchase (“AP”) is the best-targeted intervention. Even though it only focuses on IG bonds, it is, in fact, close to the theoretical maximum-price-impact benchmark (“MAX”). This is because purchases targeted short-term IG bonds, which are significantly fragile due to being held by especially flow-sensitive investors. This gives support to the policy choice of the Federal Reserve in Spring 2020, at least if the goal was to maximize price impact under a limited budget. On the other hand, conventional monetary policy (“MP”) is the least well-targeted because it has the biggest price effect on less fragile long-term IG assets, which have the highest duration. This is not necessarily surprising: the return to the zero lower bound was dictated by many considerations other than addressing the bond market turmoil specifically. The two other interventions targeting the mutual fund sector (direct lending “DL” and redemption restrictions “RR”)

³²A formal derivation can be found in Appendix D.

are better targeted, although quantitatively, the effect is perhaps not as large as could be expected.

6.4 Preventative policy: swing pricing

We can also use our framework to evaluate preventative policies that could mitigate a negative feedback loop in the first place. For example, in November 2022, the SEC proposed a policy to avoid selling pressure of open-ended mutual funds called swing pricing.³³ This policy would require funds to adjust their NAV to pass trading costs to shareholders who are redeeming (or purchasing) shares in the fund. Jin et al. (2021) show that implementation of this policy in the UK led to a significant reduction in flow-to-performance sensitivity.

Motivated by this policy proposal, we test how swing pricing would affect the propagation of the negative shock via a reduction in flow-to-performance sensitivities. To implement this, we refer to Jin et al. (2021) Table 3, Panel B, which reports the reduction in flow sensitivity estimates due to swing pricing across different magnitudes of fund outflows. We adjust each fund’s flow-to-performance sensitivity according to their estimates and see how prices and fund valuations respond to the same negative shocks to bond prices in March 2020. Figure 11 shows that swing pricing inhibits significant outflows and further price declines, thereby avoiding the onset of a negative feedback loop. It reduces by about 10 percentage points the decline in bond prices as well as in the size of the mutual sector, even if, naturally the policy does not fully prevent the effect of a negative shock. Our quantitative result thus supports the recent regulatory proposal to mandate swing pricing for mutual funds

This exercise comes with important caveats. Implementation of swing pricing would likely have equilibrium effects on fund investment decisions, as documented by Jin et al. (2021) and Ma et al. (2023). In this counterfactual, we hold asset characteristics fixed.

³³See, for example, “SEC proposes mutual fund-pricing rule to protect long-term investors”, *Financial Times*, November 2, 2022.

Estimating a counterfactual that endogenizes holding characteristics would be useful but outside the scope of this paper.

7 Conclusion

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

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

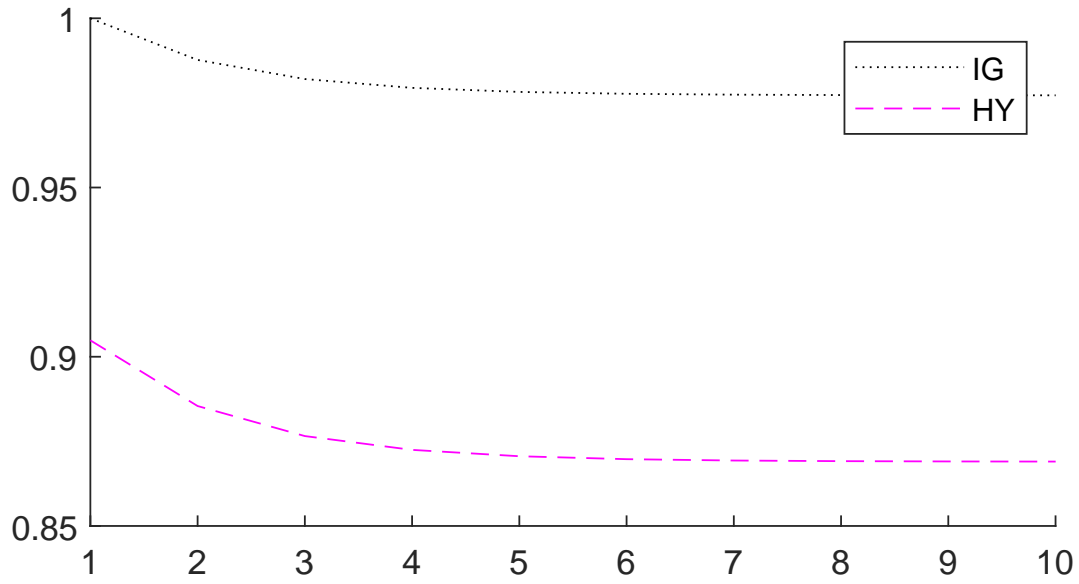
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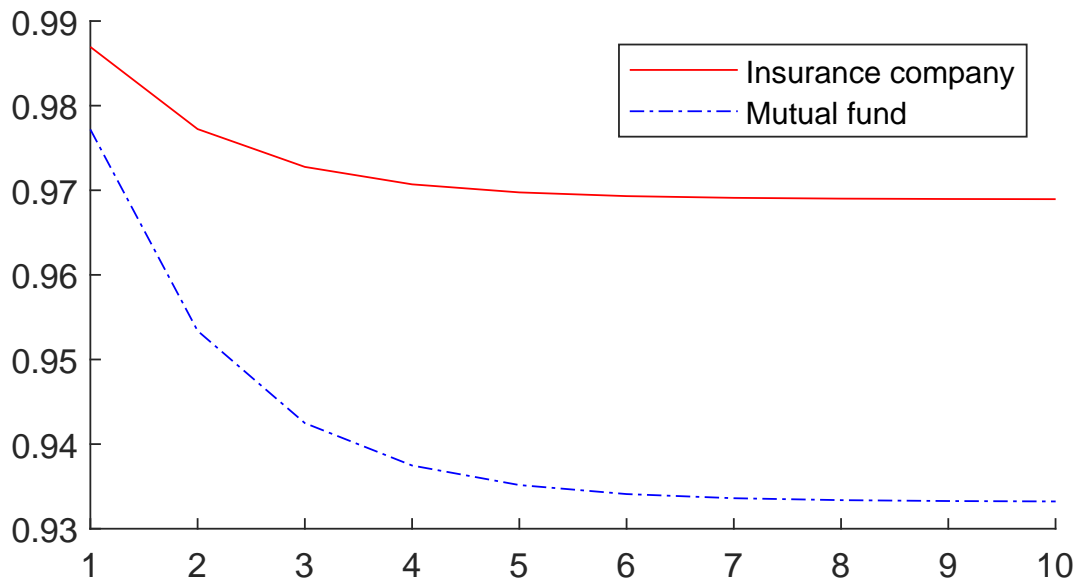
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Figure 1: Model dynamics: example



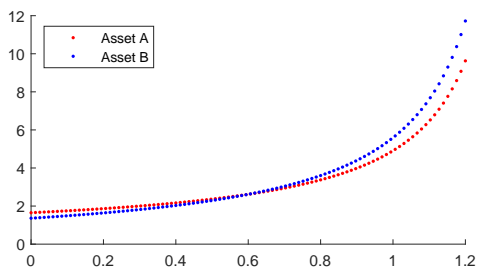
(a) Prices



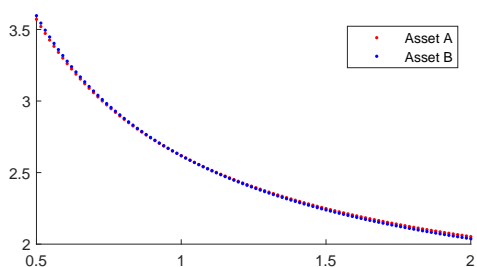
(b) AUM

Note: This graph shows simulated paths of AUM and asset prices for a two-sector-two-asset model. Parameters values are described in Section 3.2.

Figure 2: Asset fragility: numerical example



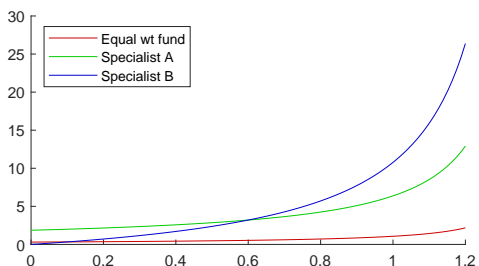
(a) Flow sensitivity of Specialist B



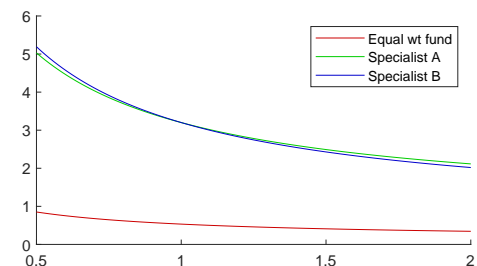
(b) Demand elasticity over B: Specialist B

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



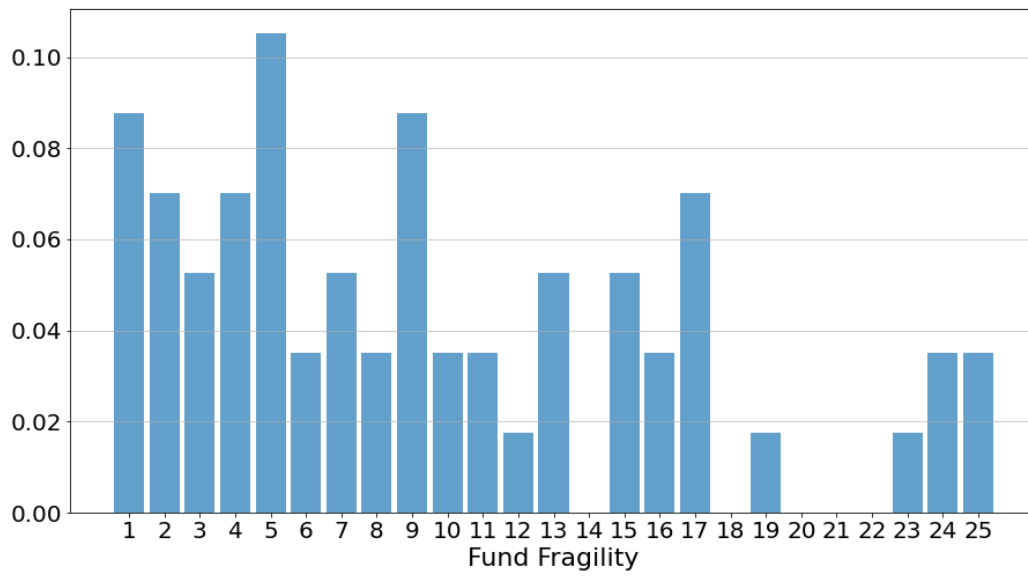
(a) Flow sensitivity of Specialist B



(b) Demand elasticity over B: Specialist B

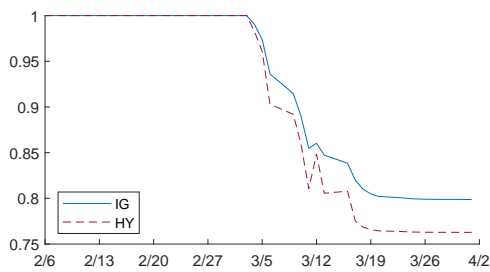
Note: Reports on the y-axis the fund fragility of three funds in an illustrative numerical example. The left panel holds fixed the demand elasticities of all funds and varies only the flow sensitivity (beta) of Specialist B. The right panel holds fixed the flow sensitivities of all funds and varies only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

Figure 4: Fund fragility distribution

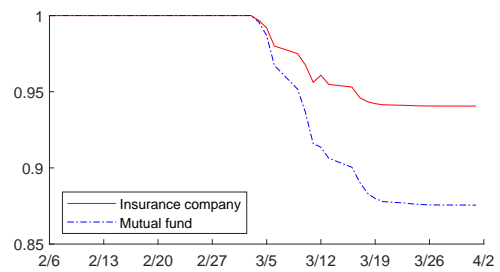


Note: This table summarizes the fund fragilities estimated across our sample of mutual funds for year-end 2019.

Figure 5: March 2020: Model-implied dynamics



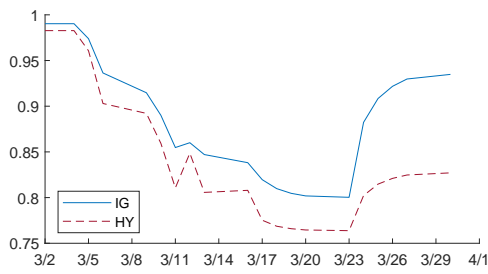
(a) Asset prices



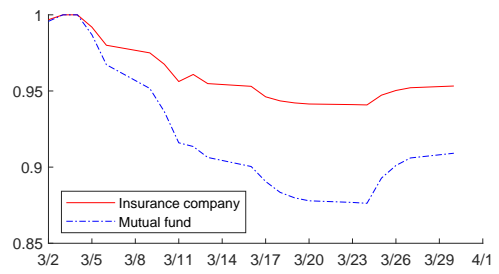
(b) Fund AUM

Note: This graph shows the counterfactual AUM and asset prices following 10 days of fundamental shocks to asset prices in line with the corporate bond CDS changes in the first half of March 2020. There is no policy intervention in this simulation.

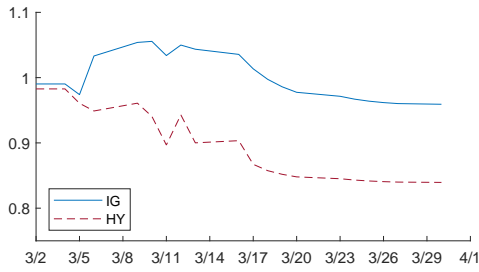
Figure 6: Counterfactual simulation: rate cut



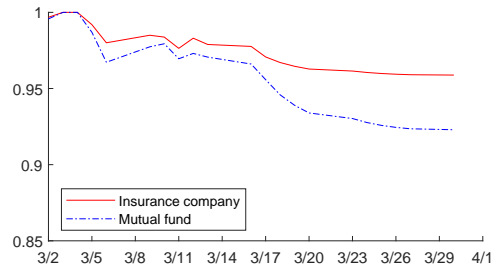
(a) Prices with $T = 14$



(b) AUM with $T = 14$



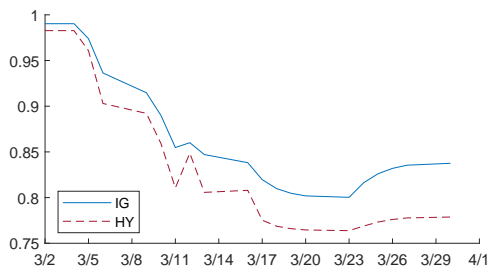
(c) Prices with $T = 2$



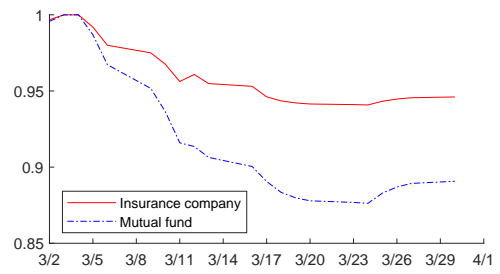
(d) AUM with $T = 2$

Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices in line with CDS yields. The central bank cut the policy rate by 100 basis points on day 14 and day 2 for the upper and lower panels, respectively.

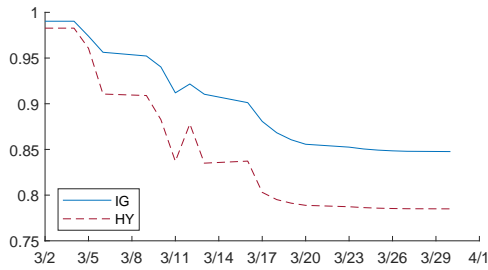
Figure 7: Counterfactual simulation: asset purchases



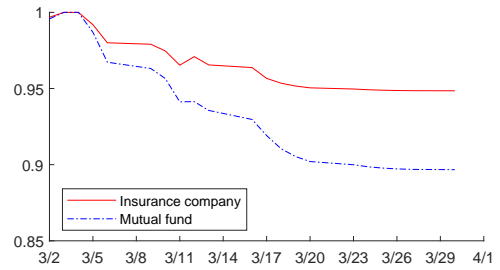
(a) Prices with $T = 14$



(b) AUM with $T = 14$



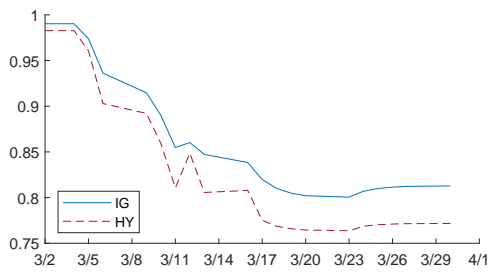
(c) Prices with $T = 2$



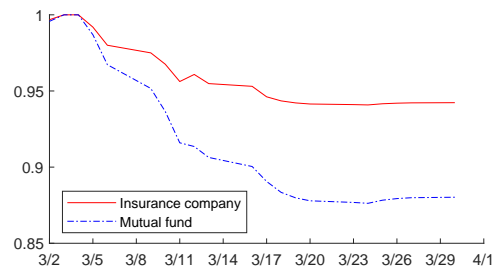
(d) AUM with $T = 2$

Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices in line with CDS yields. The central bank conducts asset purchases of 5% of short-term IG bonds on day 14 and day 2 for the upper and lower panels, respectively.

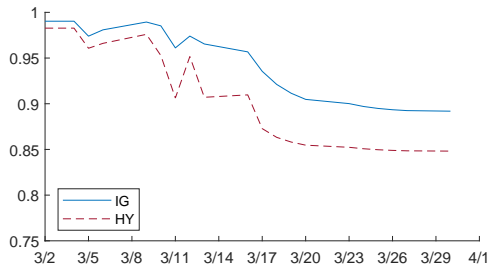
Figure 8: Counterfactual simulation: central bank lending to mutual funds



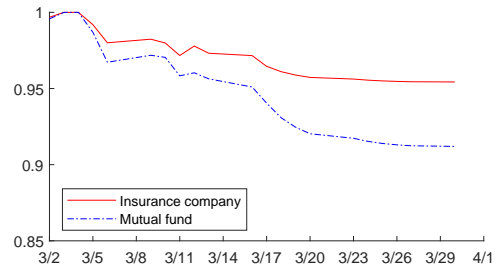
(a) Prices with $T = 14$



(b) AUM with $T = 14$



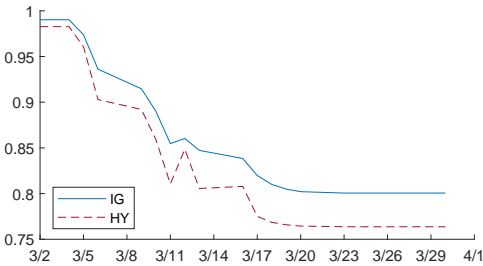
(c) Prices with $T = 2$



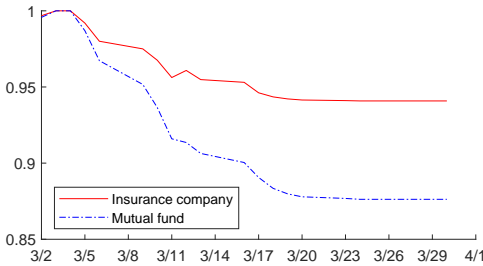
(d) AUM with $T = 2$

Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices in line with CDS yields. The central bank allows all mutual funds to borrow up to 2% of their IG holdings on day 14 and day 2 for the upper and lower panels, respectively.

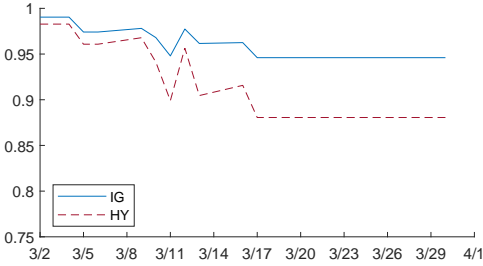
Figure 9: Counterfactual simulation: limits to redemption for mutual funds



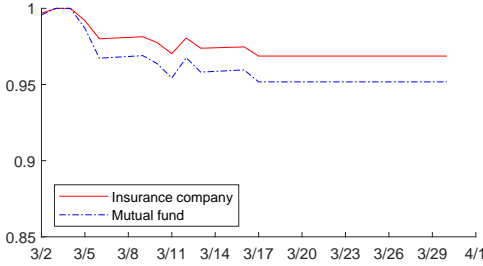
(a) Prices with $T = 14$



(b) AUM with $T = 14$



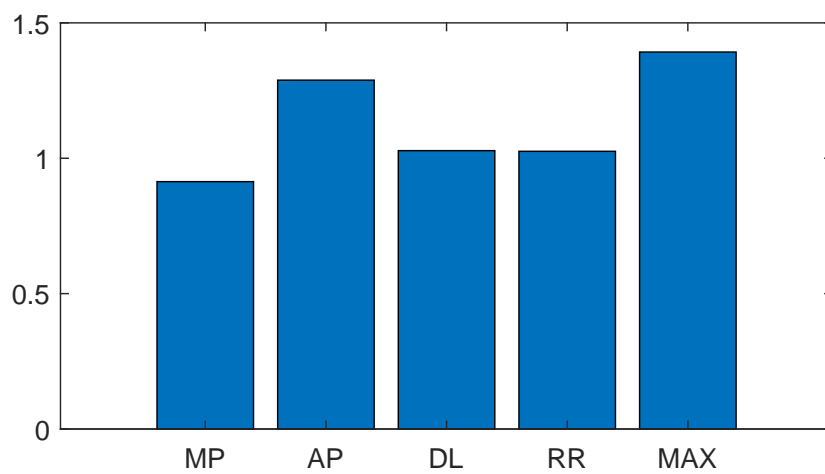
(c) Prices with $T = 2$



(d) AUM with $T = 2$

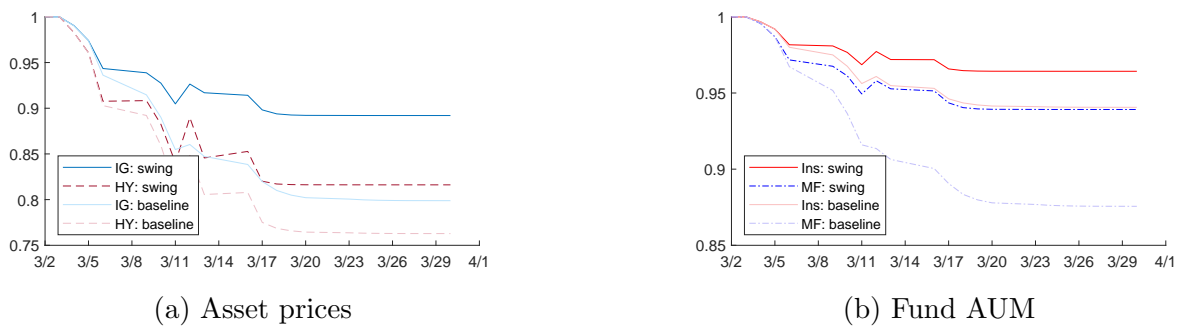
Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices in line with CDS yields. Mutual funds restrict suspend redemption on day 14 and day 2 for the upper and lower panels, respectively.

Figure 10: Price impact multipliers of various interventions



Note: This graph shows the policy targeting multipliers of various interventions at $T = 2$, as described in Section 6.2. “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 (23).

Figure 11: Counterfactual simulation: swing pricing for mutual funds



Note: This graph shows the counterfactual AUM and asset prices following fundamental shocks to corporate bond prices in line with CDS yields. 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	0.60	X1
Demand elasticity over Asset A	1.00	1.00	1.00
Demand elasticity over Asset B	1.00	1.00	X2

Note: This table summarizes parameters in the numerical example illustrating asset and fund fragility metrics. The X1 and X2 values take on various values in Figures 2 and 3 to demonstrate how fragility metrics respond to variations 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)	(2)	(3)
	All funds	Insurers	Mutual funds
Z_icq	-0.00512*** (0.00142)	-0.00622*** (0.00154)	-0.00455** (0.00150)
U.S. Treasury	-3.807** (1.339)	-4.224*** (1.304)	-2.959* (1.523)
Bidask	6.183*** (1.550)	5.953*** (1.545)	6.891*** (1.552)
Original tenor (log)	0.0457*** (0.00619)	0.0538*** (0.00713)	0.0356*** (0.00669)
Years remaining	0.0163*** (0.00112)	0.0158*** (0.00110)	0.0163*** (0.00126)
Amount issued (log)	-0.00401* (0.00193)	-0.00347 (0.00210)	-0.00196 (0.00190)
Issuer rating	-0.245*** (0.0181)	-0.261*** (0.0185)	-0.236*** (0.0232)
Constant	0.683*** (0.0540)	0.729*** (0.0543)	0.647*** (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 (18) 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), the number of years remaining, the initial amount issued (logged), and the issuer credit rating. The sample period is from 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 levels.

Table 4: Summary of demand elasticity estimates

	10%	mean	90%
2010-2019 estimates			
All fund-bonds	0.782	0.998	1.203
IG holdings	0.765	0.991	1.234
HY holdings	0.798	1.004	1.181
Non-mutual funds	0.807	0.973	1.179
Mutual funds	0.639	1.106	1.350
ETFs	0.823	1.126	1.215
Index funds	0.814	1.068	1.230
Other MF	0.538	1.097	1.425
Time periods			
Pre-2008	0.543	0.805	0.983
2008 financial crisis	0.865	1.148	1.343
2020-2022	0.421	1.514	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. Values are winsorized at 0.1%.

Table 5: Flow to return sensitivity: monthly

	(1)	(2)	(3)	(4)	(5)
	F.Flow	F.Flow	F.Flow	F.Flow	F.Flow
Return	0.288*** [0.021]	0.294*** [0.021]	0.274*** [0.029]	0.259*** [0.029]	
Flow	0.193*** [0.004]	0.165*** [0.004]	0.185*** [0.004]	0.140*** [0.004]	0.140*** [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 management from the previous month. The dependent variable is the one-month forward fund flow. Data source: CRSP Mutual Fund Database.

Table 6: Flow to return sensitivity: daily

	(1)	(2)	(3)	(4)	(5)
	F.Flow	F.Flow	F.Flow	F.Flow	F.Flow
Return	0.137*** [0.038]	0.058 [0.036]	0.171*** [0.063]	0.067* [0.037]	
Flow	0.292* [0.163]	0.292* [0.163]	-0.010 [0.037]	-0.011 [0.037]	-0.011 [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 management 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

	10%	mean	90%
2010-2019 estimates			
All fund-bonds	-3.079	0.585	4.677
ETFs	-2.729	0.790	4.870
Index funds	-2.437	0.928	4.810
Other MF	-3.125	0.482	4.514
Time periods			
Pre-2008	-2.392	0.120	2.632
2008 financial crisis	-0.699	0.104	1.453
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	1.311	2.043	1.883	2.140
Market share of asset	0.482	0.248	0.142	0.128
Mutual fund holding share of asset	0.084	0.159	0.160	0.276
Holdings-weighted average beta	0.218	0.679	0.409	0.592
Holdings-weighted average elasticity	1.009	1.188	1.111	1.277

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.

Appendix: derivations and proofs

A Log-linearization of household demand

For simplicity, we drop the time and household subscript. Take log and then the first difference on equation (3) gives

$$\Delta \ln Q(i) = \kappa \Delta X(i) - \Delta \ln \sum_{i=0}^I \exp(\kappa X(i)) + \Delta \ln A - \Delta \ln P(i). \quad (25)$$

Note the dollar flows into the institution is $f(i) = \Delta \ln Q(i)$. The change in the NAV equals the return, so $\Delta \ln P(i) = r(i)$. Using Taylor expansion, we have

$$\Delta \ln \sum_{i=0}^I \exp(\kappa X(i)) \simeq \sum_{i=0}^I \frac{\exp(\kappa X(i))}{\sum_{i=0}^I \exp(\kappa X(i))} \kappa \Delta X(i) = \sum_{i=0}^I \theta(i) \kappa \Delta X(i). \quad (26)$$

Therefore, we have

$$f(i) = \kappa \Delta X(i) - \sum_{i=0}^I \theta(i) \kappa \Delta X(i) + a - r(i). \quad (27)$$

Plugging in the special case $\Delta X_t(i) = r_{t-1}(i)$, we obtain the flow-to-performance relationship for each household:

$$f_{h,t}(i) = \beta_h r_{i,t-1} - \kappa_h \sum_{i=0}^I \theta_{h,t}(i) r_{i,t-1} + a_{h,t}, \quad (28)$$

where $f_{h,t}(i) = q_{h,t}(i)$ is the inflow into institution i in dollars by household h , and $\beta_h = \kappa_h - 1$ is the flow-to-performance sensitivity.

Finally, we aggregate this flow-to-performance relationship across households by multiplying equation (28) by the wealth share of each household $s_{h,t} = A_{h,t} / \sum_{h=0}^H A_{h,t}$ and summing them up, which gives rise to the equation in the main text:

$$f_{i,t} \simeq \beta_i r_{i,t-1} - \kappa_i \bar{r}_{t-1} + \bar{a}_t,$$

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

B Log-linearization of institution demand

For simplicity, we drop the time and institution subscript. Take log and then the first difference on equation (8) gives

$$\Delta \ln Q(n) = \kappa \Delta X(n) - \Delta \ln \sum_{m=0}^N \exp(\kappa X(m)) + \Delta \ln W - \Delta \ln P(n). \quad (29)$$

Note that

$$\Delta \ln W = \Delta \ln P + \Delta \ln Q = \sum_{m=0}^N \theta(m) \Delta \ln P(m) + f = \sum_{m=0}^N \theta(m) p(m) + f \quad (30)$$

Using Taylor expansion, we have

$$\Delta \ln \sum_{m=0}^N \exp(\kappa X(m)) \simeq \sum_{n=0}^N \frac{\exp(\kappa X(n))}{\sum_{m=0}^N \exp(\kappa X(m))} \kappa \Delta X(n) = \sum_{m=0}^N \theta(m) \kappa \Delta X(m). \quad (31)$$

Therefore, we have

$$q(n) = \kappa \Delta X(n) - \sum_{m=0}^N \theta(m) \kappa \Delta X(m) + \sum_{m=0}^N \theta(m) p(m) + f - p(n). \quad (32)$$

Plug in the special case $\Delta X(i) = \rho(n) (d(n) - p(n))$, we get

$$q_{i,t}(n) = -\zeta_{i,t}(n)p_t(n) + \kappa_i\rho(n)d(n) + \sum_{m=0}^N \theta(m) (\zeta_{i,t}(m)p_t(m) - \kappa_i\rho(m)d(m)) + f_{i,t}, \quad (33)$$

where $\zeta_{i,t}(n) = 1 + \kappa_i\rho(n)$, which is equation (12).

C Flow shocks

The baseline model studies the amplification of shocks to asset values, such as shocks to fundamentals. The framework is equally well suited to study another type of shock, namely, *flow* shocks to the size of the mutual fund sector and how they propagate across asset values and institutions. Gabaix and Koijen (2021) study the impact of flows in equity markets.

We find that flow shocks have a large impact on asset values and institutions even absent other fundamental shocks. Figure IA.2 plots the dynamics of asset prices and institutions AUM following a 5% fund outflow shock to all mutual funds at time 1. We make three observations. First, the flow shock depresses both IG and HY bonds by a significant amount: a 5% outflow lead to a drop in asset values of almost 5%. This suggests that other investors like insurers and pensions provide limited elasticity to the market when mutual funds have to reduce their bond holdings. Second, outflows beget more outflows: after a few periods, the decrease in the size of the mutual fund sector is 17%. That is more than three times the initial flow shock of 5%. Flow sensitivities and limited price elasticity in the market imply a sizeable amount of dynamic amplification of flow shocks. Third, the spillover to the insurance sector is non-trivial: even though they are not directly affected by the flow shock, the value of their AUM eventually drops by about 3%.

D The maximum-price-impact benchmark

The policy-maker's problem is

$$\begin{aligned} \max_{\mathbf{0} \leq \mathbf{g} \leq \bar{\mathbf{g}}} \quad & \boldsymbol{\alpha}'(\mathbf{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}\mathbf{g}, \\ \text{subject to:} \quad & \boldsymbol{\gamma}'\mathbf{g} \leq b, \end{aligned} \tag{34}$$

The Lagrangian function is

$$\mathcal{L}(\mathbf{g}, \lambda) = \boldsymbol{\alpha}'(\mathbf{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}\mathbf{g} + \lambda(b - \boldsymbol{\gamma}'\mathbf{g}) + \bar{\boldsymbol{\mu}}'(\bar{\mathbf{g}} - \mathbf{g}) + \underline{\boldsymbol{\mu}}'\mathbf{g}, \tag{35}$$

We have

$$\frac{\partial \mathcal{L}}{\partial g_n} = \boldsymbol{\alpha}'(\mathbf{I} - \boldsymbol{\Psi}\boldsymbol{\Phi})^{-1}\mathbf{e}_n - \gamma_n - \bar{\mu}_n + \underline{\mu}_n, \tag{36}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = b - \boldsymbol{\gamma}'\mathbf{g}, \tag{37}$$

$$\frac{\partial \mathcal{L}}{\partial \bar{\mu}_n} = \bar{g}_n - g_n, \tag{38}$$

$$\frac{\partial \mathcal{L}}{\partial \underline{\mu}_n} = g_n, \tag{39}$$

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

$$\sum_{n=1}^{N^*} \gamma_n g_n \leq b, \tag{40}$$

$$\sum_{n=1}^{N^*+1} \gamma_n g_n \geq b. \tag{41}$$

The optimal solution is $g_n = \bar{g}_n$ 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 IA.1: 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

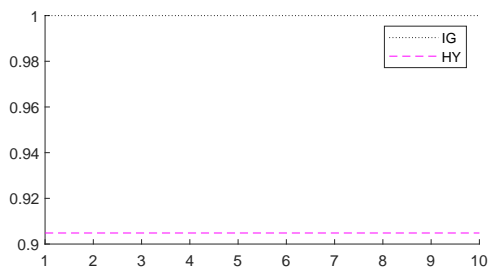
Note: This table summarizes the top 10 classes by the number of bonds within the class. A classifier is defined as a 2-digit NAIC industry category, a tenor at issuance, and the credit rating of the bond. The TS avg num funds reports the average number of funds that hold this class of bond each quarter.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

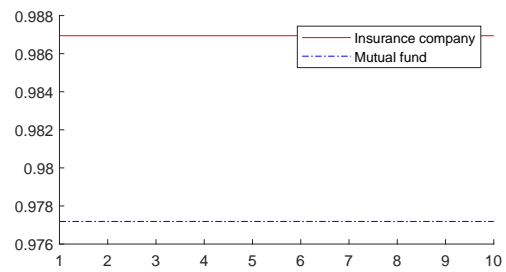
	2002 mean	2002 median	2010 mean	2010 median	2019 mean	2019 median
Avg AUM	804,708	95,095	1,016,236	100,204	1,386,188	118,482
Num classes per fund-qtr	12	7	23	15	35	24
Num bonds per fund-qtr	17	8	49	21	98	36
Avg holding	1,965	700	1,542	513	2,614	441
Std_holding	1,335	388	1,221	319	1,925	324

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

Figure IA.1: Model dynamics with exogenous wealth



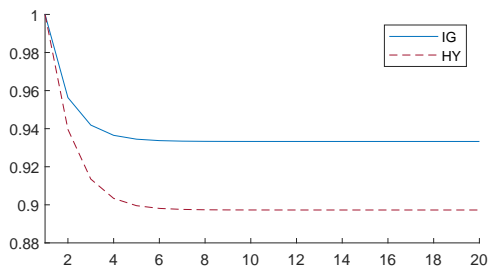
(a) Asset prices



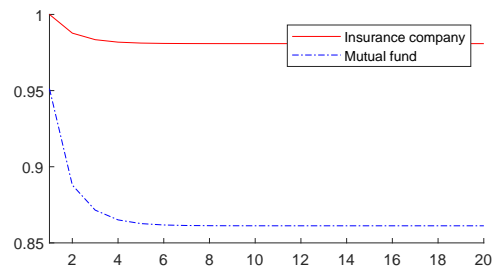
(b) Fund AUM

Note: This graph shows simulated paths of AUM and asset prices for a two-sector-two-asset model. Parameters values described in Section 3.2. Flow-to-performance sensitivities are set to zero to mimic exogenous wealth distributions.

Figure IA.2: Simulation: negative flow shock to mutual funds



(a) Asset prices



(b) Fund AUM

Note: This graph shows the counterfactual AUM and asset prices following a 5% fund outflow shock to all mutual funds at time 1.