Fire-Sale Spillovers in Debt Markets

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Abstract

We assess fire-sale spillovers empirically using a new approach to measure network linkages across financial institutions and rich micro data for the universe of open-end fixed-income mutual funds. We find evidence that flows are interdependent across funds with asset class overlap, consistent with the hypothesis that one fund's redemptions may spill-over on to those of other funds by leading to distressed sales that adversely impact other funds' performance. We use several strategies to identify the causal link between any given fund's flows and those of its peers, including a regression discontinuity (RD) design that exploits sharp changes in peer flows around Morningstar 5-star ratings. The source of identification of our RD approach is quasi-random variation in peer flows around the arbitrary performance cutoffs used by Morningstar to assign their 5-star ratings, which is plausibly unrelated to changes in common industry fundamentals. Consistent with a fire-sale mechanism, not just fund flows, but also fund performance and liquidity, as well as the pricing of corporate bonds sold by funds under peer pressure, are adversely affected. Our approach yields simple measures of vulnerability of a fund family to system-wide flow pressures, which can be used for policy evaluation of alternative financial stability tools.

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." In the wake of the 2008-09 financial crisis, academics (see, for example, Feroli et at (2014)) and policy makers (see, for example, recent FSOC request for feedback on stress testing asset managers and SEC regulations) have raised concerns about potential threats to financial stability coming from non-bank financial institutions. In particular, episodes of heightened credit market volatility such as the Taper Tantrum of the summer of 2013 and the dramatic shift in credit intermediation away from the banking sector toward the asset management industry highlight the importance to better understand the systemic consequences of asset managers in debt markets.[1]

Yet, the role of asset managers in debt markets is relatively understudied, with the literature traditionally focusing on equity funds. And, though theoretically appealing, fire-sale spillovers are notoriously challenging to detect empirically. In an attempt to break new ground on these fronts, 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

[1]The asset management industry has 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 during that period. 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 increasingly important 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.

spillovers because bonds are relatively illiquid assets, 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)). To define network linkages across financial institutions, we use an 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)). We identify peers as those funds that have a higher degree of similarity in the type of assets they hold. We present reliable evidence that flows are interdependent across funds with asset class overlap. Directly consistent with the fire-sale story, investor redemptions at peer funds also have a negative spillover effect on funds' performance and lead to asset sales that have a negative bond price impact.

The key measurement hurdles are to identify peers and to address endogeneity. We construct an empirical measure of pair-wise asset class co-investment or degree of overlap in asset allocation between any two given funds. The intuition is that flow pressure is more likely to be transferred between funds that are "exposed" to each others through common asset ownership. Peer flows are defined as the weighted sum of flows of other funds, where the weights are the "exposure" measure of asset overlap. Due to endogenous selection of funds into peer groups, one concern with our measure is that it may erroneously pick up latent asset-class specific common shocks. To address this issue, which is an instance of the classic "reflection problem" discussed by Manski (1993), we use two strategies that are geared toward generating a plausibly random assignment of funds to different types of peer treatment status. First, we construct exposure-weighted sums of plausibly independent peer flows shocks due to the 2003 mutual fund scandal and to peers' differential exposure to monetary policy. Second, we use a peer treatment based on a regression discontinuity (RD) design that exploits sharp changes in peer flows around Morningstar 5-star ratings. The source of identification of this RD approach is quasi-random variation in peer flows around the arbitrary performance cutoffs used by Morningstar to assign their 5-star ratings, which is plausibly unrelated to changes in common industry fundamentals.

We assess (fire sale) spillovers in the most basic terms possible: are the flows and performance of a given fund sensitive to the flows of its peers? We show reliable evidence that flows are interdependent across funds with asset class overlap. There is a strong positive association between a fund's flows and those of its peers. This result is robust to using a dummy version for large peer inflows or outflows similar to Coval and Stafford (2007), is not sensitive to adding controls for fund characteristics and lagged flows or to using a variety of other implementations of the peer measures. The result continues to hold when we sharpen our identification to address omitted common factors by using our peer treatment variables, which include the Morningstar 5-star rating of peer funds that are close to their rating-category threshold as per our RD approach. The economic magnitude of the relation between own and peer fund flows is substantial, with a one standard-deviation change in peer flows moving a fund's flows by a full quartile of their conditional distribution. Consistent with a fire-sale mechanism, also fund performance is adversely affected by peer outflows. The performance effect of peer flows is also economically significant, with a one standard deviation increase in large peer outflows leading to about 14 bps decrease in monthly returns. Taken together, our evidence is broadly supportive of the idea that fire-sale feedbacks give rise to strategic complementarity between own and peer fund flows.

Next, we probe the fire-sale mechanism more directly by looking at a host of fund real, liquidity, and portfolio decisions, as well as at the price impact of trades by funds under peer flow pressure. Funds tend to lower fees, introduce rear load fees, and decumulate cash in response to and possibly in an effort to attract investments and mitigate the harm of peer outflows. Yet, these actions do not appear to fully undo the negative spillover effect of peer flows, as there is a negative relation between peer flows and measures of fund's asset illiquidity. In addition, large peer outflows increase the likelihood that a fund makes a large asset or corporate bond sale. We also consider an event-study setting where we regress monthly (changes in log) corporate bond prices on a variable that proxies for trades under peer fund (net) flow pressure. The independent variable, Peer Flow Pressure, is defined analogously to PRESSURE_3 in Coval and Stafford (2007) and is meant to capture bonds where large fractions of trading are accounted for by mutual funds experiencing significant peer outflow pressure. Sales by mutual funds whose peers are experiencing outflow pressure tend to harm bond valuations, a result that continues to hold if we exclude bond-quarters when there are either no trades or no trades by institutions under flow pressure as recommended by Kahn et al (2012) and when we replicate the bond event study analysis using the three peer treatments an independent variables. The evidence on price impact from our event study directly supports a fire-sale story by which asset sales under peer flow pressure are costly because they involve securities whose valuations are depressed.

Finally, we show that the valuation effect of sales by funds under peer flow pressure varies predictably both in the cross-section and in the time-series with proxies for illiquidity and fire-sale costs. Valuation is more adversely impacted by sales under peer fund pressure when bonds are relatively more illiquid and at times when the overall market is more illiquid, as proxied, for example, by higher VIX and Libor. The contrast between estimates in sub-samples offers additional reassurance that mechanical explanations based on omitted common factors are unlikely to be driving our results, because such explanations would counterfactually predict the same response across sub-groups. As such, this additional evidence of heterogeneity in the peer effect on bond values constitutes a useful falsification test. We also show that our approach yields simple measures of vulnerability of a single fund family to system-wide outflows. Based on our measures of vulnerability, fund families such as TIAA-CREF, T. Rowe Price, and PIMCO are among the funds that rank as most vulnerable. Another potential use of our approach is that it offers a gauge of how the vulnerability of the fund industry has evolved over time. Our estimates indicate that as the fixed-income asset management sector has been growing over time, it has also become more vulnerable to system-wide outflows.

Our paper has implications for three literatures. First, we contribute to the literature on fire sales in finance (see Shleifer and Vishny (2011) for a detailed overview) and more specifically in the asset management industry. Using quarterly data on flows and holdings by equity mutual funds, Coval and Stafford (2007) show evidence of stock price pressure based on abnormal stock returns in a 12-month window around large mutual fund sales. Kahn 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 pressure. Ellul et al (2011) also document evidence of significant price pressure around downgrades for bonds with high exposure to insurance companies fire sale risk. This literature has mostly focused on equity markets and on documenting that fire sales are costly due to the price impact. Our contribution is to examine debt markets and assess cross-fund externalities that arise from the two-way feedback between flows and performance. Our evidence highlights the equilibrium aspect of the fire-sale story, as not only own- but also peer-fund distressed sales have a price impact. In addition, our RD approach furthers the literature by addressing the challenge that flows and flow-induced trading are endogenous to fund characteristics, which makes it difficult to distinguish flow-related trading from fundamentals-driven fund trading (Barrott (2016) is a related recent paper that uses Morningstar ratings for identification).

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)). 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 (Chen, Goldstein, and Jiang (2010),.Goldstein, Jiang & Ng (2015), and Feroli et al (2014)). Our contribution to this literature is to explore fire-sale externalities in debt markets, which had not yet been the subject of formal empirical testing. By doing so, we highlight the importance of the fire-sale mechanism as a source of vulnerability of non-bank financial intermediaries. By examining the link between own fund flows and peer flows, we also contribute to the classic literature on determinants of fund flows since Chevalier and Ellison (1997), which has mainly focused on the relation between flows and fund performance.

Third, recent empirical research in finance and macroeconomics has examined the link between investor sentiment and credit market volatility. For example, 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 (2015) 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)).[2]

2 Data, Measurement, and Research Design

In this section, we detail our sample construction procedure, our approach to measure peer fund-flows, and our research design to assess spillovers.

[2]This literature also focuses on equity markets. 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. An earlier literature on institutional "herding" following Lakonishok, Shleifer, and Vishny (1992) finds evidence of price impact of correlated institutional trades.

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 586,646 fund share class-month observations for 4,533 (297) unique funds (families) between January 1992 and December 2014.[3] Data on investment objective and quarterly security-level fund holdings are from the Thomson Reuter/Lipper eMAXX fixed income database, whose coverage starts in the third quarter of 2002. 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 $\mathrm{TNA}_{i,t}$ is the total net assets under management of fund i in month t and $\mathrm{r}_{i,t}$ is the fund's return (net of fees and expenses) over the period.[4] Mutual fund performance is measured using monthly fund returns, either raw or as an alpha, which captures the return in excess to those of a benchmark that can be traced to the fund's exposure to market-wide factors. The fund's alpha is calculated following Goldstein, Jiang, and Ng (2015) as the intercept from a regression of excess fund returns on excess aggregate bond market and aggregate stock market returns. Excess fund

[3]CRSP coverage of bond funds is sparse prior to 1991. Since we use up to one-year lag to construct some of our main variables (e.g., alphas), January 1992 is our earliest available date. Becasue we are interestd in actively-managed funds, we exclude from the analysis funds that CRSP identifies as index and exchange traded funds.

[4]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.

returns are estimated by performing a rolling-window time-series regression for each fund using 12 months of data for the past year. Aggregate bond and stock market returns are measured using the Vanguard total bond market index fund return and CRSP value-weighted market return, respectively. As such, this measure of the fund's alpha adjusts performance for the funds' exposure to market-wide bond and stock risk.

2.2 Measuring proximity and network linkages among funds

The key measurement challenge for our tests 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 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)).

The basic idea of our approach is to identify peers as those funds that have a higher degree of similarity in the type of assets they hold, which we operationalize by constructing an empirical measure of pair-wise asset class co-investment or degree of overlap in asset allocation between any two given funds. Heuristically, the intuition is that flow 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 proximity of the different asset classes in which the two funds invest, with the polar case of two focused funds that are invested exclusively in the same asset class representing the highest exposure and that of two focused funds that are invested in two different asset classes representing the lowest. Spanning the continuum of intermediate cases when funds are realistically invested in multiple and sometime overlapping asset classes, the expected flow spillover from one fund to another is an aggregate of these transfers from multiple funds.

Specifically, we construct the measure of peer fund-flows spillover as the weighted sum of flows of other funds, where the weights are the "exposure" measure of proximity. To implement this definition, for each of the $n = 297$ fund families in the sample we start with a vector $S_i = (S_{i1}, S_{i2}, ..., S_{i26})$ of its $N = 26$ asset class shares – i.e., the shares of total net assets under management (TNA) for each fund family in each Lipper asset class.[5] Based on these vectors, we construct "exposure" – i.e., the correlation matrix of the network linkages among funds, excluding own-fund interconnections (network diagonals). The elements of this matrix are for each fund family i a vector of n "weights", defined as pair-wise correlations of asset allocations across Lipper classes with each of the $j \neq i$ fund families, $w_{ij} = \frac{(S_i, S_j')}{(S_i, S_i')^{1/2} (S_j, S_j')^{1/2}}$. For example, for PIMCO this procedure assigns highest exposure weights to AMM, Bishop Street, T Rowe Price, and Templeton, and lowest weights to Delaware Group Government Funds, Oppenheimer Corporate, and TIAA-CREF.[6]

Using these weights, the final step is to construct peer flows for each fund (family) as a sum of monthly flows of other funds weighted by their respective exposure:

$$Peer\ Flows_{i,t} = \sum_{j \neq i} w_{i,j} Flow_{j,t}$$

In our main analysis, we also present results for dummy versions of this measure, which are constructed similarly to the "pressure" variable of Coval and Stafford (2007) as weighted sums of

[5]To aggregate over time, we take the mean of TNA by each fund-class over the sample period. We impose as a filter a mild 5% winsorization to exclude asset classes that are very sparsely populated.

[6]We note that an attractive feature of our definition of weights is that it is invariant to rescaling because correlation is not scale-dependent. As such it is robust to moving to either more aggregated or more disaggregated bins for asset types.

dummies for other funds' flows in the lowest or highest ten percent of the distribution of flows:

$$\begin{aligned} Peer\ Extreme\ Outflows_{i,t} &= \sum_{j \neq i} w_{i,j} I\left(Flow_{j,t} < Percentile\,(10th)\right) \\ Peer\ Extreme\ InFlows_{i,t} &= \sum_{j \neq i} w_{i,j} I\left(Flow_{j,t} > Percentile\,(90th)\right) \end{aligned}$$

Later in the analysis, we ensure that our result is not sensitive to the implementation details of these measures by showing robustness to many alternative versions of our baseline definition of Peer Flows, which include alternative definitions of the distance weights based on the correlation of performance or the (par) value of fund asset holdings across Lipper classes, as well as using an alternative level of aggregation, fund rather than fund-family, and calculating the weights based on correlation of the (par) value of fund holdings in each fixed-income security (cusip) to measure overlap.

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, medians, and standard deviations in Panel B). In line with previous studies, there is substantial heterogeneity in fund flows, performance, and decisions such as portfolio composition and cash holdings, as well as in fund characteristics such as size. In addition, our Peer Flow measure also differs much across fund-years.

2.3 Research Design and Identification Strategy

We assess (fire sale) spillovers in the most basic terms possible: are the flows, performance, and portfolio holding decisions of a given fund sensitive to the flows of its peers? To that end, we examine the following main relation:

$$Y_{i,t} = \alpha + \beta \times Peer\ Flows_{i,t-1} + \gamma \times X_{i,t-1} + \eta_i + \lambda_t + \nu_{i,t} \tag{1}$$

where the outcome variables $Y_{i,t}$ for fund i in month t, include primarily the fund's net flows, $Flow_{i,t}$, its performance, and its portfolio holdings, and the main variable of interest is the spillover measure, $Peer\ Flows_{i,t-1}$. $X_{i,t-1}$ is a vector of controls for standard fund characteristics, which include fund family size, fund performance (alpha), expense ratio, and rear load fees. In robustness analysis, we present results for the specification that includes the full vector of these controls, but opt for not including it in the main analysis to mitigate the concern that the inclusion of these potentially endogenous "bad controls" may lead to selection bias in our estimates (see Section 3.2.3 in Angrist and Pischke (2009)). In estimating equation (1) for our main analysis, we address two important issues, unobserved heterogeneity and endogeneity. We take on a third potential issue, dynamics, in additional robustness tests, by showing that our estimates are robust to considering a more dynamic specification that includes lagged fund's net flows.

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, 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, we control directly for sector-wide shocks that are common across funds by controlling for time fixed effects with the inclusion of a full set of year-specific dummies, λ_t.[7] 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 context is an instance of the classical "reflection problem," which in essence refers to the concern that correlation with peer flows may arise due to endogenous selection of funds into peer groups and pick up latent common shocks. As such, weighting peer flows by exposure and including time effects helps to ameliorate, but does not fully resolve the challenge of overcoming endogenous selection.

[7]We have experimented with including alternative larger sets of higher-frequency quarter- or month-specific dummies, both of which leave our estimates little changed.

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 (1) 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 (family) similarly to Peer Flows as an exposure-weighted sum of either fund-specific shocks or (functions of) thresholds that affect monthly peer flows but are otherwise plausibly independent from own flows:

$$Peer\ Treatment_{i,t} = \sum_{j \neq i} w_{i,j} Treatment_{j,t}$$

Our identification strategy is to estimate a version of the reduced-form model of equation (1), where we replace the potentially endogenous spillover measure, $Peer\ Flows_{i,t-1}$, with its plausibly exogenous counterpart, $Peer\ Treatment_{i,t-1}$.

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), 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. Our first treatment is a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003").[8]

Second, we consider a "shift-share" treatment that exploits peers' differential exposure to monetary policy (MP) shocks. The intuition for this variable is based on the well-documented finding that changes in the stance of monetary policy lead to flight-to-quality and reach-for-yield type effects (e.g., Di Maggio and Kacperczyk (2015)). We construct this treatment by interacting the federal funds rate, the "shift" variable, with a dummy that is equal to one for funds that have below median holdings of government securities, the "exposure" variable. This approach is similar to the one commonly used in labor economics to analyze the impact of labor demand shocks (Bartik (1991), Blanchard and Katz (1992)). Note that by constructing the treatment as an interaction, we are not using common variation from the MP shocks, which is differenced out from the comparison between fund with high vs. low exposure.

To further alleviate concerns about the exclusion restriction, we construct a third 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.[9] 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. This treatment is defined as the Morningstar 5-star rating of funds that are close to their rating-category threshold, which we take to be those funds whose Morningstar risk-

[8] 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).

[9] 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.

adjusted return is within three percentage points around the respective rating category threshold. 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 the the outcome variable, say fund i's flows, $\nu_{i,t}$ exhibits an identical discontinuity around peer funds' performance as that defined by Morningstar 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 $\mathit{Peer\ Treatment}_{i,t-1}$.

Figure 1 illustrates the gist 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.2 replicates this first-stage analysis in a regression setting both in the entire sample (Column 3) and in the discontinuity sample of funds that are close to the rating thresholds (Column 4), respectively. In both samples, we confirm that higher Morningstar ratings are associated with a sharp increase in fund flows. In the table, we also confirm the validity of our first two treatments. In line with the findings in the prior literature, we confirm that funds experience significant outflows subsequent to becoming implicated in the 2003 scandal (Column 1). Finally, at time when monetary policy is tight, fixed-income funds that do not primarily invest in government securities experience relative outflows. In all, the results of these first-stage tests support the internal validity of our three treatments.

3 Results

In this section, we present our main results. First, we show reliable evidence of a spillover effect of flows across funds with asset class overlap, in that any given fund's flows are sensitive to those of its peers. Consistent with a fire-sale mechanism, not just a fund's flows, but also its performance is adversely affected by peer outflows. Second, we probe the fire-sale mechanism more directly, by looking at a host of fund real, liquidity, and portfolio decisions, as well as at the price impact of trades by funds under peer flow pressure.

3.1 Fund Flows and Performance

Table 2 presents the estimates from equation (1) using fund flows as the outcome variable and Peer Flows (Panel A) and Peer Treatment (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 Flows (Panel A, Column 1), which is broadly supportive of the presence of strategic complementarity between own and peer fund flows. The result is robust to using a dummy version for extreme flows similar to Coval and Stafford (2007) (Panel A, Columns 2 to 9) and does not appear to be sensitive to either alternative specifications that add controls for fund characteristics, to address omitted variables, and lagged flows, to address dynamics (Panel A of Appendix Table A.5). And it remains strongly statistically significant across alternative clustering of the standard errors, which include clustering by either fund, or fund family, or Lipper fund objective (Panel B of Appendix Table A.5). Finally, the result continues to hold when we sharpen our identification to address omitted common factors and use Peer Treatment defined based on either fund-specific negative shocks to peer flows due to the 2003 scandal or their differential exposure to monetary policy (Panel B, Columns 1 to 6), or a plausibly exogenous increase in peer flows due to a higher Morningstar 5-star rating for peer funds that are close to their rating-category threshold (Panel B, Columns 7 to 9), 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.[10]

The economic magnitude of the relation between own and peer fund flows is substantial. To gauge the economic significance of the estimates and assess their plausibility, we conduct two exercises based on Column (1) of Table 2, Panel A for Peer Flows and on Columns (1), (4), and (7) of Table 2, Panel B for each of the three Peer Treatments, respectively. First, we examine how a 1 standard deviation (SD) movement in Peer Flows moves a fund in the flow distribution.[11] Our estimates imply that a 1-SD drop in Peer Flows moves a fund's flows by roughly 180 basis points, which is large considering that the unconditional mean of flows is about 180 basis points and corresponds to a full quartile (a movement from the 50th to the 25th percentile) of the conditional distribution of flows (Column 1, Appendix Table A.4). Second, we compare the marginal effect of Peer Flows to that of fund characteristics that the prior literature has included as covariates in flow regressions, such as fund (family) size, fees, and performance. We calculate these marginal effects by multiplying the respective estimates by the within-fund standard deviation of each right hand side variable. The marginal impact of Peer Flows is a bit larger than that of a 1-SD change in performance (77 bps) and is substantially larger than that of a change in size or fees (up to about 20 bps). Finally, the effect of Peer Treatment is also economically significant, despite the

[10]We also run the same two batteries of sensitivity tests for the spcification that uses Peer Treatment. The results are summarized in Table A.9, with Panel A showing that the results are robust to alternative specifications that add constrols for fund characteristics, to address omitted variables, and lagged flows, to address dynamics; and Panel B showing that the results are robust to alternative clustering of the standard errors, which include clustering by either fund, or fund family, or Lipper fund objective.

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

local nature of our three treatment variables. As shown in Appendix Table A.8, a 1-SD change in Peer Treatment leads to a change in fund flows by about 20 bps for the two shocks treatments and about 10 bps for the RD treatment, which are smaller than Peer Flows but of the same order of magnitude as standard covariates.

In Table 3, we summarize results from estimating equation (1) with fund performance (returns and alphas) as the outcome. The coefficient on Peer Flows is positive and highly statistically significant (Panel A, Columns 1 and 4), in line with the mechanism behind fire-sale spillovers that capital withdrawals from peer funds harm own fund performance.[12] The relation between peer flows and own fund performance is strongly economically significant for both the continuous Peer Flow variable and the Coval and Stafford (2007) (Columns 1 and 2 of Appendix Table A.6). Interestingly, the large Peer Outflow variable has the strongest relation with a 1-SD increase in it leading to about 14 bps decrease in monthly returns, which is about one third of the sample mean and one fifth of a quartile of the conditional distribution of returns. Omitted common factors do not appear to be driving the result, which continues to hold robustly across out three Peer Treatment variables (Panel B of Table 3). Finally, the positive coefficient estimates for Peer Flows in the performance as well as the own flows equations remain remarkably stable when we examine a variety of other implementations of the measures of spillovers, including giving more weight to exposure depending on the (relative) size of Lipper classes and calculating the distance weights based on the correlation of performance or the (par) value of fund asset holdings across Lipper classes. And they are somewhat strengthened when we consider a more disaggregated fund-level aggregation to define network links and measure exposure using the pair-wise correlation between funds (instead of families) in the shares held in each individual security (cusip, instead of Lipper asset class).

[12]Columns 1 and 2 of the four panels of Table A.7 show that the result is not sensitive to either alternative specifications that add constrols for fund characteristics, to address omitted variables (Panel A), and lagged flows, to address dynamics (Panel B), and the coefficient estimate remains strongly stitistically significant if we clusted standard errors by either fund, or fund family (Panel C), or Lipper fund objective (Panel D).

3.2 Fund Behavior and Price Impact

The results so far indicate that not just a fund's flows, but also its performance, are adversely affected by outflow spillovers, both consistent with the idea that fire-sale feedbacks give rise to strategic complementarity between own and peer fund flows. But how do peer outflows matter for fund behavior? Specifically, do funds take actions in response to peer outflows, perhaps in an effort to mitigate the negative impact of such outflows? And, more directly needed to establish the fire-sale mechanism, do peer outflows affect fund asset liquidation decisions and do they depress asset values?

Tables 4 and 5 present results from estimating equation (1) for funds' real and liquidity decisions, where the outcome is fund fees and cash holdings, respectively. The coefficient on Peer Flows is positive and highly statistically significant for both outcomes (Panel A, Column 1), indicating that funds tend to lower fees and decumulate cash in response to and possibly in an effort to attract investments and mitigate the harm of peer outflows on own flows. 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 (Panel A of Table 4, Columns 4 to 6). Yet, these attempts do not appear to undo the negative spillover effect of peer flows on asset holdings, as there is a negative relation between Peer Flows and a common measure of the fund's asset illiquidity, the bid-ask spread (Panel A of Table 4, Columns 4 to 6).

In an attempt to better understand why peer outflows increase illiquidity, Tables 6 and 7 examine funds' portfolio holding decisions. There is a positive (negative) relation between Peer Flows and funds' holdings of relatively liquid (illiquid) securities such as corporate bonds (securitized products) (Panel A of Table 6).[13] Directly supporting a fire-sale mechanism, large Peer Outflows increase the likelihood of a large asset or corporate bond sale. Interestingly, the effect is asymmetric, as large Peer Inflows reduce the likelihood of a large sale but their estimate is much smaller

[13] Table A.3 summarizes results for the analysis of additional asset types. Peer Flows do not appear to affect government or foreign holdings. Our baseline result for securitized products is robust to considering finer sub-sets of such products, which include asset-backed securities (ABS) and mortgage-backed securities (MBS).

and not statistically significant (Panel A of Table 7).[14] The positive relation between large peer outflows and large bond sales is economically significant. As shown in Column 8 of Appendix Table A.6, a 1-SD increase in the large Peer Outflow variable leads to about half a percentage point increase in the likelihood of large corporate bonds sales.[15]

In order to firmly establish fire-sale mechanism, in our final set of main tests we show that asset sales under peer flow pressure in fact bear the hallmark of costly fire-sales – i.e., do they involve securities whose valuations are depressed? We adapt the approach of Coval and Stafford (2007) to identify whether a fire-sale mechanism is at work in our spillovers context, by which peer outflows lead to asset sales that, in turn, have a negative price impact. The results of our event study are summarized in Table 8 and show that peer outflows-induces sales of corporate bonds do in fact have material valuation consequences. This table reports regressions of monthly (changes in log) bond prices on a variable that proxies for trades under peer fund (net) flow pressure. The independent variable, Peer Flow Pressure, is defined analogously to PRESSURE_3 in Coval and Stafford (2007) and is meant to capture bonds where large fractions of trading are accounted for by mutual funds experiencing significant peer outflow pressure.

Specifically, we start with each corporate bond security with information on holdings available from eMAXX and combine it with information on peer fund flows from CRSP to construct Peer Flow Pressure as the sum of the value of net "peer forced" fund buys (relative to the offering value of the bond), with "peer forced" sales and buys defined based on Extreme Peer Outflows and Extreme Peer Inflows, our dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. More formally, the main independent variable of interest for our bond

[14] Panel B of Table 7 confirms the negative relation between Peer Flows and asset illiquidity using an alternative measure, which is also commonly employed in teh literature, the Roll Index (Columns 1 to 3). It also shows that asset maturity is similarly impacted (Columns 4 to 6).

[15] Omitted common factors do not appear to be driving these result, which are robust across out three Peer Treatment variables (Panel B of Tables 4-6). In addition, the four panels of Table A.7 show that these results are not sensitive to either alternative specifications that add constrols for fund characteristics, to address omitted variables (Panel A), and lagged flows, to address dynamics (Panel B), and the coefficient estimates remain strongly stitistically significant if we clusted standard errors by either fund, or fund family (Panel C), or Lipper fund objective (Panel D).

event study is defined as follows:

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

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

We retrieve monthly bond price information from the Merrill Lynch database and bond characteristics at issuance from FISD. Panel A of Table 8 reports the main results for either a specification that controls for time (month-year) effects (Column 1) or for bond (cusip) effects (Column 2).[16] 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. Looking at the timing of the price impact, the bulk of the effect is concentrated in the immediate quarter when the sales happen or in the previous one (Columns 3 and 4). The result does not appear to be simply related to the direct effect of peer outflows on own outflows, as it continues to hold and it is if anything somewhat stronger when we add a control for own flow pressure constructed based on own fund flows (Columns 5 and 6).

The challenge with interpreting the bond event study results, much like for our baseline results, is again a manifestation of the "reflection problem" and boils down to a standard endogeneity issue: flows are endogenous to fund characteristics, as it is fund trading, so the challenge is to distinguish flow-related trading from information- or fundamentals-driven fund trading. To address endogeneity, we run two sets of robustness tests. First, we ensure that the positive regression coefficient is at least in part driven by asset sales by replicating the analysis using a dummy variable for bond-quarters when there are net-sales (Panel B, Columns 2, 4, and 5). We also verify that the result continues to hold if we exclude bond-quarters when there are either no trades or no trades by institutions under flow pressure as recommended by Kahn et al (2012) (Panel B, Column

[16] The time period is 1998-2014. All specifications include controls for bond characteristics (maturity) and either bond effects or time effects.

6). [17] Second, we replicate the bond event study analysis using an independent variable, Peer Treatment Pressure, which is defined analogously to Peer Flow Pressure but replacing the peer flow dummies with our three peer treatment variables, in turn (Panel C of Table 8). This approach is similar to Ellul et al (2011), which documents document evidence of significant price pressure around downgrades to speculative-grade for bonds with high exposure to insurance companies fire sale risk.

4 Heterogeneity and Implications for Fund Vulnerability

Our last test examines whether there is heterogeneity in the valuation effect of sales by funds under peer flow pressure. To explore this possibility, we repeat our analysis of monthly (changes in log) bond prices on a variable that proxies for trades under peer fund (net) flow pressure but now add an interaction term of this variable with several cross-sectional (bond-level) and time-series (aggregate) proxies for illiquidity. In Panel A of Table 9 we rank bonds in each month based on the empirical distribution of three proxies for illiquidity, lagged bond spreads over comparable-maturity treasuries (Columns 1-2), junk vs. investment-grade rated bonds (Columns 3-4), Roll liquidity index (Columns 5-6), and effective bid-ask spread (Columns 7-8). We include in the specification an interaction term of the Peer Flow Pressure variable with a dummy that equals one for relatively illiquid bonds, which are defined as those in the top-quartile of the distribution of the continuous proxies. In Panel B, we define the macro illiquidity dummy based on a dummy for the financial crisis (Columns 1-2) as well as high (top-quartile) values of macroeconomic variables that should be associated with illiquidity and "fire sale" costs, which include the St. Louis Fed Financial Stress Index (Columns 3-4), the Libor-OIS spread (Columns 5-6), and the VIX (Columns

[17] Based on Kahn et al (2012), we exclude $Unforced\ Peer\ Flow\ Induced\ Trades_{b,t} = \sum_j \left(\Delta Holdings_{j,b,t}|_{Percentile(10th)<Peer\ Flows_{j,t}<Percentile(90th)} \right) / Offering\ Value_b$. We also verify that the result continues to hold if we exclude bonds that are subject to high unforced peer pressure, defined as those in the top/bottom deciles of this variable.

7-8).[18]

Based on our fire-sale mechanism, we expect that there should be cross-sectional and time-series heterogeneity in the valuation effect of sales by funds under peer flow pressure. Specifically, the valuation effect should be more negative whenever peer outflows impose greater liquidation costs on funds' portfolio adjustment decisions. In line with this reasoning, the estimated coefficient on the interaction term is positive and strongly significant across proxies, indicating that sales by mutual funds whose peers are experiencing outflow pressure tend to harm valuations more for more illiquid bonds and at times when the VIX and Libor are high. The statistical significance of the interaction effect also indicates that estimates of Peer Flow Pressure are different in each of the two liquidity sub-groups, which offers additional reassurance that mechanical explanations based on omitted common factors are unlikely to be driving our results. This is the case because such explanations would counterfactually predict the same response across sub-groups. As such, heterogeneity by illiquidity constitutes a falsification test that further corroborates the fire-sale mechanism.

4.1 Implications for Vulnerability of Individual Funds to System-Wide Fund Flows

Finally, we show that our approach yields simple measures of vulnerability of a single fund family to system-wide outflows, which can be used for policy evaluation of alternative financial stability tools. We calculate these measures as follow. Recall from our definition that Peer Flows for fund (family) i are a weighted sum of other funds' flows with weights equal to the pair-wise correlation of funds' asset allocations across Lipper objective classes, $w_{i,j}$. Using these weights and our baseline estimate from equation equation (1) in Column 1 of Table 2 (Panel A), $\widehat{\beta}$, we construct an $n \times n = 297 \times 297$ matrix B, which is defined as follows:

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

$$
B \equiv \begin{bmatrix} . & \hat{\beta w}_{12} & . & . & \hat{\beta} w_{1N}. \\ \hat{\beta w}_{21} & . & . & . & . \\ . & . & . & . & . \\ . & . & . & . & \hat{\beta} w_{1,N-1} \\ \hat{\beta} w_{N1} & . & . & \hat{\beta} w_{N-1,1} & . \end{bmatrix}
$$

Each element of B, b_{ij}, gives the effect of 100 basis points increase in fund j's (lagged) flows on i's current flows. Given $\hat{B}$ and an assumption for the attenuation factor a (set as 0.9), we can calculate a fund n asset manager i's vulnerability and systemicness, respectively, as:

$$
\begin{aligned}
Vu\ln erability_i &= \frac{1}{n}\sum_{s=1}^{\infty}\sum_{j=1}^{n} a^s b_{ij}^s \\
Systemicness_i &= \frac{1}{n}\sum_{s=1}^{\infty}\sum_{j=1}^{n} a^s b_{ji}^s
\end{aligned}
$$

Because $w_{ij} = w_{ji}, : j \neq i$, $B = B'$ and, thus, these two measures are the same for each fund family. Table 10 lists fund families that are ranked as most (Panel A) and least (Panel B) vulnerable based on our measure. Fund families such as TIAA-CREF, T. Rowe Price, and PIMCO are among the funds classified as most vulnerable.

Figure 2 highlights that another potential use of our approach is to gauge how the vulnerability of the fund industry has evolved over time. We do so by plotting estimates of β based on a 3-year rolling window. Clearly, as the fixed-income asset management sector has been growing over time, it has also become more vulnerable to system-wide outflows.

5 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. Consistent with the idea that costly liquidation may lead to strategic complementarities in flows across funds by creating an incentive for any given investor to pull out of fund A if he or she sees a large number of investors pulling out of fund B, we have shown that flows are highly interdependent across funds that are interlinked by asset class overlap. We used several strategies to identify the causal link between any given fund's flows and those of its peers, including an RD design that exploits sharp changes in peer flows around Morningstar 5-star ratings. Directly consistent with a fire-sale story in which the strategic complementarity in investors' flow decisions is due to higher risk of future declines in asset values, also fund performance and liquidity, as well as the pricing of corporate bonds sold by funds under peer pressure, are adversely affected.

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, 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.

While we look forward to these extensions, we believe that 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 formal 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).

References

[1] Acemoglu, Daron, Ufuk Akcigit, and William Kerr, 2015. "Networks and the Macroeconomy: An Empirical Exploration," Forthcoming, NBER Macroeconomics Annual.

[2] Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2012. "Cascades in Networks and Aggregate Volatility," Econometrica, 80(5), pp. 1977-2016

[3] Acemoglu, Daron, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2015. "Systemic Risk and Stability in Financial Networks," American Economic Review, 105(2), pp. 564-608

[4] Angrist J.D. and J. Pischke, 2009. *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press.

[5] Anton, M. and C. Polk, 2014. "Connected Stocks," The Journal of Finance 69, pp. 1099-1127.

[6] Barrott, J.N., 2016. "Mutual Fund Flows and the Allocation of Capital: Evidence from a Natural Experiment," Working Paper, MIT Sloan.

[7] Bartik, T. J., 1991. *Who Benefits from State and Local Economic Development Policies?* Kalamazoo, Mich.: W. E. Upjohn Institute for Employment Research.

[8] Blanchard, O. J. and L. F. Katz, 1992. "Regional Evolutions," Brookings Papers on Economic Activity 1, pp.1-75.

[9] Bloom, N., M. Schankerman, and J. Van Reenen, 2013. "Identifying Technology Spillovers and Product Market Rivalry," Econometrica, Vol. 81, No. 4 (July, 2013), 1347–1393

[10] Brunnermeier, M., and L. H. Pedersen, 2009. "Market Liquidity and Funding Liquidity," Review of Financial Studies, 22(6), 2201–2238.

[11] Chen, Qi, Itay Goldstein, and Wei Jiang (2010). "Payoff Complementarities and Financial Fragility: Evidence from Mutual Fund Outflows," Journal of Financial Economics, vol. 97 (2), pp. 239-62.

[12] Chevalier, J., and G. Ellison, 1997. "Risk taking by mutual funds as a response to incentives," Journal of Political Economy 105:1167–200.

[13] Coval, J., and E. Stafford, 2007. "Asset fire sales (and purchases) in equity markets," Journal of Financial Economics 86:479–512.

[14] Del Guercio, Diane, and Paula A. Tkac, 2008. "Star power: The effect of Morningstar Ratings on Mutual Fund Flow," Journal of Financial and Quantitative Analysis 43, pp. 907-936.

[15] Di Maggio, M. and M. Kacperczyk, 2015. "The Unintended Consequences of the Zero Lower Bound Policy," Journal of Financial Economics, Forthcoming.

[16] Di Maggio, Marco, and Alireza Tahbaz-Salehi, 2015. "Collateral Shortages and Intermediation Networks," Woking Paper, Harvard Business School.

[17] Egan, Mark, Ali Hortacsu, and Gregor Matvos, 2015. "Deposit Competition and Financial Fragility: Evidence from the US Banking Sector," American Economic Review, Forthcoming.

[18] Ellul, A., Jotikasthira, C., Lundblad, C.T., 2011. "Regulatory Pressure and Fire Sales in the Corporate Bond Market," Journal of Financial Economics, 101,3, 596-620.

[19] Feroli, Michael, Anil K. Kashyap, Kermit Schoenholtz, and Hyun Song Shin, 2014, "Market Tantrums and Monetary Policy," paper presented at the 2014 U.S. Monetary Policy Forum, New York, February 28.

[20] Goldstein, I., H. Jiang, and D. T. Ng, 2015, "Investor Flows and Fragility in Corporate Bond Funds," working paper, University of Pennsylvania.

[21] Greenwood, R., and S. G. Hanson, 2013. “Issuer Quality and Corporate Bond Returns,” Review of Financial Studies, 26(6), 1483–1525.

[22] Greenwood, R., S. G. Hanson, and L.J. Jin, 2016. "A Model of Credit Market Sentiment,’ Working Paper, Harvard Business School.

[23] Greenwood, R., A. Landier, and D. Thesmar, 2015. "Vulnerable Banks," Journal of Financial Economics, 115(3), pp. 471–485.

[24] Greenwood, Robin and David Thesmar, 2011. "Stock Price Fragility," Journal of Financial Economics 102, pp 471-490.

[25] Jaffe, A., 1986. “Technological Opportunity and Spillovers of R&D: Evidence From Firms’ Patents, Profits and Market Value,” American Economic Review, 76, 984–1001.

[26] Jotikasthira, C., Lundblad, C.T., Ramadorai, T., 2012. "Asset Fire Sales and Purchases and the International Transmission of Financial Shocks," forthcoming Journal of Finance

[27] Khan, Mozaffar, Kogan, Leonid and Serafeim, George, 2012. "Mutual Fund Trading Pressure: Firm-Level Stock Price Impact and Timing of SEOs," Journal of Finance, 67(4), pp. 1371–1395.

[28] Kisin, Roni, 2011. "The Impact of Mutual Fund Ownership on Corporate Investment: Evidence from a Natural Experiment," Working Paper, Olin Business School, Washingon University in St. Louis.

[29] Lakonishok, J., Shleifer, Andrei, and Robert Vishny, 1992. "The Impact of Institutional Investors on Stock Prices", Journal of Financial Economics, 32(1) , pp 23-43.

[30] López-Salido, David, Jeremy C. Stein, and Egon Zakrajšek, 2016. “Credit-Market Sentiment and the Business Cycle,” Working paper, Federal Reserve Board and Harvard University.

[31] Manski, Charles, 1993. "Identification of Endogenous Social Effects: The Reflection Problem," Review of Economic Studies 60, pp. 531–542.

[32] McCabe, Patrick E., 2009. "The Economics of the Mutual Fund Trading Scandal," Working paper 2009-06, Federal Reserve Board.

[33] Morningstar, 2009. "The Morningstar Rating Methodology," Morningstar Methodology Paper.

[34] Petersen, M., 2006, "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches," Review of Financial Studies, 22: 435-480.

[35] Shleifer, Andrei, and Robert Vishny, 1992. "Liquidation Values and Debt Capacity: A Market Equilibrium Approach," Journal of Finance 47, 1343–1366.

[36] Shleifer, Andrei, and Robert Vishny, 2011. "Fire Sales in Finance and Macroeconomics," Journal of Economic Perspectives, 25(1), pp. 29-48.

[37] Stein, Jeremy C., 2012. "Monetary Policy as Financial Stability Regulation," Quarterly Journal of Economics 127, pp. 57-95.

Appendix A: Details of Variable Definitions

The variables used in this paper are extracted from three major data sources for the 1992Q1–2014Q4 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:

Fund-Level Outcome Variables:

- Fund Flow (%) is defined as $FLOW_{j,t} = (TNA_{j,t} - (1 + r_{j,t})TNA_{j,t-1})/TNA_{j,t-1}$, where $TNA_{j,t-1}$ is the total net assets under management at the end of the previous period, and $r_{j,t}$ 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 flow.
- Fund Return (%) is the monthly net fund return.
- Fund Excess Return (%) (alpha). We estimate a bond fund's average alpha in the past year by performing rolling-window time-series regression for each fund using past 12 months of data. Fund Alpha is the intercept from a regression of excess corporate bond fund returns on excess aggregate bond market and aggregate stock market returns. We use the Vanguard total bond market index fund return and CRSP value-weighted market return to proxy for aggregate bond and stock market returns.
- 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).
- 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.
- Portfolio Holdings, Corporate (%) is the ratio of corporate bond holdings to the fund's total fixed income holdings based on par values.
- Portfolio Holdings, Foreign (%) is the ratio of foreign bond holdings to the fund's total fixed income holdings based on par values.
- Portfolio Holdings, Government (%) is the ratio of government bond holdings to the fund's total fixed income holdings based on par values.
- Portfolio Holdings, Securitized (%) is the ratio of securitized products holdings to the fund's total fixed income holdings based on par values.
- 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):

$$Liq_{i,d}^{Roll} = \sqrt[2]{-cov(\Delta P_{i,d}^{j}, \Delta P_{i,d}^{j-1})}$$

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

- Illiquidity (bid-ask spread) is the difference between weighted average dealer ask prices and weighted average dealer bid prices. The weights are par volume of trades.
- Average maturity of the holdings Natural logarithm of the average maturity of the fixed-income holdings of the mutual fund, expressed in quarters.
- Fire Sales is a dummy that equals one for fund-quarter observations that are in the lowest decile of the distribution of the smallest quarterly change in asset allocation across the main asset classes (corporate, government, foreign, ABS, and MBS), which correspond to reduction in asset holding equal to or larger than 8%.
- Corporate Bond Fire Sales is a dummy that equals one for fund-quarter observations that are in the lowest decile of the distribution of the quarterly change in corporate bond holdings of funds, which correspond to reduction in asset holding equal to or larger than 4%.

Additional Fund-Level Variables:

- Portfolio turnover ratio is the turnover ratio of the mutual fund's portfolio, defined as the minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month total net assets (TNA) of the fund.
- 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.

Macro Variables:

- VIX is the CBOE's VIX index.
- Libor-OIS is the three-month London Interbank Offered Rate (LIBOR).
- FSI is the St. Louis Fed Financial Stress Index.

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 1992-December 2014 and consists of 493,630 fund (at share class level)-month observations for 4,227 (297) unique funds (families).

Panel A: Sample Distribution			
	Obs	Funds (share class level)	Families
1992	3,276	287	108
1993	4,545	381	124
1994	5,786	491	130
1995	7,072	589	136
1996	8,061	676	141
1997	9,437	815	147
1998	11,167	960	151
1999	12,648	1,075	159
2000	14,002	1,191	165
2001	15,671	1,324	170
2002	17,518	1,515	177
2003	19,540	1,666	184
2004	21,126	1,793	190
2005	22,816	1,926	197
2006	24,528	2,088	203
2007	26,611	2,287	207
2008	29,254	2,523	212
2009	31,927	2,758	220
2010	35,213	3,072	245
2011	39,182	3,436	268
2012	42,906	3,736	286
2013	45,551	3,939	296
2014	45,771	3,984	296
Tot.	493,608	4,227	297

Panel B: Summary Statistics			
	Mean	Median	Std Dev
Main Explanatory Variable(s):			
Peer Flows (%)	0.44	0.26	0.83
Main Outcome Variables:			
Fund Flows (%)	1.84	0.06	8.39
Fund Return (%)	0.47	0.48	1.90
Fund Excess Return (%)	0.01	0.01	1.21
Expense ratio (%)	1.12	1.00	0.53
Rear Load	0.66	0.00	1.29
Portfolio Holdings, Corporate (%)	40.51	34.00	30.82
Portfolio Holdings, World (%)	18.42	9.70	24.21
Portfolio Holdings, Government (%)	14.14	6.21	20.38
Portfolio Holdings, Munis (%)	1.50	0.00	7.86
Portfolio Holdings, ABS (%)	3.43	0.93	5.97
Cash Holdings (%)	4.21	2.85	13.69
Fund Characteristics:			
Fund Size (log$Million)	4.06	4.17	2.31
Family Size (log$Million)	7.77	7.91	2.10
Retail Fund	0.60	1.00	0.49
Equity Fund (primarily)	18.45	0.00	38.79

Table 2: Analysis of Fund Flows and Distress

This table reports regressions of monthly fund (net) flows (Panel A, Columns 1-3; and Panel B, Columns 1, 3, and 5) and large outflows (Panel A, Columns 4-6; and Panel B, Columns 2, 4, and 6) on peer fund (net) flows. In Panel A, the independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. In Panel B, the independent variable, Peer Treatment, is defined analogously as a weighted sum of peer treatment, where we consider three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Columns 1-2); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Columns 3-4); and the Morningstar 5-star rating of funds that are close to 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 time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators									
	Monthly % Flows			Extreme Outflows			Extreme Inflows		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Flows$_{i,t-1}$	2.324***			-1.862***			6.365***		
	(0.021)			(0.058)			(0.057)		
Peer Extreme Outflows$_{i,t-1}$		-0.259***	-0.201***		1.371***	1.335***			-0.101***
		(0.008)	(0.008)		(0.024)	(0.024)			(0.023)
Peer Extreme Inflows$_{i,t-1}$			1.077***			-0.281***		2.731***	2.720***
			(0.011)			(0.024)		(0.021)	(0.021)
Fund Controls	No	No	No	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	493,476	493,476	493,476	493,476	493,476	493,476	493,476	493,476	493,476
R^2(%)	13.30	11.20	12.91	8.33	8.77	8.80	14.98	15.62	15.62
Panel B: Identification – IV & RD Estimators									
Treatment=	Spitzer 2003			Fed Rate*Low Gov Exposure			MS 5-Star Rating RD		
	Monthly % Flows	Extreme Outflows	Extreme Inflows	Monthly % Flows	Extreme Outflows	Extreme Inflows	Monthly % Flows	Extreme Outflows	Extreme Inflows
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Treatment$_{i,t-1}$	-0.051***	0.423***	-0.083**	-0.009***	0.003	-0.028***	0.005***	-0.036***	0.013***
	(0.014)	(0.042)	(0.039)	(0.001)	(0.003)	(0.004)	(0.002)	(0.005)	(0.004)
Fund Controls	No	No	No	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	138,072	138,072	138,072	493,476	493,476	493,476	135,086	135,086	135,086
R^2(%)	12.61	10.39	14.66	11.04	12.44	12.79	10.72	7.59	13.06

Table 3: Analysis of Fund Performance

This table reports regressions of monthly fund returns (Panel A, Columns 1-3; and Panel B, Columns 1, 3, and 5) and excess returns (Panel A, Columns 4-6; and Panel B, Columns 2, 4, and 6) on peer fund (net) flows. In Panel A, the independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. In Panel B, the independent variable, Peer Treatment, is defined analogously as a weighted sum of peer treatment, where we consider three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Columns 1-2); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Columns 3-4); and the Morningstar 5-star rating of funds that are close to 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 time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators						
	Monthly Return			Monthly Excess Return (Alpha)		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flows$_{i,t-1}$	0.117***			0.032***		
	(0.004)			(0.002)		
Peer Extreme Outflows$_{i,t-1}$		-0.082***	-0.079***		-0.014***	-0.013***
		(0.001)	(0.001)		(0.001)	(0.001)
Peer Extreme Inflows$_{i,t-1}$			0.023***			0.009***
			(0.001)			(0.001)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	493,476	493,476	493,476	493,476	493,476	493,476
R^2(%)	8.47	8.85	8.91	9.94	9.95	9.98
Panel B: Identification – IV & RD Estimators						
Treatment=	Spitzer 2003		Fed Rate*Low Gov Exposure		MS 5-Star Rating RD	
	Monthly Return (1)	Monthly Alpha (2)	Monthly Return (3)	Monthly Alpha (4)	Monthly Return (5)	Monthly Alpha (6)
Peer Treatment$_{i,t-1}$	-0.003**	-0.002*	-0.001***	-0.003***	0.046***	0.001***
	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	137,802	137,802	493,476	493,476	135,086	135,086
R^2(%)	7.70	7.36	8.12	8.42	14.41	8.30

Table 4: Analysis of Fund Real Decisions

This table reports regressions of monthly fund fees (Panel A, Columns 1-3; Panel B, Columns 1, 3, and 5) and rear load fees (Panel A, Columns 4-6; and Panel B, Columns 2, 4, and 6) on peer fund (net) flows. In Panel A, the independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. In Panel B, the independent variable, Peer Treatment, is defined analogously as a weighted sum of peer treatment, where we consider three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Columns 1-2); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Columns 3-4); and the Morningstar 5-star rating of funds that are close to 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 time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators						
	Expense Ratio (%)			Rear Load Fee Introduction (%)		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flows$_{i,t-1}$	0.420***			-0.041*		
	(0.026)			(0.022)		
Peer Extreme Outflows$_{i,t-1}$		-0.025***	-0.009		0.019**	0.020**
		(0.009)	(0.013)		(0.008)	(0.008)
Peer Extreme Inflows$_{i,t-1}$			0.204***			0.000
			(0.010)			(0.008)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	480,861	480,861	480,861	328,550	328,550	328,550
R^2(%)	94.65	94.65	94.65	3.34	3.34	3.34

Panel B: Identification – IV & RD Estimators						
Treatment=	Spitzer 2003		Fed Rate*Low Gov Exposure		MS 5-Star Rating RD	
	Expense Ratio	Rear Load Fee	Expense Ratio	Rear Load Fee	Expense Ratio	Rear Load Fee
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Treatment$_{i,t-1}$	-0.246***	0.169***	-0.005***	0.233***	0.005***	-0.011***
	(0.015)	(0.020)	(0.001)	(0.007)	(0.002)	(0.002)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	133,821	110,745	480,861	328,550	129,009	92,753
R^2(%)	94.23	4.46	94.65	4.19	94.96	2.36

Table 5: Analysis of Fund Liquidity Decisions

This table reports regressions of monthly fund cash holdings (Panel A, Columns 1-3; and Panel B, Columns 1, 3, and 5) and quarterly asset liquidity as measured by the holding-weighted average of the bid-ask spread of the corporate bonds held in a given quarter (Panel A, Columns 4-6; and Panel B, Columns 2, 4, and 6) on peer fund (net) flows. In Panel A, the independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. In Panel B, the independent variable, Peer Treatment, is defined analogously as a weighted sum of peer treatment, where we consider three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Columns 1-2); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Columns 3-4); and the Morningstar 5-star rating of funds that are close to 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 time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators						
	Cash Holdings (%)			Asset Illiquidty (Bid-Ask Spread)		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flows$_{i,t-1}$	32.834***			-0.318***		
	(1.992)			(0.082)		
Peer Extreme Outflows$_{i,t-1}$		-11.265***	-10.378***		0.638***	0.641***
		(0.738)	(0.744)		(0.031)	(0.031)
Peer Extreme Inflows$_{i,t-1}$			7.458***			-0.021
			(0.754)			(0.031)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	457,285	457,285	457,285	317,404	317,404	317,404
R^2(%)	37.23	37.22	37.24	60.83	60.89	60.89

Panel B: Identification – IV & RD Estimators						
Treatment=	Spitzer 2003		Fed Rate*Low Gov Exposure		MS 5-Star Rating RD	
	Cash Holdings	Asset Liquidity	Cash Holdings	Asset Liquidity	Cash Holdings	Asset Liquidity
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Treatment$_{i,t-1}$	-10.080***	0.051**	-0.695***	0.160***	0.436***	-0.115***
	(0.763)	(0.025)	(0.240)	(0.014)	(0.148)	(0.005)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	133,191	87,558	457,285	317,404	135,283	90,341
R^2(%)	47.28	56.36	38.25	60.92	35.67	60.85

Table 6: Analysis of Fund Portfolio Decisions

This table reports regressions of quarterly changes in fund asset allocation, as measured by the change in percentage of assets held in corporate bonds (Panel A, Columns 1-3; and Panel B, Columns 1, 3, and 5) and in securitized products (Panel A, Columns 4-6; and Panel B, Columns 2, 4, and 6) on peer fund (net) flows. In Panel A, the independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. In Panel B, the independent variable, Peer Treatment, is defined analogously as a weighted sum of peer treatment, where we consider three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Columns 1-2); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Columns 3-4); and the Morningstar 5-star rating of funds that are close to 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 time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators						
	% Corporate Holdings			% Securitized Products Holdings		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flows$_{i,t-1}$	6.353***			-8.355***		
	(2.289)			(1.906)		
Peer Extreme Outflows$_{i,t-1}$		-0.875	-1.104		3.408***	3.337***
		(0.978)	(0.987)		(0.705)	(0.713)
Peer Extreme Inflows$_{i,t-1}$			1.496*			-0.463
			(0.896)			(0.681)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	134,930	134,930	134,930	134,930	134,930	134,930
R^2(%)	2.32	2.32	2.32	1.67	1.90	1.90

Panel B: Identification – IV & RD Estimators						
Treatment=	Spitzer 2003		Fed Rate*Low Gov Exposure		MS 5-Star Rating RD	
	% Corporate Holdings	% Securitized Holdings	% Corporate Holdings	% Securitized Holdings	% Corporate Holdings	% Securitized Holdings
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Treatment$_{i,t-1}$	-12.215***	0.370**	-0.612***	0.536***	0.130	-0.386**
	(2.445)	(0.164)	(0.195)	(0.088)	(0.125)	(0.155)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	44,660	44,660	134,930	134,930	38,157	38,157
R^2(%)	1.01	1.02	2.34	3.02	3.25	1.95

Table 7: Analysis of Fire Sale Mechanism

This table reports regressions of quarterly fund large sales and fire sales (Panel A), monthly fund portfolio turnover and asset maturity as measured by the holding-weighted average of the maturity of the corporate bonds held in a given quarter (Panel B) on peer fund (net) flows. The independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. In Columns 1-3 of Panel A, the dependent variable "Fire Sales" is a dummy that equals one for fund-quarter observations that are in the lowest decile of the distribution of the smallest quarterly change in asset allocation across the main asset classes (corporate, government, foreign, ABS, and MBS), which correspond to reduction in asset holding equal to or larger than 8%. In Columns 4-6 of Panel A, the dependent variable "Corporate Bond Fire Sales" is a dummy that equals one for fund-quarter observations that are in the lowest decile of the distribution of the quarterly change in corporate bond holdings of funds, which correspond to reduction in asset holding equal to or larger than 4%. For this analysis, we restrict the sample to funds that have relatively large prior-quarter percentage holdings of corporate bonds (above-mean). The time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators						
	Fire Sales			Corporate Bond Fire Sales		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flows$_{i,t-1}$	-0.069			-0.242***		
	(0.089)			(0.086)		
Peer Extreme Outflows$_{i,t-1}$		0.111***	0.115***		0.256***	0.254***
		(0.036)	(0.036)		(0.041)	(0.042)
Peer Extreme Inflows$_{i,t-1}$			-0.043			-0.024
			(0.032)			(0.047)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	134,930	134,930	134,930	92,955	92,955	92,955
R^2(%)	2.24	2.25	2.25	2.39	2.42	2.42

Panel B: Fund & Time Fixed Effects Estimators, Additional Outcomes						
	Asset Illiquidty (Roll Measure)			Asset Maturity		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flows$_{i,t-1}$	-0.805***			-3.320***		
	(0.085)			(0.699)		
Peer Extreme Outflows$_{i,t-1}$		0.903***	0.903***		1.392***	1.402***
		(0.045)	(0.045)		(0.348)	(0.349)
Peer Extreme Inflows$_{i,t-1}$			-0.012			-0.202
			(0.046)			(0.383)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	289,103	289,103	289,103	262,447	262,447	262,447
R^2(%)	63.69	63.73	63.73	82.43	85.22	85.22

Table 8: Analysis of Bond Price Impact

This table reports regressions of monthly (changes in log) bond prices on a variable that proxies for trades under peer fund (net) flow pressure. The independent variable, Peer Flow Pressure, is defined analogously to Coval and Stafford (2007) based on Peer Flows, which is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Specifically, we start with each corporate bond security with information on holdings available from eMAXX and combine it with information on peer fund flows from CRSP to construct Peer Flow Pressure as the sum of the value of net "peer forced" fund buys (relative to the offering value of the bond), with "peer forced" sales and buys defined based on Extreme Peer Outflows and Extreme Peer Inflows, our dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. We retrieve monthly bond price information from the Merrill Lynch database and bond characteristics at issuance from FISD. We report results for a specification that controls for time (month-year) effects (Column 1), for bond (cusip) effects (Column 2), includes different lags of Peer Flow Pressure (Columns 3 and 4), and for specifications that control for own flow pressure constructed as in Coval and Stafford (2007) based on own fund flows (Columns 5 and 6). The time period is 1998-2014. All specifications include controls for bond characteristics (maturity) and either bond effects or time effects. Standard errors are clustered by time (month-year), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Analysis of Price Impact – Monthly % Bond Price Changes						
	(1)	(2)	(3)	(4)	(5)	(6)
Specification=	Baseline with time effects	Baseline with bond effects	Timing	Timing	Controlling for own flow pressure	Controlling for own flow pressure with time and bond effects
Peer Flow Pressure$_{b,t}$	0.078**	0.190***		0.218**	0.207***	0.093**
	(0.039)	(0.046)		(0.088)	(0.047)	(0.037)
Peer Flow Pressure$_{b,t-3}$			0.139***	0.007		
			(0.040)	(0.080)		
Peer Flow Pressure$_{b,t-6}$				0.026		
				(0.058)		
Peer Flow Pressure$_{b,t-9}$				0.087		
				(0.057)		
Own Flow Pressure$_{b,t}$					0.027	0.026
					(0.029)	(0.026)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustering, FE	Time, Time	Time, Bond	Time, Bond	Time, Bond	Time, Bond	Time, Bond
N obs	429,449	429,449	429,449	407,326	429,449	429,449
N Bonds	10,880	10,880	10,880	10,880	10,880	10,880
R^2(%)	14.85	3.45	3.41	3.57	11.59	8.00

Table 8: Analysis of Bond Price Impact (continued)

This table reports regressions of monthly (changes in log) bond prices on a variable that proxies for trades under peer fund (net) flow pressure. Panel B shows results for a variable constructed using own flows as in Coval and Stafford (2007) (Column 1), and for two sets of robustness checks on own and peer fund pressure, which include using a dummy variable for bond-quarters when there are net-sales (Columns 2, 4, and 5) and excluding bond-quarters when there are either no trades or no trades by institutions under flow pressure as recommended by Kahn et al (2012). Panel C shows results for the independent variable, Peer Treatment Pressure, defined analogously to Coval and Stafford (2007) based on Peer Treatment, which is defined as a weighted sum of three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Columns 1-2); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Columns 3-4); and the Morningstar 5-star rating of funds that are close to their rating-category threshold, as defined by those funs whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold (Columns 5-6). The time period is 1998-2014. All specifications include controls for bond characteristics (maturity) and either bond effects or time effects. Standard errors are clustered by time (month-year), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel B: Replication of Coval and Stafford (2007) and Kahn et al (2012) Refinement						
	Coval and Stafford (2007) Replication			Additional Analysis of Peer Flow Pressure		
Specification=	Own Flow	Pressure is Dummy for Net-Sales	Kahn et al (2012) Refinement	Pressure is Dummy	Pressure is Dummy Controlling for own	Kahn et al (2012) Ref. Controlling for own
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flow Pressure$_{b,t}$				-0.005***	-0.004***	-0.006***
				(0.002)	(0.002)	(0.002)
Own Flow Pressure$_{b,t}$	0.091**	-0.003***	-0.004***		-0.001***	-0.002***
	(0.033)	(0.001)	(0.001)		(0.000)	(0.001)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustering, FE	Time, Bond	Time, Bond	Time, Bond	Time, Bond	Time, Bond	Time, Bond
N obs	429,449	429,449	224,969	407,326	429,449	129,221
N Bonds	10,880	10,880	10,032	10,880	10,880	8,737
R^2(%)	3.38	3.42	4.86	3.47	3.48	6.72

Panel C: Analysis of Price Impact – Monthly % Bond Price Changes						
	Spitzer 2003		Fed Rate*Low Gov Exposure		MS 5-Star Rating RD	
	Time effects	Bond effects	Time effects	Bond effects	Time effects	Bond effects
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Treatment Pressure$_{b,t}$	0.010	0.005***	0.027*	0.036**	0.125***	0.351***
	(0.009)	(0.013)	(0.015)	(0.018)	(0.044)	(0.069)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes
Clustering, FE	Time, Time	Time, Bond	Time, Time	Time, Bond	Time, Time	Time, Bond
N obs	370,548	370,548	429,449	407,326	429,449	429,449
N Bonds	9,698	9,698	10,880	10,880	10,880	10,880
R^2(%)	15.48	3.50	14.85	3.37	14.85	3.46

Table 9: Additional Analysis of Fire Sale Mechanism

This table reports regressions of monthly (changes in log) bond prices on a variable that proxies for trades under peer fund (net) flow pressure and its interaction of cross-sectional and time-series proxies for illiquidity. The independent variable, Peer Flow Pressure, is defined analogously to Coval and Stafford (2007) based on Peer Flows, which is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Specifically, we start with each corporate bond security with information on holdings available from eMAXX and combine it with information on peer fund flows from CRSP to construct Peer Flow Pressure as the sum of the value of net "peer forced" fund buys (relative to the offering value of the bond), with "peer forced" sales and buys defined based on Extreme Peer Outflows and Extreme Peer Inflows,our dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. We retrieve monthly bond price information from the Merrill Lynch database and bond characteristics at issuance from FISD. Panel A reports results for a specification that adds an interaction with cross-sectional bond-level proxies of illiquidity, which include a dummy for high (top-quartile) lagged bond spreads over comparable-maturity treasuries (Columns 1-2), junk vs. investment-grade rated bonds (Columns 3-4), high (top-quartile) Roll liquidity index (Columns 5-6), and high (top-quartile) effective bid-ask spread (Columns 7-8). Panel B reports results for a specification that adds an interaction with time-series aggregate proxies of illiquidity, which include a dummy for the financial crisis (2007Q4-2009Q2, Columns 1-2), high (top-quartile) St. Louis Fed Financial Stress Index (FSI, Columns 3-4), high (top-quartile) Libor-OIS spread (Columns 5-6), and high (top-quartile) VIX index of implied stock market volatility (Columns 7-8). The time period is 1998-2014. All specifications include controls for bond characteristics (maturity) and either bond effects or time effects. Standard errors are clustered by time (month-year), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators, Cross-Sectional Interactions								
	$X=I^{High\ Spread}$		$X=I^{Junk\ Bond}$		$X=I^{High\ Roll}$		$X=I^{High\ Bid-Ask}$	
	Time FE	Bond FE	Time FE	Bond FE	Time FE	Bond FE	Time FE	Bond FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Flow Pressure$_{b,t}$	-0.032	0.067*	-0.061	-0.061	-0.035	-0.017	0.032	0.041
	(0.024)	(0.034)	(0.061)	(0.058)	(0.038)	(0.036)	(0.055)	(0.055)
Peer Flow Pressure$_{b,t}$*X	0.228***	0.234***	0.290**	0.294**	0.401***	0.361***	0.205**	0.188**
	(0.072)	(0.088)	(0.122)	(0.126)	(0.119)	(0.116)	(0.081)	(0.083)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering, FE	Time, Time	Time, Fund	Time, Time	Time, Fund	Time, Time	Time, Fund	Time, Time	Time, Fund
N obs.	429,449	429,449	145,787	145,787	132,621	132,621	127,684	127,684
N Bonds	10,880	10,880	5,766	5,766	5,498	5,498	5,390	5,390

Panel B: Fund & Time Fixed Effects Estimators, Time-Series Interactions								
	X=Crisis		$X=I^{High\ FSI}$		$X=I^{High\ Libor-OIS}$		$X=I^{High\ VIX}$	
	Time FE	Bond FE	Time FE	Bond FE	Time FE	Bond FE	Time FE	Bond FE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer Flow Pressure$_{b,t}$	0.058	0.144**	0.003	-0.002	0.063	0.052	0.013	0.006
	(0.050)	(0.059)	(0.033)	(0.032)	(0.054)	(0.044)	(0.032)	(0.037)
Peer Flow Pressure$_{b,t}$*X	0.333***	0.720***	0.241**	0.264***	0.519**	0.537**	0.166**	0.184**
	(0.092)	(0.184)	(0.096)	(0.098)	(0.262)	(0.258)	(0.067)	(0.091)
Bond Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering, FE	Time, Time	Time, Fund	Time, Time	Time, Fund	Time, Time	Time, Fund	Time, Time	Time, Fund
N obs.	429,449	429,449	429,449	429,449	344,243	344,243	429,449	429,449
N Bonds	10,880	10,880	10,880	10,880	9,390	9,390	10,880	10,880

Table 10: Vulnerability of Individual Funds to System-Wide Fund Flows

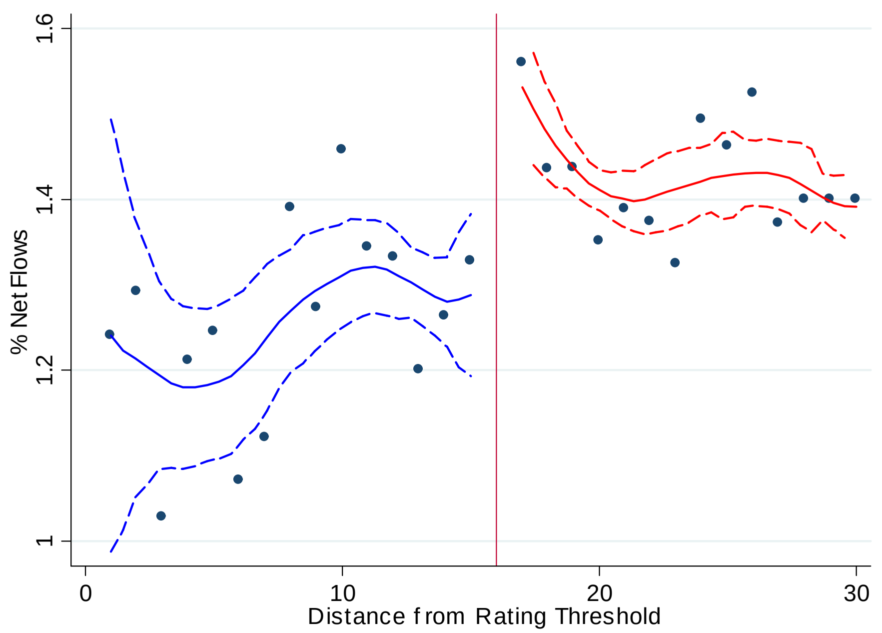
This table reports names and scores for the 40 fund families that rank in the top 20 (Panel A) and bottom 20 (Panel B) based on their vulnerability to system-wide flows Details on the definition of the vulnerability scores are in Appendix B.

Panel A: Funds with High Vulnerability		
	Vulnerability Score	Vulnerability Rank
	(1)	(2)
Highland Capital Mgmt Fund Advisors LP	6.02	1
Rainier Investment Management Inc	5.86	2
MassMutual Life Insurance Company	5.75	3
Nationwide Fund Advisors	5.60	4
Transamerica Asset Management Inc	5.51	5
Dodge & Cox	5.49	6
TIAA-CREF	5.44	7
T Rowe Price Associates Inc	5.37	8
GE Asset Management Inc	5.34	9
CUNA	5.34	10
Aberdeen Asset Management Inc	5.24	11
Hartford Series Fund Inc	5.23	12
Saturna Capital Corporation	5.18	13
Metropolitan West Asset Management LLC	5.09	14
Voya Investments LLC	5.09	15
PIMCO	5.08	16
Wilmington Funds	5.05	17
Aston Asset Management LP	5.05	18
Legg Mason	5.03	19
Scout Investments Inc	5.02	20
Panel B: Funds with Low Vulnerability		
	Vulnerability Score	Vulnerability Rank
	(1)	(2)
Diamond Hill Capital Management Inc	1.97	272
Northeast Mgmt & Research Company Inc	1.97	273
Trinity Fiduciary Partners LLC	1.97	274
Cutler Investment Counsel LLC	1.97	275
Cohen & Steers Capital Management Inc	1.96	276
RS Investment Management Co LLC	1.89	277
Credit Suisse Asset Management LLC	1.88	278
Acadian Asset Management LLC	1.86	279
Guinness Atkinson Asset Management Inc	1.86	280
HSBC Global Asset Management (USA) Inc	1.86	281
Matthews International Capital Mgmt LLC	1.86	282
Callahan Credit Union Finl Svcs	1.84	283
Compass Efficient Model Portfolios LLC	1.84	284
Merganser Capital Management Inc	1.84	285
Community Capital Management Inc	1.78	286
Shay Assets Management Inc	1.78	287
DoubleLine Funds	1.66	288
Azzad Asset Management Inc	1.60	289
Euro Pacific Asset Management LLC	1.60	290
Wellesley Investment Advisors Inc	1.54	291

Figure 1 – "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. 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

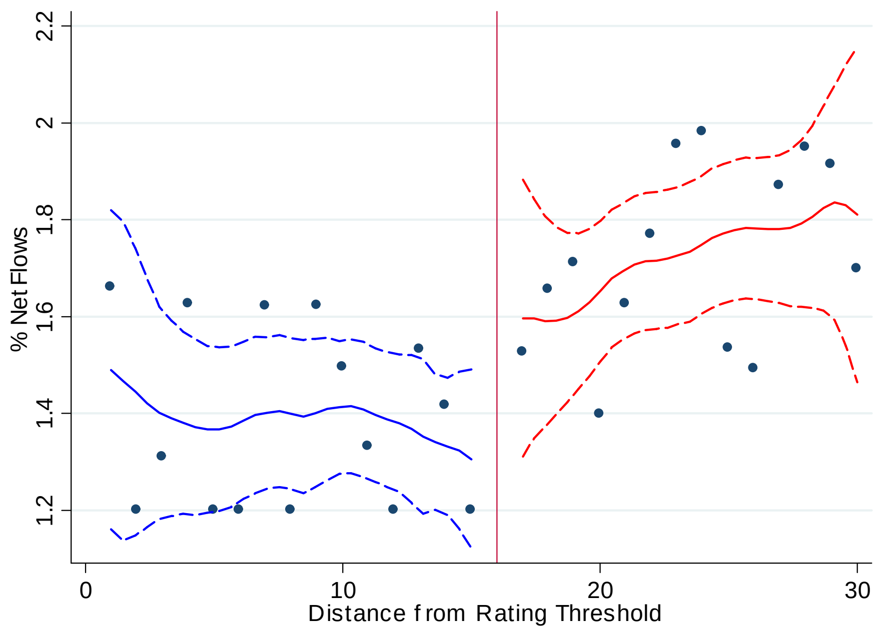
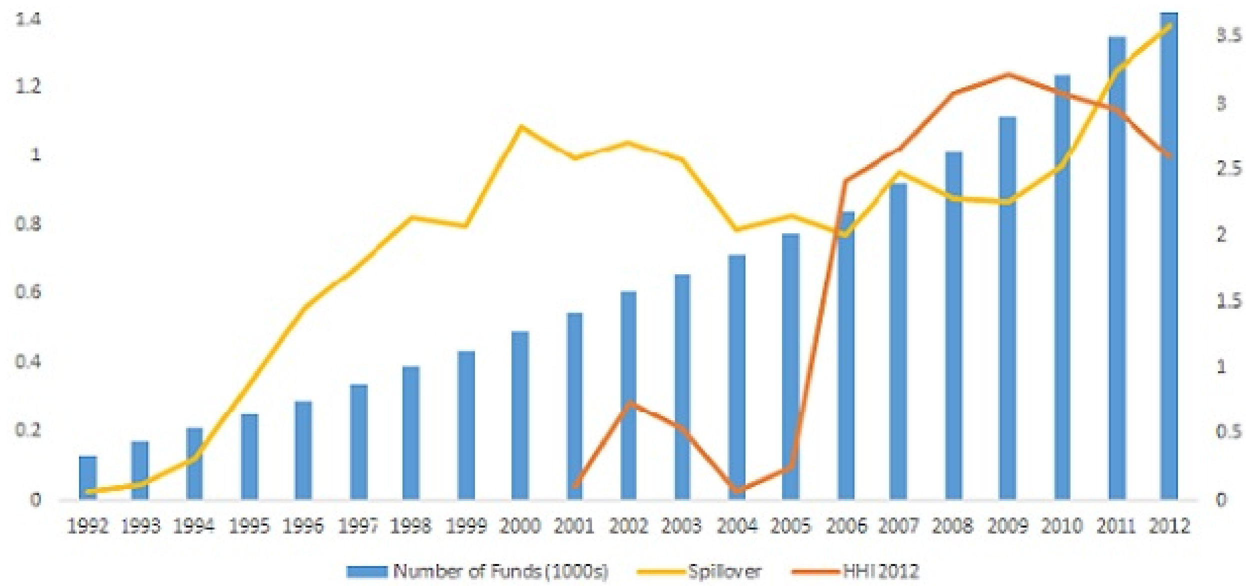


Figure 2 – The Growth of the Size and Vulnerability to Spillovers of the Fixed-Income Mutual Funds Industry

This figure shows the evolution over time of the size (number of funds) and vulnerability to spillovers of the fixed-income mutual funds industry between 1992 and 2014. The blue bars show the number of funds (1000s, right scale) and the yellow line shows vulnerability to spillovers (left scale) as measured by the estimated regression coefficient from a specification of fund flows on peer flows as in Table 3, to which we have added fund controls and the lagged dependent. Peer Flows are defined as a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Each reported observation is for a rolling 3-year window. For example, 1992 refers to the 1992-1994 window. For reference, we also report ownership concentration (HHI) of relatively illiquid bonds, which is defined as the sum of the squared shares of a given corporate bond held by mutual funds weighted by the effective bid-ask spread of the bond .



Additional Results For "Fire-Sale Spillovers in Debt Markets"

Table A.1: Descriptive/Motivating Evidence on Peer Fund Flows

Panel A of this table reports regressions of monthly fund returns (Columns 1-3) and excess returns (Columns 4-6) on own and average fund (net) flows within a Lipper asset class, while Panel B reports regressions of monthly fund (net) flows (Columns 1-3) and large outflows (Columns 4-6) on average fund (net) flows. The independent variables are the cumulative density of net fund flows scaled by average assets (Own Flows) and of the average net fund flows scaled by assets across other funds within a Lipper asset class-month (Average Flows), and the average incidence of funds in the lowest and highest five percent of the unconditional distribution of flows, respectively (Extreme Asset-Class Outflows and Extreme Asset-Class Inflows). The third and sixth columns include fund controls (fund and family size). All columns include Lipper Objective fixed-effecs. The time period is 1992-2014. Standard errors are clustered by Lipper Objective, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund Performance						
	Monthly % Return			Monthly % Excess Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Flows$_{i,t-1}$	0.091***			0.162***		
	(0.000)			(0.000)		
Own Extreme Outflows$_{i,t-1}$		-0.020***	-0.014***		-0.033***	-0.018***
		(0.000)	(0.000)		(0.000)	(0.000)
Own Extreme Inflows$_{i,t-1}$			0.063***			0.122***
			(0.000)			(0.000)
Average Flows$_{i,t-1}$	0.358***			0.205***		
	(0.000)			(0.000)		
Extreme Asset-Class Outflows$_{i,t-1}$		-0.829***	-0.613***		-0.918***	-0.768***
		(0.003)	(0.002)		(0.008)	(0.003)
Extreme Asset-Class Inflows$_{i,t-1}$			1.030***			0.511
			(0.006)			(0.000)
Fund Controls	No	No	Yes	No	No	Yes
Clustering, FE	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.

Panel B: Fund Flows						
	Monthly % Flows			Extreme Outflows		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Flows$_{i,t-1}$	0.197***			-0.033***		
	(0.000)			(0.000)		
Extreme Asset-Class Outflows$_{i,t-1}$		-0.874***	-0.791***		0.410***	0.420***
		(0.002)	(0.001)		(0.001)	(0.001)
Extreme Asset-Class Inflows$_{i,t-1}$			0.608***			-0.007
			(0.008)			(0.003)
Fund Controls	No	No	Yes	No	No	Yes
Clustering, FE	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.
R^2(%)	3.63	2.07	4.05	0.15	0.71	1.56

Table A.1: Descriptive/Motivating Evidence on Peer Fund Flows (Continued)

Panel A of this table reports regressions of monthly fund returns (Columns 1-3) and excess returns (Columns 4-6) on own and average fund (net) flows within a Lipper asset class, while Panel B reports regressions of monthly fund (net) flows (Columns 1-3) and large outflows (Columns 4-6) on average fund (net) flows. The independent variables are the cumulative density of net fund flows scaled by average assets (Own Flows) and of the average net fund flows scaled by assets across other funds within a Lipper asset class-month (Average Flows), and the average incidence of funds in the lowest and highest five percent of the unconditional distribution of flows, respectively (Extreme Asset-Class Outflows and Extreme Asset-Class Inflows). The third and sixth columns include fund controls (fund and family size). All columns include time fixed-effecs. The time period is 1992-2014. Standard errors are clustered by time, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund Performance						
	Monthly % Return			Monthly % Excess Return		
	(1)	(2)	(3)	(4)	(5)	(6)
Own Flows$_{i,t-1}$	0.060**			0.150***		
	(0.027)			(0.012)		
Own Extreme Outflows$_{i,t-1}$		-0.016*	-0.024***		-0.023***	-0.018**
		(0.009)	(0.009)		(0.008)	(0.007)
Own Extreme Inflows$_{i,t-1}$			0.007			0.123***
			(0.015)			(0.025)
Average Flows$_{i,t-1}$	0.054			0.057*		
	(0.086)			(0.030)		
Extreme Asset-Class Outflows$_{i,t-1}$		-0.640	-0.639		-0.267	-0.223
		(0.448)	(0.470)		(0.244)	(0.249)
Extreme Asset-Class Inflows$_{i,t-1}$			0.037			0.037
			(0.085)			(0.052)
Fund Controls	No	No	Yes	No	No	Yes
Clustering, FE	Time	Time	Time	Time	Time	Time

Panel B: Fund Flows						
	Monthly % Flows			Extreme Outflows		
	(1)	(2)	(3)	(4)	(5)	(6)
Average Flows$_{i,t-1}$	0.181***			-0.035***		
	(0.008)			(0.003)		
Extreme Asset-Class Outflows$_{i,t-1}$		-0.821***	-0.692***		0.414***	0.404***
		(0.048)	(0.044)		(0.029)	(0.032)
Extreme Asset-Class Inflows$_{i,t-1}$			0.266***			-0.009**
			(0.013)			(0.004)
Fund Controls	No	No	Yes	No	No	Yes
Clustering, FE	Time	Time	Time	Time	Time	Time
R^2 (%)	6.42	5.31	6.74	1.46	1.81	2.35

Table A.2: Validation Analysis of Peer Treatment

This table reports regressions of monthly fund (net) flows on treatment for peer funds. As in the baseline analysis of Table 3, we consider three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Column 1); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Column 2); and the Morningstar 5-star rating of funds that are close to 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 (Column 4; Column 3 shows results for the full sample). The time period is 1992-2014. All specifications include controls for fund performance (alpha) as well as fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: First-Stage Analysis of the Effect of Treatment on Monthly % Flows				
Treatment=	Spitzer 2003	Fed Rate*Low Gov Exposure	MS 5-Star Rating RD	
	Monthly % Flows	Monthly % Flows	Full Sample	Discontinuity Sample
	(1)	(2)	(3)	(4)
$\text{Treatment}_{i,t-1}$	-0.013***	-0.002***	0.006***	0.003***
	(0.003)	(0.000)	(0.000)	(0.001)
Fund Controls	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	141,214	488,335	342,761	82,530
R^2(%)	11.93	10.48	7.66	12.06

Table A.3: Additional Analysis of Fund Portfolio Decisions

This table reports regressions of quarterly changes in fund asset allocation, as measured by the change in percentage of assets held in government bonds (Panel A, Columns 1-3), foreign fixed-income securities (Panel A, Columns 4-6), in asset backed securities (ABS) (Panel B, Columns 1-3), and in mortgage backed securities (MBS) (Panel B, Columns 4-6) on peer fund (net) flows. The independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest five percent of the distribution, respectively. The time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators						
	% Government Holdings			% Foreign Holdings		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flows$_{i,t-1}$	2.507			2.998		
	(3.701)			(2.406)		
Peer Extreme Outflows$_{i,t-1}$		-0.924	-1.016		-1.077	-0.914
		(1.580)	(1.596)		(1.017)	(1.024)
Peer Extreme Inflows$_{i,t-1}$			0.597			1.218
			(1.449)			(0.933)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	134,930	134,930	134,930	134,930	134,930	134,930
R^2(%)	0.88	0.88	0.88	2.02	2.02	2.02

Panel B: Fund & Time Fixed Effects Estimators						
	% ABS Holdings			% MBS Holdings		
	(1)	(2)	(3)	(4)	(5)	(6)
Peer Flows$_{i,t-1}$	-1.659*			-1.562**		
	(0.901)			(0.785)		
Peer Extreme Outflows$_{i,t-1}$		1.467***	1.429***		1.492***	1.490***
		(0.385)	(0.386)		(0.335)	(0.336)
Peer Extreme Inflows$_{i,t-1}$			-0.424			-0.022
			(0.359)			(0.313)
Fund Controls	No	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	134,930	134,930	134,930	134,930	134,930	134,930
R^2(%)	1.61	1.62	1.62	1.15	1.16	1.16

Table A.4: Analysis of Fund Flows and Distress – Economic Significance

This table present an assessment of the economic magnitude of the effect of peer fund (net) flows on monthly fund (net) flows (columns 1 to 3) and large outflows and inflows (Columns 4 to 6; and 7 to 9). We assess economic significance relative to other standard fund characteristics (fund family size, performance (alpha), expense ratio, and rear load fees), as well as relative to the within-fund distribution of flows. Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. The time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Columns 1, 4, and 7 report the effect of a one-standard deviation change in the right-hand side variable on fund flows from our baseline regression specification in Table 3. For example, a one-standard deviation increase in peer flows is associated with a 183.2 bps increase in fund flows. This specification is the same as Column (1) of Panel A, Table 3. Columns 2, 5, and 8 report the effect of a large, two standard deviation change in the right-hand side variable on flows, and Columns 3, 6, and 9 report the effect of a change in the RHS variable from its smallest to its largest value. The three rows at the bottom report the within-firm median, variance and quartile change of the left-hand side variables.

Panel A: Fund & Time Fixed Effects Estimators (basis points)									
	Monthly % Flows			Extreme Outflows			Extreme Inflows		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate * X Increase in RHS, X=	1 SD Δ RHS	2 SD Δ RHS	Min-Max Δ RHS	1 SD Δ RHS	2 SD Δ RHS	Min-Max Δ RHS	1 SD Δ RHS	2 SD Δ RHS	Min-Max Δ RHS
Peer Flows$_{i,t-1}$	183.2***	366.4***	997.6***						
Peer Extreme Outflows$_{i,t-1}$				250.4***	500.8***	1,315.2***			
Peer Extreme Inflows$_{i,t-1}$							570.1***	1,140.2***	3,072.6***
log(Fund Family Size)	18.6***	37.2***	243.4***	49.8***	99.6***	608.5***	32.1***	64.2***	413.8***
Alpha	76.5***	153.0***	933.2***	-72.9***	-145.8***	-888.6***	103.5***	207.0***	1,250.8***
Expense Ratio	-11.7***	-23.4***	-651.7***	-19.9***	-39.8***	-997.5***	-34.2***	-68.4***	-1,903.9***
Rear Load Fees	22.8***	45.6***	424.3***	-59.7***	-119.4***	-996.8***	27.9***	55.8***	514.0***
N	493,476	493,476	493,476	493,476	493,476	493,476	493,476	493,476	493,476
Median of LHS	-156.5			-325.2			-428.6		
Variance. of LHS	112.2			488.1			516.7		
50^{th}-25^{th} Percentile of LHS	-154.4			-405.1			339.0		

Table A.5: Analysis of Fund Flows and Distress – Robustness Tests

This table reports results for two sets of robustness checks on the baseline regressions of monthly fund (net) flows (Panel A, Column 1 of Table 3) and large outflows (Panel A, Columns 4 and 7 of Table 3) on peer fund (net) flows. In Columns 1-3, the independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. In columns 4-9, Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. Panel A summarizes robustness checks to alternative specifications. Columns 1, 4, and 7 are for the baselines specification in Table 3, to which we add controls for fund characteristics that include fund family size, fund performance (alpha), fund expense ratio, and rear load fees (Columns 2, 5, and 8), and lagged flows (Columns 3, 6, and 9). Panel B summarizes robustness to alternative clustering of the standard errors, which include clustering by fund as in the baseline (Columns 1, 4, and 7), clustering by fund family (Columns 2, 5, and 8), and clustering by Lipper fund objective class (Columns 3, 6, and 9), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators – Robustness to Alternative Specifications

	Monthly % Flows			Extreme Outflows			Extreme Inflows		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specification=	levels	levels	lagged dep	levels	levels	lagged dep	levels	levels	lagged dep
Peer Flows$_{i,t-1}$	2.324***	1.375***	0.871***						
	(0.021)	(0.020)	(0.019)						
Peer Extreme Outflows$_{i,t-1}$				1.371***	1.353***	0.620***			
				(0.024)	(0.025)	(0.023)			
Peer Extreme Inflows$_{i,t-1}$							2.731***	1.909***	1.079***
							(0.021)	(0.022)	(0.020)
Fund Controls	No	Yes	No	No	Yes	No	No	Yes	No
Clustering, FE	Fund, Time	Fund, Time	Fund Obj, Time	Fund, Time	Fund, Time	Fund Obj, Time	Fund, Time	Fund, Time	Fund Obj, Time
N	493,476	460,601	488,461	493,476	460,601	488,461	493,476	460,601	488,461
R^2(%)	13.30	13.86	16.15	8.77	9.52	7.04	15.62	15.98	20.39

Panel B: Fund & Time Fixed Effects Estimators – Robustness to Alternative Clustering

	Monthly % Flows			Extreme Outflows			Extreme Inflows		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Flows$_{i,t-1}$	2.324***	2.324***	2.324***						
	(0.021)	(0.182)	(0.161)						
Peer Extreme Outflows$_{i,t-1}$				1.371***	1.371***	1.371***			
				(0.024)	(0.094)	(0.084)			
Peer Extreme Inflows$_{i,t-1}$							2.731***	2.731***	2.731***
							(0.021)	(0.204)	(0.173)
Fund Controls	No	No	No	No	No	No	No	No	No
FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
Clustering	Fund	Fund Family	Fund Obj.	Fund	Fund Family	Fund Obj.	Fund	Fund Family	Fund Obj.
N	493,476	493,476	493,476	493,476	493,476	493,476	493,476	493,476	493,476
R^2(%)	13.30	13.30	13.30	13.30	13.30	13.30	13.30	13.30	13.30

Table A.6: Analysis of Fund Performance and Decisions – Economic Significance

This table present an assessment of the economic magnitude of the effect of peer fund (net) flows on fund performance and decisions. We assess economic significance relative to other standard fund characteristics (fund family size, performance (alpha), expense ratio, and rear load fees), as well as relative to the within-fund distribution of performance and decisions. Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. The time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. All columns report the effect of a one-standard deviation change in the right-hand side variable flows from the baseline regression specification in Tables 4-8. For example, a one-standard deviation increase in peer flows is associated with a 9 bps increase in fund monthly returns. The three rows at the bottom report the within-firm median, variance and quartile change of the left-hand side variables.

Panel A: Fund & Time Fixed Effects Estimators									
	Performance & Fees			Portfolio & Liquidity			Fire-Sale Mechanism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome (%) =	Return	Alpha	Rear Fees (bps)	Corp. Holdings	Cash Holdings	Illiquidity	Fire Sales	Bond Fire Sales	Maturity
Estimate * X Increase in RHS, X=	1 SD Δ RHS	1 SD Δ RHS	1 SD Δ RHS	1 SD Δ RHS	1 SD Δ RHS	1 SD Δ RHS	1 SD Δ RHS	1 SD Δ RHS	1 SD Δ RHS
Peer Flows$_{i,t-1}$	0.09***	0.03***	-0.03*	0.05***	0.26***	-0.25***	-0.02	-0.15***	-1.93***
Peer Extreme Outflows$_{i,t-1}$	-0.14***	-0.02***	0.04***	-0.02	-0.19***	1.17***	0.21***	0.40***	1.39***
Peer Extreme Inflows$_{i,t-1}$	0.05***	0.01***	-0.00	0.08*	0.16***	-0.04	-0.07	-0.03	-0.39
log(Fund Family Size)	-0.07***	-0.01***	-0.01	-0.03	0.06***	-0.21*	-0.33***	0.65***	-8.60***
Alpha			0.07***	-0.04*	0.20***	-2.65***	0.12*	0.13	0.95*
Expense Ratio	0.01**	0.01***		-0.07***	-0.16	-1.28***	0.12*	0.18**	2.38***
Rear Load Fees	0.00	-0.00***		0.03	0.19***	-1.09***	0.88***	0.59***	-9.37***
N	493,476	493,476	328,550	134,930	457,285	317,404	134,930	92,955	262,447
Median of LHS	0.10	-0.02	0	0	-0.34	-5.60	-4.34	-5.13	21.01
Variance of LHS	0.05	0.01	0.02	36.301	80.61	16.66	6.11	5.27	476.20
50^{th}-25^{th} Percentile of LHS	-0.81	-0.19	-0.04	-1.202	-2.63	19.20	-4.41	-3.49	-75.01

Table A.7: Analysis of Fund Performance and Decisions – Robustness Tests

This table reports results for two sets of robustness checks on the regressions of fund performance and decisions (Table 4-8) on peer fund (net) flows. The main independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. Panels A and B summarize robustness checks to alternative specifications. Panel A adds to the baseline specification controls for fund characteristics that include fund family size, fund performance (alpha), fund expense ratio, and rear load fees. Panel B adds the lagged dependent variable. Panels C and D summarize robustness to alternative clustering of the standard errors, which include clustering by fund family (Panel C), and by Lipper fund objective class (Panel D), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators – Robustness to Alternative Specification with Fund Controls									
	Performance & Fees			Portfolio & Liquidity			Fire-Sale Mechanism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome=	Return	Alpha	Rear Fees (%)	Corp. Holdings	Cash Holdings	Illiquidity	Fire Sales	Bond Fire Sales	Maturity
Peer Flows$_{i,t-1}$	0.136***	0.035***	-0.035	4.374*	28.959***	-0.340***	-0.018	-0.131	-3.089***
	(0.004)	(0.001)	(0.024)	(2.446)	(2.085)	(0.093)	(0.098)	(0.117)	(0.743)
Peer Extreme Outflows$_{i,t-1}$	-0.080***	-0.013***	0.022**	-0.401	-10.455***	0.617***	0.127***	0.176***	1.292***
	(0.002)	(0.001)	(0.009)	(1.002)	(0.752)	(0.032)	(0.037)	(0.049)	(0.355)
Peer Extreme Inflows$_{i,t-1}$	0.024***	0.009***	-0.006	0.069	5.324***	-0.015	-0.064*	-0.105	-0.412
	(0.002)	(0.001)	(0.009)	(0.951)	(0.786)	(0.035)	(0.034)	(0.065)	(0.410)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	493,476	493,476	328,550	134,930	457,285	317,404	134,930	92,955	262,447

Panel B: Fund & Time Fixed Effects Estimators – Robustness to Alternative Specification with Lagged Dependent									
	Performance & Fees			Portfolio & Liquidity			Fire-Sale Mechanism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome=	Return	Alpha	Rear Fees (%)	Corp. Holdings	Cash Holdings	Illiquidity	Fire Sales	Bond Fire Sales	Maturity
Peer Flows$_{i,t-1}$	0.107***	0.028***	-0.008	5.903***	3.456***	-0.101***	-0.095	-0.104	-1.099***
	(0.003)	(0.002)	(0.020)	(2.032)	(0.835)	(0.033)	(0.084)	(0.082)	(0.104)
Peer Extreme Outflows$_{i,t-1}$	-0.067***	-0.011***	0.030***	-1.021	-1.021***	0.493**	0.236***	0.242***	4.445***
	(0.001)	(0.001)	(0.008)	(0.869)	(0.204)	(0.228)	(0.033)	(0.039)	(0.529)
Peer Extreme Inflows$_{i,t-1}$	0.025***	0.008***	-0.019**	0.570	0.570	-0.011	-0.024	-0.009	-0.732
	(0.001)	(0.001)	(0.008)	(0.780)	(0.780)	(0.023)	(0.029)	(0.044)	(0.672)
Fund Controls	No	No	No	No	No	No	No	No	No
Clustering, FE	Fund Obj, Time	Fund Obj, Time	Fund Obj, Time	Fund Obj, Time	Fund Obj, Time	Fund Obj, Time	Fund Obj, Time	Fund Obj, Time	Fund Obj, Time
N	493,476	493,476	328,550	134,930	457,285	317,404	134,930	92,955	262,447

Table A.7: Analysis of Fund Performance and Decisions – Robustness Tests (Continued)

This table reports results for two sets of robustness checks on the regressions of fund performance and decisions (Table 4-8) on peer fund (net) flows. The main independent variable, Peer Flows, is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes. Extreme Peer Outflows and Extreme Peer Inflows are dummies for Peer Flows in the lowest and highest ten percent of the distribution, respectively. Panels A and B summarize robustness checks to alternative specifications. Panel A adds to the baseline specification controls for fund characteristics that include fund family size, fund performance (alpha), fund expense ratio, and rear load fees. Panel B adds the lagged dependent variable. Panels C and D summarize robustness to alternative clustering of the standard errors, which include clustering by fund family (Panel C), and by Lipper fund objective class (Panel D), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel C: Fund & Time Fixed Effects Estimators – Robustness to Alternative Clustering by Fund Family

	Performance & Fees			Portfolio & Liquidity			Fire-Sale Mechanism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome=	Return	Alpha	Rear Fees (%)	Corp. Holdings	Cash Holdings	Illiquidity	Fire Sales	Bond Fire Sales	Maturity
Peer Flows$_{i,t-1}$	0.117***	0.032***	-0.041	6.353	32.834***	-0.318	-0.069	-0.242	-3.320
	(0.018)	(0.008)	(0.053)	(5.336)	(10.390)	(0.788)	(0.252)	(0.205)	(4.131)
Peer Extreme Outflows$_{i,t-1}$	-0.079***	-0.013***	0.020	-1.104	-10.378**	0.641***	0.115**	0.254**	1.402**
	(0.009)	(0.002)	(0.020)	(2.654)	(4.733)	(0.130)	(0.051)	(0.123)	(0.620)
Peer Extreme Inflows$_{i,t-1}$	0.023***	0.009***	0.000	1.496	7.458**	-0.021	-0.043	-0.024	-0.202
	(0.005)	(0.002)	(0.008)	(2.121)	(3.749)	(0.268)	(0.083)	(0.104)	(1.878)
Fund Controls	No	Yes	No	No	Yes	No	No	Yes	No
FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
Clustering	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family	Fund Family
N	493,476	493,476	328,550	134,930	457,285	317,404	134,930	92,955	262,447

Panel D: Fund & Time Fixed Effects Estimators – Robustness to Alternative Clustering by Fund Objective

	Performance & Fees			Portfolio & Liquidity			Fire-Sale Mechanism		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome=	Return	Alpha	Rear Fees (%)	Corp. Holdings	Cash Holdings	Illiquidity	Fire Sales	Bond Fire Sales	Maturity
Peer Flows$_{i,t-1}$	0.117***	0.032***	-0.041*	6.353**	32.834***	-0.318	-0.069	-0.242*	-3.320
	(0.022)	(0.008)	(0.021)	(2.968)	(8.362)	(0.573)	(0.207)	(0.140)	(3.561)
Peer Extreme Outflows$_{i,t-1}$	-0.079***	-0.013***	0.020**	-1.104	-10.378***	0.641**	0.115**	0.254**	1.402***
	(0.014)	(0.002)	(0.009)	(2.115)	(3.175)	(0.249)	(0.050)	(0.096)	(0.543)
Peer Extreme Inflows$_{i,t-1}$	0.023***	0.009**	0.000	1.496*	7.458*	-0.021	-0.043	-0.024	-0.202
	(0.004)	(0.003)	(0.009)	(0.865)	(3.634)	(0.166)	(0.061)	(0.098)	(1.532)
Fund Controls	No	No	No	No	No	No	No	No	No
FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
Clustering	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.	Fund Obj.
N	493,476	493,476	328,550	134,930	457,285	317,404	134,930	92,955	262,447

Table A.8: Identification of Fund Flows and Distress – Economic Significance

This table present an assessment of the economic magnitude of the effect of peer treatment on monthly fund (net) flows for each of the three types of treatment considered in the baseline analysis of Table 3, Panel B (Columns 1, 4, and 7, respectively). We assess economic significance relative to other standard fund characteristics (fund family size, performance (alpha), expense ratio, and rear load fees), as well as relative to the within-fund distribution of flows. Peer Treatment is defined as a weighted sum of three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Columns 1-3); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Columns 4-6); and the Morningstar 5-star rating of funds that are close to their rating-category threshold, as defined by those funs whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold (Columns 7-9). The time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively. Columns 1, 4, and 7 report the effect of a one-standard deviation change in the right-hand side variable on fund flows from our baseline regression specification in Table 3. For example, a one-standard deviation increase in peer Spitzer 2003 treatment is associated with a 23.6 decrease in fund flows. This specification is the same as Column (1) of Panel B, Table 3. Columns 2, 5, and 8 report the effect of a large, two standard deviation change in the right-hand side variable on flows, and Columns 3, 6, and 9 report the effect of a change in the RHS variable from its smallest to its largest value. The three rows at the bottom report the within-firm median, variance and quartile change of the left-hand side variables.

Panel A: Fund & Time Fixed Effects Estimators (basis points)									
	Spitzer 2003			Fed Rate*Low Gov Exposure			MS 5-Star Rating RD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimate * X Increase in RHS, X=	1 SD Δ RHS	2 SD Δ RHS	Min-Max Δ RHS	1 SD Δ RHS	2 SD Δ RHS	Min-Max Δ RHS	1 SD Δ RHS	2 SD Δ RHS	Min-Max Δ RHS
Peer Treatment$_{i,t-1}$	-23.6***	-47.2***	-168.8***	-17.9***	-35.8***	-140.2***	10.6***	21.2***	92.5***
log(Fund Family Size)	18.6***	37.2***	243.4***	49.8***	99.6***	608.5***	32.1***	64.2***	413.8***
Alpha	76.5***	153.0***	933.2***	-72.9***	-145.8***	-888.6***	103.5***	207.0***	1,250.8***
Expense Ratio	-11.7***	-23.4***	-651.7***	-19.9***	-39.8***	-997.5***	-34.2***	-68.4***	-1,903.9***
Rear Load Fees	22.8***	45.6***	424.3***	-59.7***	-119.4***	-996.8***	27.9***	55.8***	514.0***
N	138,072	138,072	138,072	493,476	493,476	493,476	135,086	135,086	135,086
Median of LHS	-184.6			-156.5			-147.9		
Variance. of LHS	107.4			112.2			119.9		
50^{th}-25^{th} Percentile of LHS	-151.3			-154.4			-147.5		

Table A.9: Identification of Flows and Distress – Robustness Tests

This table reports results for two sets of robustness checks on the effect of peer treatment on monthly fund flows (Panel B, Columns 1, 4, and 7 of Table 3, respectively). Peer Treatment is defined as a weighted sum of three different treatments, in turn: a dummy that is equal to one after a fund is involved in the mutual fund scandal of 2003 ("Spitzer 2003," Columns 1-3); the interaction of the federal funds rate with a dummy that is equal to one for funds that have below median exposure to government assets, as measured by their percentage holdings of government securities ("Fed Rate*Low Gov Exposure," Columns 4-6); and the Morningstar 5-star rating of funds that are close to their rating-category threshold, as defined by those funs whose Morningstar risk-adjusted return is within three percentage points around the respective rating category threshold (Columns 7-9). Panel A summarizes robustness checks to alternative specifications. Columns 1, 4, and 7 are for the baselines specification in Table 3, Panel B to which we add controls for fund characteristics that include fund family size, fund performance (alpha), fund expense ratio, and rear load fees (Columns 2, 5, and 8), and lagged flows (Columns 3, 6, and 9). Panel B summarizes robustness to alternative clustering of the standard errors, which include clustering by fund as in the baseline (Columns 1, 4, and 7), clustering by fund family (Columns 2, 5, and 8), and clustering by Lipper fund objective class (Columns 3, 6, and 9), with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Fund & Time Fixed Effects Estimators – Robustness to Alternative Specifications

	Spitzer 2003			Fed Rate*Low Gov Exposure			MS 5-Star Rating RD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specification=	levels	levels	lagged dep	levels	levels	lagged dep	levels	levels	lagged dep
Peer Treatment$_{i,t-1}$	-0.051***	-0.095***	-0.040***	-0.009***	-0.003***	-0.005***	0.005***	0.004***	0.011***
	(0.014)	(0.010)	(0.008)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Fund Controls	No	Yes	No	No	Yes	No	No	Yes	No
Clustering, FE	Fund, Time	Fund, Time	Fund Obj, Time	Fund, Time	Fund, Time	Fund Obj, Time	Fund, Time	Fund, Time	Fund Obj, Time
N	138,072	131,873	136,907	493,476	460,601	488,461	135,086	127,060	133,665
R^2(%)	12.61	13.62	17.80	11.04	12.96	15.80	10.72	13.04	14.31

Panel B: Fund & Time Fixed Effects Estimators – Robustness to Alternative Clustering

	Spitzer 2003			Fed Rate*Low Gov Exposure			MS 5-Star Rating RD		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Peer Treatment$_{i,t-1}$	-0.051***	-0.051**	-0.051**	-0.009***	-0.009**	-0.009**	0.005***	0.005**	0.005**
	(0.014)	(0.025)	(0.021)	(0.001)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Fund Controls	No	No	No	No	No	No	No	No	No
FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
Clustering	Fund	Fund Family	Fund Obj.	Fund	Fund Family	Fund Obj.	Fund	Fund Family	Fund Obj.
N	138,072	138,072	138,072	493,476	493,476	493,476	135,086	135,086	135,086
R^2(%)	12.61	12.61	12.61	11.04	11.04	11.04	10.72	10.72	10.72

Table A.10: Analysis of Fund Flows and Performance – Robustness to Alternative Network Definitions

This table reports results for four robustness checks on the regression analysis of monthly fund (net) flows (Panel A) and monthly fund performance (Panel B) on peer fund (net) flows. For reference, Column 1 report results for the main independent variable, Peer Flows, which is a weighted sum of peer fund families' net flows, with weights calculated as the pair-wise degree of overlap (correlation) in asset allocation across Lipper Objective classes using the shares of total TNA for each fund family in each (major) Lipper asset class to measure overlap. Columns 2 to 5 summarize robustness checks to alternative definitions of the weights, which are calculated as a weighted average of peer fund families' net flows for alternative definitions of the pair-wise correlation across Lipper classes in Columns 2 to 4, and as a weighted average of peer funds' net flows using the shares of the total asset holding portfolio for each fund in each fixed-income security (cusip) to measure overlap in Column 5. The weights are calculated adjusting for differences in scale (Total TNA) in each Lipper class (Column 2), based on correlation in fund family performance (returns, Column 3), and using the shares of total holding value for each fund family in each (major) Lipper asset class to measure overlap (Column 4). The time period is 1992-2014. All specifications include fund and time (year) fixed effects. Standard errors are clustered by fund, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Analysis of Fund Flows – Monthly % Flows					
	(1)	(2)	(3)	(4)	(5)
Network Definition=	Baseline	Size-weighted by asset class	Correlation is performance-based	Correlation is holding-based	Fund-level, correlation is secutiry-based
Peer Flows$_{i,t-1}$	2.324***	2.185***	1.983***	2.148***	18.862***
	(0.021)	(0.019)	(0.017)	(0.019)	(0.115)
1 SD Δ RHS	183.2***	183.0***	186.5***	188.4***	263.3***
Fund Controls	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	493,476	493,476	493,476	493,476	493,476
R^2(%)	13.30	13.28	13.36	13.34	15.67
Panel B: Analysis of Fund Performance – Monthly Return					
	(1)	(2)	(3)	(4)	(5)
Peer Treatment$_{i,t-1}$	0.117***	0.108***	0.101***	0.109***	0.879***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.021)
1 SD Δ RHS	0.09***	0.09***	0.10***	0.10***	0.12***
Fund Controls	No	No	No	No	No
Clustering, FE	Fund, Time	Fund, Time	Fund, Time	Fund, Time	Fund, Time
N	493,476	493,476	493,476	493,476	493,476
R^2(%)	8.47	8.46	8.48	8.47	8.61