Fire-Sale Spillovers in Debt Markets

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Abstract

Fire-sales induced by investor redemptions have powerful spillover effects among funds that hold the same assets, hurting peer funds' performance and flows, and leading to further asset sales with negative bond price impact. A 1-standard deviation increase in our fire-sale spillover measure leads to a 45 (90) bps decrease in peer fund returns (flows) and a 2 pp increase in the likelihood of a large bond price drop. The results hold up in a regression-discontinuity design addressing identification concerns. Timing, heterogeneity, instrumental-variable, and placebo tests further support the price-impact mechanism. Model-based counterfactual and stress-test analyses quantify the financial stability implications.

1 Introduction

Starting with the influential work of Shleifer and Vishny (1992), a major topic in finance is that basic equilibrium considerations may compound the cost of financial distress, thus aggravating the fragility of the financial system. Broadly the idea is that distressed asset sales are particularly costly in circumstances when the pool of potential buyers of a specialized or illiquid asset is equally likely to be financially constrained and therefore unable to supply liquidity. More specifically, as noted by Coval and Stafford (2007), "the cycle whereby capital flows can force widespread trading in individual securities, resulting in institutional price pressure, which in turn affects fund performance and eventually feeds back into capital flows, is intriguing."

Though theoretically appealing, there has been no systematic attempt to test fire-sale spillovers empirically. In an attempt to fill this gap in the literature, we take the idea of fire-sale spillovers seriously and develop a novel approach to assess it empirically. We use rich microdata on flows, performance, and asset holdings for the universe of open-end fixed-income mutual funds. These data are an ideal laboratory to study fire-sale spillovers because bonds are relatively illiquid assets (Bao, Pan, and Wang (2011), Madhur et al. (2010)), which can give rise to liquidity mismatch or transformation for open-end funds that provide daily redemption rights to their investors (see, for example, Goldstein, Jiang, and Ng (2015)). We identify the peers of any given fund as those funds that hold the same assets. We present reliable evidence that there are powerful spillover effects among funds that hold the same assets, with fire-sales induced by investor redemptions hurting peer funds' performance and flows and leading to further asset sales that have a negative bond price impact.

Our study also contributes to the post-crisis debate regarding threats to financial stability coming from non-bank financial institutions.[1] Episodes of heightened credit market volatility such as

[1] See, for example, Feroli et at. (2014), the FSOC 2014 Notice Seeking Comment on Asset Management Products and Activities, 79 Fed. Reg. 77488 (Dec. 24, 2014), the SEC request of public feedback on the OFR report (http://www.sec.gov/comments/am-1/am-1.shtml), and the 2014 Financial Stability Board (FSB) Consulation on "Assessment Methodologies for Identifying Non-Bank Non-Insurer Global Systemically Important Financial Institutions" (http://www.fsb.org/2014/01/r_140108-2/), which all included consideration of stress testing for asset managers.

the Taper Tantrum of the summer of 2013, the dramatic shift in credit intermediation away from banks and toward bond markets since the crisis, and the fact that funds have become one of the largest holders of corporate debt highlight the importance to better understand their systemic consequences.[2]

The key measurement hurdles are to identify peer funds whose asset sales may affect others within the group, and to address endogeneity concerns. Intuitively, a fund with high exposure to fire-sale spillovers holds a high proportion of assets that are fire-sold by other funds. To operationalize this measure, we build on Coval and Stafford (2007)'s well-known "flow pressure" measure for a given security, which is constructed by looking at changes in holdings of a security by mutual funds that experience large investor outflows or inflows. For each asset held by a given fund i, we calculate the Coval-Stafford pressure measure based on out/inflows experienced by funds *other than* i. The weighted sum (according to i's portfolio weights) of this asset-specific flow pressure then creates our measure of fund i's exposure to flow-induced asset sales/purchases by "peer" funds holding the same assets.

Our empirical approach allows us to trace the chain of events that is associated with price pressure from peer funds' flow-related trading. Specifically, we show evidence that 1) outflow-induced asset sales have a negative price impact in the corporate bond market, 2) there is a strong negative association between a fund's performance and the outflow-related asset sales of its peers, 3) fund flows are also adversely affected by peer outflow-related asset sales, and finally, 4) there is a "second-round" price impact, with peer fire sales leading to further fire sales that have a negative bond price impact. The fire-sale spillover effect on other funds via exposure through common holdings is economically large.

[2]Corporate debt trading volumes roughly doubled since the crisis from about $14B in 2008 to over $30B in 2017, and outstandings increased by roughly 50%. The asset management industry experienced fast growth in the fixed income sector, with assets in open-end fixed-income funds growing from $1.5 trillion in 2008 to $3.5 trillion by the end of 2014, and net inflows exceeding $1.3 trillion. Corporate bond funds also grew dramatically, with assets in open-end investment-grade (high-yield) mutual funds growing from about $500 billion ($100B) in 2008 to $1.5 trillion ($300B) in 2014. As a result, mutual funds have become major players in debt markets, with their market share – the ratio of their assets to total outstandings – growing from about 15% (10%) in 2008 to over 30% (20%) for investment-grade (high-yield) corporate bonds.

For example, suppose that a given fund's monthly performance is flat, but that its peers underperform, on average, by 3% in a given month. In this case, we estimate that the resulting 1-standard deviation increase in outflow-induced asset sales by peer funds will decrease the returns of a given fund by about 45 bps and will increase its outflows by about 90 bps, which are roughly equal to the sample mean of returns and half the sample mean of fund flows, respectively. And this second round of outflows will lead to an additional increase in the likelihood of a large bond price drop of almost 2%.[3] The relative magnitudes plausibly square together, with the estimates of the spillover effect corresponding to about one quarter (one tenth) of a standard deviation movement in fund returns (flows), and the estimate of the price impact corresponding to about one third of a standard deviation movement in bond price changes. And the magnitudes of the spillover effects are large but plausible relative to those of the "first-round" effects, where peer funds experience outflows of about 4.5% and the resulting first round of fire-sales increases the likelihood of a large bond price drop by about 8%.

An important concern with our measure is that it may erroneously pick up latent asset-specific shocks that are commonly observed by funds that choose to hold the same securities. To address this issue, which is an instance of the classic "reflection problem" discussed by Manski (1993), we use two main empirical strategies: First, inspired by Anton and Polk (2014), we construct our peer flow pressure measures based on funds' exposure to the 2003 mutual fund scandal. McCabe (2009) and Kisin (2011) have shown that funds of implicated fund families experienced significant outflows which were long-lasting, arguably due to reputation effects, but were not due to concerns about the quality of assets held by the funds. Second, we use regression discontinuity strategy based on sharp changes in fund flows around the (un)assignment of Morningstar 5-star ratings (as documented by e.g. Del Guercio and Tkac (2008) and Barrot (2016)). The source of identification here is that the sharp difference in (peer) fund flows observed for funds that fall slightly short of Morningstar's 5-star performance cutoffs vs. funds that are slightly above these cutoffs is likely

[3] Large price drops are defined as observations in the bottom decile of their respective distributions.

not related to changes in common industry fundamentals. Importantly, the results all continue to hold when we focus on plausibly exogenous drivers of peer outflows/pressure.[4] Taken together, there is strong evidence of fire-sale feedbacks in debt markets.

The economic mechanism that leads to spillovers is downward-sloping demand for corporate bonds, through which fire-sales – i.e., sales that are forced by redemptions – have a negative price-impact. To the extent that purchasing a corporate bond requires the use of significant capital, any of the factors that sideline arbitrage capital can plausibly lead to downward sloping demand for bonds. Several pieces of direct evidence support this fire-sale mechanism. First, the spillover effect is concentrated among bonds and funds that are illiquid and at times when the market is illiquid.[5] The effect is robustly smaller and sometime even insignificant for peer buy pressure; and is lasting, though reversing over the course of three to four quarters. These facts are all consistent with slow moving capital factors making high-valuation bidders relatively scarce and leading to persistence of arbitrage opportunities (see, for example, Mitchell, Pedersen, and Pulvino (2007) and Duffie (2010)). Finally, in placebo tests, there is no spillover for asset sales that are not flow-driven or for funds that operate in the same markets but do not have common holdings, which both help to build confidence in the price-impact mechanism relative to information and investor learning alternatives.

Fire-sale spillovers can affect financial market stability by amplifying the effect of an initial shock to fund flows that is otherwise unrelated to fundamental asset values, thus increasing volatility.[6] To clarify the conditions and circumstances under which fire-sale spillovers increase volatility, we use our estimates to construct two measures of fund exposure to spillovers, systemicness and vulnerability, and explore their relation with the volatility of fund and bond re-

[4]The results are also robust to several specification checks that include adding controls for bond and fund characteristics as well as lagged performance and flows.

[5]The fact that we find larger effects for illiquid funds and in illiquid times offers additional reassurance that mechanical explanations based on omitted common factors are unlikely to be driving our results, as such explanations do not necessarily predict the same response across sub-samples.

[6]The mechanism that can potentially hinder financial stability is that, as we have shown, spillovers lead to additional outflows and further impact bond prices over and above the initial effect of a given adverse shock.

turns. Generally, these measures are higher whenever 1) there is a higher degree of overlap in bond holdings with other funds, and 2) debt market conditions are such that forced sales have a larger price impact. We use regression analysis and a model-based calibration to illustrate these mechanisms. First, we use forecasting regressions of fund and bond return volatility similar to Greenwood and Thesmar (2011) to test whether exposure to fire-sale spillover forecasts volatility. Our measure of fund vulnerability to peer fire-sales is positively correlated with one-quarter ahead monthly volatilities of fund returns. For example, a 1-standard deviation increase in fund vulnerability to fire-sale spillovers leads to an increase in annual volatility of about 0.6%, which is approximately 1/3 of the sample mean. A model-based calibration shows that spillovers increased fund return volatility by up to one and a half times in the crisis, and continue to have a smaller but non-negligible effect in recent years. Second, sector-wide and security-level averages of our measures of systemicness and vulnerability are positively correlated with the future volatility of an aggregate index of bond fund returns and of individual bonds, respectively. Further corroborating the idea that fire-sale spillovers matter in the aggregate, shocks to even just the 10 most systemic fund families lead to large sector-wide outflows in a stress-test exercise for several alternative adverse scenarios.

Our paper makes two main contributions. First, we contribute to the literature on fire sales in finance (see Shleifer and Vishny (2011) for an overview) and more specifically in the asset management industry, which has shown convincing evidence regarding the price impact of forced asset sales.[7] Coval and Stafford (2007) show evidence of stock price impact based on abnormal stock returns in a 12-month window around large mutual fund sales. Khan et al. (2012) and Jotikatshira et al. (2012) use similar data in a US and international setting, respectively, and confirm the finding of significant price impact. Ellul et al. (2011) and Feldhütter (2012) document evidence of significant price pressure around downgrades for bonds with high exposure to insurance compa-

[7]This literature, in turn, builds on the well-established evidence of downward-sloping demand curves for single securities. Shleifer (1986) shows evidence of a price effect of index inclusion and, more recently, Chang et al. (2015) provide causal evidence using a regression discontinuity design that exploits Russell 2000 index inclusion.

nies fire sale risk and looking at the price difference between small trades and large trades on the same bond, respectively. Our contribution to this literature is to provide, to the best of our knowledge, the first systematic study of the spillover effect of fire-sales induced by *peer* fund flows. That spillovers may result from price impact is clear conceptually from theory, but whether the price impact is strong enough to matter for other funds remains an empirical question. As such, our result that fire-sales are strong enough to spill over onto other funds that hold the same securities is new to the literature.[8] The result is complementary to recent evidence in Chernenko and Sunderam (2017) that exposure to fire sales affects the liquidity policies of equity funds. And it is important because it supports feedback mechanisms that are central in the narrative of the crisis and in the theory of fire-sales starting from Shleifer and Vishny (1992).

Second, there is a growing literature on vulnerability of financial institutions and stability in financial networks, which has been mostly theoretical and focused on banks (Greenwood, Landier, and Thesmar (2015), Acemoglu et al. (2012, 2015), Di Maggio and Tahbaz-Salehi (2015), Egan, Hortacsu, and Matvos (2015)).[9] A handful of recent papers have started to recognize the importance of run-like incentives in non-levered non-bank financial intermediaries like fixed-income mutual funds. Goldstein, Jiang, and Ng (2015) emphasize that these funds exhibit a concave flow-performance sensitivity, their outflows are sensitive to bad performance more than their inflows are sensitive to good performance, which can lead to instability (see, also, Chen, Goldstein, and Jiang (2010) and Feroli et al. (2014)). Our contribution to this literature is to introduce a mechanism, fire-sale spillovers, which had not yet been the subject of formal empirical testing, and to show that it is strong enough to matter not just for individual funds, but for the overall fixed-income fund sector, and not just for the sector, but more broadly for bond market valuations. As such, our work helps to inform the current policy and academic debate by clarifying a specific source

[8]Our direct evidence that flow-induced *trading* has a spillover effect is also complementary to earlier evidence of flow-based predictability of equity fund performance in Lou (2012).

[9]There is also a recent related literature on measuring interconnectedness for banks and insurance companies (Billio et al. (2012), Girardi et al. (2018), Ellul et al. (2018), and Duarte and Eisenbach (2019)). Our findings contribute to this literature by broaden this literature to mutual funds and flow-driven spillover and corroborate the importance of portoflio overlp to measure interconnectedness.

of vulnerability of non-bank financial intermediaries which is well-grounded in theory, and by establishing its relevance in the context of debt markets, which is important given the spectacular growth of these markets since the crisis.[10]

2 Data, Measurement, and Research Design

In this section, we detail our sample construction procedure, our approach to measure peer fund flow-related trading, and our research design to assess spillovers. Details of all variables' definitions are in Appendix A.

2.1 Fund Flows, Returns, and Portfolio Holdings

The primary data for our analysis comes from two standard sources. Monthly mutual fund flows and returns, as well as fund characteristics such as size (net assets), are from the CRSP Survivorship-Bias-Free Mutual Fund database. From the CRSP database, we retrieve information on the universe of open-end fixed-income US funds, which leads to a sample of 330,429 fund share class-month observations for 3,666 (254) unique funds (families) between January 1998 and December 2014. Data on investment objectives and quarterly security-level fund holdings are from the Thomson Reuter/Lipper eMAXX fixed income database, whose coverage starts in the

[10]Third, recent empirical research in finance and macroeconomics has examined the link between investor sentiment and credit market volatility. Greenwood and Hanson (2013) show that periods of credit growth are associated with low future returns to credit investors, as well as bust periods when credit declines. Greenwood, Hanson, and Jin (2016) develop a model of the endogenous two-way feedback between credit market sentiment and credit market outcomes. López-Salido, Stein, and Zakrajšek (2016) show that fluctuations in credit market sentiment are closely tied to future movements in aggregate economic activity, which is consistent with the idea that changes in credit market valuations may drive business cycle volatility. While these papers show convincing theory and evidence that credit market sentiment matters, the ultimate sources or determinants of sentiment are still relatively understudied. Our contribution is to highlight the role of correlated flows among interconnected institutions as a potentially important driver of credit market sentiment. As such, our analysis also contributes to the literature on the valuation consequences of ownership linkages among mutual funds (see, for example, Greenwood and Thesmar (2011) and Anton and Polk (2014)). Using quarterly data on equity mutual funds' holdings, Greenwood and Thesmar (2011) show that equity return volatility should and, in fact, is higher for stocks that rank high based on their proposed measure of "fragility," which is high when ownership concentration is high or when mutual fund flows volatility and cross-correlation are high. Anton and Polk (2014) document that cross-sectional variation in (quarterly) common ownership by equity funds predicts higher four-factor abnormal return correlation, controlling for standard risk factors as well as the degree of common analyst coverage.

first quarter of 1998.[11] When necessary for the analysis, we retrieve additional information on security-level corporate bond trading volume and liquidity from TRACE, prices from the Merrill Lynch database, and bond characteristics at issuance from FISD.

Our main dependent variables of interest are fund flows and performance. Mutual fund flows are estimated following the prior literature (e.g., Chevalier and Ellison (1997)), which is to define net flows of funds to mutual fund (share class) i in month t as the percentage growth of new assets:

$$Flow_{i,t} = (TNA_{i,t} - (1 + r_{i,t})TNA_{i,t-1})/TNA_{i,t-1}$$

where $\text{TNA}_{i,t}$ is the total net assets under management of fund i in month t and $\text{r}_{i,t}$ is the fund's return (net of fees and expenses) over the period.[12] Mutual fund performance is measured using monthly fund returns.

2.2 Measuring Network Linkages among Funds

The key measurement challenge is to define network linkages across financial institutions. Our notion of a fire-sale spillover requires that several different owners of a given security experience capital withdrawals, which lead them to sell the security at depressed prices in an effort to cover redemptions. It is through this "downstream" price pressure channel that redemptions "upstream" at fund A may spill-over on to those of fund B. Based on this notion, our spillover measure needs to capture two main features: 1) common asset ownership, and 2) intensity of flow-driven capital withdrawals at other funds. To capture these features, we use a new approach that is similar to the recent literature on networks in macroeconomics (e.g., Acemoglu, Akcigit and Kerr (2015)) and knowledge spillovers in the economics of innovation (e.g., Jaffe (1986), Bloom, Schankerman and Van Reenen (2013)).

[11] Since we use holdings to construct our main peer variables, January 1998 is our earliest available date. Because we are interested in actively-managed funds, we exclude from the analysis funds that CRSP identifies as index and exchange traded funds.

[12] As it is also standard practice in the literature, fund flows are winsorized at the 1% and 99% percentiles to mitigate the influence of outliers.

The basic idea of our approach is that flow-induced price pressure is transferred between funds that are "exposed" to each others. For any given fund, the probability that flow pressure is transferred to another depends on the extent to which the two funds invest in the same assets, with the polar case of two focused funds that are invested exclusively in the same asset representing the highest exposure and that of two focused funds that are invested exclusively in two different assets representing the lowest. Spanning the continuum of intermediate cases when funds are invested in multiple assets which are sometimes overlapping, the expected fire-sale spillover from one fund to another is an aggregate of these transfers from multiple funds across multiple assets.

Specifically, we identify the peers of any given fund as those funds that hold the same assets. We construct the measure of fire-sale spillover, $Peer\ Flow\ Pressure_{i,t}$, for each fund i as the weighted sum of fire-sale pressure from other funds, with weights capturing "exposure." To implement this definition, for each of the $N = 3,666$ funds in the sample and for each month t we start with a vector $w_{i,t} = (w_{i1t}, ...w_{ibt}, ..., w_{int})$ of its n portfolio share holdings – i.e., the portfolio percentage share holdings of each fund, i, in each asset, b, in each period, t. Using these portfolio share holdings as weights, for each fund we take a weighted sum of price pressure from other funds' flow-related trading in each of the securities it holds:

$$Peer\ Flow\ \mathrm{Pr}essure_{i,t} = \sum_{b=1}^{n} Flow\ Pressure_{b,t}^{j \neq i} * w_{i,b,t-1} \tag{1}$$

where, for each asset b, we define $Flow\ Pressure_{b,t}$ similarly to Coval and Stafford (2007) as the proportion of flow-induced net buys by peer funds:

$$Flow\ Pressure_{b,t}^{j \neq i} = \frac{Flow\ Induced\ Buys_{b,t}^{j \neq i} - Flow\ Induced\ Sales_{b,t}^{j \neq i}}{Offering\ Value_b},$$

where $Flow\ Induced\ Buys_{b,t}^{j \neq i} = \sum_{j \neq i} \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Flows_{j,t} > Percentile(90th)} \right)$ and $Flow\ Induced$

$Sales^{j\neq i}_{b,t} = \sum_{j\neq i}\left(\max\left(0, -\Delta Holdings_{j,b,t}\right)|_{Flows_{j,t},<Percentile(10th)}\right)$.[13] Note that, to avoid mechanical correlation, we exclude own-funds, $j = i$, from the calculation of flow pressure, so that for each fund we isolate fire-sale pressure from *other* funds. Intuitively, a fund with high exposure to fire-sale spillovers holds a high proportion of assets that are fire-sold by other funds.

To examine potential asymmetric effects of buy vs. sell pressure we also present results for two versions of this measure, which are constructed as weighted sums of $Flow\ Induced\ Buys^{j\neq i}_{b,t}$ and $Flow\ Induced\ Sales^{j\neq i}_{b,t}$:

$$
\begin{aligned}
Peer\ Buy\ \mathrm{Pr}essure_{i,t} &= \sum_{b=1}^{n} \frac{Flow\ Induced\ Buys^{j\neq i}_{b,t}}{Offering\ Value_b} * w_{i,b,t-1} \\
Peer\ Sell\ \mathrm{Pr}essure_{i,t} &= \sum_{b=1}^{n} \frac{Flow\ Induced\ Sales^{j\neq i}_{b,t}}{Offering\ Value_b} * w_{i,b,t-1}
\end{aligned}
$$

Finally, for consistency and comparability of the spillover estimates with those of the price impact, we include only corporate bonds in our peer pressure measures throughout. Table 1 provides basic descriptive statistics of the time-distribution of our sample (number of funds and fund families in Panel A) and of our main explanatory and dependent variables (means, standard deviations, and p95-p5 ranges in Panel B). In line with previous studies, there is substantial heterogeneity in fund flows and performance, as well as in fund characteristics such as size. In addition, our Peer Flow Pressure measure also displays significant variation across fund-years, with a standard deviation of 0.114. To ease exposition and help gauge economic significance, throughout the analysis we report results in standard deviation units – i.e., for versions of our main variables that are standardized by dividing each raw variable by its respective standard deviation.

2.3 Research Design and Identification Strategy

We assess fire-sale spillovers in the most basic terms possible: are the flows and performance of a given fund sensitive to the fire–sale pressure that is induced by the flows of its peers? To that end,

[13] Bond offering value is from FISD.

we examine the following main relation:

$$Y_{i,t} = \alpha + \beta \times \mathit{Peer\ Flow\ Pressure}_{i,t} + \gamma \times X_{i,t-1} + \eta_i + \lambda_t + \nu_{i,t} \tag{2}$$

where the outcome variables $Y_{i,t}$ for fund i in month t, include primarily the fund's performance and net flows, and the main variable of interest is the spillover measure, $\mathit{Peer\ Flow\ Pressure}_{i,t}$, which is defined in equation (1). $X_{i,t-1}$ is a vector of controls for standard fund characteristics, which include fund family size, lagged own fund flows or performance, and expense ratio. In robustness analysis, we present results for the specification that includes the full vector of these controls. In estimating equation (2) for our main analysis, we address two important issues, unobserved heterogeneity and endogeneity. We take on a third potential issue, dynamics, in graphical analysis and additional robustness tests that estimate a more dynamic specification with distributed or various lags of the main explanatory variable.

To address unobserved heterogeneity, in all specifications we control for fund fixed effects by including a full set of fund-specific dummies, η_i. The inclusion of fund effects ensures that the parameter of interest, β, which represents the impact of peer fund flows pressure, is estimated only from within-fund time-series variation. We address endogeneity due to transitory common shocks, which are a potential confound that may be erroneously picked up by the spillover measure, in two ways. First, in all the tests we report results for a specification that controls directly for sector-wide shocks that are common across funds by adding controls for time fixed effects with the inclusion of a full set of year-specific dummies, λ_t.[14] The idiosyncratic error term, $\nu_{i,t}$, is assumed to be correlated within fund and potentially heteroskedastic (Petersen (2006)). Second, we recognize that the endogeneity issue in our peer-effect context is an instance of the classical "reflection problem," which refers to the concern that correlation with peer flow pressure may arise due to endogenous selection of funds into peer groups and pick up latent shocks that are common

[14] We have experimented with including alternative larger sets of higher-frequency dummies, either quarter-specific or month-specific, both of which lead to only minor changes in our estimates.

to fund that hold the same securities. As such, including time effects helps to ameliorate but does not fully resolve the challenge of endogenous selection.

As discussed by Manski (1993), the ideal natural experiment would randomly assign similar types of funds to different types of peer treatment status. In other words, for our estimates of β in the reduced-form model of equation (2) to be identified, we need to show that fund flows are significantly correlated with plausibly exogenous characteristics of their peers that affect peer flows. The identification challenge is to find events or factors that are relevant for peer fund flows but that are otherwise plausibly random with respect to fund i's flows and performance.

We design three "quasi-natural" experiments that are geared toward generating this random assignment. Specifically, we propose three candidate peer treatment variables, which are constructed for each fund similarly to Peer Flow Pressure as an exposure-weighted sum of either fund-specific shocks or (functions of) thresholds that affect peer flows but are otherwise plausibly independent from own flows:

$$Peer\ Treatment\ \Pr essure_{i,t} = \sum_{b=1}^{n} Treatment\ Pressure_{b,t}^{j \neq i} * w_{i,b,t-1} \tag{3}$$

where for each asset we define $Treatment\ Pressure_{b,t}^{j \neq i}$ similarly to flow pressure as the proportion of treatment-induced net buys:

$$TreatmentPressure_{b,t}^{j \neq i} = \frac{Treatment\ Induced\ Buys_{b,t}^{j \neq i} - Treatment\ Induced\ Sales_{b,t}^{j \neq i}}{Offering\ Value_b},$$

where $Treatment\ Induced\ Buys_{b,t}^{j \neq i} = \sum_{j \neq i} \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=0} \right)$ and $Treatment\ Induced\ Sales_{b,t}^{j \neq i} = \sum_{j \neq i} \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=1} \right)$. Note that to avoid mechanical correlation we again exclude own-fund treatment from the calculation of treatment pressure. Our identification strategy is to estimate a version of the reduced-form model of equation (2), where we replace the potentially endogenous spillover measure, $Peer\ Flow\ Pressure_{i,t}$, with its plausibly exogenous counterpart, *Peer Treatment* $\mathrm{Pr}\,essure_{i,t}$. We consider three treatment variables, which are detailed in Section 4.

3 Motivating Evidence and Baseline Results

In this section, we present our baseline results on the chain of events that is associated with fire-sales spillovers and provide direct evidence in support of the price-impact mechanism. The key steps start with the price impact of bond fire sales, followed by our evidence on the spillover effect of peer fire sales on fund performance, flows, and bond valuations, which shows that fire-sale externalities matter not just for funds but more broadly for debt markets. To motivate the analysis, we show evidence of predictability of own fund performance by peer funds's performance, in that the performance of peer funds has strong predictive power for the performance up to one quarter ahead of any given fund that holds the same bonds. Predictability is a key reduced-form implication of fire-sale spillovers, because any given fund's performance is likely to be harmed if the underperformance of its peers leads to capital withdrawals that depress its asset valuations via fire sales.

3.1 Motivating Evidence and Bond Price Impact

Table 2 summarizes our motivating evidence. We present estimates from predictability regressions of fund performance (Panel A) and extreme underperformance (Panel B) up to a quarter ahead as the outcome variables, respectively, and Peer Fund Performance as the explanatory variable of interest. Peer Performance is defined analogously to Peer Flow Pressure, as a weighted sum of peer funds returns using portfolio holdings as "exposure" weights and (average) performance of the holders of any given security instead of flow-related trading to sum over securities. Even after controlling for past own fund performance, there is a strong positive and highly statistically significant association between a fund's future performance and the past performance of its peers (Panel A, Columns 1 to 3). This evidence of predictability is a first indication that fire-sale spillovers are likely to be important, as poor performance of funds with overlapping holdings tends to be followed by poor performance of a given fund. In further support of fire-sale spillovers, predictability is even stronger in illiquid times (Columns 4-6) and holds also for large underperformance (Panel B).

Before establishing fire-sale spillovers, we start with assessing whether asset sales under fund flow pressure, in fact, bear the hallmark of costly fire-sales – i.e., do they involve securities whose valuations are depressed? Price impact of flow-related trading is the first step of the causal chain that leads to spillovers. The results of our bond event study are summarized in Table 3, which reports the main results of regressions of monthly (changes in log) bond prices on the *Flow* $Pressure_{b,t}$ variable for a baseline specification that controls for bond (cusip) effects (Panel A). The coefficient on Flow Pressure in Column1 is positive and highly statistically significant, indicating that sales by mutual funds that are experiencing outflow pressure tend to harm bond valuations. The bond valuation effect is economically significant, as the coefficient estimate of about 1 percentage point in Column 1 corresponds to a full quartile movement in the distribution of bond price changes.

The next two columns examine whether there is heterogeneity in the valuation effect. We expect that the valuation effect should be more negative whenever liquidation costs are higher. To explore this possibility, we repeat our analysis in sub-samples splits based on cross-sectional (bond-level) and time-series (aggregate) proxies for illiquidity and fire sale costs. The cross-sectional proxy for illiquidity in Column 2 is lagged bond spreads over comparable-maturity treasuries. We repeat our analysis in the sub-sample of relatively illiquid bonds, which are defined as those in the top-quartile of the distribution of lagged spreads. In Column 3, we define the macro illiquidity dummy based on a dummy for the financial crisis.[15] The results support a costly fire-

[15]Brunnermeier and Pedersen (2009) show that asset market liquidity co-moves with the funding liquidity of financial institutions that supply liquidity to asset markets.

sale interpretation, as the estimated coefficients are much larger in both columns, indicating that sales by mutual funds that experience outflow pressure tend to harm valuations more for more illiquid bonds and at times when debt markets are relatively illiquid. Columns 4 to 6 verify that the baseline and heterogeneity results continue to hold if we exclude bond-quarters when there are either no trades or no trades by institutions under flow pressure as recommended by Khan et al. (2012).

Panel B further corroborates the fire-sale mechanism. Specifically, we repeat the analysis with $Flow\ Induced\ Buys_{b,t}$ and $Flow\ Induced\ Sales_{b,t}$ to allow for potentially asymmetric effects of buy vs. sell pressure. The coefficient estimates in Column 1 are statistically and economically significant for both variables, but the valuation effect is clearly asymmetric with the negative effect of sale pressure being much larger than the positive effect of buy pressure. In fact, there is even stronger evidence of asymmetry in the alternative specification that controls for time effects by including month dummies (Column 2) and in the matched sample analysis that considers the valuation effect relative to similar bonds based on bond offering value, bond maturity, and previous spread (Column 3), as in both alternatives only the coefficient estimate on sale pressure remains significant.

Finally, graphical analysis in Panel A of Figure 1 and additional regression analysis in Panels A and B of Appendix Table A.1 examine the timing of the price impact, in an attempt to better distinguish flow-related trading from information- or fundamentals-driven interpretations. In line with flow-related trading, the bulk of the valuation effect is concentrated in the immediate quarter when the sales happen and the following one, but it eventually reverses over the course of the third and fourth quarters. In all, evidence from our bond event study shows that outflows-induced sales of corporate bonds have large and lasting, though not permanent, valuation consequences.[16] In addition to being an internal validity check for our mechanism, these results replicate the ap-

[16] Appendix Figure A.1 shows a non-parametric version of the price path, which is in line with the results discussed in the main text. Panel B of Appendix Table A.1 shows that none of the coefficient estimates on various leads of the flow pressure variable is significant, indicating the absence of statistically significant pre-event trends.

proach and evidence of Coval and Stafford (2007) in the corporate bond market.

3.2 Fund Performance and Flows

The next three tables present our evidence of fire-sale spillovers. In Table 4, we summarize results from estimating equation (2) with fund performance (returns, Columns 1 to 3) and extreme underperformance (a dummy for returns in the bottom decile of the distribution, Columns 4 to 6) as the outcome variables, and Peer Flow Pressure (Panel A) and Peer Buy Pressure and Peer Sell Pressure (Panel B) as the explanatory variables of interest (see eq. (1) for definitions), respectively. The coefficient on Peer Flow Pressure is positive (negative) and highly statistically significant for fund returns (extreme underperformance) (Panel A, Columns 1 and 4), in line with the key mechanism behind fire-sale spillovers that capital withdrawals from peer funds harm own fund performance by depressing asset valuations. Finally, the spillover effect is larger for relatively illiquid funds (defined as those whose Lipper asset class is high-yield, Columns 2 and 5) and in relatively illiquid times (during the financial crisis, Columns 3 and 6), and remains strongly significant when we address omitted variables and dynamics by adding controls for time effect (Columns 2 and 5, Panel B) and for standard fund-level covariates which include fund and family size, expense ratios, and lagged performance (Columns 3 and 6, Panel B).

Table 5 presents the estimates from equation (2) using fund flows (Columns 1 to 3) and extreme outflows (a dummy for fund flows in the bottom decile of the distribution, Columns 4 to 6) as the outcome variables, and Peer Flow Pressure (Panel A) and Peer Buy Pressure and Peer Sell Pressure (Panel B) as the explanatory variables of interest, respectively. There is a strong positive and highly statistically significant association between a fund's flows and Peer Flow Pressure (Panel A, Column 1), which is broadly supportive of the presence of strategic complementarity between own and peer fund flows. The result is stronger when illiquidity is higher (Columns 2,3 and 5,6) and for peer sell pressure relative to peer buy pressure (Columns 1 and 4, Panel B) and it is robust to controlling for common shocks by including time effects (Columns 2 and 5, Panel B) and for omitted variables and dynamics by including lagged flows and other standard fund-level covariates (Columns 3 and 6, Panel B).

Finally, we examine the timing of the spillover effect using graphical analysis in Panels B and C of Figure 1 and additional regression analysis in Panel C of Appendix Table A.1. In line with the timing of the bond price reaction, the bulk of the spillover effect is concentrated in the immediate quarter and the following one and eventually reverses over the course of the third and fourth quarters. The dynamics of the effect on flows is somewhat more delayed and persistent.[17]

3.2.1 Economic Significance

Our estimates of the spillover effect on fund performance and flows are strongly economically significant but plausible. For example, the estimates imply that a 1-SD increase in the Peer Sell Pressure variable leads to about 45 bps decrease in monthly returns, which is roughly equal to the sample mean of returns, and to over 4 percentage points increase in the likelihood of extreme underperformance. The spillover effect on fund flows is also economically significant, with a 1-SD increase in Peer Sell Pressure leading to about 90 bps decrease in monthly flows, which is roughly half the sample mean of flows, and to about 2 percentage points increase in the likelihood of extreme outflows. And our estimates of the price impact in Table 3 are also economically large, with a 1-SD increase in Sell Pressure leading to about 1.7 percentage points drop in bond prices.

To further gauge the economic significance of the estimates and assess their plausibility, we conduct two exercises. First, we examine how a 1-SD change in our key explanatory variable

[17] Appendix Table A.6 summarizes additional analysis of funds' real and liquidity decisions to explore whether funds take actions in response to peer outflows, perhaps in an effort to mitigate the negative impact of such outflows. Specifically, we present results from estimating equation (2) for funds' real and liquidity decisions, where the primary outcomes are fund fees and cash holdings, respectively. The coefficient on Peer Flow Pressure is positive and highly statistically significant for both outcomes (Columns 1 and 3), indicating that funds tend to lower fees and deaccumulate cash in response to and possibly in an effort to attract investments and mitigate the harm of peer outflows on own flows. This result is consistent with recent evidence in Chernenko and Sunderam (2017) that exposure to fire sales is an important determinant of equity funds' liquidity policies. There is also evidence that funds are more likely to introduce rear load fees in response to peer outflows, which is also consistent with an attempt to reduce harm (Column 2). Yet, these attempts do not appear to undo the negative spillover effect, as there is a negative relation between Peer Flow Pressure and a common measure of the fund's asset illiquidity, the Roll index (Column 4).

moves a firm in the distribution of the outcomes.[18] The estimated 45 (90) bps decrease in monthly returns (flows) in response to a 1-SD increase in Peer Sell Pressure corresponds to about one quarter (one tenth) of a standard deviation movement in the (conditional) distribution of fund returns (flows). And the estimate for the price impact corresponds to about one third of a standard deviation movement in the distribution of (log) bond price changes. Thus, the relative magnitudes of our estimates at the different steps of the chain of events that leads to spillovers plausibly square together. Second, we compare the marginal effect of Peer Sell Pressure to that of standard fund-level covariates, such as fund and family size and fund fees, as well as lagged flows and performance. We calculate these marginal effects by multiplying the respective estimates by the within-fund standard deviation of each right-hand side variable (see Appendix Table A.9). The marginal impact of Peer Sell Pressure for both performance and flows is of the same order of magnitude as any of these covariates, and is much larger than that of a change in fees, which further corroborates the notion that spillover effects are strong.

3.3 Second-round Price Impact

If fire-sale spillovers lead to redemptions, as we have shown in Table 5, an intriguing possibility is that redemptions may in turn lead to further sales, thus potentially leading to a spillover effect on prices or "second-round" price impact. Our final set of tests considers this fourth and last step of the spillover chain. In addition to closing the fire-sale feedback by tracing its effect back to prices, the analysis shows that fire-sale spillovers matter more broadly for debt markets.

To test whether peers' flow-related trading generates feedbacks that are strong enough to further depress asset values – i.e., whether fire-sale spillovers lead to a second-round price impact on debt securities – we take a bond event study approach analogous to the initial analysis of the price impact. The results are summarized in Table 6, which reports regressions of monthly (changes

[18] Given the inclusion of firm fixed effects in the regression analysis that produces the point estimates, we use the within-firm distributions (i.e., the distribution after removing firm fixed effects) as a benchmark.

in log) bond prices on a variable that proxies for trades under peer fund (net) flow pressure. The independent variable, Peer Flow Pressure, is meant to capture bonds where large fractions of trading are accounted for by mutual funds experiencing significant peer outflow pressure and is now defined as the bond-level counterpart of our fund-level spillover measure (see equation (1)) as follows:

$$Peer\ Flow\ Pressure_{b,t} = \frac{Peer\ Flow\ Induced\ Buys_{b,t} - Peer\ Flow\ Induced\ Sales_{b,t}}{Offering\ Value_b}$$

where $Peer\ Flow\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Peer\ Flows\ Pressure_{j,t} > Percentile(90th)} \right)$ and $Peer\ Flow\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Peer\ Flows\ Pressure_{j,t} < Percentile(10th)} \right)$.

Panel A of Table 6 reports the main results for a baseline specification that controls for bond (cusip) effects with monthly (changes in log) bond prices (Columns 1 to 3) and crash (a dummy for monthly changes in log bond prices in the bottom decile of the distribution, Columns 4 to 6) as the outcome variables, and Peer Flow Pressure (Panel A) and Peer Buy Pressure and Peer Sell Pressure (Panel B) as the explanatory variables of interest, respectively. The coefficient on Peer Flow Pressure is positive and highly statistically significant for both specifications, indicating that sales by mutual funds whose peers are experiencing outflow pressure tend to harm bond valuations. The result is stronger when illiquidity is higher (Columns 2,3 and 5,6) and for peer sell pressure relative to peer buy pressure (Columns 1 and 4, Panel B) and it is robust to controlling for common shocks by including time effects (Columns 2 and 5, Panel B) and for omitted variables by matching on similar bonds based on bond offering value, bond maturity, and previous spread (Columns 3 and 6, Panel B). The spillover effect on bond prices is also economically significant and strongly asymmetric for crash likelihood, with a 1-SD increase in peer sell pressure leading to almost 2 percentage point higher likelihood of a large bond price drop.[19] In all, these results

[19]Panel B of Appendix Table A.1 examines the timing of the price impact, with the bulk of the effect concentrated in the immediate quarter when the sales happen and the following one (Column 3). In untabulated results, we have verified that all the results in Table 6 are robust to controlling for the first-round Flow Pressure variable, which leaves the estimates in all specifications little chanced relative to those that are reported.

indicate that fire-sale spillovers have material valuation consequences in the bond market.

4 Evidence from Three Experiments and Mechanism

The challenge with interpreting the baseline OLS estimates of the spillover effect is a manifestation of the "reflection problem" and boils down to a standard endogeneity issue: flows are endogenous to fund characteristics, so the challenge is to distinguish peer funds' flow-driven trading from trading driven by changes in fund flows due to changes in fundamentals or "shocks" that are common across funds that hold the same securities. To address this endogeneity issue, we use three quasi-experiments. Details of the regression specification are in Section 2.3. Next, we detail the definitions of the treatment variables for each experiment. Additional details are in Appendix A.

The three peer treatment variables are as follows. First, we exploit plausibly independent time-series variation in peer flows, or peer flow "shocks," due to the 2003 mutual fund trading scandal, which is similar to Anton and Polk (2014). The scandal was unexpected and involved 25 fund families settling allegations of illegal trading that included market timing and late trading with the then Attorney General of the state of New York Elliot Spitzer. A well-replicated finding (for example, Kisin (2011) and McCabe (2009)) is that funds of implicated families experienced significant outflows which were long-lasting, arguably due to reputation effects. Important to convincingly rule out common shocks, fund families not implicated in the scandal did not experience direct contemporaneous shocks to their flows. For our first experiment, $Treatment_{j,t}$ is a dummy that equals one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003") and zero otherwise.[20]

[20] We retrieve information on the identity and timing of the fund families involved from FACTIVA searches and from multiple standard sources in the prior literature (primarily McCabe (2009) and references therein). After cross-checking the sources for consistency, we were able to include the following 18 treated fund families in our analysis (Alliance Bernstein 9/03, American Funds 12/03, Excelsior/Charles Schwab 11/03, Columbia Funds 1/04, DWS Investments 1/04, Federated 10/03, Franklin Templeton 2/04, Gabelli Funds 9/03, Invesco 11/03, Janus 9/03, Loomis Sayles 11/03, Massachusetts Financial Services 12/03, PIMCO 2/04, Prudential Investments 11/03, Putnam 10/03, RS Investments 3/04, Sentinel 10/04, and Waddell & Reed 7/06).

To further alleviate concerns about the exclusion restriction, we construct a second treatment based on a regression discontinuity (RD) design that exploits sharp changes in peer flows around Morningstar 5-star ratings. Each month, Morningstar issues mutual fund ratings based on arbitrary performance cut-offs of a risk-adjusted return, which are plausibly unrelated to changes in common industry fundamentals.[21] Ratings are coarse and range from one star for worst to five stars for best funds. It is well-documented that higher-rated funds tend to enjoy inflows (for example, Del Guercio and Tkac (2008)). We exploit the coarse nature of the ratings and the fact that Morningtar makes its sorting variable, the risk-adjusted return, also available to construct our treatment variable. For this second experiment, $Treatment_{j,t}$ is a dummy that takes value of one for funds that are right below their respective rating-category threshold and zero for funds that are right above it. To better isolate "quasi random" variation around the thresholds, as it is standard in RD designs, we only include funds that are close to their respective rating-category threshold, which we measure as those funds whose Morningstar (annualized) risk-adjusted return is within three percentage points around the respective rating category threshold. This choice of bandwidth involves roughly 1/4 of the peer fund-month observations. The identifying assumption of this RD approach is that for funds that are "close" to their rating threshold, differences in ratings are close to a coin toss and, as such, constitute a plausible "quasi-random" treatment.

Because Morningstar ratings are coarse, there is a sharply nonlinear relation between flows and performance around the arbitrary performance thresholds that determine the rating assignment, which is what our RD strategy exploits for identification. The sharp nonlinearity provides for identification of the treatment effect under mild conditions. Technically, identification requires that the so-called local continuity assumption holds, which requires that all factors other than the treatment variable vary continuously around the rating thresholds. Intuitively, in order for the treatment effect β to not be identified, it must be the case that the unobserved component of

[21] Specifically, the arbitrary cutoffs are defined so that the distribution of funds within stars is an approximate bell curve: one (10%), two (22.5%), three (35%), four (22.5%), and five stars (10%). See Morningstar Methodology Paper (2009) for additional details. Barrott (2016) is a related recent paper that uses Morningstar ratings for identification.

the outcome variable, say fund i's flows, $\nu_{i,t}$ exhibits an identical discontinuity around peer funds' performance as that defined by Morningtar rating thresholds. That is, even if $\nu_{i,t}$ is correlated with the distance between the peers' performance and their respective rating thresholds, our estimate of β is unbiased as long as $\nu_{i,t}$ does not exhibit precisely the same discontinuity around peer fund performance as *Peer Treatment* $\Pr essure_{i,t}$. To further isolate the discontinuity, we control in all the RD specifications for smooth (linear) functions of the distance from thresholds (see Roberts and Whited (2013) for a treatment of RD implementation with a focus on finance applications).

We also consider a third "shift-share" treatment that exploits peers' differential exposure to the collapse of the convertible bond market in 2005.[22] The collapse is documented in Mitchell et al (2007), who show that funds specializing in convertible bonds experienced large redemptions starting from the first quarter of 2005, which were long lasting and, in turn, led to fire sales and the eventual collapse of valuations in this asset class. An appealing feature of this event is that it was not anticipated and it originated from a specialized asset class. Similarly to the mutual fund scandal, the fact that funds not specialized in convertible bonds did not experience direct contemporaneous shocks to their flows over this period helps to convincingly address common shocks. We construct the $Treatment_{j,t}$ indicator variable for this additional experiment by interacting an indicator for the time period after the collapse of the convertible bond market (in 2005), the "shift" variable, with a dummy that is equal to one for funds whose Lipper asset class is convertible bonds, the "exposure" variable. By constructing the peer treatment as an interaction, we are not exploiting common variation across funds over time, but rather the differential behavior of convertible bond funds over time, an approach analogous to the one commonly used in labor economics to analyze the impact of labor demand shocks (Bartik (1991), Blanchard and Katz (1992)).

In Panel A of Tables 7 to 9, we repeat the bond event study (Columns 1 and 2), the analysis of fund performance (Columns 3 and 4) and flows (Columns 5 and 6) and the analysis of the second-

[22]We thank Erik Stafford for suggesting this test.

round price impact (Columns 7 and 8) using Peer Treatment Pressure as independent variable (see eq. (3) for definitions). The three peer treatments are defined based on either fund-specific negative shocks to peer flows due to the 2003 scandal (Table 7) or a plausibly exogenous decrease in peer flows due to a close miss of their next Morningstar 5-star rating for peer funds that are close to their rating-category threshold (Table 8), as per our RD approach that restricts the sample of peers to those funds whose Morningstar risk-adjusted return is within a narrow range (three percentage points) around the respective rating category threshold. Results for the additional third experiment that exploits peer funds' exposure to the collapse of the convertible bond market in 2005 are in Table 9 (see Section 2.3 and Appendix A for details on the definition of the Peer Treatment Pressure variable for each treatment).[23] Omitted common factors do not appear to be driving the spillover effect, which continues to hold robustly across fund performance, flows, and bond pricing for all of the three experiments.

In Panel B of Tables 7 to 9, we estimate equation (2) in a 2SLS-IV setting using Peer Treatment Pressure as an instrument for Peer Flow Pressure in the first-stage regression. Robustly across the three treatments, the IV estimates, reported in Panel B of the respective tables, remain strongly significant and are generally of the same order of magnitude and somewhat larger than their OLS counterparts in Tables 3-6 (Panel A, Column 1), consistent with the spillover effect from unanticipated flows being larger than that from anticipated ones and omitted common shocks leading to, if anything, downward bias in our OLS estimates. The estimated elasticities are large but plausible across outcomes. For example, a 1-SD change in instrumented Peer Flow Pressure leads to about 1 percentage point change in fund returns and 1 percentage point change in flows for the specification that uses the RD treatment.

[23]In Appendix Table A.7 we summarize additional evidence for the collapse of the ABS market in (the third quarter of) 2007. The intuition for this variable is based on anecdotal evidence from the financial crisis as well as the evidence in Chernenko, Hanson, and Sunderam (2014) that funds with relatively high holdings of private-label ABS experienced larger than average outflows from the second half of 2007.

4.0.1 Identification Assumptions, Falsification, and Additional Sensitivity Tests

The key identifying assumption for our treatments to be valid is that they are driven by events that are relevant for peer fund flows (the so-called "relevance condition"), but that are otherwise plausibly random with respect to fund i's flows and performance (the so-called "exclusion restriction condition"). More specifically, the identification assumption behind the RD strategy is the local continuity assumption, which requires that all factors other than the treatment variable vary continuously at the rating thresholds. For the DD strategies, the identifying assumption is that there are no differential trends pre-treatment between treated vs. untreated funds. If these assumptions hold, then estimates of β in equation (2) can be interpreted as causal.

To alleviate concerns about the internal validity of our estimates, we implement a battery of formal diagnostic tests, which include a first-stage validity test, as well as a balancing test on the covariates. Panels A and B of Appendix Table A.4 report first-stage diagnostics that confirm the validity of our three treatments. In line with the findings in the prior literature, we confirm that funds experience significant flow-driven pressure subsequent to becoming implicated in the 2003 scandal (Column 1), after close misses of Morningstar ratings thresholds (Column 2), and after the collapse of the convertible bond market. The first-stage estimates are all large, strongly statistically significant, and have good explanatory power (high R^2), all supporting the relevance condition. In a standard test of pre-trends, we do not detect significant differences in bond valuations based on the three treatment variables pre-treatment (Panel C). We use balancing tests to further assess whether funds are otherwise similar in terms of observables. For example, if funds have a discontinuity in characteristics around the rating thresholds, that would constitute a violation of the local continuity assumption. Panels D of Table A.4 reports estimates of our baseline specification with observable pre-determined fund characteristics as outcome variables, none of which is statistically significant.

Figure 2 illustrates the gist and supports the internal validity of our RD approach. Graphical analysis of average fund flows reveals that there is in fact a sharp discontinuity in the relation between funds and performance (the risk-adjusted return) around the Morningstar rating performance thresholds, which is especially pronounced for funds that are in the top (4 or 5) and bottom (1 or 2) rating bins (Panel A). Appendix Table A.5 reports additional specification checks on the RD tests. Panel A of Table A.5 allows for heterogeneity of the RD estimates by each of the four Morningstar rating-category thresholds. While the estimates remain generally significant across thresholds, in line with Figure 2, there is evidence of heterogeneity, with the estimates for the top and especially the bottom thresholds driving the overall result. We also implement an additional battery of tests to examine the sensitivity of our RD estimates to alternative specifications, which include using higher-order polynomials of the distance from the rating threshold (Panels B and C of Table A.5), and using a narrower bandwidth for the discontinuity sample (Panel D of Table A.5).[24] Estimates remain close to our baseline robustly across all these alternatives. These findings lend further support to the notion that our baseline peer effects represent valid regression discontinuity estimates.

Finally, we conducted two falsification tests to further build confidence about the exclusion restriction. The first is a test of pre-trends for the fund-level DD analysis. Specifically, we estimate our baseline specification using the one-quarter ahead lead of Peer Treatment Pressure, both for the 2003 MF scandal and the 2005 collapse of the convertible bond market. If the scandal or the market collapse were anticipated or reflected omitted fund characteristics, one might expect an "effect" of the peer treatment even prior to the events. The results in Panel B of Appendix Table A.8 indicate that this is not the case, as the estimates are small and statistically insignificant for both placebo treatments (Columns 1-2 and 5-6).

The second falsification test corroborates the exclusion restriction for the RD analysis and fol-

[24]Panel E of Table A.5 summarizes the results of an additional specification check. We show that the statistical significance of the baseline RD estimates is little changed when we use an alternative double-clustering of the standard errors that adds clustering by time. We report results for double-clustering on month, but we have experimented with double-clustering by lower-frequency time variables, either quarter or year, both of which leave the standard errors little changed relative to the baseline.

lows an implementation recommended by Imbens and Lemieux (2008). We define the placebo dummy as the median of the forcing variable in the two subsamples on either side of the threshold. To that end, we take funds whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold and, for each subsample right-above or right-below the rating-category thresholds, we replace the treatment dummy with a placebo treatment dummy based on whether the distance from the threshold is above or below the median within the subsample. The results in Columns 3-4 of Table A.8 show that the jump in peer returns and flows occurs only at the true rating threshold.[25]

In all, graphical evidence and the results of the more formal diagnostic and falsification tests support our conclusion that the peer treatment effects represent valid estimates and bolster a causal interpretation of our results.

4.1 Mechanism

The economic mechanism that makes fire-sales costly and leads to spillovers is downward-sloping demand for corporate bonds, by which fire-sales of a fund's portfolio securities – i.e., sales that are forced by redemptions – have a price-impact. Several factors have been identified in the literature as potentially leading to downward-sloping demand, including illiquidity due to transaction costs as well as, more broadly, slow-moving capital factors that make high-valuation bidders relatively scarce and lead to arbitrage persistence. A number of recent papers have put forward potential explanations for the existence of persistent mispricing in financial markets. Mitchell, Pedersen, and Pulvino (2007) and Duffie (2010) discuss the role that slow-moving capital may play in allowing arbitrage opportunities to exist for extended periods of time.[26] To the extent that purchasing

[25]To offer further reassurance about the exclusion restriction, in Panels B-C of Table A.10 we examined the sensitivity of the estimates to adding fund and time controls. The effects for each of the three treatments remain stable and strongly statistically and economically significant even after controlling for potential differences in the composition of treated funds (that are time-varying and, as such, may not be captured by fund effects) as well as for aggregate shocks with the inclusion of time effect to further address concerns about common shocks.

[26]Shleifer and Vishny (1997), Gromb and Vayanos (2002), Liu and Longstaff (2005), Fostel and Geanakoplos (2008), Gorton and Metrick (2009), and Ashcraft, Garleanu, and Pederson (2010) argue that margins, haircuts, and other collateral-related frictions may allow arbitrage or deviations from the law of one price to occur. Brunnermeier and

a corporate bond requires the use of significant capital, a combination of any of these factors that sideline arbitrage capital can plausibly lead to downward sloping demand for bonds.

By depressing security prices, flow-related sales lead to spillovers because the valuation losses hurt the performance of peer funds that hold the same securities. In turn, spillovers may lead to redemptions at peer funds through the performance-flow relationship. The evidence on fund performance and flows we document in Tables 4 and 5 is in line with this mechanism. In Appendix Tables A.2 and A.3 we present additional tests to further corroborate the mechanism. Specifically, to build confidence that the source of the spillover is indeed bond price changes we rerun our baseline fund-level regressions for returns and flows using as the main explanatory variable either exposure to the percentage price changes of the funds' bond holdings (the "reduced-form," Table A.2) or in a 2SLS-IV setting where we instrument for exposure to price changes using Peer Flow Pressure and then include the price changes as predicted by peer flow pressure in the second-stage tests (Table A.3, Panels A and B). Estimates of the reduced-form are strongly statistically significant and large, confirming that fund performance and flows are indeed quite sensitive to the value of asset holdings. Importantly, estimates for instrumented bond price changes are also large, which helps to build confidence that fire-sale spillovers affect performance and flows in an instrumental variables sense via their impact on the value of securities.

Finally, Panel C of Appendix Table A.3 also uses a 2SLS-IV approach to clarify the flow-performance relation in the spillover to fund flows. We replicate the main analysis of flows using performance instrumented with peer flow pressure as the main explanatory variable. The 2SLS estimates are remarkably close to their reduced-form counterpart presented in the main analysis (Table 5), which supports the notion that the spillover to flows is via fund performance. While the two sets of 2SLS estimates help to reassure about the price-impact mechanism, they do not rule out the possibility that other economic mechanisms may also contribute to the spillover. One important such mechanism is information and investor learning, whereby fire-sales lead to rep-

Pedersen (2009) emphasize the role that the availability of funding may play in liquidity effects on security prices.

utation spillovers. For example, it may be the case that severe underperformance of a high-yield fund leads investors to punish other high-yield funds.

Disentangling the relative contribution of different mechanisms is beyond the scope of this paper, and constitutes a promising venue for future work. However, in Panel A of Appendix Table A.8 we offer some reassurance about the price-impact mechanism using placebo tests.[27] We consider two placebo variables in turn, which are all constructed as a weighted sum of peers' placebo flow pressure. In Columns 1-2 of Panel A, Placebo Peer Flow Pressure is defined using weights calculated based on the asset allocation of a given fund but placebo flow pressure, which is defined using non-forced trades. Non-forced trades are measured similar to Khan, Kogan, and Serafeim (2012), who intepret them as more likely to be information-driven trades, as $Not - Flow\ Induced\ Trades_{b,t}^{j \neq i} = \sum_{j \neq i} \left(\Delta Holdings_{j,b,t}|_{Percentile(10th) < Flows_{j,t} < Percentile(90th)} \right)$. In Columns 3-4 of Panel A, Placebo Peer Flow Pressure is defined using forced sales but placebo weights, which are calculated based on the past asset allocation (over the previous year) of a given fund that remains active in a given Lipper asset class but ceases to hold a given security in a given month. The results indicate that there is no spillover for asset sales that are not flow-driven or for funds that operate in the same markets but don't have common holdings, both corroborating the price-impact mechanism.

5 Implications for Financial Stability

In this section, we examine the financial stability implications of fire-sale spillovers. The term "financial stability" is broad and has been used in the literature for different kinds of market vulnerabilities. We examine whether fire-sale spillovers aggravate a specific type of market instability – volatility – by amplifying the effect of an initial shock to fund flows that is otherwise unrelated to fundamental asset values. The mechanism is that outflows at peer funds lead to a second round of outflows that further depresses bond prices over and above the initial effect of a given adverse

[27]We thank Marco di Maggio for this suggestion.

shock. As a result, spillovers lead to higher volatility by increasing the exposure of funds and bonds to non-fundamental risk. To clarify the conditions and circumstances under which fire-sale spillovers lead to volatility, we construct measures of fund exposure to spillovers based on our estimates and explore the relation between these measures and the volatility of fund and bond returns. We also use a calibrated structural model to gauge the quantitative importance of the mechanism.

We construct two measures of exposure to fire-sale spillovers, systemicness and vulnerability, which we use in regression analysis of bond and fund return volatility similarly to Greenwood and Thesmar (2011). For ease of exposition, we calculate the measures annually and at the fund family level. Recall from our definition that Peer Flow Pressure for fund i is a weighted sum of other funds' flow pressure with weights equal to the pair-wise co-investment of funds' asset allocations across individual asset holdings, $w_{i,j}$. Using the pair-wise version of these weights, $W_{i,t}^{j} = \sum_{b} I_{b,t}^{j} * w_{b,t-1}$, for all $j \neq i$,where $I_{b,t}^{j}$ is an indicator variable that equals one for securities that are held by fund j at time t,[28] and an estimate of the spillover effect, $\widehat{\beta}$, we construct a matrix B of order $n \times n = 254 \times 254$, which is defined together with additional details in Appendix B. Each element of B, b_{ij}, gives the effect of 100 basis points increase in fund family j's pressure on i's current flows. Given B and an assumption for the attenuation factor, a, we calculate a fund i's vulnerability and systemicness, respectively, as: $Vu\ln erability_i = \frac{1}{n}\sum_{s=1}^{\infty}\sum_{j=1}^{n} a^s b_{ij}^s$ and $Systemicness_i = \frac{1}{n}\sum_{s=1}^{\infty}\sum_{j=1}^{n} a^s b_{ji}^s$. The vulnerability measure captures own fund's exposure to peer fire-sales and ranks as more vulnerable funds for which peer outflows are more likely to lead to own outflows. The systemicness measures captures how exposed other funds are to a fund's own fire-sales and ranks as more systemic those funds whose outflows are more likely to lead to peer outflows. Generally, these measures are higher whenever 1) there is a higher degree of overlap in bond holdings with other funds – i.e., if the pair-wise weights in $W_{i,t}^{j}$ are higher, and 2) debt

[28]For example, for two funds that have the following holdings of a given Bond C, Fund A holdings of Bond C=$100 and Fund B holdings of bond C=$150, the contribution of Bond C to the numerator of the pair-wise weight is $100.

market conditions are such that forced sales have a larger price impact – i.e., if the estimates of the spillover effect, $\widehat{\beta}$, are higher.[29] In the rest of this section we use regression analysis and a model-based calibration to illustrate these mechanisms.

Panel A of Table 10 provides a descriptive analysis of the main cross-sectional correlates of the two measures. Systemic (vulnerable) funds are larger and more (less) diversified. Even then, standard fund characteristics have overall relatively low explanatory power especially for vulnerability, suggesting that, although systemic and vulnerable funds share some characteristics in common, our exposure measures do not just reflect standard fund characteristics. To further develop intuition for our measures, consider the difference with concentrated holdings. A fund with relatively un-diversified holdgings would certainly be more exposed to bond-specific risks relative to a more diversified fund if it were forced to sell in response to outflows. However, holding concentration captures primarily exposure to fund-specific risk – i.e., how exposed a fund portfolio is to fund- or bond-specific shocks. By contrast, the overlap of bond holdings across funds captures the extent to which shocks to any particular bond or asset class will be borne across a wide swat of funds – i.e., the strength of transmision of fund- or bond-specific shocks to other funds. For example, if two funds, A and B, hold the same asset, and an exogenous shock forces A to liquidate the asset, the price of the asset will decline and therefore change the value of B's portfolio potentially leading to B also selling the asset at an unfavorable price. Thus, overlapping holdings are a potentially useful gauge of the strength of transmission of fire-sales across funds.

Panels B and C use regression analysis to test at the fund-level our prediction that exposure to peer fire-sales should forecast volatility. We use one-quarter or one-year ahead monthly volatilities of fund returns as the dependent variable and regress them on the fund vulnerability measure. As expected, the vulnerability measure has predictive power and is positively correlated with future volatility: for example, a 1-standard deviation increase in fund vulnerability leads to an

[29] Appendix Table A.11 lists fund families that are ranked as most systemic (Panel A) and most vulnerable (Panel B) for the most recent year (2014).

increase in annual volatility of about 0.6%, which is approximately 1/3 of the sample mean. The estimates are twice as large in the crisis, suggesting that spillovers may also contribute to procyclicality. Panel C examines this possibility more directly by testing whether the vulnerability measure also has forecasting power for peer-induced co-movement with market-wide factors. We use one-quarter ahead market betas of monthly fund returns with respect to an index of bond fund market returns as well as an index of stock market returns as the dependent variables and regress them on the vulnerability measure. As expected, the vulnerability measure has predictive power and is positively correlated with future betas, which further corroborates the notion that fire-sale spillovers are a source of non-fundamental risk.

Next, we examine sector- and market-wide implications. Panels A and C of Table 11 repeat the forecasting regressions analysis of volatility for the aggregate bond mutual fund sector and for bond returns, respectively, for the systemicness and vulnerability scores, in turn. In Panel A, we construct value-weighted indices of fund returns and use one-quarter or one-year ahead monthly volatilities of the value-weighted returns as the dependent variable, which we regress on value-weighted indices of each of the two exposure measures, in turn. In Panel C, we regress the volatility of bond returns on measures of a bond's exposure to systemic and vulnerable funds, which are calculated by taking (lagged) holding weighted averages of the systemicness and vulnerability scores of its holders. In the aggregate and at the bond level both measures have predictive power and are positively correlated with future volatility, indicating that when the mutual fund sector as a whole or a bond on average become more exposed to spillovers – either because funds are more systemic and, thus, matter more for their peers, or becasue they are more vulnerable and, thus, more exposed to their peers – that leads to higher subsequent volatility.[30]

Panel B of Table 11 reports the results of a stress-test exercise that calculates the effect of fire-sales by the most systemic funds on sector-wide flows. We report results for aggregate flows as

[30]Note that the systemicness score is included in the aggregate analysis (Table 11) but not in the fund-level analysis (Table 10) because, while systemic funds should make their peers unambiguosly riskier, it is less clear a priori whether they should be themselves riskier.

a percentage of aggregate assets under management and for several alternative adverse scenarios that vary by the size of the shock to the 10 most systemic funds (5% vs. 10% vs. 20% reduction in portfolio holdings). To illustrate how the effect changes over time, we report estimates for the most recent data (Jan-Dec 2014) as well as for the years in which spillovers had the greatest potential to lead to a systemic effect on mutual fund sector flows. For reference, we also report the estimates for the earlier data (1999) and for the case when the 10 or even 100 least systemic funds are shocked. Details of the calculations are in Appendix B. Shocks to the most systemic funds generally have large effects on the industry. In fact, it takes roughly the bottom half of the sector in terms of systemicness to be affected to trigger sector-wide outflows that are comparable in magnitude to those induced by a shock to just the 10 most systemic funds. The aggregate effects have become more severe in the crisis and post-crisis years, indicating that the degree of holding overlap has been increasing in recent years as the overall sector has dramatically increased its participation in the bond market.

Finally, we provide a quantitative assessment of the implications for volatility using a calibrated discrete-choice model of fund-flow decisions in the style of Hortacsu and Syverson (2004). Additional details are in Appendix B, but the two key features are that there is a flow-performance relation, because investors in the model decide which fund to invest in based on an array of fund characteristics that include fund returns, and there are cross-fund fire-sale spillovers, because any given fund's return is positively (negatively) affected by the inflows (outflows) of its peers. Specifically, we assume that investors' utility from investing in fund i, u_{it}, depends on fund i's return, R_{it}, as well as an array of standard fund characteristics, X_{it}, which include fund size and expense ratio:

$$u_{it} = \alpha \cdot R_{it} + X_{it}'\beta + \epsilon_{it}$$

and fund i's return R_{it} is an increasing function of its peer funds' flows as follows:

$$R_{it} = \gamma \cdot \left(\sum_{j \neq i} s_{jt} \cdot \omega_{jt} \right) + \zeta_{it}$$

where s_{jt} is peer fund flow shares, ω_{jt} measures portfolio overlap across funds, and ζ_{it} is the fund-specific component of returns. While the model is structural in the sense that we derive the equilibrium solution for fund-flow shares and returns for a given set of values of the parameters, the specification for fund returns captures in reduced-form the main mechanism through which fire-sale spillovers operate, which is that fund performance is hurt by outflows at peer funds.

The model is parsimonious enough to allow for a calibration that uses as inputs four main estimates from the data: the flow-performance relation, $\hat{\alpha}$, the relation between flows and standard fund characteristics, $\hat{\beta}$, the intensity of the spillover effect, $\hat{\gamma}$, and the time-series of monthly fund-specific return shocks, $\hat{\zeta}_{it}$. Specifically, under standard assumptions on ϵ_{it}, the model can be solved as a fixed-point problem with two equations in two unknowns, fund flow shares, s_{it}, and fund performance, R_{it}, for each fund i. For a given set of parameters and for each fund, we determine the solution to the fixed-point problem using different starting points for s_{it} and R_{it} on the $(0,1) \times (0,1)$ grid and bootstrapped residuals. To calibrate the model, we estimate the parameters α and β from the data using the first equation and data on fund flows and returns, which is analogous to estimating a standard flow-performance equation. We also estimate γ and ζ_{it} from the data using the second equation and data on fund returns and peer fund flows. Finally, we calculate the model-implied equilibrium solutions for s_{it} and R_{it} at each point in time t and their volatility (standard deviation) for the estimated $\hat{\alpha}, \hat{\beta}, \hat{\gamma}$ and bootstrapped residuals $\hat{\zeta_{it}}$.

Figure 3 reports the results of the model calibration for the volatility of fund returns (Panel A) and flows (Panel B). We plot the average model-implied volatilities (standard deviations) for four different estimates of the spillover parameter, $\hat{\gamma}$, which are respectively 0.04 in the pre-crisis period (1998-2006), 0.1 in the post-crisis period (2010-2014), 0.2 for the first crisis sub-period (2007Q4-

2008H1), and 0.3 for the second crisis sub-period (2008H2-2009H1), as well as for a counterfactual value of 0.4 which is even larger than those estimated in the crisis. We quantify the contribution of the spillover to volatility by plotting the model-implied volatilities under these different estimates of $\hat{\gamma}$ relative to the counterfactual benchmark of no-spillover – i.e., the model-implied volatilities for $\hat{\gamma} = 0$, which, for reference, implies a baseline standard deviation of returns (flows) of about 1.4% (10.4%). In the pre-crisis period, the contribution of spillovers to volatility was negligible, as the standard deviation of returns (flows) increased by just about 5% (3%) relative to the no-spillover benchmark. By contrast, the effect was very large especially in the second part of the crisis period, with the standard deviation of returns (flows) increasing by about 1 and half times (24%). And it remained significant post-crisis, leading to an increase in the standard deviation of returns (flows) by about 22% (7%). Interestingly, the effect is outsized and potentially disruptive in the "deep-crisis" scenario, pointing to a non-linear relation between volatilities and the intensity of the spillover. Overall, the model-based calibration indicates that spillovers had a large effect on volatility in the crisis, which abated but remained non-negligible in recent years.

6 Conclusion

The role of non-bank intermediaries in debt markets has attracted increasing attention in the wake of the 2008-09 financial crisis and the ensuing rapid growth of "shadow banking" institutions such as fixed-income funds. In order to better understand the sources of run-like fragility that emanate from the asset management sector, we have used rich microdata on individual fund flows, returns, and holdings, and a novel approach to measure network linkages across funds. We have shown evidence that there are powerful spillover effects among funds that hold the same assets, with fire-sales induced by investor redemptions hurting peer funds' performance and flows, and leading to further asset sales that have a negative bond price impact.

The approach developed in this paper offers a useful take on fire-sale externalities in debt markets, which had not yet been the subject of systematic empirical testing despite the fact that asset fire sales and costly liquidation are central ideas in financial economics at least since Shleifer and Vishny (1992). There are several venues along which our approach can be extended. First, we took a step in the direction of constructing measures of vulnerability of a fund family to system-wide flow pressures, but clearly more can be done in the direction of extending the framework for policy evaluation of alternative financial stability tools. Second, it would be interesting to study fire-sales spillovers in a more explicit structural setting. A structural extension would allow for quantitative evaluation of policy counterfactuals such as the stress testing scenarios that are now routinely used for banks and have been under consideration of the Financial Stability Oversight Council (FSOC) for asset managers. In addition, it would allow for welfare evaluation of the effectiveness of monetary policy as a financial stability tool (Stein (2012)) and of other policy measures aimed at reducing fire-sale spillover risk, such as imposing exit fees on open-end funds that are related to the illiquidity of the funds' assets.

Third, the framework could be extended to study in more detail additional mechanisms that may lead to strategic complementarities in fund flows, including, for example, relative-performance evaluation type features in fund managers' compensation contracts (Feroli et al. (2014)) or the concave relation between fixed-income flows and performance (Goldstein et al. (2015)). Finally, while we have started to explore the financial stability implications of spillovers, clearly more remains to be done. For example, our findings raise the intriguing possibility of cross-sector spillovers from mutual funds to other large players in debt markets, such as insurance companies. Also, extending the analysis to an international setting would help to understand the extent to which fire sale spillovers contribute to co-movement across countries and global volatility in debt markets, which have received increasing attention after the "taper tantrum" episode of the summer of 2013.

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Table 1: Summary Statistics

This table presents summary statistics (means and medians) for our sample, which comprises the universe of fixed-income funds. The data span the period January 1998-December 2014 and consists of 330,429 fund (at share class level)-month observations (Column 1, Panel A) for 3,666 unique funds and 254 unique fund families (Columns 2 and 3, Panel A, respectively). Definitions for all variables are in Appendix A.

Panel A: Sample Distribution			
	Obs	Funds (share class level)	Families
	(1)	(2)	(3)
1998	3,854	671	123
1999	8,289	759	131
2000	9,232	862	137
2001	11,121	1,022	147
2002	12,681	1,176	152
2003	13,482	1,269	153
2004	14,477	1,375	159
2005	15,173	1,510	167
2006	16,952	1,640	171
2007	19,370	1,842	177
2008	21,909	2,126	189
2009	25,073	2,354	193
2010	27,663	2,550	200
2011	30,791	2,860	218
2012	34,383	3,127	225
2013	35,634	3,341	241
2014	30,345	3,280	232
Tot.	330,429	3,666	254
Panel B: Summary Statistics			
	Mean	Std Dev	p95-p5
Main Explanatory Variable(s):			
Peer Flow Pressure $\text{Sd}_{i,t}$	0.014	1	2.62
Peer Buy Pressure $\text{Sd}_{i,t}$	0.046	1	2.44
Peer Sell Pressure $\text{Sd}_{i,t}$	0.036	1	2.28
Peer Perf.$\text{Sd}_{i,t}$	0.201	1	2.91
Peer Extreme Outperf $\text{Sd}_{i,t}$	0.114	1	2.48
Peer Extreme Underperf $\text{Sd}_{i,t}$	0.163	1	2.39
Main Outcome Variables:			
Monthly Return	0.005	0.019	0.063
Extreme Underperformance	0.097	0.296	1
Monthly Flows	0.021	0.086	0.226
Extreme Outflows	0.103	0.305	1
Fund Controls:			
Fund Size (log$Mil)	4.122	2.295	7.605
Family Size (log$Mil)	8.015	2.002	6.763
Expense ratio (%)	0.011	0.005	0.015
Retail Fund	0.612	0.487	1
Equity Fund (primarily)	0.173	0.378	1

Table 2: Motivating Evidence

This table reports predictability regressions of monthly fund returns (Panel A) and extreme underperformance (a dummy for returns in the bottom decile of the distribution, Panel B) up to a quarter ahead on peer fund performance. The independent variable in Panel A, Peer Performance, is a weighted sum of peer funds' returns, with weights calculated based on the asset allocation of a given fund. Specifically, we start with each security with information on holdings available from eMAXX and combine it with information on fund performance from CRSP to construct this measure for each fund by taking the weighted sum over the fund's securities holdings of the average return of other funds that hold a given security, with weights equal to the funds' percentage portfolio share holding of each security. The independent variable in Panel B is Peer Extreme Underperformance, which is a weighted sum of dummies for Peer Performance in the highest ten percent of the distribution, respectively. To ease interpretation, these variables are expressed in standard deviation units. We report the baselines estimates in Columns 1 to 3 and results for the crisis sub-sample in Columns 4 to 6. The time period is 1998-2014. All specifications include fund fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Descriptive Analysis of Predictability of Fund Performance, Y=Monthly Return$_{i,t+N}$ (pct)						
	All Funds			Illiquid Times		
	N=+1	N=+2	N=+3	N=+1	N=+2	N=+3
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Perf. Sd$_{i,t}$	0.57***	0.78***	0.65***	0.58***	1.56***	1.03***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
Fund Perf Sd$_t$	0.28***	-0.13***	-0.10***	0.68***	-0.31***	0.19***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
FE	Fund	Fund	Fund	Fund	Fund	Fund
N	327,418	325,005	323,120	40,561	40,059	39,612
R^2(%)	11.04	14.26	15.27	22.40	24.38	25.17

Panel B: Descriptive Analysis of Predictability of Fund Performance, Y=Extreme Underperformance$_{i,t+N}$ (pct)						
	All Funds			Illiquid Times		
	N=+1	N=+2	N=+3	N=+1	N=+2	N=+3
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Extreme Underperf. Sd$_{i,t}$	8.97***	9.72***	8.63***	5.17***	9.04***	8.31***
	(0.06)	(0.07)	(0.08)	(0.19)	(0.22)	(0.26)
Fund Extreme Underperf Sd$_t$	4.59***	-4.42***	-0.86**	11.28***	-6.72***	-18.69***
	(0.20)	(0.28)	(0.35)	(0.52)	(0.75)	(0.97)
FE	Fund	Fund	Fund	Fund	Fund	Fund
N	327,418	325,005	323,120	40,561	40,059	39,612
R^2(%)	14.26	16.31	17.29	22.89	24.76	25.51

Table 3: Analysis of Bond Price Impact

This table reports regressions of monthly (changes in log) bond prices on a variable that proxies for trades under fund flow (net) pressure. Panel A shows results for a flow-pressure variable constructed as flow-related net-buy pressure using fund flows as in Coval and Stafford (2007). Specifically, we start with each security with information on holdings available from eMAXX and combine it with information on fund flows from CRSP to construct Flow Pressure as the sum of the value of net "forced" fund buys (buys by funds with large inflows buys minus sells by funds with large outflows relative to the offering value of the bond), with "forced" buys and sales defined based on the top and bottom deciles of the distribution of fund flows, respectively (see p.9 for details). Panel B show results for the buy and sell pressure separately to allow for asymmetries. To ease interpretation, these variables are expressed in standard deviation units. We report results for the overall sample (Columns 1 and 4), for sub-samples of illiquid bonds and in the crisis (Columns 2-3 and 5-6, Panel A), for a specification with time (year) effects, and for a matched-sample estimator based on bond offering value, maturity, and lagged spread. Columns 4 to 6 limit the sample to the top vs. bottom deciles of the flow-pressure variable to exclude either no trades or no trades by institutions under flow pressure as recommended by Khan et al. (2012). The time period is 1998-2014. All specifications include controls for bond or time effects. Standard errors are clustered by bond, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Replication of Coval and Stafford (2007) – Monthly % Bond Price Changes (pct)						
	Baseline			Top and Bottom Deciles Only		
	All Bonds	Illiquid Bonds	Illiquid Times	All Bonds	Illiquid Bonds	Illiquid Times
	(1)	(2)	(3)	(4)	(5)	(6)
Flow Pressure $Sd_{b,t}$	1.04***	3.25***	9.00***	1.01***	3.04***	7.81***
	(0.11)	(0.37)	(0.90)	(0.17)	(0.40)	(1.37)
FE	Bond	Bond	Bond	Bond	Bond	Bond
N obs	429,449	83,156	47,724	76,809	30,651	9,573
N Bonds	10,880	4,698	3,008	7,295	3,246	1,693
R^2(%)	5.20	8.15	8.70	13.15	17.51	20.44
Sd LHS	4.99	9.33	9.38	7.12	9.65	12.63
IQR LHS	1.93	3.68	3.33	2.33	3.44	4.31
Panel B: Asymmetry & Robustness– Monthly % Bond Price Changes (pct)						
	Baseline			Top and Bottom Deciles Only		
	Asymmetry	Time FE	Matched Sample	Asymmetry	Time FE	Matched Sample
	(1)	(2)	(3)	(4)	(5)	(6)
Buy Pressure $Sd_{b,t}$	0.75***	0.13	0.12	0.40	0.34	0.13
	(0.19)	(0.15)	(0.18)	(0.33)	(0.22)	(0.31)
Sell Pressure $Sd_{b,t}$	-1.71***	-1.05***	-0.78***	-1.78***	-0.77***	-0.98***
	(0.19)	(0.16)	(0.17)	(0.32)	(0.23)	(0.30)
FE	Bond	Time	Bond	Bond	Time	Bond
N obs	429,449	429,449	429,449	76,809	76,809	76,809
R^2(%)	5.21	3.88	5.61	13.15	4.18	13.37

Table 4: Analysis of Fund Performance

This table reports regressions of monthly fund returns (Columns 1-3) and extreme underperformance (a dummy for returns in the bottom decile of the distribution, Columns 4-6) on peer fund flows (net) pressure. In Panel A, the independent variable, Peer Flow Pressure, is a weighted sum of peers' flow pressure, with weights calculated based on the asset allocation of a given fund. Specifically, we start with each security with information on holdings available from eMAXX and combine it with information on fund flows from CRSP to construct this measure for each fund-period by taking the weighted sum over the fund's securities holdings of the security-by-security pressure from peer funds' flows, with the weights equal to the (own) funds' percentage portfolio share holding of each respective security (see def. (1) in the text for details). Panel B show results for two variables that are constructed analogously but using buy and sell pressure separately to allow for asymmetries. To ease interpretation, these variables are expressed in standard deviation units. We report the baselines estimates in Columns 1 and 4, results for sub-samples of illiquid (high-yield) funds and in the crisis (Columns 2-3 and 5-6, Panel A), for a specification that adds time (year) effects (Columns 2 and 5, Panel B, and for a specification that adds fund covariates – fund and family size, expense ratios, and lagged performance (Columns 3 and 6, Panel B). The time period is 1998-2014. All specifications include fund fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Baseline Analysis of Fund Performance						
	Monthly Return (pct)			Extreme Underperformance (pct)		
	All Funds	Illiquid Funds	Illiquid Times	All Funds	Illiquid Funds	Illiquid Times
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flow Pressure $Sd_{i,t}$	0.35***	0.44***	1.22***	-2.52***	-3.00***	-6.69***
	(0.01)	(0.01)	(0.03)	(0.07)	(0.11)	(0.27)
Fund Controls	No	No	No	No	No	No
FE	Fund	Fund	Fund	Fund	Fund	Fund
N	330,429	58,323	40,908	330,429	58,323	40,908
R^2 (%)	1.95	4.21	8.79	6.16	2.41	13.99
Sd LHS	1.91	2.23	3.01	29.64	33.72	42.10
IQR LHS	1.58	1.99	2.82			

Panel B: Asymmetry and Robustness						
	Monthly Return (pct)			Extreme Underperformance (pct)		
	Asymmetry	Add Time Controls	Add Fund Controls	Asymmetry	Add Time Controls	Add Fund Controls
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Buy Pressure $Sd_{i,t}$	0.27***	0.15***	0.25***	-1.71***	-1.28***	-1.68***
	(0.01)	(0.01)	(0.01)	(0.09)	(0.08)	(0.09)
Peer Sell Pressure $Sd_{i,t}$	-0.46***	-0.33***	-0.47***	4.28***	3.20***	4.45***
	(0.01)	(0.01)	(0.01)	(0.11)	(0.11)	(0.11)
Fund Controls	No	No	Yes	No	No	Yes
FE	Fund	Fund, Time	Fund	Fund	Fund, Time	Fund
N	330,429	330,429	325,896	330,429	330,429	325,896
R^2 (%)	3.03	10.11	3.45	7.59	12.29	8.12

Table 5: Analysis of Fund Flows and Distress

This table reports regressions of monthly fund (net) flows (Columns 1-3) and extreme outflows (a dummy for net flows in the bottom decile of the distribution, Columns 4-6) on peer fund flows (net) pressure. In Panel A, the independent variable, Peer Flow Pressure, is a weighted sum of peers' flow pressure, with weights calculated based on the asset allocation of a given fund. Specifically, we start with each security with information on holdings available from eMAXX and combine it with information on fund flows from CRSP to construct this measure for each fund-period by taking the weighted sum over the fund's securities holdings of the security-by-security pressure from peer funds' flows, with the weights equal to the (own) funds' percentage portfolio share holding of each respective security (see def. (1) in the text for details). Panel B show results for two variables that are constructed analogously but using buy and sell pressure separately to allow for asymmetries. To ease interpretation, these variables are expressed in standard deviation units. We report the baselines estimates in Columns 1 and 4, results for sub-samples of illiquid (high-yield) funds and in the crisis (Columns 2-3 and 5-6, Panel A), for a specification that adds time (year) effects (Columns 2 and 5, Panel B, and for a specification that adds fund covariates – fund and family size, expense ratios, and lagged performance (Columns 3 and 6, Panel B). The time period is 1998-2014. All specifications include fund fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Baseline Analysis of Fund Flows						
	Monthly Flows (pct)			Extreme Outflows (pct)		
	All Funds	Illiquid Funds	Illiquid Times	All Funds	Illiquid Funds	Illiquid Times
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flow Pressure $Sd_{i,t}$	0.70***	0.99***	0.93***	-1.18***	-3.09***	-2.80***
	(0.03)	(0.11)	(0.10)	(0.05)	(0.26)	(0.21)
Fund Controls	No	No	No	No	No	No
FE	Fund	Fund	Fund	Fund	Fund	Fund
N	330,429	58,323	40,908	330,429	58,323	40,908
R^2(%)	11.00	10.91	32.48	8.50	8.36	20.02
Sd LHS	8.55	9.51	9.16	30.51	32.74	33.78
IQR LHS	3.98	4.48	4.16			

Panel B: Asymmetry and Robustness						
	Monthly Flows (pct)			Extreme Outflows (pct)		
	Asymmetry	Add Time Controls	Add Fund Controls	Asymmetry	Add Time Controls	Add Fund Controls
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Buy Pressure $Sd_{i,t}$	0.30***	0.29***	0.22***	-0.71***	-0.72***	-0.73***
	(0.03)	(0.03)	(0.03)	(0.07)	(0.07)	(0.07)
Peer Sell Pressure $Sd_{i,t}$	-0.92***	-0.67***	-0.59***	1.80***	1.75***	1.79***
	(0.03)	(0.03)	(0.03)	(0.06)	(0.07)	(0.07)
Fund Controls	No	No	Yes	No	No	Yes
Clustering, FE	Fund	Fund, Time	Fund	Fund	Fund, Time	Fund
N	330,429	330,429	320,425	330,429	330,429	320,425
R^2(%)	11.66	13.76	14.44	8.92	9.18	9.33

Table 6: Analysis of Second-Round Bond Price Impact

This table reports regressions of monthly (changes in log) bond prices (Columns 1-3) and price crash (a dummy for change in log prices in the bottom decile of the distribution, Columns 4-6) on a variable that proxies for trades under peer fund flow (net) pressure. Panel A shows results for a peer flow-pressure variable constructed as peer flow-related net-buy pressure using fund flows as in Coval and Stafford (2007). Specifically, we start with each security with information on holdings available from eMAXX and combine it with information on fund flows from CRSP to construct first a fund-level measure that for each fund-period takes the weighted sum over the fund's securities holdings of the security-by-security pressure from peer funds' flows, with the weights equal to the (own) funds' percentage portfolio share holding of each respective security (see def. (1) in the text for details). Next, we combine this measure and fund trading to rank securities based on a security-level version of Peer Flow Pressure, which is constructed similarly to Coval and Stafford (2007) as the sum of the value of net "forced" fund buys (buys by funds with peer inflow pressure minus sells by funds with peer outflow pressure relative to the offering value of the bond), with "forced" buys and sales defined based on the top and bottom deciles of the distribution of the fund-level peer flow pressure, respectively (see p.23 for details). Panel B show results for the peer buy and peer sell pressure separately to allow for asymmetries. To ease interpretation, these variables are expressed in standard deviation units. We report results for the overall sample (Columns 1 and 4), for sub-samples of illiquid bonds and in the crisis (Columns 2-3 and 5-6, Panel A), for a specification with time (year) effects, and for a matched-sample estimator based on bond offering value, maturity, and lagged spread. The time period is 1998-2014. All specifications include controls for bond or time effects. Standard errors are clustered by bond, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

	Panel A: Monthly % Bond Price Changes (pct)					
	Baseline			Crash		
	All Bonds (1)	Illiquid Bonds (2)	Illiquid Times (3)	All Bonds (4)	Illiquid Bonds (5)	Illiquid Times (6)
Peer Flow Pressure $Sd_{b,t}$	0.36***	0.63***	1.07***	-0.69***	-1.87***	-2.14***
	(0.01)	(0.03)	(0.07)	(0.06)	(0.12)	(0.27)
FE	Bond	Bond	Bond	Bond	Bond	Bond
N obs	429,449	83,156	47,724	429,449	83,156	47,724
N Bonds	10,880	4,698	3,008	10,880	4,698	3,008
R^2(%)	5.42	8.61	9.03	8.61	11.73	13.49
Sd LHS	4.99	9.33	9.38	29.64	40.15	39.70
IQR LHS	1.93	3.68	3.33			

	Panel B: Asymmetry & Robustness– Monthly % Bond Price Changes (pct)					
	Baseline			Crash		
	Asymmetry (1)	Time FE (2)	Matched Sample (3)	Asymmetry (4)	Time FE (5)	Matched Sample (6)
Peer Buy Pressure $Sd_{b,t}$	0.31***	0.15***	0.31***	0.16	-0.01	0.01
	(0.02)	(0.02)	(0.02)	(0.10)	(0.10)	(0.11)
Peer Sell Pressure $Sd_{b,t}$	-0.29***	-0.24***	-0.29***	1.84***	1.16***	1.88***
	(0.01)	(0.01)	(0.01)	(0.08)	(0.08)	(0.08)
FE	Bond	Time	Bond	Bond	Time	Bond
N obs	429,449	429,449	429,449	429,449	429,449	429,449
R^2(%)	5.62	4.61	5.62	9.25	10.36	9.26

Table 7: Experiment #1 – The 2003 Mutual Fund Scandal

This table reports results on fire-sale spillover effect of the 2003 mutual fund scandal for each of the four main outcomes, bond price impact (monthly (changes in log) bond prices, Columns 1-2), fund performance (Columns 3-4), fund flows (Columns 5-6), and second-round bond price impact (monthly (changes in log) bond prices, Columns 7-8). The independent variable for the bond price impact analysis, Treatment Pressure, is defined analogously to Coval and Stafford (2007) as treatment-related net-buy pressure, where treatment is a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003. The independent variable for the spillover effect analysis, Peer Treatment Pressure, is defined analogously to Peer Flow Pressure as a weighted sum of peers' treatment pressure, where treatment is a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 at the fund or at the security level for columns 3-6 and 7-8, respectively (see def. (3) in the text for details). Panel A reports results for OLS regressions using these variables, the 'reduced-form.' Panel B reports 2SLS-IV estimates for specifications the respective treatment variables as instruments for Flow Pressure and Peer Flow Pressure in a first-stage regression. Appendix Table A.4 shows first-stage diagnostics. To ease interpretation, the variables are expressed in standard deviation units. The time period is 2000-2006. All specifications include fund fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Baseline

	Bond Price Impact		Fund Performance		Fund Flows		Second-Round Price Impact*	
	All	Top-Bottom	Ret	Large Und.	% Flows	Large Outfl.	All	Top-Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment Pressure $Sd_{b,t}$	2.06***	3.48***						
	(0.41)	(0.52)						
Peer Treatmet Pressure $Sd_{i,t}$			0.26***	-0.95***	0.77***	-0.75***	0.31***	0.29***
			(0.03)	(0.29)	(0.07)	(0.18)	(0.03)	(0.04)
FE	Bond	Bond	Fund	Fund	Fund	Fund	Bond	Bond
N obs.	91,505	49,122	41,640	41,640	41,640	41,640	91,505	15,989
Sd LHS	4.99		1.91		8.55		4.99	
IQR LHS	1.93		1.58		3.98		1.93	

Panel B: 2SLS-IV

	Bond Price Impact		Fund Performance		Fund Flows		Second-Round Price Impact*	
	All	Top-Bottom	Ret	Large Und.	% Flows	Large Outfl.	All	Top-Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instr. Flow Pressure $Sd_{b,t}$	2.83***	2.37***						
	(1.08)	(0.51)						
Instr. Peer Flow Pressure $Sd_{i,t}$			0.68***	-2.49***	1.19***	-0.97***	0.46***	0.45***
			(0.14)	(0.17)	(0.12)	(0.24)	(0.04)	(0.06)
FE	Bond	Bond	Fund	Fund	Fund	Fund	Bond	Bond
N obs.	91,505	49,122	41,640	41,640	41,640	41,640	91,505	15,989

Table 8: Experiment #2 – Morningtar Rating RD

This table reports results on fire-sale spillover effect of Morningstar 5-star ratings for each of the four main outcomes, bond price impact (monthly (changes in log) bond prices, Columns 1-2), fund performance (Columns 3-4), fund flows (Columns 5-6), and second-round bond price impact (monthly (changes in log) bond prices, Columns 7-8). The independent variable for the bond price impact analysis, Treatment Pressure, is defined analogously to Coval and Stafford (2007) as treatment-related net-buy pressure, where treatment is a dummy that is equal to one for funds that are right below their rating-category threshold as defined by those funds whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold. The independent variable for the spillover effect analysis, Peer Treatment Pressure, is defined analogously to Peer Flow Pressure, as a weighted sum of peers' treatment pressure, where treatment is a dummy that is equal to one for funds that are right below their rating-category threshold at the fund or at the security level for columns 3-6 and 7-8, respectively (see def. (3) in the text for details). Panel A reports results for OLS regressions using these variables, the 'reduced-form.' Panel B reports 2SLS-IV estimates for specifications the respective treatment variables as instruments for Flow Pressure and Peer Flow Pressure in a first-stage regression. Appendix Table A.4 shows first-stage diagnostics. To ease interpretation, the variables are expressed in standard deviation units. The time period is 1998-2014. All specifications include fund fixed effects and control for a smooth (linear) function of the peer distance from thresholds. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Fund & Time Fixed Effects Estimators

	Bond Price Impact		Fund Performance		Fund Flows		Second-Round Price Impact*	
	All	Top-Bottom	Ret	Large Und.	% Flows	Large Outfl.	All	Top-Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment Pressure $Sd_{b,t}$	0.45***	0.45***						
	(0.02)	(0.02)						
Peer Treatment Pressure $Sd_{i,t}$			0.33***	-3.15***	0.19***	-0.85***	0.44***	0.46***
			(0.00)	(0.05)	(0.02)	(0.05)	(0.01)	(0.02)
FE	Bond	Bond	Fund	Fund	Fund	Fund	Bond	Bond
N obs.	429,449	129,956	330,429	330,429	330,429	330,429	429,449	75,733
Sd LHS	4.99		1.91		8.55		4.99	
IQR LHS	1.93		1.58		3.98		1.93	

Panel B: 2SLS-IV

	Bond Price Impact		Fund Performance		Fund Flows		Second-Round Price Impact*	
	All	Top-Bottom	Ret	Large Und.	% Flows	Large Outfl.	All	Top-Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instr. Flow Pressure $Sd_{b,t}$	5.87***	5.13***						
	(0.36)	(0.41)						
Instr. Peer Flow Pressure $Sd_{i,t}$			1.17***	-10.10***	1.05***	-2.61***	1.04***	0.87***
			(0.01)	(0.17)	(0.18)	(0.21)	(0.03)	(0.03)
FE	Bond	Bond	Fund	Fund	Fund	Fund	Bond	Bond
N obs.	429,449	129,956	330,429	330,429	330,429	330,429	429,449	75,733

Table 9: Experiment #3 – Collapse of the Convertible Bond Market

This table reports results on fire-sale spillover effect of the collapse of the convertible bond market (see Mitchell et al. (2007)) for each of the four main outcomes, bond price impact (monthly (changes in log) bond prices, Columns 1-2), fund performance (Columns 3-4), fund flows (Columns 5-6), and second-round bond price impact (monthly (changes in log) bond prices, Columns 7-8). The independent variable for the bond price impact analysis, Treatment Pressure, is defined analogously to Coval and Stafford (2007) as treatment-related net-buy pressure, where treatment is a dummy that is equal to one after the market collapse (2005) for a fund whose Lipper class is convertible bonds and zero before the collapse (2003). The independent variable for the spillover effect analysis, Peer Treatment Pressure, is defined analogously to Peer Flow Pressure as a weighted sum of peers' treatment pressure, where treatment is a dummy that is equal to one after the market collapse (2005) for a fund whose Lipper class is convertible bonds and zero before the collapse (2003) at the fund or at the security level for columns 3-6 and 7-8, respectively (see def. (3) in the text for details). Panel A reports results for OLS regressions using these variables, the 'reduced-form.' Panel B reports 2SLS-IV estimates for specifications the respective treatment variables as instruments for Flow Pressure and Peer Flow Pressure in a first-stage regression. Appendix Table A.4 shows first-stage diagnostics. To ease interpretation, the variables are expressed in standard deviation units. The time period is 2003 (pre-collapse) vs. 2005 (post-collapse). All specifications include fund fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Fund & Time Fixed Effects Estimators								
	Bond Price Impact		Fund Performance		Fund Flows		Second-Round Price Impact*	
	All	Top-Bottom	Ret	Large Und.	% Flows	Large Outfl.	All	Top-Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment Pressure $Sd_{b,t}$	0.21^{***}	0.18^{***}						
	(0.01)	(0.02)						
Peer Treatment Pressure $Sd_{i,t}$			0.12^{***}	-1.06^{***}	0.11^{**}	-0.24^{***}	0.14^{***}	0.10^{***}
			(0.00)	(0.11)	(0.04)	(0.08)	(0.02)	(0.02)
FE	Bond	Bond	Fund	Fund	Fund	Fund	Bond	Bond
N obs.	57,979	33,820	29,655	29,655	28,284	28,284	57,979	24,115
Sd LHS	4.03		1.53		9.92		5.08	
IQR LHS	2.04		1.58		4.22		1.99	

Panel B: 2SLS-IV								
	Bond Price Impact		Fund Performance		Fund Flows		Second-Round Price Impact*	
	All	Top-Bottom	Ret	Large Und.	% Flows	Large Outfl.	All	Top-Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Instr. Flow Pressure $Sd_{b,t}$	3.43^{***}	2.89^{***}						
	(0.50)	(0.61)						
Instr. Peer Flow Pressure $Sd_{i,t}$			0.46^{***}	-4.12^{***}	0.57^{***}	-1.09^{***}	0.76^{***}	0.58^{***}
			(0.03)	(0.42)	(0.22)	(0.36)	(0.05)	(0.06)
FE	Bond	Bond	Fund	Fund	Fund	Fund	Bond	Bond
N obs.	57,979	33,820	29,655	29,655	28,284	28,284	57,918	24,115

Table 10: Financial Stability – Implications for Individual Funds

This table present fund-level financial stability implications of fire-sale spillovers. Panel A reports results of annual cross-sectional regressions of the systemicness and vulnerability scores on fund family characteristics. Panel B examines predictability regressions of fund return volatility, measured as the one-quarter or one-year ahead standard deviation of fund returns (σ_{it+1}), which is regressed on the vulnerability score. We also show results for a specification where the score is interacted with the Crisis indicator. Panel C examines the implications for fund return comovement with market-wide factors, which is measured as theone-quarter ahead correlation between fund returns and Vanguard Total Bond Market Index Fund return ($\beta_{it+1}^{Bond\ Mkt}$, Column 1) and CRSP value-weighted market return ($\beta_{it+1}^{Bond\ Mkt}$, Column 2). Details on the definition of the scores are in the text (Section 5) and in Appendix B. Definitions for all other variables are in Appendix A.

Panel A: Correlates of Systemicness and Vulnerability		
	Fund Systemicness (1)	Fund Vulnerability (2)
Fund Size$_{i,t}$	0.12***	0.07***
	(0.11)	(0.01)
Fund Holding Concentration (HHI)$_{i,t}$	-0.46***	0.62***
	(0.17)	(0.17)
Fund Performance$_{i,t}$	-0.58	-1.25
	(1.22)	(1.27)
Expense Ratio$_{i,t}$	0.04	0.06
	(0.05)	(0.05)
Turnover Ratio$_{i,t}$	0.05***	0.06***
	(0.02)	(0.02)
Corporate Bond Holdings$_{i,t}$	0.12	0.24***
	(0.09)	(0.09)
Foreign Bond Holdings$_{i,t}$	0.41***	0.42***
	(0.13)	(0.13)
Government Bond Holdings$_{i,t}$	0.08	-0.22*
	(0.12)	(0.13)
N	2,237	2,237
R^2	8.07	4.18
Panel B: Implications for the Volatility of Fund Returns (p.p.)		
N=326,575	Quarterly Vol.	Annual Vol.
[1] Vulnerability$_{i,t}$	0.44***	0.57***
	(0.01)	(0.01)
R^2	0.77	1.73
[2] Vulnerability$_{i,t}$$*$Crisis	2.36***	2.14***
	(0.06)	(0.05)
R^2	10.70	14.50
Panel C: Implications for the Comovement of Fund Returns (p.p.)		
N=326,575	Quarterly β_{MKT}^{Bond}	Quarterly β_{MKT}^{Stock}
[3] Vulnerability$_{i,t}$	6.76***	8.25***
	(0.15)	(0.10)
R^2	0.92	1.89

Table 11: Financial Stability – Implications for the Mutual Fund Sector and the Bond Market

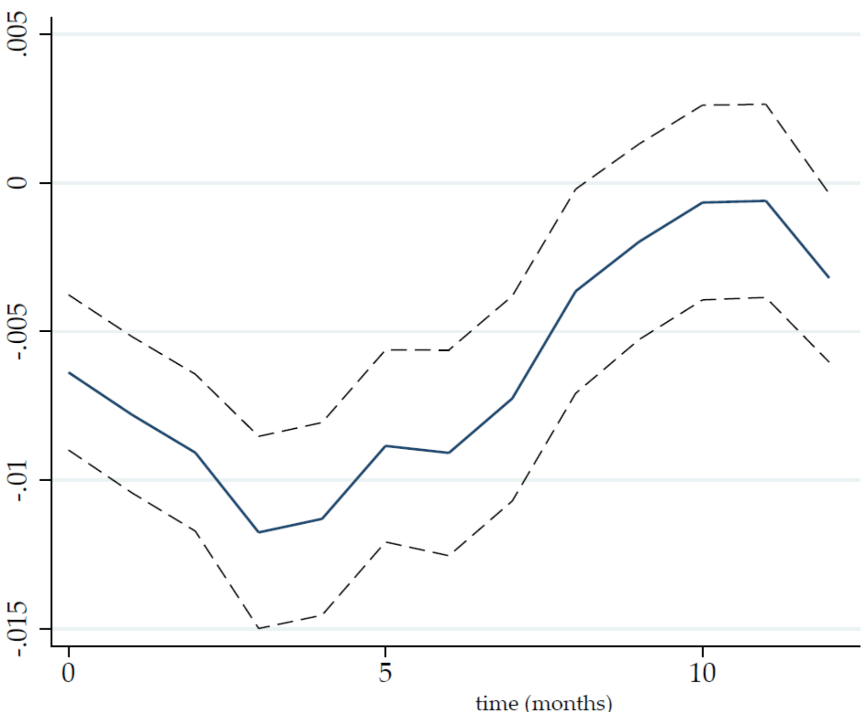
This table reports sector-wide and bond market-level financial stability implications of fire-sale spillovers. Panel A and Column 1 of Panel C repeat the volatility analysis of Table 10 (Panel B) for aggregate sector-wide returns and for bond returns, respectively, with Newey-West standard errors reported in Panel A. Column 2 of Panel C repeats the comovement analysis of Table 10 (Panel C) for bond returns. Panel B reports the results of a stress-test exercise that consists in calculating an aggregate counterfactual for the effect on sector-wide flows of flow-induced fire-sales by the most systemic fund families. We report results for aggregate flows relative to aggregate assets under management and for several alternative adverse scenarios that vary by the size of the shock (5% vs. 10% vs. 20% reduction in portfolio holdings) as well as by which funds are shocked (most vs. least systemic funds). Details on the definition of the scores are in the text (Section 5) and in Appendix B, which also has details of the implementation of the stress-test exercise. Definitions for all other variables are in Appendix A.

Panel A: Implications for the Volatility of Mutual Fund Sector Returns (p.p.)			
N=192	Quarterly Vol.		Annual Vol.
	(1)		(2)
[1] Systemicness_t	0.99***		1.03***
	(0.40)		(0.24)
R^2	1.60		6.03
[2] Vulnerability_t	1.03**		1.06***
	(0.40)		(0.24)
R^2	2.20		6.87
[3] $\text{Systemicness}_t * \text{Crisis}$	1.85***		1.81***
	(0.66)		(0.27)
R^2	18.89		45.20
[4] $\text{Vulnerability}_t * \text{Crisis}$	1.83***		1.79***
	(0.66)		(0.27)
R^2	18.93		47.89
Panel B: The Effect of Fire-Sales at Top 10 Systemic Funds – A Stress-Test Exercise			
Fire-Sale Shock Size=	5%	10%	20%
Jan-Dec 2014	–9.84%	–19.68%	–39.37%
Jan-Dec 2013	–10.86%	–21.72%	–43.45%
Jan-Dec 2009	–10.52%	–21.03%	–42.06%
Jan-Dec 2010	–10.34%	–20.68%	–41.35%
Jan-Dec 2011	–10.32%	–20.63%	–41.26%
Jan-Dec 2012	–10.25%	–20.49%	–40.98%
Jan-Dec 2008	–9.69%	–19.37%	–38.74%
Jan-Dec 1999	–4.83%	–9.67%	–19.34%
Bottom 10 Systemic Funds, Jan-Dec 2014	–0.01%	–0.02%	–0.04%
Bottom 100 Systemic funds, Jan-Dec 2014	–2.03%	–4.05%	–8.09%
Panel C: Implications for the Volatility & Comovement of Bond Returns (p.p.)			
N=423,668	Quarterly Vol.		Quarterly β^{Bond}_{MKT}
[5] $\text{Systemicness}_{b,t}$	1.74***		2.78***
	(0.03)		(0.22)
R^2	14.90		10.43
[6] $\text{Vulnerability}_{b,t}$	1.25***		2.22***
	(0.03)		(0.21)
R^2	14.60		10.39

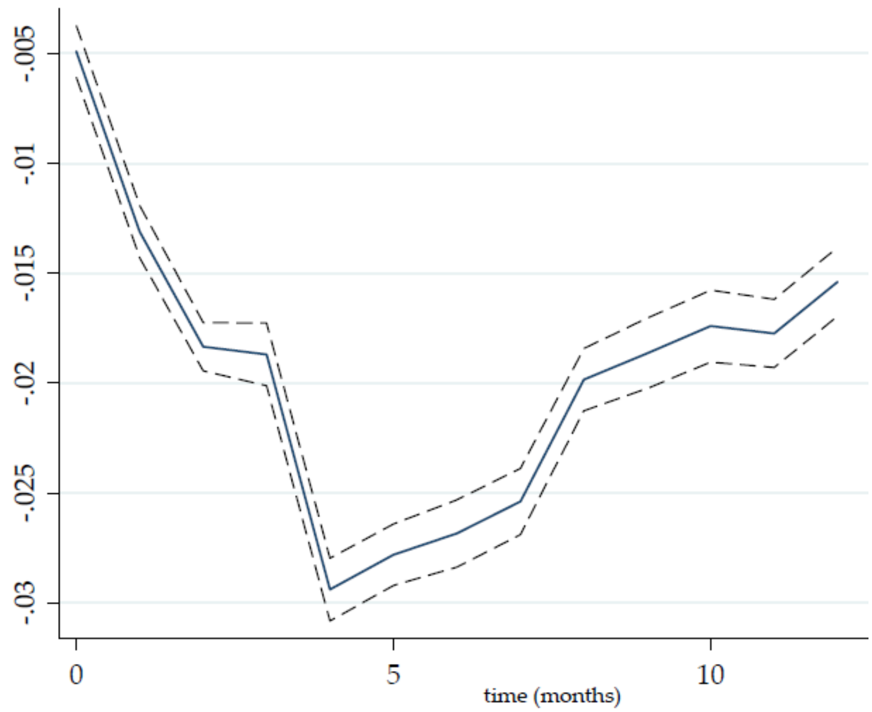
Figure 1: Timing of Bond Price Impact and Fire-Sale Spillovers

This figure reports results of calendar-time analysis of fire-sale spillovers. Panel A reports results of calendar-time analysis of the bond price impact in the overall sample by showing cumulative abnormal returns of a buy-and-hold strategy based on the top and bottom deciles of a Flow Pressure variable constructed as flow-related net-buy pressure using fund flows as in Coval and Stafford (2007). Specifically, the panel plots coefficient estimates of a distributed lags version (with 12 lags) of the baseline specification for the bond price impact in Table 3 (Column 4, Panel A) on $Net-Sale\ \Pr essure_{b,t}=\frac{Flow\ Induced\ Sales_{b,t}-Flow\ Induced\ Buys_{b,t}}{Offering\ \ Value_{b}}$ to ease interpretation. Panel B examines the cumulative effect of spillovers on fund performance by plotting coefficient estimates of a distributed lags version (with 12 lags) of the baseline specification for fund performance in Table 4 (Column 4, Panel A) where the explanatory variable of interest is Peer Flow Pressure, and the dependent variable, Extreme Underperformance, is defined as a dummy that takes value of one for fund-month observations in the bottom decile of the distribution of fund returns. Panel C examines the cumulative effect of spillovers on fund flows by plotting coefficient estimates of a distributed lags version (with 12 lags) of the baseline specification for fund flows in Table 5 (Column 4, Panel A), where the explanatory variable of interest is Peer Flow Pressure, and the dependent variable, Extreme Outflows, is defined as a dummy that takes value of one for fund-month observations in the bottom decile of the distribution of fund flows. Dotted lines denote the 95% confidence intervals. See Appendix A for detailed variable definitions and the legends of the respective tables for other specification details.

Panel A: Bond Price Impact of Fire-Sales



Panel B: Fire-Sale Spillover on Performance



Panel C: Fire-Sale Spillover on Flows

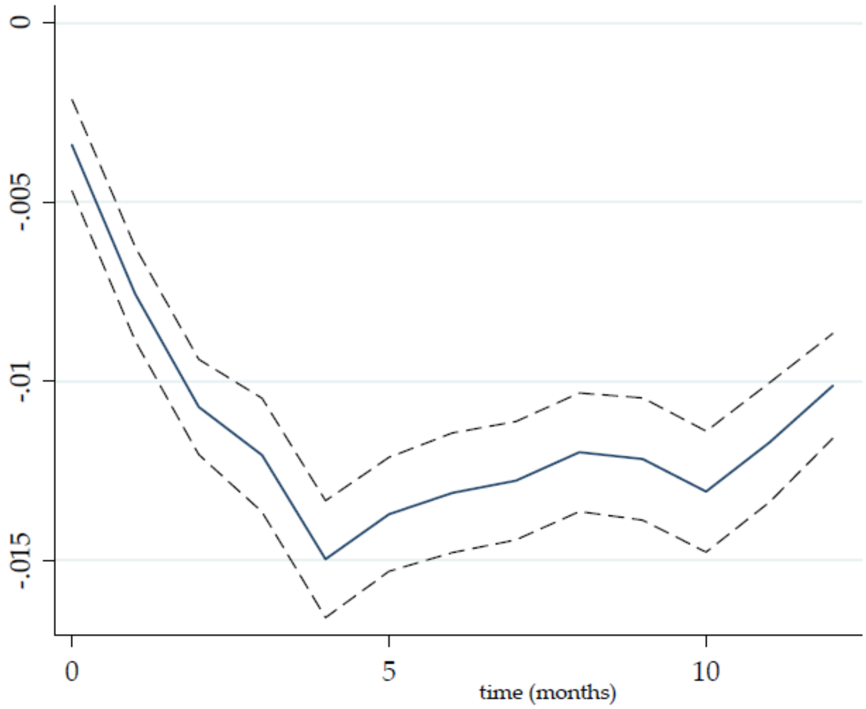
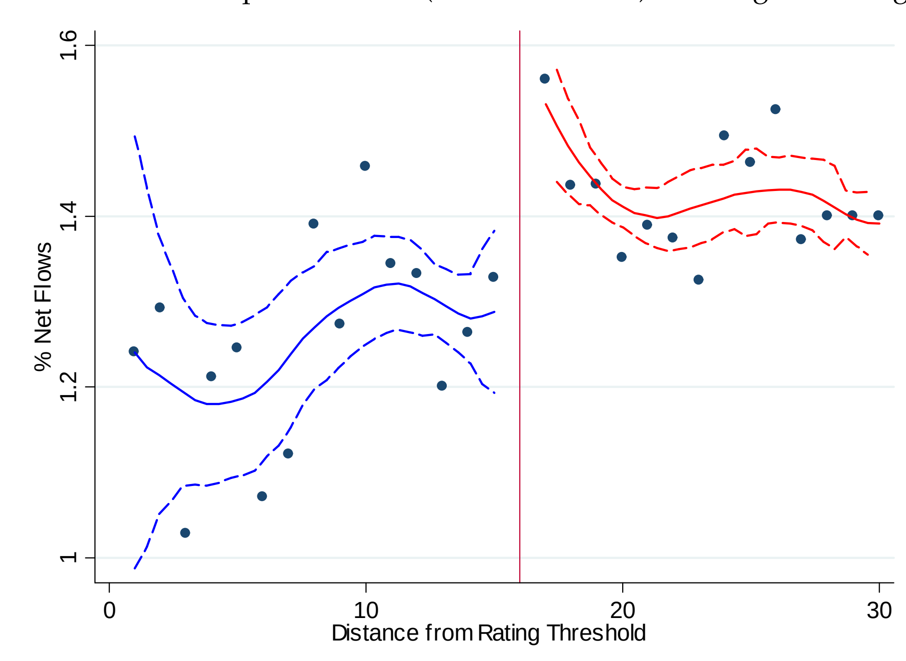


Figure 2: "Close" Morningstar Five-Star Ratings and Fund Flows

The starting sample consists of the funds whose Morningstar 5-star rating is close to their respective rating-category threshold, as defined by those funds whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold. The time period is 1992-2014. This figure plots the average of monthly (net) fund flows (vertical axis) against the forcing variable, the distance between the risk-adjusted return and its respective rating category threshold (horizontal axis). Panel A restricts the sample to top and bottom ratings only (1 or 2, and 4 or 5), while Panel B is for "close" intermediate ratings (2 or 3, and 3 or 4). Observations to the left of the red line correspond to "close" misses – i.e., funds that are right below the threshold. Each circle is the average monthly (net) fund flows within the derived bin width, with each bin containing multiple underlying observations. The plotted bin bandwidth is for 30 equidistant bins, which correspond to the range of the x-axis. Solid lines are fitted values from polynomial regressions on either side of the discontinuity. Standard errors are calculated via bootstrapping and the dashed lines represent the upper and lower 95% confidence intervals.

Panel A: "Close" top and bottom (1 or 2 and 4 or 5) Morningstar Ratings



Panel B: "Close" intermediate (2 or 3 and 3 or 4) Morningstar Ratings

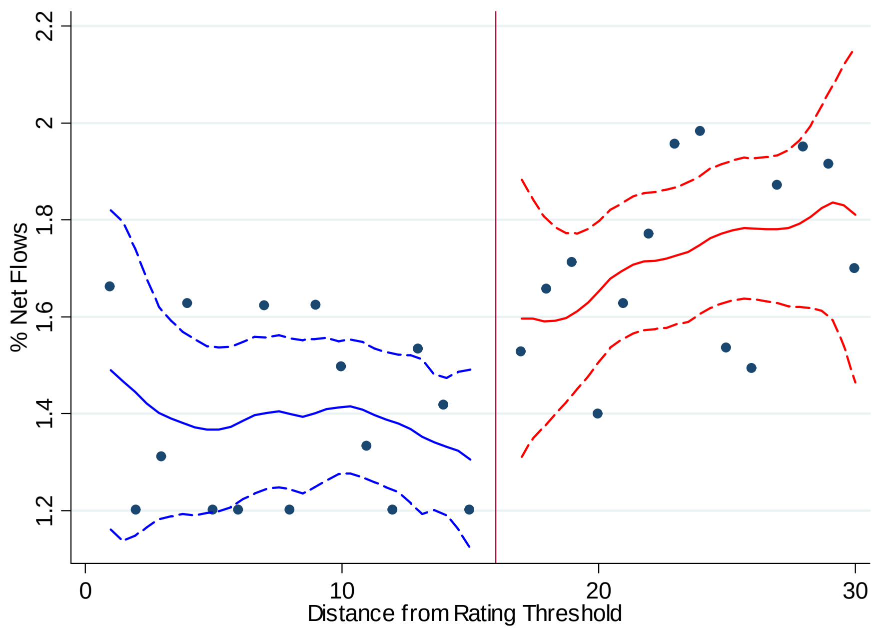
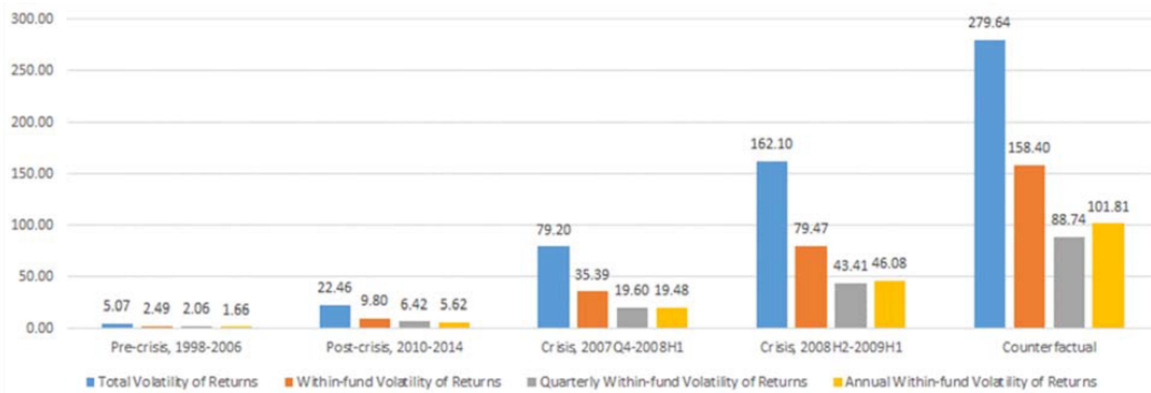


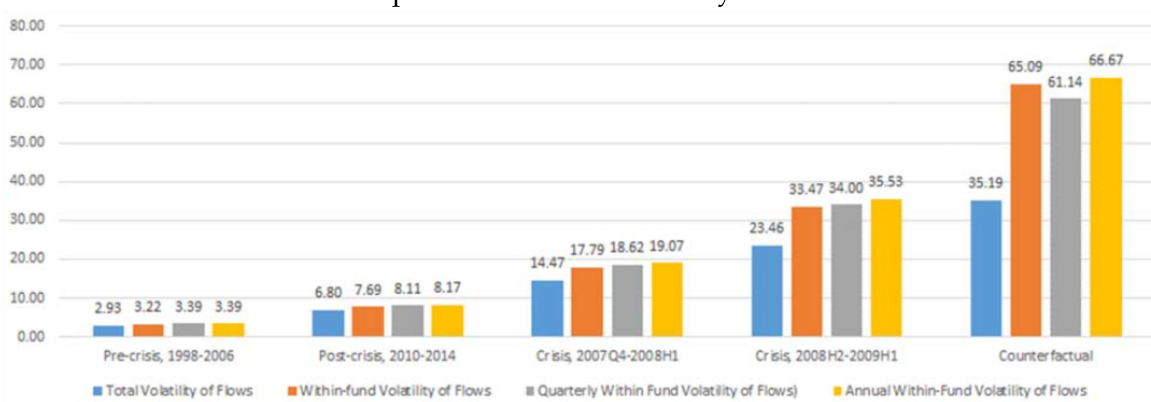
Figure 3 – The Financial Stability Implications of Fire-Sale Spillovers

This figure shows the contribution of spillovers to the volatility of fixed-income mutual funds' flows (Panel A) and returns (Panel B) between 1998 and 2014. We measure the contribution to volatility using a calibrated equilibrium model of fund flows (see Appendix B for details of the model setup and calibration). We choose the model parameters to match their empirical counterparts and show model-implied volatilities for a range of values of the parameter that measures the intensity of the spillover. Each bar in the figure shows the percentage change in volatility for the corresponding intensity of the spillover parameter relative to a benchmark model with no spillover (in percentage points). We vary the spillover parameters to match its empirical counterpart for four periods: pre-crisis (1998-2006), crisis (2007Q4-2008H1), crisis (2008H2-2009H1), and post-crisis (2010-2014), as well as for a counterfactual value which is twice as large as that of crisis (2007Q4-2008H1). For each period, we show four sets of volatilities that are calculated based on monthly model-generated series: total volatility, the mean volatility (standard deviation) of monthly fund flows and returns); within-fund volatility, the mean time-series volatility (standard deviation) of monthly fund flows and returns; and quarterly and annual within-fund volatility, the mean of 3-month and 12-month time-series volatility (standard deviation) of monthly fund flows and returns, respectively. For example, the value of 22.46 for the total volatility of returns in the post-crisis period in Panel A means that the total volatility of fund returns in the post-crisis period was about 22% higher due to spillovers, which corresponds to an increase from 1.4% in the benchmark to 1.7%.

Panel A: Implications for the Volatility of Fund Returns



Panel B: Implications for the Volatility of Fund Flows



Internet Appendix for "Fire-Sale Spillovers in Debt Markets"

Appendix A: Details of Variable Definitions[31]

The variables used in this paper are extracted from three major data sources for the 1998Q1–2014Q4 period: monthly mutual fund flows, investment objectives, net assets, and returns from the CRSP Mutual Fund Database; quarterly security-level holdings of fixed income securities by U.S.-domiciled mutual funds and insurance companies from Thompson Reuters/Lipper eMAXX database; security-level data from TRACE, FISD and the three major credit rating agencies (Fitch, Moody's, and S&P).

The variables are defined as follows:

Explanatory Variables for Fund-Level Analysis:

Peer Perf. Sd$_{i,t}$ for each fund i is the standardized (divided by the standard deviation) $Peer\ Perf_{i,t}$.

$$Peer\ Perf_{i,t} = \sum_{b=1}^{n} P\,\mathrm{erf}_{b,t}^{j \neq i} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and $P\,\mathrm{erf}_{b,t}^{j \neq i}$ is the average return of other funds that hold a given security.

Peer Extreme Outperf Sd$_{i,t}$ for each fund i is the standardized (divided by the standard deviation) $Peer\ Outp\,\mathrm{erf}_{i,t}$.

$$Peer\ Outp\,\mathrm{erf}_{i,t} = \sum_{b=1}^{n} Outp\,\mathrm{erf}_{b,t}^{j \neq i} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and $Outp\,\mathrm{erf}_{b,t}^{j \neq i}$ is an indicator variable for the average return of other funds that hold a given security, $P\,\mathrm{erf}_{b,t}^{j \neq i}$, in the highest ten percent of the distribution.

Peer Extreme Underperf Sd$_{i,t}$ for each fund i is the standardized (divided by the standard deviation) $Peer\ Underp\,\mathrm{erf}_{i,t}$.

$$Peer\ Underp\,\mathrm{erf}_{i,t} = \sum_{b=1}^{n} Underp\,\mathrm{erf}_{b,t}^{j \neq i} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and $Underp\,\mathrm{erf}_{b,t}^{j \neq i}$ is an indicator variable for the average return of other funds that hold a given security, $P\,\mathrm{erf}_{b,t}^{j \neq i}$, in the lowest ten percent of the distribution.

Peer Flow Pressure Sd$_{i,t}$ for each fund i is the standardized (divided by the standard deviation) $Peer\ Flow\ \mathrm{Pr}\,essure_{i,t}$.

$$Peer\ Flow\ \mathrm{Pr}\,essure_{i,t} = \sum_{b=1}^{n} Flow\ Pressure_{b,t}^{j \neq i} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and

$$Flow\ Pressure_{b,t}^{j \neq i} = \frac{Flow\ Induced\ Buys_{b,t}^{j \neq i} - Flow\ Induced\ Sales_{b,t}^{j \neq i}}{Offering\ Value_b},$$

[31] Citation format: Falato, Antonio, Ali Hortacsu, Dan Li, and Chaehee Shin, Internet Appendix to "Fire-Sale Spillovers in Debt Markets," Journal of Finance [DOI XX]. Please note: Wiley is not responsible for the content or functionality of any supporting information supplied by the authors. Any queries (other than missing material) should be directed to the authors of the article.

$Flow\ Induced\ Buys_{b,t}^{j\neq i} = \sum_{j\neq i}\left(\max\left(0, \Delta Holdings_{j,b,t}\right)|_{Flows_{j,t}>Percentile(90th)}\right)$ and $Flow\ Induced\ Sales_{b,t}^{j\neq i} = \sum_{j\neq i}\left(\max\left(0, -\Delta Holdings_{j,b,t}\right)|_{Flows_{j,t},<Percentile(10th)}\right)$.

Peer Buy Pressure Sd$_{i,t}$ for each fund i is the standardized (divided by the standard deviation) $Peer\ Buy\ \Pr essure_{i,t}$.

$$Peer\ Buy\ \Pr essure_{i,t} = \sum_{b=1}^{n} \frac{Flow\ Induced\ Buys_{b,t}^{j\neq i}}{Offering\ Value_b} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and $Flow\ Induced\ Buys_{b,t}^{j\neq i} = \sum_{j\neq i}\left(\max\left(0, \Delta Holdings_{j,b,t}\right)|_{Flows_{j,t}>Percentile(90th)}\right)$.

Peer Sell Pressure Sd$_{i,t}$ for each fund i is the standardized (divided by the standard deviation) $Peer\ Sell\ \Pr essure_{i,t}$.

$$Peer\ Sell\ \Pr essure_{i,t} = \sum_{b=1}^{n} \frac{Flow\ Induced\ Sales_{b,t}^{j\neq i}}{Offering\ Value_b} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and $Flow\ Induced\ Sales_{b,t}^{j\neq i} = \sum_{j\neq i}\left(\max\left(0, -\Delta Holdings_{j,b,t}\right)|_{Flows_{j,t},<Percentile(10th)}\right)$.

Peer Treatment Pressure Sd$_{i,t}$ **– Experiment #1 (The 2003 Mutual Fund Scandal)** for each fund i is the standardized (divided by the standard deviation) $Peer\ Treatment\ \Pr essure_{i,t}$.

$$Peer\ Treatment\ \Pr essure_{i,t} = \sum_{b=1}^{n} Treatment\ Pressure_{b,t}^{j\neq i} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and

$$Treatment\ Pressure_{b,t}^{j\neq i} = \frac{Treatment\ Induced\ Buys_{b,t}^{j\neq i} - Treatment\ Induced\ Sales_{b,t}^{j\neq i}}{Offering\ Value_b},$$

$Treatment\ Induced\ Buys_{b,t}^{j\neq i} = \sum_{j\neq i}\left(\max\left(0, \Delta Holdings_{j,b,t}\right)|_{Treatment_{j,t}=0}\right)$ and $Treatment\ Induced\ Sales_{b,t}^{j\neq i} = \sum_{j\neq i}\left(\max\left(0, -\Delta Holdings_{j,b,t}\right)|_{Treatment_{j,t}=1}\right)$. $Treatment_{j,t}$ is an indicator variable that equals one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003") and zero otherwise.

Peer Treatment Pressure Sd$_{i,t}$ **– Experiment #2 (Morningtar Rating RD)** for each fund i is the standardized (divided by the standard deviation) $Peer\ Treatment\ \Pr essure_{i,t}$.

$$Peer\ Treatment\ \Pr essure_{i,t} = \sum_{b=1}^{n} Treatment\ Pressure_{b,t}^{j\neq i} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and

$$Treatment\ Pressure_{b,t}^{j\neq i} = \frac{Treatment\ Induced\ Buys_{b,t}^{j\neq i} - Treatment\ Induced\ Sales_{b,t}^{j\neq i}}{Offering\ Value_b},$$

$Treatment\ Induced\ Buys_{b,t}^{j\neq i} = \sum_{j\neq i}\left(\max\left(0, \Delta Holdings_{j,b,t}\right)|_{Treatment_{j,t}=0}\right)$ and $Treatment\ Induced\ Sales_{b,t}^{j\neq i} = \sum_{j\neq i}\left(\max\left(0, -\Delta Holdings_{j,b,t}\right)|_{Treatment_{j,t}=1}\right)$. $Treatment_{j,t}$ is an indicator variable that takes value of one for funds that are right below their respective rating-category threshold and zero for funds that are right above it – i.e., it equals one if $r_{j,t} - r^0_{j,t} < 0$, where $r_{j,t}$ is the observed Morningstar risk-adjusted return and $r^0_{j,t}$ is the corresponding rating-category threshold. We only include peer funds that are close to their respective rating-category threshold, which we measure as those funds whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold.

Peer Treatment Pressure Sd$_{i,t}$ – Experiment #3 (Collapse of the Convertible Bond Market) for each fund i is the standardized (divided by the standard deviation) $Peer\ Treatment\ \Pr essure_{i,t}$.

$$Peer\ Treatment\ \Pr essure_{i,t} = \sum_{b=1}^{n} Treatment\ Pressure^{j \neq i}_{b,t} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and

$$Treatment\ Pressure^{j \neq i}_{b,t} = \frac{Treatment\ Induced\ Buys^{j \neq i}_{b,t} - Treatment\ Induced\ Sales^{j \neq i}_{b,t}}{Offering\ Value_b},$$

$Treatment\ Induced\ Buys^{j \neq i}_{b,t} = \sum_{j \neq i} \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=0} \right)$ and $Treatment\ Induced\ Sales^{j \neq i}_{b,t} = \sum_{j \neq i} \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=1} \right)$. $Treatment_{j,t}$ is an indicator variable that is constructed by interacting an indicator for the market "collapse" in 2005 with a dummy that is equal to one for funds whose Lipper class is convertible bonds.

Main Fund-Level Outcome Variables:

Monthly Return (%) is the monthly net fund return.

Extreme Underperformance is defined as a dummy that takes value of one for fund-month observations in the bottom decile of the distribution of fund returns.

Fund Flow (%) is defined as $\text{FLOW}_{j,t} = (\text{TNA}_{j,t} - (1 + \text{r}_{j,t})\text{TNA}_{j,t-1})/\text{TNA}_{j,t-1}$, where $\text{TNA}_{j,t-1}$ is the total net assets under management at the end of the previous period, and $\text{r}_{j,t}$ is the return (net of fees and expenses) over the period.

Extreme Outflows (Inflows) is defined as a dummy that takes value of one for fund-month observations in the bottom (top) decile of the distribution of fund flows.

Additional Fund-Level Outcome Variables:

Rear Load Fee Introduction (%) is a dummy that takes the value of one in the first fund-month observation when there is a (non-zero) rear-load fee.

Cash holdings is the fraction of a fund's TNA held in the form of cash.

Illiquidity (Roll). We use TRACE transaction data to calculate various daily liquidity measure for each bonds. We then take the within-quarter average of daily measures to get quarterly liquidity measure. Roll's bid-ask spread based on Roll's (1984):

$$Liq^{Roll}_{i,d} = \sqrt[2]{-cov(\Delta P^j_{i,d}, \Delta P^{j-1}_{i,d})}$$

where $\Delta P^j_{i,d}$ is the price of jth trade (ordered by time) of bond i at day d.

Fund-Level Control and Sample-Split Variables:

Expense ratio (%) is the fund's expense ratio in the most recent fiscal year, defined as the total investment that the shareholders pay for the fund's operating expenses (including 12b1 fees).

Fund Size (log$Million) is the natural log of total net assets.

Family Size (log$Million) is the natural logarithm of the total net assets under management of the fund's mutual fund family, expressed in hundred millions of dollars.

Equity Fund is an indicator variable equal to one if the fund holds any equity, zero otherwise.

Illiquid Fund is an indicator variable equal to one if the fund is classified as high-yield based on its Lipper Asset Class.

Peer Treatment Distance$_{i,t}$ **– Experiment #2 (Morningstar Rating RD)** for each fund i is

$$Peer\ Treatment\ Dist_{i,t} = \sum_{b=1}^{n} Treatment\ Dist_{b,t}^{j \neq i} * w_{i,b,t-1}$$

where $w_{i,b,t-1}$ is a vector of portfolio percentage share holdings of each fund in each asset and $Treatment\ Dist_{b,t}^{j \neq i}$ is the average difference between the observed Morningstar risk-adjusted return and the corresponding rating-category threshold of other funds that hold a given security, $r_{j,t} - r_{j,t}^{0}$.

Macro Variables:

Illiquid Times is an indicator variable equal to one in the financial crisis period, which we define as 2007Q4-2009H1.

VIX is the CBOE's VIX index.

Explanatory Variables for Bond-Level Analysis:

Flow Pressure Sd$_{b,t}$ for each bond b is the standardized (divided by the standard deviation) $Flow\ Pressure_{b,t}$.

$$Flow\ Pressure_{b,t} = \frac{Flow\ Induced\ Buys_{b,t} - Flow\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

where $Flow\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Flows_{j,t} > Percentile(90th)} \right)$ and $Flow\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Flows_{j,t}, < Percentile(10th)} \right)$.

Buy Pressure Sd$_{b,t}$ for each bond b is the standardized (divided by the standard deviation) $Buy\ Pressure_{b,t}$.

$$Buy\ Pressure_{b,t} = \frac{Flow\ Induced\ Buys_{b,t}}{Offering\ Value_b},$$

where $Flow\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Flows_{j,t} > Percentile(90th)} \right)$.

Sell Pressure Sd$_{b,t}$ for each bond b is the standardized (divided by the standard deviation) $Sell\ Pressure_{b,t}$.

$$Sell\ Pressure_{b,t} = \frac{Flow\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

where $Flow\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Flows_{j,t}, < Percentile(10th)} \right)$.

Peer Flow Pressure Sd$_{b,t}$ for each bond b is the standardized (divided by the standard deviation) $Peer\ Flow\ Pressure_{b,t}$.

$$Peer\ Flow\ Pressure_{b,t} = \frac{Peer\ Flow\ Induced\ Buys_{b,t} - Peer\ Flow\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

where $Peer\ Flow\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Peer\ Flows\ Pressure_{j,t} > Percentile(90th)} \right)$ and $Peer\ Flow\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Peer\ Flows\ Pressure_{j,t} < Percentile(10th)} \right)$. $Peer\ Flows\ Pressure_{j,t}$ is defined above.

Peer Buy Pressure Sd$_{b,t}$ is the standardized (divided by the standard deviation) $Peer\ Buy\ Pressure_{b,t}$.

$$Peer\ Buy\ Pressure_{b,t} = \frac{Peer\ Flow\ Induced\ Buys_{b,t}}{Offering\ Value_b},$$

where $Peer\ Flow\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Peer\ Flows\ Pressure_{j,t} > Percentile(90th)} \right)$. $Peer\ Flows\ Pressure_{j,t}$ is defined above.

Peer Sell Pressure Sd$_{b,t}$ for each bond b is the standardized (divided by the standard deviation) $Peer\ Sell\ Pressure_{b,t}$.

$$Peer\ Sell\ Pressure_{b,t} = \frac{Peer\ Flow\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

where $Peer\ Flow\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Peer\ Flows\ Pressure_{j,t} < Percentile(10th)} \right)$. $Peer\ Flows\ Pressure_{j,t}$ is defined above.

Treatment Pressure Sd$_{b,t}$ **– Experiment #1 (The 2003 Mutual Fund Scandal)** for each bond b is the standardized (divided by the standard deviation) $Treatment\ Pressure_{b,t}$.

$$Treatment\ Pressure_{b,t} = \frac{Treatment\ Induced\ Buys_{b,t} - Treatment\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

$Treatment\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=0} \right)$ and $Treatment\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=1} \right)$. $Treatment_{j,t}$ is an indicator variable that equals one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003") and zero otherwise.

Treatment Pressure Sd$_{b,t}$ **– Experiment #2 (Morningtar Rating RD)** for each bond b is the standardized (divided by the standard deviation) $Treatment\ Pressure_{b,t}$.

$$Treatment\ Pressure_{b,t} = \frac{Treatment\ Induced\ Buys_{b,t} - Treatment\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

$Treatment\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=0} \right)$ and $Treatment\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=1} \right)$. $Treatment_{j,t}$ is an indicator variable that takes value of one for funds that are right below their respective rating-category threshold and zero for funds that are right above it – i.e., it equals one if $r_{j,t} - r^0_{j,t} < 0$, where $r_{j,t}$ is the observed Morningstar risk-adjusted return and $r^0_{j,t}$ is the corresponding rating-category threshold. We only include peer funds that are close to their respective rating-category threshold, which we measure as those funds whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold.

Treatment Pressure Sd$_{b,t}$ **– Experiment #3 (Collapse of the Convertible Bond Market)** for each bond b is the standardized (divided by the standard deviation) $Treatment\ Pressure_{b,t}$.

$$Treatment\ Pressure_{b,t} = \frac{Treatment\ Induced\ Buys_{b,t} - Treatment\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

$Treatment\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=0} \right)$ and $Treatment\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Treatment_{j,t}=1} \right)$. $Treatment_{j,t}$ is an indicator variable that is constructed by interacting an indicator for the market "collapse" in 2005 with a dummy that is equal to one for funds whose Lipper class is convertible bonds.

Peer Treatmet Pressure Sd$_{b,t}$ – Experiment #1 (The 2003 Mutual Fund Scandal) for each bond b is the standardized (divided by the standard deviation) $Peer\ Treatment\ Pressure_{b,t}$.

$$Peer\ Treatment\ Pressure_{b,t} = \frac{Peer\ Treatment\ Induced\ Buys_{b,t} - Peer\ Treatment\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

where $Peer\ Treatment\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Peer\ Treatment\ Pressure_{j,t} > Percentile(90th)} \right)$ and $Peer\ Treatment\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Peer\ Treatment\ Pressure_{j,t} < Percentile(10th)} \right)$. $Peer\ Treatment\ Pressure_{j,t}$ for Experiment #1 is defined above.

Peer Treatmet Pressure Sd$_{b,t}$ – Experiment #2 (Morningtar Rating RD) for each bond b is the standardized (divided by the standard deviation) $Peer\ Treatment\ Pressure_{b,t}$.

$$Peer\ Treatment\ Pressure_{b,t} = \frac{Peer\ Treatment\ Induced\ Buys_{b,t} - Peer\ Treatment\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

where $Peer\ Treatment\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Peer\ Treatment\ Pressure_{j,t} > Percentile(90th)} \right)$ and $Peer\ Treatment\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Peer\ Treatment\ Pressure_{j,t} < Percentile(10th)} \right)$. $Peer\ Treatment\ Pressure_{j,t}$ for Experiment #2 is defined above.

Peer Treatmet Pressure Sd$_{b,t}$ – Experiment #3 (Collapse of the Convertible Bond Market) for each bond b is the standardized (divided by the standard deviation) $Peer\ Treatment\ Pressure_{b,t}$.

$$Peer\ Treatment\ Pressure_{b,t} = \frac{Peer\ Treatment\ Induced\ Buys_{b,t} - Peer\ Treatment\ Induced\ Sales_{b,t}}{Offering\ Value_b},$$

where $Peer\ Treatment\ Induced\ Buys_{b,t} = \sum_j \left(\max\left(0, \Delta Holdings_{j,b,t}\right) |_{Peer\ Treatment\ Pressure_{j,t} > Percentile(90th)} \right)$ and $Peer\ Treatment\ Induced\ Sales_{b,t} = \sum_j \left(\max\left(0, -\Delta Holdings_{j,b,t}\right) |_{Peer\ Treatment\ Pressure_{j,t} < Percentile(10th)} \right)$. $Peer\ Treatment\ Pressure_{j,t}$ for Experiment #3 is defined above.

Appendix B: Details of Calibrated Model and Financial Stability Implications

Details of Constructing the Systemicness and Vulnerability Scores

Our approach yields simple measures of systemicness and vulnerability of a given fund family to system-wide outflow-driven fire-sales, which can be used for policy evaluation of alternative financial stability tools. Our method follows Bonaldi, Hortaçsu, and Kastl (2015) closely. We start with Equation (2) and use $PeerFlowPressure_{it}$ to instrument for $PeerFlows_{i,t}$ where

$$PeerFlows_{i,t} \equiv \sum_{j \neq i} w_{ij} \cdot OwnFlows_{j,t} \tag{4}$$

and w_{ij}, for each $j \neq i$, is the ratio of common portfolio holdings of asset managers i and j to the total portfolio holdings of i. In this way, w_{ij} acts as a weight that is given to the (i, j) pair and is "directed" from j to i – i.e., it summarizes the impact of j on i. We then estimate the network using the following simple model where asset manger i's own flows are regressed on the instrumented peer flows and its own lagged flows, controlling for a vector of standard fund characteristics, $X_{i,t-1}$, which includes fund size and expense ratio:

$$OwnFlows_{i,t} = \alpha + \beta \widehat{PeerFlows}_{i,t-1} + \delta X_{i,t-1} + \epsilon_{i,t} \tag{5}$$

β captures the spillover effect of flows of i's peers on i's own flows, which we can now use to describe a network of spillovers by defining the following $N \times N$ matrix B:

$$B_t \equiv \begin{bmatrix} 0 & \beta w^t_{12} & . & . & \beta w^t_{1N} \\ \beta w^t_{21} & 0 & . & . & . \\ . & . & . & . & . \\ . & . & . & 0 & \beta w^t_{1,N-1} \\ \beta w^t_{N1} & . & . & \beta w^t_{N-1,1} & 0 \end{bmatrix} \tag{6}$$

where each element of B — b_{ij} — indicates the effect of a 100 basis points increase in asset manager i's lagged flows on j's current flows and w^t_{ij} is the time t-varying version of the (i, j) pair-wise weight w_{ij} as previously defined. All own effects are set to zero to isolate the spillover effect. The matrix B is analogous to the adjacency matrix from the network literature, and our method to derive the systemicness and vulnerability measures follows closely that used to derive the Katz centrality measure, which is commonly employed in the networks literature. Katz centrality is a measure of directed network and it treats a node as important if the node has many links or is linked to many other important nodes, where links are penalized with an attenuation factor as the distance between links increases.

We use $\hat{\beta} = 0.449$, which is obtained from estimating equation (5) for the whole sample period. We calculate the pairwise weights $\hat{w}^t_{ij}$ for each year t from 1999 to 2014. The estimates $\hat{\beta}$ and $\hat{w}^t_{ij}$ for each year allow us to compute the following measures of systemicness and vulnerability for each asset manager i at year t:[32]

$$Systemicness_{it} = \sum_{s=1}^{\infty} \sum_{j=1}^{N} \alpha^s b^s_{ijt}$$

$$Vu\ln erability_{it} = \sum_{s=1}^{\infty} \sum_{j=1}^{N} \alpha^s b^s_{jit}$$

which are can be equivalently written, in matrix for, as follows:

[32]For each year, we choose an attenuation factor α set eual to 0.9 that satisfies: $\alpha < \frac{1}{|eig_{max}(\hat{B})|}$ where $eig_{max}(\hat{B})$ is the largest eigenvalue of matrix $\hat{B}$.

$$Systemicness_{it} = ((I - \alpha B_t)^{-1} - I) \cdot 1$$
$$Vu \ln erability_{it} = ((I - \alpha B_t')^{-1} - I) \cdot 1$$

Details of the Stress-Test Exercise

The stress test exercise that uses the systemicness scores proceeds in four steps. In Step 1, we take the top T asset managers, where $T = 5, 10, 20$, with the highest systemicness scores and assume an outflow shock S, where $S = 5\%, 10\%, 20\%$, to the top T asset managers. In other words, we assume that the top T asset managers simultaneously experience a decline in their total assets by S. In Step 2, we calculate $PeerFlows_{i,t-1}$ for each asset manager i using equation (4), the w_{ij}^t defined in the previous section, and the assumed outflows shocks to the top T asset managers from Step 1. In Step 3, we calculate $OwnFlows_{i,t}$ using equation (5) and the same estimate of β as in the previous section. In Step 4, we calculate the new total asset holdings of each asset manager using $OwnFlows_{i,t}$ from Step 3, and sum over all asset managers' new assets to see how much outflows the fund sector experiences.

Additional Analysis of Financial Stability Implications

Panel D of Appendix Table A.11 examines additional implications on cross-sectional transmission. We estimate a quantile regression version of equation (2) with fund performance and monthly (changes in log) bond prices as the outcome variables, which allows us to contract the effect of fire-sales spillovers at different points of the (conditional) distribution of these variables. The estimates show that the effect of fire-sale spillovers is clearly not "neutral" in the cross-section, as spillovers affect the tails much more than the intermediate ranges of the distribution of outcomes. Interestingly, consistent with our baseline results on asymmetry, peer sell (buy) pressure has a disproportionate effect in the lower (upper) tail, indicating that spillover effects contribute to instability in the cross-section by exacerbating differences in performance between winners and losers –i.e., top vs. bottom performing funds and securities.

Panels E and F of Appendix Table A.11 examine additional implications on time-series instability. Panel E repeats the analysis for a specification that adds to equation (2) an interaction term of peer fire-sale pressure with a proxy for aggregate volatility, the VIX. Consistent with spillovers contributing to instability in the time-series, the coefficient estimates are significant and indicate that fire-sale spillover effects are larger at times when aggregate volatility is high. Panel F shows a more direct estimate of the potential contribution of spillovers to aggregate volatility. We report results of a simple regression-based counterfactual exercise that compares the realized aggregate time-series variance of fund returns ("Realized") to the variance that is implied by an in-sample prediction based on the regression specification used in Panel E ("Predicted") as well as to a counterfactual variance which is as predicted by a model where the interaction terms with VIX are set equal to zero ("Counterfactual"). Counterfactual volatility is an order of magnitude smaller than realized volatility and between a fifth and about a tenth of predicted volatility, suggesting that the pro-cyclicality of spillovers is strong enough to aggravate sector-wide instability of fixed-income funds.

Details of the Calibrated Model

We consider a static discrete choice model of investor's fund-investing decisions where a fund's return is affected by the flows in and out of its peer funds (peers are defined in the same way as in our main analysis, based on portfolio holdings). There are $i = 1, ..., I$ funds to invest in, at each time t. The indirect utility of investor's investing in fund i is a function of i's return R_{it} at time t and controls for standard fund characteristics at t, X_{it}:

$$u_{it} = \alpha \cdot R_{it} + X_{it}'\beta + \epsilon_{it}$$

Assuming that the idiosyncratic error term ϵ_{it} follows a Type 1 Extreme Value distribution, the discrete choice problem turns into solving the following simultaneous equations for each $i = 1, ..., I$:

$$s_{it} = \frac{exp\left(\alpha R_{it} + X_{it}'\beta\right)}{1 + \sum_{i=1}^{I} exp\left(\alpha R_{it} + X_{it}'\beta\right)} \tag{7}$$

To incorporate the spillover effect, we assume that fund i's return R_{it} is an increasing function of how much you invest in fund i's peer funds, i.e., the funds with high portfolio overlaps with fund i, as follows:

$$R_{it} = \gamma \cdot \left(\sum_{j \neq i} s_{jt} \cdot \omega_{jt}\right) + \zeta_{it} \tag{8}$$

ω_{jt} is the "weight" used to measure fund i's portfolio overlap with fund j where $j \neq i$. Additionally, there is an idiosyncratic shock to fund i's return, ζ_{it}. Equation (8) is a reduced-form way to describe the price channel by which we assume the fire-sale spillover is taking place. The more one invests in peer funds that are similar in portfolio holdings to the fund under interest, the higher the return of the fund under interest becomes. This effect also works in the opposite direction: the less one invests in peer funds that are similar in portfolio holdings to the fund under interest, the lower the return of the fund under interest becomes. The model can be solved as a fixed-point problem with two equations, (7) and (8), in two unknowns, fund flow shares, s_{it}, and fund performance, R_{it}, for each fund i. For a given set of parameters and foreach fund, we determine the solution to the fixed-point problem using different starting points for s_{it} and R_{it} on the $(0,1) \times (0,1)$ grid and bootstrapped residuals. To calibrate the model, we estimate the parameters α and β from the data using equation (7) and data on fund flows and returns, as well as fund size and expense ratio as fund controls, which is analogous to estimating a standard flow-performance equation. We also estimate γ and ζ_{it} from the data using equation (8) and data on fund returns and peer fund flows. Finally, we calculate the model-implied equilibrium solutions for s_{it} and R_{it} at each point in time t and their volatility (standard deviation) for the estimated $\hat{\alpha}, \hat{\beta}, \hat{\gamma}$ and bootstrapped residuals $\hat{\zeta}_{it}$.

Table A.1: Additional Timing Analysis

This table examines the timing of the effects reported in the main analysis of Tables 3-6. Panels A and B examine the timing of the bond price impact. We report regressions of monthly (changes in log) bond prices on a variable that proxies for trades under fund (net) flow pressure constructed using flows as in Coval and Stafford (2007) and on its lags to examine persistence and reversals (Panel A) or on its leads to examine pre-event trends (Panel B). The specification used is otherwise the same as in the baseline Panel A of Table 3 (Column 1). Panel C examines the timing of the spillover effect on fund performance (Column 1) and flows (Column 2) as well as the second-round price impact (Column 3) by adding various lags of the key explanatory variable. The specification used is otherwise the same as in the baseline Panel A of Table 4 (Column 1) for performance, Table 5 (Column 1) for flows, and Table 6 (Column 1) for the second-round price impact, respectively. The time period is 1998-2014, and ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Replication of Coval and Stafford (2007) – Testing for Persistence and Reversals			
	Monthly % Bond Price Changes (pct)		
	All Bonds	Illiquid Bonds	Illiquid Times
	(1)	(2)	(3)
Flow Pressure $\text{Sd}_{b,t}$	0.81***	1.91***	4.64***
	(0.15)	(0.45)	(1.00)
Flow Pressure $\text{Sd}_{b,t-3}$	-0.15	0.07	3.16*
	(0.15)	(0.37)	(1.72)
Flow Pressure $\text{Sd}_{b,t-6}$	-0.48***	-1.32***	-6.10***
	(0.15)	(0.42)	(2.07)
Flow Pressure $\text{Sd}_{b,t-9}$	-0.27*	-0.97**	-0.11
	(0.15)	(0.41)	(0.22)
Flow Pressure $\text{Sd}_{b,t-12}$	-0.27	-0.35	-0.10
	(0.23)	(0.40)	(0.19)
N obs	318,924	62,647	38,166
R^2(%)	9.73	14.66	13.90

Table A.1: Additional Timing Analysis

This table examines the timing of the effects reported in the main analysis of Tables 3-6. Panels A and B examine the timing of the bond price impact. We report regressions of monthly (changes in log) bond prices on a variable that proxies for trades under fund (net) flow pressure constructed using flows as in Coval and Stafford (2007) and on its lags to examine persistence and reversals (Panel A) or on its leads to examine pre-event trends (Panel B). The specification used is otherwise the same as in the baseline Panel A of Table 3 (Column 1). Panel C examines the timing of the spillover effect on fund performance (Column 1) and flows (Column 2) as well as the second-round price impact (Column 3) by adding various lags of the key explanatory variable. The specification used is otherwise the same as in the baseline Panel A of Table 4 (Column 1) for performance, Table 5 (Column 1) for flows, and Table 6 (Column 1) for the second-round price impact, respectively. The time period is 1998-2014, and ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel B: Replication of Coval and Stafford (2007) – Testing for Pre-trends		
	Monthly % Bond Price Changes (pct)	
	Baseline, All Bonds	Baseline, All Bonds
	(1)	(2)
Flow Pressure $Sd_{b,t}$	1.00^{**}	0.94^{**}
	(0.)	(0.45)
Flow Pressure $Sd_{b,t+3}$	0.67	0.62
	(0.55)	(0.51)
Flow Pressure $Sd_{b,t+6}$		-0.33
		(0.50)
Flow Pressure $Sd_{b,t+9}$		-0.34
		(0.45)
N obs	318,924	318,924
R^2(%)	2.80	1.72

Table A.1: Additional Timing Analysis

This table examines the timing of the effects reported in the main analysis of Tables 3-6. Panels A and B examine the timing of the bond price impact. We report regressions of monthly (changes in log) bond prices on a variable that proxies for trades under fund (net) flow pressure constructed using flows as in Coval and Stafford (2007) and on its lags to examine persistence and reversals (Panel A) or on its leads to examine pre-event trends (Panel B). The specification used is otherwise the same as in the baseline Panel A of Table 3 (Column 1). Panel C examines the timing of the spillover effect on fund performance (Column 1) and flows (Column 2) as well as the second-round price impact (Column 3) by adding various lags of the key explanatory variable. The specification used is otherwise the same as in the baseline Panel A of Table 4 (Column 1) for performance, Table 5 (Column 1) for flows, and Table 6 (Column 1) for the second-round price impact, respectively. The time period is 1998-2014, and ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

	Panel C: Timing of the Fire-Sale Spillover		
	Monthly Return (pct)	Monthly Flows (pct)	Bond Price Changes (pct)
	(1)	(2)	(3)
Peer Flow Pressure $\text{Sd}_{i,t}$	0.35***	0.39***	0.46***
	(0.01)	(0.02)	(0.02)
Peer Flow Pressure $\text{Sd}_{i,t-3}$	0.21***	0.18***	0.28***
	(0.01)	(0.02)	(0.02)
Peer Flow Pressure $\text{Sd}_{i,t-6}$	-0.08***	0.11***	-0.02
	(0.01)	(0.02)	(0.02)
Peer Flow Pressure $\text{Sd}_{i,t-9}$	-0.07***	-0.10***	-0.09***
	(0.01)	(0.02)	(0.02)
Peer Flow Pressure $\text{Sd}_{i,t-12}$	-0.01	-0.08***	-0.07***
	(0.01)	(0.02)	(0.02)
N obs	285,163	285,163	319,301
R^2(%)	3.55	9.58	6.86

Table A.2: Additional Analysis of the Price-Impact Mechanism

This table presents additional analysis of the price-impact mechanism. We report regressions of monthly fund returns (Panel A) and (net) flows (Panel B) on funds' exposure to the percentage price changes of their bond holdings. The main independent variable, Exposure to Bond Price Change, is defined analogously to Peer Flow Pressure, as a weighted sum of bonds' percentage price changes with weights calculated based on the asset allocation of a given fund. The specification used is otherwise the same as in the baseline Panel A of Table 4 (Column 1) for performance and Table 5 (Column 1) for flows, respectively. The time period is 1998-2014. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Additional Analysis of Fund Performance				
	Monthly Return (pct)		Extreme Underperformance (pct)	
	(1)	(2)	(3)	(4)
Exposure to Bond. Price Change $Sd_{i,t}$	0.81***		-7.37***	
	(0.00)		(0.05)	
Exposure to Bond. Price Crash $Sd_{i,t}$		-0.83***		11.34***
		(0.01)		(0.06)
N	330,429	330,429	330,429	330,429
R^2(%)	15.64	10.58	13.96	17.35
Panel B: Additional Analysis of Fund Flows				
	Monthly Flows (pct)		Extreme Outflows (pct)	
Exposure to Bond. Price Change $Sd_{i,t}$	0.41***		-1.53***	
	(0.02)		(0.05)	
Exposure to Bond. Price Crash $Sd_{i,t}$		-0.18***		1.63***
		(0.02)		(0.06)
N	330,429	330,429	330,429	330,429
R^2(%)	10.95	10.82	8.61	8.56

Table A.3: Additional Analysis of the Mechanism – Price-Impact and the Flow-Performance Relation

This table presents additional analysis of the price-impact mechanism. Panels A and B address the price-impact mechanism. We report regressions of monthly fund returns (Panel A) and (net) flows (Panel B) on funds' exposure to the percentage price changes of their bond holdings in a 2SLS-IV setting where we instrument for exposure to price changes using Peer Flow Pressure and then include the price changes as predicted by peer flow pressure in the second-stage regressions. Exposure to Bond Price Change is defined analogously to Peer Flow Pressure, as a weighted sum of bonds' percentage price changes with weights calculated based on the asset allocation of a given fund. The specification used is otherwise the same as in the baseline Panel A of Table 4 (Column 1) for performance and Table 5 (Column 1) for flows, respectively. Panel C also uses a 2SLS-IV approach to clarify the flow-performance relation. We report regressions of monthly fund (net) flows on monthly fund returns in a 2SLS-IV setting where we instrument for fund returns using Peer Flow Pressure and then include the furn returns as predicted by peer flow pressure in the second-stage regressions. The specification used is otherwise the same as in the baseline Panel A of Table 5 (Column 1). The time period is 1998-2014. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Additional Analysis of Fund Performance				
	Monthly Return (pct)		Extreme Underperf. (pct)	
	(1)	(2)	(3)	(4)
Instr. Exposure to Bond.	1.08***		-7.61***	
Price Change $\mathrm{Sd}_{i,t}$	(0.02)		(0.21)	
Instr. Exposure to Bond.		-2.22***		15.56***
Price Crash $\mathrm{Sd}_{i,t}$		(0.04)		(0.42)
N	330,429	330,429	330,429	330,429

Panel B: Additional Analysis of Fund Flows				
	Monthly Flows (pct)		Extreme Outflows (pct)	
Instr. Exposure to Bond.	2.67***		-6.37***	
Price Change $\mathrm{Sd}_{i,t}$	(0.10)		(0.29)	
Instr. Exposure to Bond.		-5.67***		23.11***
Price Crash $\mathrm{Sd}_{i,t}$		(0.46)		(1.22)
N	330,429	330,429	330,429	330,429

Table A.3: Additional Analysis of the Mechanism – Price-Impact and the Flow-Performance Relation

This table presents additional analysis of the price-impact mechanism. Panels A and B address the price-impact mechanism. We report regressions of monthly fund returns (Panel A) and (net) flows (Panel B) on funds' exposure to the percentage price changes of their bond holdings in a 2SLS-IV setting where we instrument for exposure to price changes using Peer Flow Pressure and then include the price changes as predicted by peer flow pressure in the second-stage regressions. Exposure to Bond Price Change is defined analogously to Peer Flow Pressure, as a weighted sum of bonds' percentage price changes with weights calculated based on the asset allocation of a given fund. The specification used is otherwise the same as in the baseline Panel A of Table 4 (Column 1) for performance and Table 5 (Column 1) for flows, respectively. Panel C also uses a 2SLS-IV approach to clarify the flow-performance relation. We report regressions of monthly fund (net) flows on monthly fund returns in a 2SLS-IV setting where we instrument for fund returns using Peer Flow Pressure and then include the furn returns as predicted by peer flow pressure in the second-stage regressions. The specification used is otherwise the same as in the baseline Panel A of Table 5 (Column 1). The time period is 1998-2014. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel C: Additional Analysis of Fund Flows		
	Monthly Flows (pct)	Extreme Outflows (pct)
	(1)	(2)
Instr. Perf. with Peer Flow Pressure $Sd_{i,t}$	0.70^{***}	-1.66^{***}
	(0.10)	(0.23)
N	330,429	330,429

Table A.4 Diagnostics for 2SLS-IV Analysis

This table reports diagnostics for the three main experiments in Tables 7-9. Panels A and B report first-stage estimates of the 2SLS-IV analysis in Panel B of each experiment, in turn. Panel A is for the bond-level analysis, while Panel B is for the fund-level analysis. For the details of each specification we refer to the respective table legend. Panels C and D report estimates of a pre-trends test at the bond level and of a covariate balancing test at the fund level, respectively, which is to run regressions of pre-trends and fund characteristics on each treatment variable, in turn. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: First-Stage Estimates, Y=Flow Pressure $Sd_{d,t}$			
	Experiment #1 – 2003 Mutual Fund Scandal	Experiment #2 – Morningstar Rating RD	Experiment #3 – Collapse of the Conv. Bond Market
	(1)	(2)	(3)
Treatment Pressure $Sd_{d,t}$	69.07***	26.85***	18.71***
	(0.23)	(0.14)	(0.13)
N obs.	91,505	429,449	57,979
R^2 (%)	37.26	7.22	14.16
Panel B: First-Stage Estimates, Y=Flow Pressure $Sd_{i,t}$			
Peer Treatment Pressure $Sd_{i,t}$	65.11***	40.92***	22.35***
	(0.41)	(0.17)	(0.21)
N obs.	41,640	330,429	29,655
R^2 (%)	38.11	16.27	23.64
Panel C: Additional Validation of the "First-Stage" Estimates, Pre-Trends			
Treatment Pressure $Sd_{d,t+3}$	0.02	0.03	0.03
	(0.03)	(0.05)	(0.03)
N obs.	91,505	429,449	57,979
Panel D: Additional Validation of the "First-Stage" Estimates, Covariate Balancing			
Fund $size_{i,t}$	-7.20	0.15	-5.43
	(8.24)	(2.96)	(8.40)
Fund family $size_{i,t}$	-3.59	0.16	-2.27
	(5.20)	(2.63)	(2.60)
Expense $ratio_{i,t}$	0.00	0.00	0.00
	(0.02)	(0.01)	(0.01)
Lagged $performance_{i,t}$	0.04	0.03	-0.07
	(0.11)	(0.07)	(0.74)
N obs.	41,640	330,429	29,655

Table A.5: Additional Analysis of Morningstar Rating RD

This table repeats the analysis of each step of the chain on the spillover effect of Morningstar 5-star ratings for each of the four rating threshold-categories, in turn (Panel A), for an alternative specification that uses higher-order polynomials to control for distance from the rating thresholds (Panels B-C), for a narrower bandwidth around the threshold (Panel D), and for an alternative double-clustering of the standard errors that adds clustering by time to the baseline clustering (Panel E). In Panel A, the four independent variables, RD1-4 Treatment Pressure, are defined otherwise the same as Peer Treatment Pressure in Table 8 except for the fact that we now construct four separate treatment dummies each equal to one for funds that are right below each of their respective four rating-category thresholds. As in the baseline, "close" rating misses are defined as those funds whose Morningstar risk-adjusted return is within three percentage points around their respective rating category threshold. In Panel D, we use a narrower bandwidth and define "close" rating misses as those funds whose Morningstar risk-adjusted return is within one percentage point around their respective rating category threshold, which involves about 1/10 of the peer fund-month observations. Panel E uses an alternative double-clustering of the standard errors that adds clustering by time (month) to the baseline clustering by bond or fund. The time period is 1998-2014. All specifications are otherwise the same as their counterpart in Table 8. ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

	Bond Price* Impact	Fund Performance	Fund Flows % Flows	Second-Round* Price Impact
	(1)	(2)	(3)	(4)
Panel A: RD Analysis by each of the four thresholds				
RD1 Treatment Pressure $Sd_{i,t}$	0.53***	0.38***	0.17***	0.49***
	(0.02)	(0.00)	(0.02)	(0.01)
N obs.	294,594	320,219	320,219	429,556
RD2 Treatment Pressure $Sd_{i,t}$	0.09***	0.05***	0.18***	0.11***
	(0.02)	(0.00)	(0.02)	(0.01)
N obs.	308,661	320,219	320,219	429,556
RD3 Treatment Pressure $Sd_{i,t}$	0.01	0.03***	0.10***	0.06
	(0.01)	(0.00)	(0.02)	(0.05)
N obs.	305,892	320,219	320,219	429,556
RD4 Treatment Pressure $Sd_{i,t}$	0.38***	0.25***	0.19***	0.21***
	(0.01)	(0.00)	(0.02)	(0.01)
N obs.	262,193	320,219	320,219	429,556
Panel B: RD Analysis, Robustness to Second-Order Polynomial Distance Controls				
RD Treatment Pressure $Sd_{i,t}$	0.52***	0.30***	0.19***	0.56***
	(0.02)	(0.00)	(0.02)	(0.01)
N obs.	429,449	330,429	330,429	429,449
Panel C: RD Analysis, Robustness to Third-Order Polynomial Distance Controls				
RD Treatment Pressure $Sd_{i,t}$	0.52***	0.30***	0.19***	0.56***
	(0.02)	(0.00)	(0.02)	(0.01)
N obs.	429,449	330,429	330,429	429,449
Panel D: RD Analysis, Robustness to Narrower Bandwidth				
RD Treatment Pressure $Sd_{i,t}$	0.29***	0.23***	0.31***	0.30***
	(0.01)	(0.00)	(0.02)	(0.01)
N obs.	429,449	330,429	330,429	429,449
Panel E: RD Analysis, Robustness to Double-Clustering				
RD Treatment Pressure $Sd_{i,t}$	0.45***	0.33***	0.19***	0.44***
	(0.08)	(0.06)	(0.06)	(0.09)
N obs.	429,449	330,429	330,429	429,449

Table A.6: Additional Outcomes: Real & Liquidity Decisions

This table reports results of regression analysis of additional outcomes, which include monthly real and liquidity decisions. The independent variable, Peer Flow Pressure, is defined as in equation (1). The time period is 1998-2014. The specification used is otherwise the same as in the baseline Panel A, Table 4 (Column 1). Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

	Analysis of Additional Outcomes			
	Real Decisions, X=		Liquidity Decisions, X=	
	Expense Ratio (%)	Rear Load Fee Introduction (%)	Cash Holdings (%)	Asset Illiquidity (Roll)
	(1)	(2)	(3)	(4)
Peer Flow Pressure $Sd_{i,t}$	0.02***	-0.03***	0.07***	-1.44***
	(0.00)	(0.01)	(0.02)	(0.05)
N	330,429	330,429	330,429	330,429
R^2 (%)	96.75	2.78	34.09	2.74
Mean LHS	1.11	0.13	4.07	0.88
Sd LHS	0.50	3.59	10.54	17.97
IQR LHS	2.26	0.00	6.93	11.51

Table A.7: Additional Evidence from the Collapse of the ABS Market

This table reports results on fire-sale spillover effect of the collapse of the ABS market for each of the four main outcomes, bond price impact (monthly (changes in log) bond prices, Columns 1-2), fund performance (Columns 3-4), fund flows (Columns 5-6), and second-round bond price impact (monthly (changes in log) bond prices, Columns 7-8). The independent variable for the bond price impact analysis, Treatment Pressure, is defined analogously to Coval and Stafford (2007) as treatment-related net-buy pressure, where treatment is a dummy that is equal to one after the market collapse (2007Q3) for a fund that had a top quartile exposure to ABS assets. The independent variable for the spillover effect analysis, Peer Treatment Pressure, is defined analogously to Peer Flow Pressure as a weighted sum of peers' treatment pressure, where treatment is a dummy that is equal to one after the market collapse (2007Q3) for a fund that had a top quartile exposure to ABS assets at the fund or at the security level for columns 3-6 and 7-8, respectively (see def. (3) in the text for details). Panel A reports results for OLS regressions using these variables, the 'reduced-form.' To ease interpretation, the variables are expressed in standard deviation units. The time period is the crisis. All specifications include fund fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Panel A: Fund & Time Fixed Effects Estimators								
	Bond Price Impact		Fund Performance		Fund Flows		Second-Round Price Impact*	
	All	Top-Bottom	Ret	Large Und.	% Flows	Large Outfl.	All	Top-Bottom
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment Pressure $\mathrm{Sd}_{b,t}$	7.59***	8.04***						
	(2.09)	(2.30)						
Peer Treatment Pressure $\mathrm{Sd}_{i,t}$			0.27***	-1.41***	0.46***	-1.75***	0.44***	0.37***
			(0.05)	(0.05)	(0.13)	(0.40)	(0.06)	(0.09)
FE	Bond	Bond	Fund	Fund	Fund	Fund	Bond	Bond
N obs.	47,724	28,429	40,908	40,908	40,908	40,908	47,724	15,052
Sd LHS	4.99		1.91		8.55		4.99	
IQR LHS	1.93		1.58		3.98		1.93	

Table A.8: Falsification Tests

This table reports results of placebo tests for monthly fund returns and flows for the OLS analysis (Panel A) and for the 2SLS-IV analysis (Panel B). In Panel A, the specification used replaces our main explanatory variable with a placebo peer flow pressure variable in the baseline specifications for returns (Table 4, Panel A – Column 1) and flows (Table 5, Panel A – Column 1). We consider two placebo variables in turn, which are all constructed as a weighted sum of peers' placebo flow pressure. In Columns 1-2, Placebo Peer Flow Pressure is defined using weights calculated based on the asset allocation of a given fund but placebo flow pressure, which is defined using non-forced sales. Non-forced saled measures as $Not-Flow\ Induced\ Buys^{j\neq i}_{b,t} = \sum_{j\neq i}\left(\max\left(0, \Delta Holdings_{j,b,t}\right)|_{Flows_{j,t}<Percentile(90th)}\right)$ and $Not-Flow\ Induced\ Sales^{j\neq i}_{b,t} = \sum_{j\neq i}\left(\max\left(0, -\Delta Holdings_{j,b,t}\right)|_{Flows_{j,t},>Percentile(10th)}\right)$. In Columns 3-4, Placebo Peer Flow Pressure is defined using forced sales but placebo weights, which are calculated based on the past asset allocation of a given fund that remains active in a given Lipper asset class but ceases to hold a given security in a given month. The past asset allocation used is over the previous year. In Panel B, the specification used replaces our main explanatory variable with a placebo peer treatment pressure variable in the baseline specifications for returns (Tables 7-9, Panel A – Column 3) and flows (Tables 7-9, Panel A – Column 5). We consider three placebo variables in turn, which are all constructed as a weighted sum of peers' placebo treatment pressure. In Columns 1-2 and 5-6, Placebo Treatment Pressure is defined as the one-quarter ahead lead of Peer Treatment Pressure, which is the weighted sum of peers' treatment dummies that equal one after a fund is involved in the mutual fund scandal of 2003 and after the collapse (2005) for a fund whose Lipper class is convertible bonds, respectively (see def. (3) in the text for details). If the MF scandal or the collapse of the convertible bond market were anticipated or reflected omitted fund characteristics, one might expect an "effect" of the peer treatment even prior to the events. In Columns 3-4, Placebo Treatment Pressure is defined following an implementation recommended by Imbens and Lemieux (2008), which is to define the placebo dummy as the median of the forcing variable in the two subsamples on either side of the threshold. Specifically, we take funds whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold and, for each subsample right-above or right-below the rating-category thresholds, we replace the treatment dummy with a placebo treatment dummy based on whether the distance from the threshold is above or below the median within the subsample. This specification shows that the jump in peer returns and flows occurs only at the true rating threshold. The time period is 1998-2014. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

	Panel A: Placebo Tests for OLS Analysis of Fund Performance and Flows			
	Non-Forced Sales		Past Holdings	
	Monthly Return (pct)	Monthly Flows (pct)	Monthly Return (pct)	Monthly Flows (pct)
	(1)	(2)	(3)	(4)
Placebo Peer Flow Pressure $Sd_{i,t}$	0.03	0.11	0.04	-0.06
	(0.03)	(0.10)	(0.03)	(0.05)
N	330,429	330,429	260,472	260,472

	Panel B: Placebo Tests for 2SLS-IV Analysis of Fund Performance and Flows					
	Experiment #1 – 2003 MF Scandal		Experiment #2 – MS Rating RD		Experiment #3 – Conv. Bond	
	Monthly Return (pct)	Monthly Flows (pct)	Monthly Return (pct)	Monthly Flows (pct)	Monthly Return (pct)	Monthly Flows (pct)
	(1)	(2)	(3)	(4)	(5)	(6)
Placebo Peer Treatment Pressure $Sd_{i,t}$	-0.01	0.03	0.04	0.01	-0.04	-0.10
	(0.01)	(0.07)	(0.10)	(0.04)	(0.05)	(0.14)
N	41,640	41,640	330,429	330,429	29,655	29,655

Table A.9: Additional Economic Significance

This table presents an assessment of the economic magnitude of the spillover effect on monthly fund performance (Columns 1-2) and flows (Columns 3-4). We assess economic significance relative to other standard fund characteristics (fund and fund family size, expense ratio, and lagged performance and flows). Columns 1-2 report the effect of a one-standard deviation change in the right-hand side variable on fund returns and extreme underperformance from our baseline regression specification in Table 4, Panel B (Columns 3 and 6, respectively). For example, a one-standard deviation increase in peer sell pressure is associated with a 47 bps drop in fund returns. Columns 3-4 report the effect of a one-standard deviation change in the right-hand side variable on fund flows and extreme outflows from our baseline regression specification in Table 5, Panel B (Columns 3 and 6, respectively). The time period is 1998-2014. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

Additional Analysis of Economic Significance				
	Fund Performance		Fund Flows	
	Monthly Return (pct) (1)	Extreme Underperf. (pct) (2)	Monthly Flows (pct) (3)	Extreme Outflows (pct) (4)
Peer Buy Pressure $\text{Sd}_{i,t}$	0.25***	-1.68***	0.22***	-0.73***
Peer Sell Pressure $\text{Sd}_{i,t}$	-0.47***	4.45***	-0.59***	1.79***
Fund Size (log$Mil) $\text{Sd}_{i,t-3}$	-0.14***	0.86***	-0.90***	2.31***
Family Size (log$Mil) $\text{Sd}_{i,t-3}$	-0.09***	-1.18***	0.49***	-1.56***
Expense ratio (%) $\text{Sd}_{i,t-3}$	0.06**	-2.09***	-0.30**	-0.94***
Monthly Return $\text{Sd}_{i,t-3}$	0.22***	-2.51***		
Monthly Flows $\text{Sd}_{i,t-3}$			0.95***	-1.32***
N	330,429	330,429	330,429	330,429

Table A.10: Additional Robustness for 2SLS-IV Analysis – Adding Fund and Time Controls

This table reports results of an additional robustness check on the 2SLS-IV analysis of fire-sale spillovers (Tables 7-9) for each of the main fund-level outcomes, fund performance (Columns 1, 3, and 5), and fund flows (Columns 2, 4, and 6). Panel A reports the baseline results for reference. Panels B and C summarize robustness to alternative specifications that add fund-level controls (fund and family size, expense ratios, and lagged performance) and time (year) effects, respectively. Variable definitions, specifications, and time period are otherwise as in Tables 7-9, Panel A. ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. Definitions for all variables are in Appendix A.

	Experiment #1 – 2003 MF Scandal		Experiment #2 – MS Rating RD		Experiment #3 – Conv. Bond	
	Monthly Return (pct) (1)	Monthly Flows (pct) (2)	Monthly Return (pct) (3)	Monthly Flows (pct) (4)	Monthly Return (pct) (5)	Monthly Flows (pct) (6)
Panel A: Baseline						
Peer Treatment Pressure $Sd_{i,t}$	0.26***	0.77***	0.33***	0.19***	0.12***	0.11**
	(0.03)	(0.07)	(0.00)	(0.02)	(0.00)	(0.04)
N	41,640	41,640	330,429	330,429	29,655	29,655
Panel B: Add Fund Controls						
Peer Treatment Pressure $Sd_{i,t}$	0.25***	0.70***	0.29***	0.16***	0.11***	0.10**
	(0.01)	(0.06)	(0.00)	(0.02)	(0.01)	(0.04)
N	41,640	41,640	330,429	330,429	29,655	29,655
Panel C: Add Time Controls						
Peer Treatment Pressure $Sd_{i,t}$	0.23***	0.66***	0.27***	0.19***	0.10***	0.10**
	(0.02)	(0.07)	(0.00)	(0.02)	(0.01)	(0.04)
N	41,640	41,640	330,429	330,429	29,655	29,655

Table A.11: Aditional Financial Stability Implications

This table reports names and scores for the fund families that rank in the top 10 based on their systemicness and vulnerability to system-wide flow pressure (Panels A and B) and summary stats of the time-series of the systemicness and vulnerability scores (Panel C). For ease of exposition, we aggregate holdings at the fund family level and show rankings for the most recent year (2014) only. Additional details on the definition of the vulnerability scores are in the text (Section 5) and in Appendix B.

Panel A: Funds with High Systemicness		
	Systemicness Score	Systemicness Rank
	(1)	(2)
RS Investment Management	87.52	1
Investment Partners Asset Management	84.40	2
Bessemer Investment Management	83.65	3
Trinity Fiduciary Partners	77.25	4
Oakmark Family of Funds	75.27	5
Everence Capital Management	72.23	6
Performance Trust Inv Advisors	61.28	7
Portfolio Strategies	60.93	8
JP Morgan Investment Management	58.22	9
City National Rochdale LLC	58.00	10
Panel B: Funds with High Vulnerability		
	Vulnerability Score	Vulnerability Rank
	(1)	(2)
First Pacific Advisors LLC	33.08	1
Shay Assets Management	30.50	2
USAA Asset Management	30.44	3
Driehaus Capital Management LLC	30.26	4
Alpine Woods Capital Investors LLC	27.32	5
First Trust Advisors LP	27.02	6
GuideStone Funds Trust	26.28	7
Monte Capital Group LLC	26.19	8
DoubleLine Funds	26.17	9
Corbyn Investment Management	26.07	10
Panel C: Systemicness and Vulnerability – Summary Stats		
	Mean	q75
	(1)	(2)
Systemicness		
1998-2006	4.67	4.22
2007-2014	79.29	34.07
Vulnerability		
1998-2006	4.65	3.35
2007-2014	77.98	85.23

Table A.11: Additional Financial Stability Implications (Continued)

This table reports additional financial stability implications of fire-sale spillovers. Panel D reports results of quantile regressions of fund returns (Column 1) and change in (log) bond prices (Column 2) on Peer Buy Pressure and Peer Sell Pressure. Panel E reports results of OLS regressions that add to our baseline specification in Table 4 (Column 1, Panel B) an interaction term of the peer pressure variables with the VIX. Panel F compares the aggregate variance implied by this regression specification to a counterfactual one which is predicted by a model where the interaction terms are set equal to zero. See Appendix B for additional details and a discussion of the results. Definitions for all variables are in Appendix A.

Panel D: Financial Stability Implications I: Cross-Section		
	Fund Returns (1)	Bond Price Changes (2)
Bottom Decile		
Peer Buy Pressure $\text{Sd}_{i,t}$	1.20***	0.85***
	(0.09)	(0.17)
Peer Sell Pressure $\text{Sd}_{i,t}$	-3.68***	-2.61***
	(0.28)	(0.24)
Median		
Peer Buy Pressure $\text{Sd}_{i,t}$	0.93***	0.41***
	(0.03)	(0.05)
Peer Sell Pressure $\text{Sd}_{i,t}$	-0.91***	-0.22***
	(0.03)	(0.03)
Top Decile		
Peer Buy Pressure $\text{Sd}_{i,t}$	2.14***	3.69***
	(0.06)	(0.27)
Peer Sell Pressure $\text{Sd}_{i,t}$	-0.81***	-0.25***
	(0.06)	(0.05)
Panel E: Financial Stability Implications II: Time-Series		
Peer Buy Pressure $\text{Sd}_{i,t} * \text{VIX}_t$	2.87***	0.92***
	(0.08)	(0.16)
Peer Sell Pressure $\text{Sd}_{i,t} * \text{VIX}_t$	-5.75***	-3.74***
	(0.08)	(0.12)
Panel F: Financial Stability Implications III: Aggregate Volatility Counterfactual		
St. Dev. of Bond Fund "Sector" Returns	All	Crisis
Realized	0.85	1.87
Predicted	0.52	0.85
Counterfactual	0.13	0.10

Figure A.1: Univariate Bond Price Path after Fire-Sales

This figures reports results of additional calendar-time analysis. Panel A reports results of non-parametric calendar-time analysis of the bond price impact in the overall sample by showing cumulative abnormal retuns of a buy-and-hold strategy based on the top and bottom deciles of a Flow Pressure variable constructed as flow-related net-buy pressure using fund flows as in Coval and Stafford (2007) (see Appendix A for detailed definitions).