Vulnerable Asset Management? The Case of Mutual Funds*

Christoph Fricke
Deutsche Bundesbank

Daniel Fricke
Deutsche Bundesbank
University College London

Abstract

Is the asset management sector a source of financial instability? This paper develops a macroprudential stress test model which enables the quantification of systemic vulnerabilities due to fire sales in this sector. The model incorporates the flow-performance relationship as an additional funding shock in the model of Greenwood, Landier, and Thesmar (2015). Using data on US equity mutual funds for the period 2003-14, we quantify both fund-specific and system-wide (aggregate) vulnerabilities to fire sales over time. Our main finding is that the aggregate vulnerability, according to this propagation mechanism, is relatively small in comparison with values reported for banks. However, during periods of low market liquidity, the vulnerability of the system can become significant. Our paper also contributes to the ongoing discussion on the SIFI designation of Non-Bank Non-Insurer entities. For this purpose, we explore the determinants of individual funds' vulnerability to systemic asset liquidations, highlighting the importance of size and portfolio illiquidity. Therefore, regulators should monitor structural vulnerabilities in the fund sector arising through liquidity transformation.

Keywords: asset management; mutual funds; systemic risk; fire sales; liquidity

JEL classification: G10; G11; G23.

*Corresponding author: Daniel Fricke, Phone: +49 (0)69 9566 2359. E-Mail: daniel.fricke@bundesbank.de. Christoph Fricke, Phone: +49 (0)69 9566 7520. E-Mail: christoph.fricke@bundesbank.de. An earlier version of the manuscript was entitled *Vulnerable Funds?*. We thank Fernando Duarte and Thomas Eisenbach for providing information on the NY Fed's approach to estimate fund sector vulnerabilities. We also thank participants of the Second Conference on Network Models and Stress Testing for Financial Stability 2017, Annual Meeting Verein für Socialpolitik 2017, 33rd SUERF Colloquium & Bank of Finland Conference on Shadow Banking, Deutsche Bundesbank Shadow Banking Seminar 2016, an ECB Seminar in January 2017, a seminar at UCL in April 2017, a seminar at the Bank of England in November 2017, and Deutsche Bundesbank German Economists Abroad Meeting 2017. The paper especially benefited from valuable comments by Yuliya Baranova, Stephen Cecchetti, Thomas Eisenbach, Stephan Jank, Harun Mirza, Sofia Priazhkina, Laura Silvestri, Christian Upper, and Nick Vause. The views expressed in this paper represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank or its staff.

1 Introduction

Ever since the global financial crisis of 2007-09, the shadow banking system (or more accurately non-bank non-insurer financial intermediaries) has been under close scrutiny with regard to its potential contribution to financial instability (Financial Stability Board (2011, 2015); Office of Financial Research (2013); European Central Bank (2014); International Monetary Fund (2015); Bauguess (2017)). This is particularly true of the global asset management industry – comprising, among others, mutual funds and hedge funds – which has grown tremendously both in terms of size and importance over the last decades. Figure 1, which is reproduced from (Bank for International Settlements, 2014, p. 115), illustrates this growth for the period 2002-12 by showing the total assets held by the 500 largest global asset managers over this period. The increasing importance of market-based financial intermediation offers new funding opportunities for businesses and households but might also entail new risks (Bank for International Settlements (2014)). For example, the asset management industry became more concentrated: the share of assets held by the 20 largest institutions has grown over time (see Figure 1 and European Central Bank (2014)). Thus, the behavior of a relatively small number of asset managers might have a strong impact on market dynamics and ultimately on funding costs for the real economy.[1]

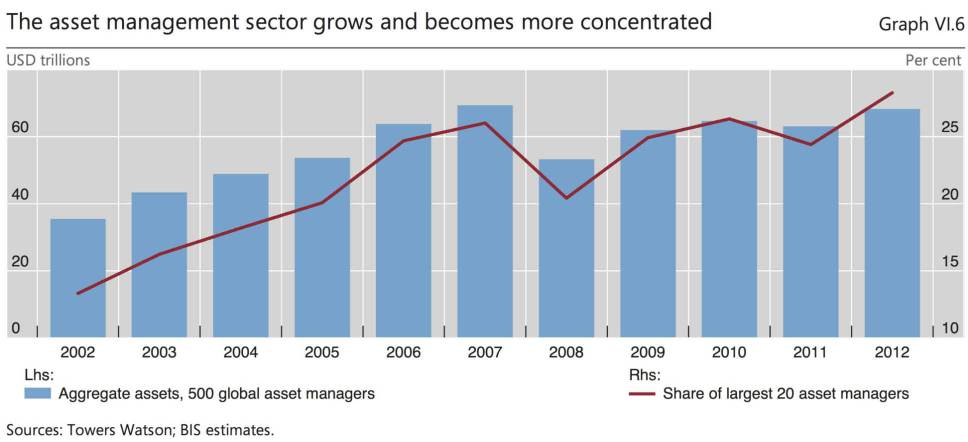

Figure 1: Growth and concentration in the asset management industry. The plot is taken from (Bank for International Settlements, 2014, p. 115) and shows both the total assets under management for 500 global asset managers and the share of assets held by the 20 largest institutions.

There is no clear consensus on whether the asset management industry contributes to financial instability. On the one hand, historical examples suggest that significant portfolio overlap and correlated trading strategies can indeed have major systemic repercussions. Two prominent examples are the role of portfolio insurers in the market crash of October 1987, and the systemic repercussions of the hedge fund Long Term Capital Management in 1998. On the other hand, leading industry representatives repeatedly argue that asset managers in general, and mutual funds in particular, are not a source of systemic risks.

[1] Asset managers are typically evaluated on the basis of short-term performance, and fund revenues are linked to fluctuations in customer fund flows. These arrangements can exacerbate the procyclicality of asset prices, and greater concentration in the sector could in fact strengthen this effect (see Feroli, Kashyap, Schoenholtz, and Shin (2014)).

For example, the Investment Company Institute claims that existing microprudential regulations for investment funds (e.g. leverage and liquidity constraints) are effective (Investment Company Institute (2016)). Therefore, there is a general need for regulators and policymakers to understand whether the fund industry is vulnerable to systemic crises and might contribute to financial instability. Our paper tackles this question.

How to quantify systemicness of asset managers is an open question. The Financial Stability Board (2015) mentions asset liquidation and exposure risk as channels through which stress can propagate within the sector, and therefore size and leverage could serve as systemicness indicators. Danielsson and Zigrand (2015) advocate focusing on asset managers' negative externalities in order to gauge their impact on financial instability. The externality stems from the price impacts generated by the asset liquidations of asset managers, which affect the market value of other investors' portfolios.

In this paper we quantify the vulnerability of asset managers to systemic asset liquidations, incorporating both funding liquidity shocks and fire sale price dynamics into a stress test.[2] For this purpose, we propose an extension of Greenwood et al. (2015), who introduced a simple fire sale model for the banking sector. In the original model, systemic risks are largely driven by leverage - something that makes sense for highly leveraged financial actors, such as commercial banks or broker-dealers (Adrian and Shin (2010)). However, stress test models for asset managers must take into account the specifics of mutual funds' business models. Mutual funds generally make little use of leverage and rely on short-term funding by promising daily redeemable fund shares (e.g., Pozen and Hamacher (2011)).

Structures in the redemption process confront funds with a fragile funding base (Securities and Exchange Commission (2018)). The idea is that, in order to generate sufficient cash to finance outflows due to investor redemptions, mutual funds might have to liquidate assets which can affect market prices. These costs of liquidation are borne by the remaining fund investors, suggesting the existence negative externalities. These externalities create incentives for shareholders to redeem their fund shares as early as possible (first-mover advantage). In a theoretical model, Chen, Goldstein, and Jiang (2010) show that information on fund returns can allow fund investors to learn about redemption decisions of others. In this regard, negative returns can serve as a signal for flow-driven asset liquidations. Empirical evidence underlines the existence of a positive flow-performance relationship: investors tend to redeem their fund shares in response to negative performances (see Sirri and Tufano (1998); Berk and Green (2004)). This implies that, in order to generate sufficient cash to finance these outflows, mutual funds might have to sell additional assets in a declining market. Hence, fire sale price cascades might occur even in the absence of leverage. In order to adequately model this channel, we incorporate the flow-performance relationship into the Greenwood et al. (2015) model, such that a small initial shock could potentially wipe out significant parts of the fund sector's total assets under management.

Our new stress test model allows to quantify the vulnerabilities of both the aggregate mutual fund sector and those of individual funds over time. We apply the model to the economically meaningful subset of U.S. domestic equity mutual funds for the period 2003-

[2]Thus, our macroprudential stress test includes the two key components of stress tests identified by Greenwood and Thesmar (2011), and Tarullo (2016).

14.[3] At the end of 2014, this fund type accounted for more than 52% of the U.S. investment industry's total assets (Investment Company Institute (2015)). The main advantages of focusing on this subset of funds are the availability of detailed data on these funds' stock holdings for the period 2003-14, and detailed information of the individual stocks in the holdings data (most importantly price impact parameters).

Our main finding is that mutual funds' aggregate vulnerability, according to this propagation mechanism, is modest in most specifications. However, during periods of low market liquidity, the vulnerability of the system can become more significant. For example, in the most relevant scenario with time-varying and asset-specific price impacts, in response to a 5% shock on asset values we find a maximum value of aggregate vulnerability (AV, the fraction of equity wiped out due to the fire sale mechanism, relative to total equity) of 1.3%. These vulnerabilities are significantly smaller than those reported for banks. For the sake of comparison, Greenwood et al. (2015) report an AV of 245% among the largest European banks in response to a shock of comparable magnitude as the one considered in our paper (50% reduction of GIIPS sovereign debts). Differences in the systemic risk contribution between asset managers (mutual funds in particular) and banks are founded in their different business models. Two of these structural differences are particularly relevant, namely that the flow-performance relationship is relatively weak for mutual equity funds and, more importantly, mutual funds use much less leverage than banks. These results suggest that systemic risks among mutual funds are unlikely to be a major concern, at least when looking at this part of the financial system in isolation. We also find that the time dynamics of AV strongly depend on the choice of price impact parameters. Despite the strong growth of the system over our sample period, we find that aggregate vulnerability only exhibits a significantly positive time trend when we ignore the time dynamics in our price impact parameters. Lastly, we also explore the determinants of individual funds' contribution to systemic asset liquidations. Here, we highlight the importance of fund size, diversification levels, and portfolio illiquidity. We also discuss implications for the design of future stress tests and the monitoring of fund vulnerabilities more general.

Our paper proposes a macroprudential stress test for asset managers with an application to the U.S. mutual fund industry. Closest to our work is a blogpost by the New York Fed (Cetorelli, Duarte, and Eisenbach (2016)), which performs a comparable stress test for U.S. high-yield bond funds. Dunne and Shaw (2017) relate fund-specific characteristics, such as leverage or usage of derivatives, to funds' exposure to a tail event in the fund sector (Marginal Expected Shortfall). By contrast, the vast majority of existing work on systemic risk tends to concentrate on the banking sector (see Glasserman and Young (2016) for a recent survey). Note that this literature is mainly concerned with default contagion in interbank markets, where banks can be connected either directly (e.g. via borrowing and lending relationships on the interbank market) or indirectly (e.g., via holding similar assets in their portfolios). Portfolio similarity exposes intermediaries to the same market risk exposure which serves as an amplification mechanism for fire

[3] Within the asset management industry, mutual funds are by far the most important players. For example, in the U.S. more than 90.4 million individuals, or roughly 43% of all households, invested their money through mutual funds in 2014. Furthermore, mutual funds have been among the largest investors in U.S. financial markets for the last two decades, holding roughly one quarter of all outstanding stocks at the end of 2014 (Investment Company Institute (2015)).

sale related market price drops. Here, the selling-inducing price decline triggers fire sales of other intermediaries with investments in the same securities. Glasserman and Young (2015) showed that direct connections between banks are unlikely to be a major source of systemic risk, but contagion can be dramatically amplified when allowing for indirect connections as well. In line with mounting empirical literature on the existence of fire sales in various asset markets (e.g., Pulvino (1998) for real assets; Coval and Stafford (2007) for equities; Ellul, Jotikasthira, and Lundblad (2011) and Manconi, Massa, and Yasuda (2012) for corporate bonds), a growing literature is looking at the importance of overlapping portfolios and asset liquidations as a source of systemic risk (Cifuentes, Ferrucci, and Shin (2005); Wagner (2011); Greenwood et al. (2015); Cont and Schaanning (2017); Getmansky, Girardi, Hanley, Nikolava, and Pelizzon (2016)). Much of this literature predicts a positive relationship between portfolio overlap and systemic risk, at least up to a certain point (Caccioli, Shrestha, Moore, and Farmer (2014)). We add to the literature by quantifying the vulnerability of the asset management industry to systemic asset liquidations over a relatively long sample period.

Relative to Cetorelli et al. (2016), we make several important contributions both in terms of stress-test modelling and the actual model application. With regards to the model design, our extension of the model of Greenwood et al. (2015) is flexible enough to be applicable for different kinds of financial intermediaries. The model provides simple closed-form formulae for a fire sale model that incorporates both leverage targeting and funding shocks. The leverage targeting element is arguably better suited for leveraged investors such as banks and broker-dealers, while equity funding shocks are particularly relevant for modelling fund share redemptions in the mutual fund sector. Debt funding shocks, on the other hand, could be relevant for banks during debt market freezes which hamper the rolling-over of existing short-term debt as exemplified by the financial crisis (e.g. Acharya, Gale, and Yorulmazer (2011)). We can recover the original equations of Greenwood et al. (2015) by switching off the equity and debt funding channels, such that leverage targeting would remain the only channel for fire sales. Accordingly, our extended model allows to calculate fire sale vulnerabilities of any given financial system over time, where different channels can be switched off/on to adequately capture the specifics of different sets of institutions. As such, our model could serve as a starting point for proper system-wide stress tests in the future that take into account different sets of financial institutions in a coherent way.

With regards to the model application, we make several contributions that set our paper apart from Cetorelli et al. (2016). First, we focus on a different subset of U.S. mutual funds, namely (domestic) equity funds instead of corporate bond funds. Domestic equity funds represent more than half of the U.S. investment industry's total assets (Investment Company Institute (2015)) and thus are an economically meaningful subset of intermediaries to analyze. We acknowledge that these funds' asset portfolios are likely to be very liquid, in particular in comparison with corporate bond funds, which implies that the price impacts suffered by equity funds' fire sales might be comparably small. However, as documented in the seminal paper of Coval and Stafford (2007), fire sales are a relevant phenomenon for equity funds nonetheless. Our results support these findings, in the sense that the vulnerability of the system is generally modest but can become significant when market liquidity is low. Second, we highlight the importance of allowing for time-varying and asset-specific price impacts. In contrast, much of the existing literature ignores within-asset-class heterogeneity and does not adequately capture the liquidity situation of individual market segments at any point in time (see Greenwood et al. (2015); Cetorelli et al. (2016)). Our results show that such an approach should be avoided as it can yield unreliable fund-level vulnerabilities. Third, in contrast to existing work, we assess the robustness of the empirical flow-performance relationship at great length. Fourth, we also apply our model on different levels of portfolio aggregation, showing that the vulnerability of the system depend on the modeller's choice/granularity of the data at hand. Lastly, our fund-level regressions are novel in the sense that we relate these vulnerability indicators to fund-level characteristics such as size and portfolio illiquidity. These results can be useful for guiding future fund sector regulations.

The remainder of this paper is organized as follows: in Section 2, we introduce an extended version of the model developed by Greenwood et al. (2015). In Section 3, we describe the dataset and explain how we calibrate the model parameters. Section 4 shows aggregate vulnerabilities for different price impact scenarios over time and includes various robustness analyses. Section 5 takes a closer look at fund-specific vulnerabilities. Section 6 discusses the main findings, and Section 7 concludes.

2 Modelling Vulnerabilities

In this section we present an extended version of the model introduced by Greenwood et al. (2015) which is more applicable to the fund sector. What is special about mutual funds compared to banks is their funding model. Mutual fund equity corresponds to redeemable investment shares which investors can purchase/redeem directly with the mutual fund at prices that are fixed (typically once per day). Given that many mutual funds do not use significant leverage, redeemable fund equity typically makes up the entire liability side. Therefore, investor redemptions can force funds to sell assets in order to pay out redeeming investors. This funding structure is in contrast to the predominant liability structure of banks, which generally involves significant debt financing and non-redeemable equity shares. We describe the required model modifications in the following.

2.1 Model

There are N asset managers (institutions) and K assets (investments). Let $M_{\{N\times K\}}$ denote the matrix of portfolio weights, where each element $0 \leq M_{i,k} \leq 1$ is the market-value-weighted share of asset k in investor i's portfolio, and $\sum_k M_{i,k} = 1$ by definition. Each institution i is financed with a mix of debt, D_i, and equity, E_i. $A_{\{N\times N\}}$ is the diagonal matrix of institutions' assets with $A_{i,i} = E_i + D_i\ \forall i$. $B_{\{N\times N\}}$ is the diagonal matrix of leverage ratios with $B_{i,i} = D_i/E_i\ \forall i$. Finally, F_1 denotes a $(K \times 1)$ vector of asset-specific returns (this is the initial shock). All pre-shock variables have a time index of 0.

The four main steps are as follows:

1. We impose an initial shock on the value of asset managers' asset holdings.

2. Investors in these asset managers react to the initial shock by withdrawing some of their investments (flow-performance relationship).

3. Asset managers have fixed leverage targets and liquidate assets according to their original portfolio weights.
4. Asset liquidations affect market prices, with more illiquid assets showing larger price changes for a given liquidation amount (price impacts).

In the following, we describe these steps in detail.

2.1.1 Step 1: Initial Shock

In matrix notation, we obtain asset managers' portfolio returns as

$$R_1 = MF_1, \tag{1}$$

with R_1 being a $(N \times 1)$ vector. This gives us the updated total assets

$$A_1 = A_0(1 + R_1), \tag{2}$$

which yields an equivalent change in the net asset value of equity

$$E_1 = E_0 + A_0 R_1,\text{[4]} \tag{3}$$

and debt (assuming that the initial shock does not wipe out all of the institution's equity)

$$D_1 = D_0. \tag{4}$$

2.1.2 Step 2: Response on the Funding Side

In line with a vast existing literature (e.g. Sirri and Tufano (1998); Berk and Green (2004)), we assume a positive linear relationship between asset managers' performances and net inflows. Hence, negative (positive) performance is followed by an outflow (inflow) of money. To allow for different responses for different types of funding, we derive the equations for the general case where equity and debt may have different flow-performance sensitivities, γ^E and γ^D, as introduced below.[5]

The most simple scenario is that net equity inflows (in absolute terms) are a linear function of an institution's realized return on assets from step 1. This can be written as

$$\frac{\Delta E_2}{E_1} = \gamma^E R_1, \tag{5}$$

where γ^E is the flow-performance sensitivity parameter of equity, and ΔE_2 is the net inflow in dollars. Note that the assumed linearity implies that positive and negative

[4] If the initial shock is large enough, equity could become negative. To prevent this from happening, we could write E_1 as $\max(E_0 + A_0R_1, 0)$ and D_1 as $D_0 + \min(E_0 + A_0R_1, 0)$. For simplicity, we assume that the initial shock is small enough to not wipe out the entire equity.

[5] In the case of investment funds, investors can redeem their equity shares, while in the case of banks, some short-term borrowing may dry up. In the general case, equity and debt may be redeemed simultaneously.

returns are treated symmetrically. This is in line with the findings of Spiegel and Zhang (2013). Similarly, we can write the change in refinancing power as

$$\Delta D_2 = \gamma^D R_1 D_1 = \gamma^D R_1 D_0, \tag{6}$$

where γ^D is the flow-performance sensitivity parameter of debt, and ΔD_2 is the net inflow in dollars.[6]

With these additional adjustments on the liability side of the balance sheet, updated equity and debt can be written as

$$E_2 = E_1(1 + \gamma^E R_1), \tag{7}$$

and

$$D_2 = D_1(1 + \gamma^D R_1). \tag{8}$$

Using the above definitions for D_1 and E_1, we can write total assets as

$$\begin{aligned} A_2 &= A_1 + \Delta E_2 + \Delta D_2 \\ &= A_0 \left(1 + R_1 \left(1 + \gamma^E \left(R_1 + \frac{1}{1+B}\right) + \gamma^D \frac{B}{1+B}\right)\right), \end{aligned} \tag{9}$$

where we used $E_0/A_0 = 1/(1 + B)$. The asset manager has to liquidate assets in order to make the payments, which will affect demand in step 3 below.

Note that the additional funding shock can be seen as an amplifier of the original shock. More precisely, we can write the *adjusted portfolio return* (before asset liquidation) as

$$\begin{aligned} R_2 &= \frac{A_2 - A_0}{A_0} \\ &= R_1 \left(1 + \gamma^E \left(R_1 + \frac{1}{1+B}\right) + \gamma^D \frac{B}{1+B}\right). \end{aligned} \tag{10}$$

Hence, all other things equal, R_2 will be closer to R_1 for more leveraged firms (higher B), with a weaker flow-performance sensitivity (lower γ^E and γ^D).[7]

For the case of no withdrawal of debt, we would impose $\gamma^D = 0$ and $\gamma^E > 0$, in which case the *adjusted return* reads as

$$R_2 = R_1 \left(1 + \gamma^E \left(R_1 + \frac{1}{1+B}\right)\right). \tag{11}$$

The relationship between R_2 and the parameters γ^E and B is nonlinear and can have a substantial impact on the resulting portfolio returns in the model. For example, a mutual

[6] Eq. (6) seems most reasonable for institutions with very short-term debt financing. In fact, we would achieve similar results to those presented here if we distinguish between short- and long-term debt financing, respectively, $D_0 = D_0^L + D_0^S$. That would allow us to assume more realistically that only short-term creditors would be prone to withdrawing their funds (not rolling over the loans), while long-term debt is much more slow-moving, see Gorton and Metrick (2012).

[7] If we were to distinguish between short- and long-term debt, see footnote 6, the last term would read $\gamma^D \frac{D_0^S}{A_0}$, where D_0^S is the amount of short-term debt in the initial balance sheet.

fund without leverage ($B = 0$) and $\gamma^E = 2.5$ will have a R_2 that is amplified by a factor of 3 compared to the original R_1. Note that the flow-performance relationship will be somewhat milder for less levered asset managers (higher B amplifies R_1 less strongly) since their equity tranche is relatively small. As we will see below, highly levered institutions will, however, liquidate more assets in order to achieve their leverage target (Step 2.1.3).

Finally, note that in the case where equity and debt have the same flow-performance sensitivity, i.e., where $\gamma = \gamma^E = \gamma^D$, Eq. (10) reduces to

$$R_2 = R_1 \left(1 + \gamma(1 + R_1)\right). \tag{12}$$

2.1.3 Step 3: Leverage Targeting with Fixed Portfolio Weights

In line with Greenwood et al. (2015), we assume that asset managers target their leverage and aim at holding their portfolio weights constant when liquidating (or buying) assets. These two assumptions are quite realistic, particularly so for investment funds: first, asset managers generally need to specify the composition of both their asset and liability side in their sales prospectuses and are unlikely to deviate significantly from these proposed targets. Second, empirical evidence suggests that mutual funds tend to sell assets according to the liquidity pecking-order during normal times, but in a pro-rata fashion during times of market stress (Jian, Li, and Wang (2016)).

Given that asset managers will have to liquidate an amount $\Delta E_2 + \Delta D_2$ due to the withdrawal of short-term funding (equity and debt) after a negative shock, we need to add another leverage targeting component to the total amount to be liquidated. In the original paper, this component is easily found to be $A_0 B R_1$. In our case, things are slightly more complicated, because the original reduction in equity might have been followed by additional outflows of debt and equity, respectively. Given the definition of B, we know that the new value of debt should be $D_3 = E_2 \times B$, or, equivalently,

$$\Delta D_3 = E_2 B - D_2 = A_0 B(R_2 - \gamma^D R_1). \tag{13}$$

Thus, adding all of the above component we end up with total assets to be liquidated per investor of

$$\underbrace{\Phi}_{\text{Amount to be liquidated}} = \underbrace{\Delta E_2}_{\text{Net inflow of equity}} + \underbrace{\Delta D_2}_{\text{Net inflow of debt}} + \underbrace{\Delta D_3.}_{\text{Leverage targetting}} \tag{14}$$

This can be written compactly as

$$\begin{aligned}
\Phi &= \gamma^E E_1 R_1 + \gamma^D D_1 R_1 + A_0 B(R_2 - \gamma^D R_1), \\
&= A_0 \left[\gamma^E \left(\frac{1}{1+B} + R_1 \right) + \gamma^D \left(\frac{B}{1+B} \right) + B(R_2 - \gamma^D R_1) \right].
\end{aligned}$$

This can be broken down into

$$\phi = M' \Phi, \tag{15}$$

which gives a $(K \times 1)$ vector of net asset purchases by all asset managers in period 3. The last term in Eq. (15) corresponds to the ϕ in the Greenwood et al. (2015) model, which we recover when we set $\gamma^D = \gamma^E = 0$. Eq. (15) assumes that both γ^D and γ^E are the same across institutions. We can easily account for a more general case by setting up two diagonal matrices ${\Gamma^E}_{\{N\times N\}}$ and ${\Gamma^D}_{\{N\times N\}}$, where each element $\gamma^E_{i,i}$ and $\gamma^D_{i,i}$ can be institution-specific.[8] With this formulation, we write

$$\phi = M'\Phi = M'A_0\left[\Gamma^E\left(\frac{1}{1+B}+R_1\right)+\Gamma^D\left(\frac{B}{1+B}\right)+B(R_2-\Gamma^D R_1)\right], \tag{16}$$

where the vectorized version of Eq. (10) can be written as

$$R_2 = R_1 \circ \left[1_N + \Gamma^E(R_1+\mathrm{diag}(1+B)^{-1}) + \Gamma^D\mathrm{diag}(B(1+B)^{-1})\right], \tag{17}$$

where $\mathrm{diag}(\cdot)$ retrieves the main diagonal and $\circ$ indicates element-wise multiplication.

2.1.4 Step 4: Fire Sales Generate Price Impact

Asset sales generate a linear price impact

$$F_4 = L\phi = LM'\Phi, \tag{18}$$

where L is the matrix of price impact ratios, expressed in units of returns per dollar of net sales.[9] This gives a final return of

$$R_4 = MF_4 = MLM'\Phi. \tag{19}$$

Note that, empirically, it has been documented that price impact appears to follow a square-root law, i.e. it is a concave function (see Engle, Ferstenberg, and Russell (2012)). Hence, if anything, the assumed linearity of Eq. (18) overestimates the actual price impacts and thus the vulnerability of the system, because liquidating twice as many assets should lead to a price change that is less than twice the original one.

2.2 Measuring Vulnerability Exposures

Suppose there is a negative shock on asset prices, $F_1 = (f_1, f_2, \cdots, f_K), \forall f \in [-1;0)$: this translates into dollar shocks to institutions' assets given by A_1MF_1. The aggregate direct effect on all institutions' assets is the sum of these values: $1'_N A_1 M F_1$. This shock will have additional knock-on effects for individual institutions due to investors' redemptions. The net inflows of equity and debt can also be aggregated as before by multiplying with 1_N. Note that these direct effects do not involve any contagion between institutions.

Using Eq. (19), we can compute the aggregate dollar effect of shock F_1 on institutions' assets through fire sales. To do so, we pre-multiply by $1'_N A_0$, and normalize by the initial total equity, E_0,

$$AV = \frac{1'_N A_0 R_4}{E_0} = \frac{1'_N A_0 MLM'\Phi}{E_0}. \tag{20}$$

AV measures the percentage of aggregate equity that would be wiped out by institutions' asset liquidation in case of a shock of F_1 to asset returns. Similar to Greenwood et al.

[8] Assuming that the Γ matrices are diagonal implies that we ignore cross-institutional correlations in the net inflows.

[9] As in Greenwood et al. (2015), we always make sure that asset prices cannot become negative.

(2015), we can decompose aggregate vulnerability into each asset manager's individual contribution

$$S_i = \frac{1'_N A_0 M L M' \delta_i \delta_i' \Phi}{E_0}, \tag{21}$$

where δ_i is a $(N \times 1)$ vector with all zeros except for the ith element, which is equal to one, and $\sum_i^N S_i = AV$.

Finally, we also define an institution's indirect vulnerability with respect to shock F_1 as the impact of the shock on its equity through the deleveraging of other institutions:

$$IV_i = \frac{\delta_i' A_0 M L M' \Phi}{E_{i,i}}. \tag{22}$$

3 Model Application: Vulnerable Funds?

In this section, we apply our model to the economically meaningful set of U.S. domestic equity funds. We restrict ourselves to this particular fund type since we have accurate information on their asset holdings over a relatively long sample period. Moreover, we can match these holdings with stock-specific information from CRSP-Compustat, which allows us to estimate the price impact parameters separately for each stock over time. In the following, we introduce the data set (Section 3.1) and explain the calibration of model parameters (Section 3.2).

To the best of our knowledge, there is no documented evidence of a flow-performance relationship with regard to debt financing for asset managers in general; therefore, we set $\gamma^D = 0$ in everything that follows. In summary, the model relies on five crucial inputs: (1) size; (2) leverage; (3) portfolio weights; (4) flow-performance relationship; (5) price impact parameters.

3.1 Data

The data used here come from two different sources. First, we obtain mutual funds' portfolio holdings and additional fund-specific information from the CRSP Survivor-Bias-Free Mutual Fund Database (following the literature, we aggregate different share classes to the fund level, e.g., Cremers and Petajisto (2009)). Portfolio holdings are available at the quarterly level from March 2003 onwards and our final sample comprises 48 quarters between Q1 2003 and Q4 2014.[10] In everything that follows, we disregard short positions. Second, we obtain daily stock-specific information from the merged CRSP-Compustat data. The final dataset gives us detailed information on the domestic equity holdings of U.S. mutual funds and we therefore restrict ourselves to equity funds with a focus on domestic stocks (we only keep funds with CRSP objective codes starting with 'ED'). While we include index mutual funds in our sample, we drop exchange-traded funds in everything that follows due to structural differences in their redemption process compared to those of mutual funds.

[10] Note that there is a structural break in the fund identifiers in CRSP: all fund ID's were replaced with new ones from Q3 2010 to Q4 2010. Moreover, there are no holdings data available for Q4 2010 which we replace by the portfolio holdings from Q3 2010 for this particular quarter, which is in line with the typical buy-and-hold strategy of mutual funds.

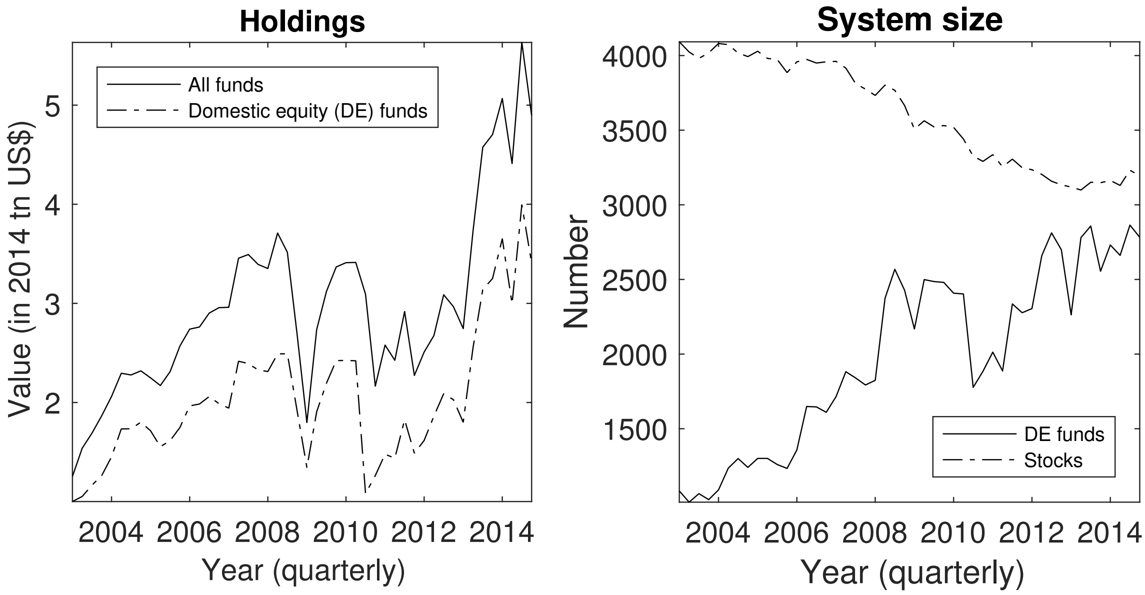

Figure 2: System size. Left: total dollar value of mutual funds' equity holdings over time in 2014 US$ (trillion). The solid line shows the values when including all funds that report their holdings in the CRSP Mutual Fund Database, and the dashed line shows the values for domestic equity (DE) funds only which will be the main focus of this study. Right: number of DE funds and stocks in our sample over time.

The final sample contains 7,936 unique stocks, 7,345 unique funds and 86,898 fund-quarter observations. The flow-performance regressions will be based on monthly data, in which case we have 429,330 fund-month observations.

3.2 Estimation of Model Parameters

In the following, we describe the computation of model parameters. In detail, we discuss fund specific size, leverage, portfolio holdings and corresponding portfolio weights and funds portfolio overlap with other fund portfolios.

3.2.1 Fund Size

Fund size is defined as the dollar value of a fund's portfolio as reported in the matched holdings data. The left panel of Figure 2 shows the total dollar volume of the system over time in trillion dollars, adjusted for inflation (indexed to Q4 2014 based on the CPI available from the St. Louis Fed) to make them comparable over time.[11] The solid line shows the total volume when including all reported holdings, and the dashed-dotted line shows the values for domestic equity funds (DE) only. Clearly, the system has grown over the sample period, partly because the market value of the asset holdings depends on market prices, which also explains the strong effect of the global financial crisis in Figure 2. The right panel of Figure 2 shows the number of active DE funds and the

[11]For the sake of comparability, we adjusted all nominal dollar volumes for inflation (including price impacts). This generally does not affect our vulnerability estimates below since these are always ratios of nominal values.

number of active stocks.[12] Over the sample period the number of active funds (black line) increased quite significantly, while the number of stocks (dotted line) has been shrinking over time.

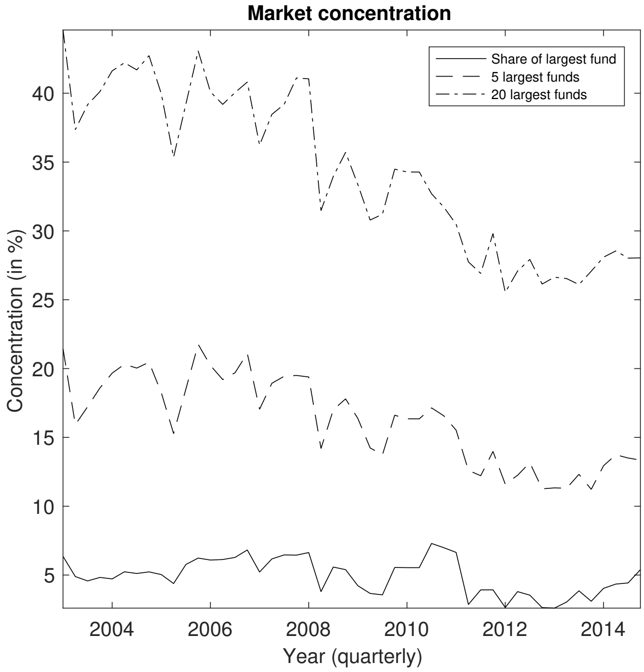

Figure 3: Market concentration. This Figure shows the relative market share of the largest 1, 5, and 20 fund(s) over time, respectively.

As discussed by Greenwood et al. (2015), a more concentrated system might be more vulnerable to systemic asset liquidations. Figure 1 above documents the increase of asset holding concentration of the 500 largest global asset managers over the last decade. An obvious question is whether there is a similar trend for the set of DE mutual funds considered in this study. Figure 3 shows the relative market share of the largest fund(s) over time. More precisely, we divide the total assets under management of the 1, 5, and 20 largest funds by the total size of the system. Somewhat surprisingly, we find that the fraction of assets held by the largest and the 5 largest funds has been relatively stable, while the share of the largest 20 funds has actually decreased over time. This finding could be driven by the growing number of active mutual funds over our sample period and the relatively high levels of competition in the industry (Malkiel (2013)). Overall, based on these dynamics alone, we do not necessarily expect aggregate vulnerabilities of the system to increase over time.

3.2.2 Leverage

Since the CRSP Mutual Fund database does not provide information on funds' leverage ratios, we apply two different approaches to address this shortcoming. These two

[12]Funds are defined as those DE funds that report their holdings in CRSP in a given quarter. Active stocks are defined as those stocks that are held by at least one fund and for which we have additional information in CRSP/Compustat.

approaches are based on the theoretical lower and upper bounds of mutual fund leverage.

First, the upper bound is explicitly stated in the regulatory framework, since mutual funds in the U.S. are subject to tight leverage constraints. According to the Investment Company Act of 1940, "[b]y law, the value of its borrowings may not exceed one-third of the value of its assets" (see Pozen and Hamacher (2011)). In terms of our model, this means that the maximum value of $\frac{D}{A}$ is 0.33, or equivalently, the maximum value of leverage is $\bar{B} = 0.5$. This upper bound is relatively small compared to the values reported for the largest European banks whose leverage can exceed 30 (Greenwood et al. (2015)).

Second, the lower bound is based on the empirical observation that mutual funds often self-impose zero leverage constraints and many investment policies prohibit debt borrowing (Almazan, Brown, Carlson, and Chapman (2004); Boguth and Simutin (2017)). Hence, the most natural baseline scenario is to assume that all mutual funds use zero leverage.

Given that leverage clearly has a positive impact on aggregate vulnerabilities, we contrast the zero-leverage case with the case where all mutual funds use their maximum leverage of $\bar{B}$. These two approaches provide us with the minimum and maximum values of aggregate vulnerabilities at any point in time.

3.2.3 Portfolio Weights and Overlap

In our dataset, we observe the actual equity holdings of U.S. mutual funds. The most granular holdings matrix is $M_{\{N \times K\}}$, where N is the number of active funds and K the number of active stocks.[13] Recall that an element $M_{i,k} \geq 0$ gives the weight of stock k in fund i's portfolio (share of market value), with $\sum_k M_{i,k} = 1 \ \forall i$.

Since we observe additional information on the stocks, we also run our model based on more coarse-grained portfolios, say $M^{\text{agg}}_{\{N \times K^a\}}$ with total number of aggregated assets $K^{\text{agg}} < K$. In the following, we focus on SIC industry codes (4-digits, 2-digits, and 1-digit).[14] For example, the 4-digit SIC classification defines 1,353 unique industry codes, and each element $M^a_{i,k}$ shows the portfolio weight of stocks from industry k in fund i's portfolio. The 2- and 1-digit classifications are defined in a similar fashion, and contain 84 and 10 industries, respectively. Clearly, fewer asset classes lead to a higher average overlap between any pair of investors, meaning that the system's vulnerability for the more granular portfolios M^a should be positively affected compared with the most granular portfolios M.

In Greenwood et al. (2015), aggregate vulnerability depends on the typical overlap of investors' portfolios. One obvious question, therefore, is whether we observe an increase in the typical portfolio overlap over time. In order to answer this question, we define the overlap of two funds' portfolios as

$$\text{Overlap}_{i,j} = \frac{\sum_{k=1}^{K} M_{i,k} M_{j,k}}{\sqrt{\sum_{k=1}^{K} (M_{i,k})^2} \times \sqrt{\sum_{k=1}^{K} (M_{j,k})^2}}, \tag{23}$$

[13] Note that only active stocks are of interest in the following, since stocks need to be held by at least one mutual fund to be subject to any kind of fire sale cascades.

[14] We also classified stocks into different size deciles (based on market capitalization). In terms of aggregate vulnerability, the results are comparable to those reported below for the SIC classification.

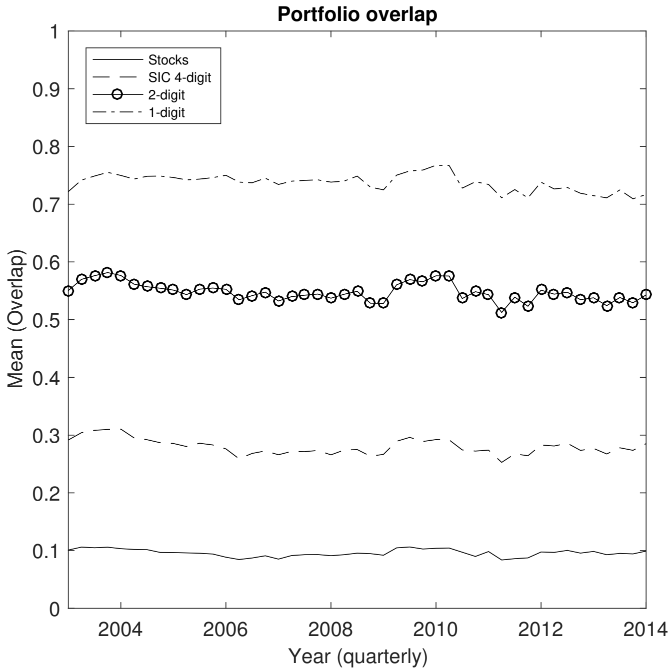

Figure 4: Portfolio overlap. For each quarter we show the cross-sectional average value of Eq. (23) for different aggregation levels. 'Stocks' corresponds to the original holdings reported in the CRSP Mutual Fund Database.

where $i \neq j$. Technically, Overlap is defined as the angle between the vectors of portfolio weights between fund i and fund j (cosine overlap). Overlap ranges between 0 and 1, with higher values indicating more similar portfolios. If two funds have no assets in common, their overlap equals 0; if they hold the exact same portfolios, their overlap corresponds to 1.

Figure 4 shows the cross-sectional average overlap over time for different levels of portfolio aggregation. The solid line shows the typical overlap based on the most granular stock-specific portfolios; the other cases show the results for the aggregated industry-specific portfolios. As expected, portfolio overlap increases with fewer asset classes. In all cases, the values are significantly larger than the minimum value of zero, but similarly the values are also always substantially below its maximum possible value of 1. With regards to the time dynamics, the values appear to be remarkably stable on all aggregation levels.[15] From these numbers one would not expect a strong trend in aggregate vulnerability purely due to the dynamics of portfolio overlap.

3.2.4 Price Impact

We estimate stocks' price impact parameters based on the daily CRSP data. For this purpose, we use the standard Amihud (2002)-ratio as our measure of price impact. Goyenko, Holden, and Trzcinka (2009) have shown that the Amihud-ratio is indeed an adequate proxy for monthly illiquidity conditions.

[15] Fricke (2017) finds a significant but small time trend in the portfolio overlap among the same set of U.S. mutual funds.

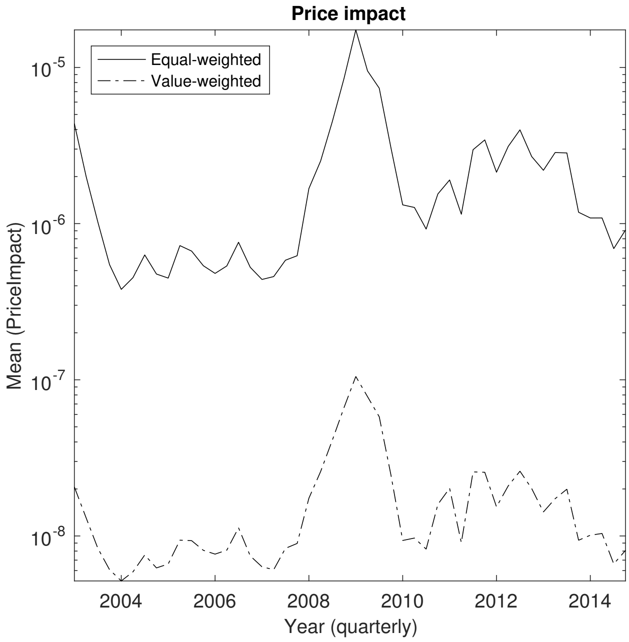

Figure 5: Price impact. For each stock, we calculate the daily Amihud-ratio as $|\text{Return}_{k,t}|/\text{DVolume}_{k,t}$, where $|\text{Return}_{k,t}|$ and $\text{DVolume}_{k,t}$ are the absolute return and the dollar volume of stock k on day t, respectively. We then take the quarterly average of these daily values separately for each stock. Dollar-trading volumes are adjusted for inflation. For each quarter, we show the cross-sectional average values (equal-weighted and weighted by market capitalization). The y-axis is displayed in logarithmic scale.

The Amihud-ratio for asset k on day d is defined as the daily absolute return over the total dollar volume,

$$\text{Amihud}_{k,d} = \frac{|\text{Return}_{k,d}|}{\text{DVolume}_{k,d}}. \tag{24}$$

For each seperate asset, we take the quarterly average of these daily observations and define the price impact of that asset in quarter t as

$$\text{PriceImpact}_{k,t} = \frac{1}{D_{k,t}} \sum \text{Amihud}_{k,d}, \tag{25}$$

where $D_{k,t}$ is the number of daily observations for asset k in quarter t. As for the value of the total holdings above, we adjust the price impacts for inflation (the denominator is based on nominal dollar volumes).

As an illustration of the overall dynamics, Figure 5 shows the cross-sectional average (equal-weighted and value-weighted, respectively) price impact over time, as defined in Eq. (25), on semi-logarithmic scale. The average values in Figure 5 are 4.77×10^{-6} and 1.11×10^{-8}, respectively. The magnitude of the price impact measures is comparable to those reported by Brennan, Huh, and Subrahmanyam (2013). It is worth noting that the typical price impact in our data set is several orders of magnitude larger than the values reported by Greenwood et al. (2015) who assume a price impact of 10^{-13} for most of their asset classes.

Not surprisingly, the value-weighted average is much smaller since stocks with a higher market capitalization tend to be more liquid than assets with a lower market capitalization. In fact, the value-weighted price impact is two orders of magnitude smaller than the equal-weighted price impact. Due to the dependence of the Amihud-ratio on volatility, it also comes as no surprise that there is a clear peak in price impacts during the global financial crisis.[16]

3.2.5 Flow-Performance Relationship

The existence of a flow-performance relationship has become something of a 'stylized fact' in the mutual fund literature. The basic idea is that there is a positive relationship between funds' past performance and their future net inflows. The estimation equation is

$$\text{Flows}_{i,t} = a + b \times \text{Controls}_{i,t} + \gamma^E \times \text{Return}_{i,t-1} + \epsilon_{i,t}, \tag{26}$$

where $\text{Flows}_{i,t}$ is the net inflow of fund i in month t, which we calculate as

$$\text{Flows}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1}(1 + \text{Return}_{i,t})}{\text{TNA}_{i,t-1}}, \tag{27}$$

with TNA as total net assets. Given that we think of the stress test happening at relatively short time-scales, we will estimate Eq. (26) using data at the highest available frequency, namely monthly.[17]

There are many different ways to estimate parameter γ^E: first, one has to decide on the time dimension, i.e., do we estimate parameters for the full sample (γ^E is constant over time) or based on rolling window regressions? Secondly, one has to decide whether the parameter should be estimated separately for each fund (in which case γ^E would have a fund-specific index i), or whether one wants to pool data for different funds (e.g. across all funds or by fund type). Since there are no obvious answers to these questions, in the baseline scenario we use the most transparent approach and pool observations for all funds over time and estimate one γ^E for all funds.[18] This way, the estimated vulnerabilities in the next section will not be driven by any time dynamics in the flow-performance relationship. We discuss this assumption below and relax it in section 4.2.3, where we introduce heterogeneity regarding γ^E across fund types and explore how this affects the aggregate vulnerabilities relative to the baseline scenario.

Lastly, we should stress that the existing literature typically uses adjusted performance measures (returns relative to some benchmark) rather than raw returns. Clearly, adjusting all funds' returns using the same benchmark (such as S&P 500) will not have an impact on our estimate of γ^E when using the Fama and MacBeth (1973) methodology. The results might, however, differ when different funds' returns are adjusted using a different benchmark. In this regard, we find comparable results to those reported below when using style-adjusted and fund-family-adjusted returns, respectively (see Appendix B). Many studies also use factor-model alphas instead of returns (e.g. Goldstein, Jiang, and

[16] In Appendix A we show the typical price impacts for very active trading days.

[17] We also experimented with quarterly data. In this case, the estimates for γ^E are even smaller than those shown below (results available upon request from the authors).

[18] We add further data filters for these regressions: we exclude funds that are less than one year old, and we also drop extreme flow/return observations (above/below +200%/-50%).

Ng (2017)).[19]

Results. Table 1 shows the results of this exercise, using different control variables and estimation approaches, with Newey-West standard errors in parentheses. Columns (1) to (5) show the results using simple pooled OLS: the first column only includes the lagged (1-month) return and flow as control variables. The other columns then add further lags, fund size, and fund-/time-FEs to the regressions. Overall, we find that the parameter on Return(t-1) is always strongly positively significant, but generally rather small. In fact, the maximum value for γ^E is 0.1490 when using pooled OLS. The last column shows the results when using Fama-MacBeth regressions, which yields $\gamma^E = 0.2748$. Given that the typical R^2 is highest in this case, and in order to explore the worst case scenario in the model application, we stick to this value of γ^E in the following. Note that our estimates are broadly comparable with those of Franzoni and Schmalz (2017), who used a similar methodology. We should stress, however, that this is still a small value: a return of -5% would translate into additional net outflows of only $-5\% \times .2748 \approx$ -1.37%, suggesting that the vulnerability of the system is likely to be small even when including the flow-performance relationship.

Discussion. Before moving on, it is worth stressing that the approach taken in the baseline scenario, namely fixing the same γ^E for all funds and for all periods, is mainly chosen for the sake of transparency. Given that our model already contains a number of moving parts (most importantly fund portfolios and price impacts), fixing γ^E can be seen as a reasonable benchmark. However, we do acknowledge that the assumption of a uniform flow-performance relationship across all fund types is likely unrealistic, and we therefore perform a large number of additional analyses with regards to the baseline regressions in Table 1. We report the most important results in Table 2 and leave additional analyses for Appendix B. Table 2 shows three exercises:

(1) *Subsamples.* In order to explore to what extent the estimation differs over different sample periods, we first run the same Fama-MacBeth regressions using only data from the crisis period (2008-09). In line with Franzoni and Schmalz (2017), we estimate $\gamma^E = 0.1781$ which is significantly below the pooled estimator. We also split the sample into two equal-sized subsamples, which cover the years 2003-08, and 2009-14, respectively. We estimate γ^E separately for both subsamples. It turns out that the value is slightly higher in the first subsample ($\gamma^E = 0.2951$ versus 0.2521). However, both values are roughly within one standard deviation of the original estimate for the whole sample; we therefore conclude that the values are not significantly different during the two subsamples.

[19]In the technical Appendix to their blogpost, Cetorelli et al. (2016) describe a two-step estimation approach for γ^E based on fund alphas: in the first stage, they estimate fund-specific alphas using a 12-month rolling window regression of fund returns on the market return separately for each fund. In the second stage, they regress funds' flows against the estimated alphas. For the sake of completeness, we perform a similar exercise using both fund returns and fund alphas. The results can be found in Appendix B.2. In this case, we find that the coefficients are rather broadly distributed around zero (with many negative values) and a smaller average value than our baseline estimate when using fund returns. We therefore stick to our baseline approach in the following.

Flow-Performance Relationship

	Dependent variable: Flows(t)					
	(1)	(2)	(3)	(4)	(5)	(6)
Return(t-1)	0.0508**	0.0553**	0.0629**	0.1402**	0.1490**	**0.2748****
	(0.0039)	(0.0037)	(0.0036)	(0.0111)	(0.0109)	(0.0268)
Return(t-2)		0.0125**	0.0271**	0.0671**	0.0882**	0.1885**
		(0.0037)	(0.0036)	(0.0107)	(0.0107)	(0.0330)
Return(t-3)		0.0095 *	0.0240**	0.0366**	0.0569**	0.0996**
		(0.0038)	(0.0037)	(0.0111)	(0.0110)	(0.0164)
Return(t-4)		0.0133**	0.0310**	0.0472**	0.0696**	0.0507
		(0.0038)	(0.0037)	(0.0107)	(0.0105)	(0.0349)
Return(t-5)		-0.0014	0.0188**	0.0090	0.0387**	0.0664**
		(0.0038)	(0.0037)	(0.0101)	(0.0100)	(0.0179)
Return(t-6)		0.0097 *	0.0284**	0.0413**	0.0687**	0.1047**
		(0.0039)	(0.0039)	(0.0116)	(0.0114)	(0.0273)
Return(t-7)		0.0004	0.0132**	0.0382**	0.0657**	0.0647**
		(0.0036)	(0.0035)	(0.0107)	(0.0104)	(0.0231)
Return(t-8)		0.0004	0.0100**	0.0154	0.0454**	0.0832**
		(0.0036)	(0.0035)	(0.0106)	(0.0100)	(0.0221)
Return(t-9)		0.0096 *	0.0245**	0.0273 *	0.0611**	0.0780**
		(0.0039)	(0.0038)	(0.0111)	(0.0111)	(0.0237)
Return(t-10)		-0.0139**	0.0028	-0.0207	0.0156	0.0070
		(0.0038)	(0.0037)	(0.0117)	(0.0112)	(0.0335)
Return(t-11)		0.0149**	0.0329**	0.0397**	0.0748**	0.0387 *
		(0.0035)	(0.0034)	(0.0105)	(0.0103)	(0.0177)
Return(t-12)		0.0099**	0.0331**	0.0240 *	0.0676**	0.0351 *
		(0.0034)	(0.0034)	(0.0103)	(0.0101)	(0.0164)
Flows(t-1)	0.0884**	0.0616**	0.0156 *	0.0587**	0.0119	0.0760**
	(0.0050)	(0.0065)	(0.0064)	(0.0064)	(0.0064)	(0.0098)
Flows(t-2)		0.0839**	0.0437**	0.0825**	0.0414**	0.0848**
		(0.0057)	(0.0055)	(0.0057)	(0.0055)	(0.0073)
Flows(t-3)		0.0590**	0.0252**	0.0584**	0.0235**	0.0433 *
		(0.0053)	(0.0052)	(0.0053)	(0.0052)	(0.0178)
Flows(t-4)		0.0348**	0.0033	0.0345**	0.0020	0.0332**
		(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0092)
Flows(t-5)		0.0515**	0.0242**	0.0509**	0.0226**	0.1053 *
		(0.0054)	(0.0053)	(0.0054)	(0.0053)	(0.0500)
Flows(t-6)		0.0418**	0.0169**	0.0413**	0.0155**	0.0162
		(0.0054)	(0.0052)	(0.0054)	(0.0052)	(0.0187)
Flows(t-7)		0.0247**	0.0017	0.0250**	0.0010	0.0564
		(0.0052)	(0.0050)	(0.0052)	(0.0050)	(0.0324)
Flows(t-8)		0.0332**	0.0104 *	0.0335**	0.0095	0.0114
		(0.0051)	(0.0051)	(0.0051)	(0.0050)	(0.0215)
Flows(t-9)		0.0339**	0.0137**	0.0345**	0.0132**	-0.0218
		(0.0050)	(0.0050)	(0.0050)	(0.0050)	(0.0467)
Flows(t-10)		0.0262**	0.0079	0.0270**	0.0076	0.0223**
		(0.0049)	(0.0048)	(0.0049)	(0.0048)	(0.0069)
Flows(t-11)		0.0174**	-0.0008	0.0180**	-0.0014	0.0178**
		(0.0044)	(0.0044)	(0.0044)	(0.0044)	(0.0052)
Flows(t-12)		0.0303**	0.0137**	0.0306**	0.0128**	0.0309**
		(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0060)
log(TNA(t-1))	-0.0032**	-0.0015**	-0.0232**	-0.0016**	-0.0240**	-0.0058
	(0.0001)	(0.0001)	(0.0006)	(0.0001)	(0.0006)	(0.0033)
Fund FE	No	No	Yes	No	Yes	-
Time FE	No	No	No	Yes	Yes	-
Fama-MacBeth	-	-	-	-	-	Yes
adj. R^2	0.014	0.052	0.116	0.056	0.121	0.168
Obs.	417,801	306,570	306,570	306,570	306,570	306,570

$*$ $p<0.05$; $**$ $p<0.01$

Table 1: This Table shows the results of the flow-performance regressions, with γ^E being the parameter on Return(t-1). All regressions based on monthly data using standard OLS (Newey-West standard errors in parentheses). The last column is our main specification and shows the results for Fama-MacBeth regressions, in which case we report the time-series average of cross-sectional regression coefficients and the adjusted R^2. *TNA* is a fund's total net assets, and *Flow* is defined in Eq. (27).

Robustness: Flow-Performance Relationship

	Dependent variable: Flows(t)								
	(1) Subsamples			(2) Index funds		(3) Illiquidity Quartile			
	Crisis 2008-09	Sub 1 2003-08	Sub 2 2009-14	No	Yes	(Most liquid) 1	2	3	(Least liquid) 4
Return(t-1)	0.1781**	0.2951**	0.2521**	0.2578**	0.4396**	0.2089**	0.2822**	0.3235**	0.2498**
	(0.0370)	(0.0263)	(0.0487)	(0.0236)	(0.0907)	(0.0428)	(0.0327)	(0.0302)	(0.0371)
Return(t-2)	0.1128*	0.1810**	0.1970**	0.1693**	0.2026*	0.1707**	0.1209**	0.1571**	0.1875**
	(0.0479)	(0.0217)	(0.0661)	(0.0154)	(0.0945)	(0.0370)	(0.0364)	(0.0363)	(0.0321)
Return(t-3)	0.0826*	0.1219**	0.0744**	0.0980**	0.0044	0.0664	0.1488**	0.1502**	0.1603**
	(0.0317)	(0.0206)	(0.0257)	(0.0208)	(0.0840)	(0.0444)	(0.0377)	(0.0307)	(0.0324)
Return(t-4)	0.1004*	0.0912**	0.0051	0.0926**	0.0299	0.1076*	0.0342	0.0945**	0.1032**
	(0.0375)	(0.0202)	(0.0705)	(0.0138)	(0.1013)	(0.0424)	(0.0399)	(0.0281)	(0.0286)
Return(t-5)	-0.0391	0.0558*	0.0783**	0.0696**	-0.0045	0.1431**	0.0840*	0.0890*	0.0718
	(0.0290)	(0.0252)	(0.0256)	(0.0144)	(0.0869)	(0.0442)	(0.0376)	(0.0377)	(0.0395)
Return(t-6)	0.0080	0.0782**	0.1346*	0.0895**	0.0734	0.0648	-0.0175	0.1033**	0.0650*
	(0.0324)	(0.0196)	(0.0536)	(0.0165)	(0.0969)	(0.0499)	(0.0388)	(0.0282)	(0.0314)
Return(t-7)	0.0167	0.0643**	0.0653	0.0879**	-0.1099	0.0581	0.0131	0.0660*	0.0709
	(0.0436)	(0.0227)	(0.0422)	(0.0279)	(0.0923)	(0.0395)	(0.0378)	(0.0328)	(0.0374)
Return(t-8)	0.1079**	0.0813**	0.0854*	0.0793**	0.0854	0.0430	0.0279	0.0408	0.0609
	(0.0308)	(0.0222)	(0.0399)	(0.0208)	(0.0989)	(0.0447)	(0.0329)	(0.0350)	(0.0385)
Return(t-9)	0.0631	0.0218	0.1414**	0.0570**	0.0196	0.0620	0.0629	0.0517	0.1220**
	(0.0370)	(0.0207)	(0.0434)	(0.0134)	(0.1036)	(0.0407)	(0.0393)	(0.0317)	(0.0435)
Return(t-10)	0.0077	0.0329	-0.0221	0.0461**	-0.1829*	0.0567	0.0357	0.1024**	0.0668*
	(0.0379)	(0.0210)	(0.0673)	(0.0147)	(0.0871)	(0.0446)	(0.0370)	(0.0330)	(0.0269)
Return(t-11)	0.0824	0.0517*	0.0242	0.0438**	0.0136	0.0604	0.0323	0.0563	0.0309
	(0.0471)	(0.0218)	(0.0286)	(0.0125)	(0.1037)	(0.0385)	(0.0374)	(0.0317)	(0.0315)
Return(t-12)	0.0508	0.0611**	0.0058	0.0363**	0.0526	0.0235	0.0669	0.0356	-0.0202
	(0.0373)	(0.0209)	(0.0252)	(0.0129)	(0.0914)	(0.0402)	(0.0372)	(0.0319)	(0.0273)
Flows(t-1)	0.1386**	0.1125**	0.0350*	0.1299**	-0.0778**	0.0345	0.1093**	0.0739**	0.0966**
	(0.0254)	(0.0114)	(0.0146)	(0.0101)	(0.0200)	(0.0205)	(0.0173)	(0.0212)	(0.0211)
Flows(t-2)	0.1080**	0.0929**	0.0757**	0.0903**	0.0468*	0.0968**	0.0687**	0.0689**	0.1000**
	(0.0264)	(0.0106)	(0.0098)	(0.0084)	(0.0197)	(0.0165)	(0.0205)	(0.0180)	(0.0158)
Flows(t-3)	0.0812**	0.0637**	0.0204	0.0627**	0.0238	0.0900**	0.0919**	0.0594**	0.0634**
	(0.0221)	(0.0111)	(0.0356)	(0.0194)	(0.0193)	(0.0145)	(0.0182)	(0.0202)	(0.0125)
Flows(t-4)	0.0289*	0.0501**	0.0143	0.0230	0.0139	0.0250	0.0433*	0.0658**	0.0335*
	(0.0132)	(0.0115)	(0.0143)	(0.0195)	(0.0185)	(0.0172)	(0.0182)	(0.0170)	(0.0132)
Flows(t-5)	0.0655**	0.0678**	0.1476	0.0540**	0.0763**	0.0509**	0.0382*	0.0602**	0.0575**
	(0.0208)	(0.0096)	(0.1058)	(0.0062)	(0.0185)	(0.0139)	(0.0176)	(0.0179)	(0.0121)
Flows(t-6)	-0.0160	0.0251*	0.0063	0.0457**	0.0306	0.0201	0.0587**	0.0252	0.0398**
	(0.0127)	(0.0099)	(0.0384)	(0.0134)	(0.0172)	(0.0285)	(0.0162)	(0.0174)	(0.0127)
Flows(t-7)	0.0385	0.0237*	0.0931	0.0319**	0.0334*	0.0246	0.0206	0.0299	0.0255*
	(0.0196)	(0.0110)	(0.0677)	(0.0114)	(0.0168)	(0.0147)	(0.0142)	(0.0153)	(0.0112)
Flows(t-8)	0.0102	0.0306**	-0.0103	0.0079	0.0468*	0.0409**	0.0373**	0.0334*	0.0590**
	(0.0170)	(0.0095)	(0.0445)	(0.0147)	(0.0191)	(0.0134)	(0.0134)	(0.0132)	(0.0134)
Flows(t-9)	0.0019	0.0203*	-0.0692	-0.0241	0.0352*	0.0323*	0.0312*	0.0241	0.0189
	(0.0127)	(0.0086)	(0.0989)	(0.0471)	(0.0159)	(0.0150)	(0.0136)	(0.0167)	(0.0103)
Flows(t-10)	0.0343*	0.0264**	0.0176	0.0251**	0.0506*	0.0455*	0.0290	0.0308*	0.0166
	(0.0161)	(0.0086)	(0.0111)	(0.0059)	(0.0205)	(0.0176)	(0.0148)	(0.0134)	(0.0097)
Flows(t-11)	0.0310*	0.0212**	0.0139	0.0238**	0.0143	0.0281*	0.0091	0.0193	0.0095
	(0.0134)	(0.0069)	(0.0078)	(0.0046)	(0.0149)	(0.0138)	(0.0177)	(0.0128)	(0.0109)
Flows(t-12)	0.0333*	0.0286**	0.0334**	0.0198**	0.0604**	0.0404**	0.0354*	0.0259	0.0211**
	(0.0133)	(0.0091)	(0.0076)	(0.0047)	(0.0173)	(0.0133)	(0.0144)	(0.0163)	(0.0080)
log(TNA(t-1))	-0.0019**	-0.0015**	-0.0107	-0.0056	-0.0030**	-0.0010**	-0.0001	-0.0012**	-0.0011**
	(0.0003)	(0.0002)	(0.0070)	(0.0033)	(0.0005)	(0.0002)	(0.0012)	(0.0004)	(0.0002)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.145	0.176	0.158	0.175	0.443	0.381	0.436	0.420	0.351
Obs.	35,915	126,244	180,326	272,168	34,402	35,709	34,824	35,304	35,255

$*$ p<0.05; $**$ p<0.01

Table 2: Robustness checks, flow-performance regressions. γ^E is the parameter on Return(t-1). All regressions based on monthly data using Fama-MacBeth regressions, where we report the time-series average of cross-sectional regression coefficients, their Newey-West standard errors in parentheses and the adjusted R^2. *TNA* is a fund's total net assets, and *Flow* is defined in Eq. (27).

(2) *Index funds.* Index funds have gained importance over the last few decades. For example, Malkiel (2013) reports that, within the mutual fund sector, actively managed funds had a market share of 97% in 1990, and only 71% in 2010. Given that index funds are likely to behave very differently from non-index funds, we estimate parameters separately for the two fund types.[20] Interestingly, index funds display a significantly larger value relative to non-index funds ($\gamma^E = 0.4396$ versus 0.2578). In other words, investors respond much more strongly to index funds' past performance. This finding might be caused by lower trading costs of index funds compared to actively managed funds which might attract short-term investors (see Malkiel (2013)). Due to the increasing importance of index funds over time, we explore the aggregate vulnerabilities for this scenario in Section 4.2.3 below.

(3) *Illiquid funds.* Relatively illiquid funds tend to be more fragile in the sense that there are strong first-mover advantages among investors in those funds (Goldstein et al. (2017)). Hence, we estimate the flow-performance relationship separately for funds with different liquidity profiles. For each month, we sort funds into illiquidity quartiles based on their portfolio-weighted Amihud ratio. The last four columns of Table 2 show the results for the different quartiles, where the first (fourth) quartile corresponds to the most liquid (illiquid) funds. As expected, the most liquid funds display the weakest flow-performance relationship ($\gamma^E = 0.2089$). Interestingly, the relationship is strongest for the relatively illiquid funds in quartile 3 ($\gamma^E = 0.3235$). On the other hand, for the most illiquid funds we find a substantially smaller value than for funds in quartile 3 ($\gamma^E = 0.2498$). This suggests that investors in the most illiquid funds tend to be more cautious in terms of their withdrawals. We will explore the aggregate vulnerabilities for this scenario in Section 4.2.3 below as well.

Lastly, we also looked at small versus large funds (see Table 9 in Appendix B):

(4) *Size.* Larger funds are likely to have a stronger impact on other funds, simply because their asset liquidations are larger in absolute terms. Hence, we also estimated the flow-performance relationship separately for small and large funds, respectively, based on whether a funds' TNA is below-/above-median in a given quarter. As shown in Appendix B, we find that the values are larger for small funds ($\gamma^E = 0.3239$ versus 0.2411). Again, we explore the aggregate vulnerabilities for this scenario in Section 4.2.3.

4 Results: Aggregate Vulnerabilities Over Time

In the following, we consider a shock scenario of an initial shock of -5% on all stocks[21], which is comparable in magnitude to shock scenarios considered in previous stress tests for banking systems (see Cont and Schaanning (2017) for an overview). We calculate the aggregate vulnerabilities (AV) separately for each quarter. Model parameters are

[20] For example, it is common practice in the flow-performance literature to drop index funds from the analysis (e.g., Goldstein et al. (2017)).

[21] Note that the AV scales linearly in the initial shock. Hence, an initial shock of -20% yields an AV which is approx. 4 times that of a -5% shock.

calibrated as defined above, with zero-leverage as our baseline. We will differentiate between three scenarios with regards to our choice of the price impact parameters:

- ***Scenario 1***: Price impact time-varying and asset-specific.
- ***Scenario 2***: Price impact constant and asset-specific (time-average for each stock).
- ***Scenario 3***: Homogeneous price impact for all assets in all quarters. We use a value of 1.57×10^{-13} which corresponds to the price impact of the asset class 'Developed Equity Markets' in Cetorelli et al. (2016).

We will see that the first two scenarios generate AVs of similar orders of magnitude, and much smaller values in the last scenario. Interestingly, we will also see that the time dynamics of the AVs are affected by which price impacts one chooses.

4.1 Baseline

The main results for the baseline analysis can be found in Figure 6 and Table 3. Let us briefly describe these for the three different scenarios under study here.

Aggregate Vulnerability (AV)

Panel		Scenario 1		Scenario 2		Scenario 3	
		Leverage		Leverage		Leverage	
		Zero	Maximum	Zero	Maximum	Zero	Maximum
A	**Sum. Stats.**					10^{-4}	10^{-3}
	Mean	0.005	0.021	0.016	0.054	×0.187	×0.078
	Median	0.005	0.020	0.014	0.049	×0.182	×0.076
	Min	0.003	0.011	0.009	0.029	×0.082	×0.034
	Max	0.013	0.052	0.036	0.115	×0.335	×0.140
	Std	0.002	0.006	0.007	0.019	×0.059	×0.025
B	**Correlations**						
	S1-Zero Lev.	1.000					
	S1-Max Lev.	1.000**	1.000				
	S2-Zero Lev.	0.098	0.100	1.000			
	S2-Max Lev.	0.065	0.066	0.995**	1.000		
	S3-Zero Lev.	0.376**	0.377**	0.735**	0.757**	1.000	
	S3-Max Lev.	0.376**	0.377**	0.735**	0.757**	1.000**	1.000
C	**Trend Analysis**						
	Trend	0.001	0.001	0.036**	0.031**	0.016**	0.016**
		(0.002)	(0.002)	(0.005)	(0.004)	(0.004)	(0.004)
	Constant	0.770**	0.770**	0.787**	0.917**	1.219**	1.219**
		(0.074)	(0.074)	(0.146)	(0.128)	(0.135)	(0.135)
	R^2	0.003	0.003	0.518	0.502	0.209	0.209
	Obs.	48	48	48	48	48	48

∗ p<0.05; ∗∗ p<0.01

Table 3: Results for AV. This Table shows summary statistics (top panel), correlation coefficients (center panel), and the results of a trend analysis (bottom panel). *Scenario 1* (S1) is based on time-varying and asset-specific price impacts; *Scenario 2* (S2) is based on constant and asset-specific price impacts; *Scenario 3* (S3) is based on homogeneous price impacts. The trend analysis shows results from OLS regressions of AVs on a constant and a time trend. For the sake of comparison, we divide each AV time series by its initial value in Q1 2003.

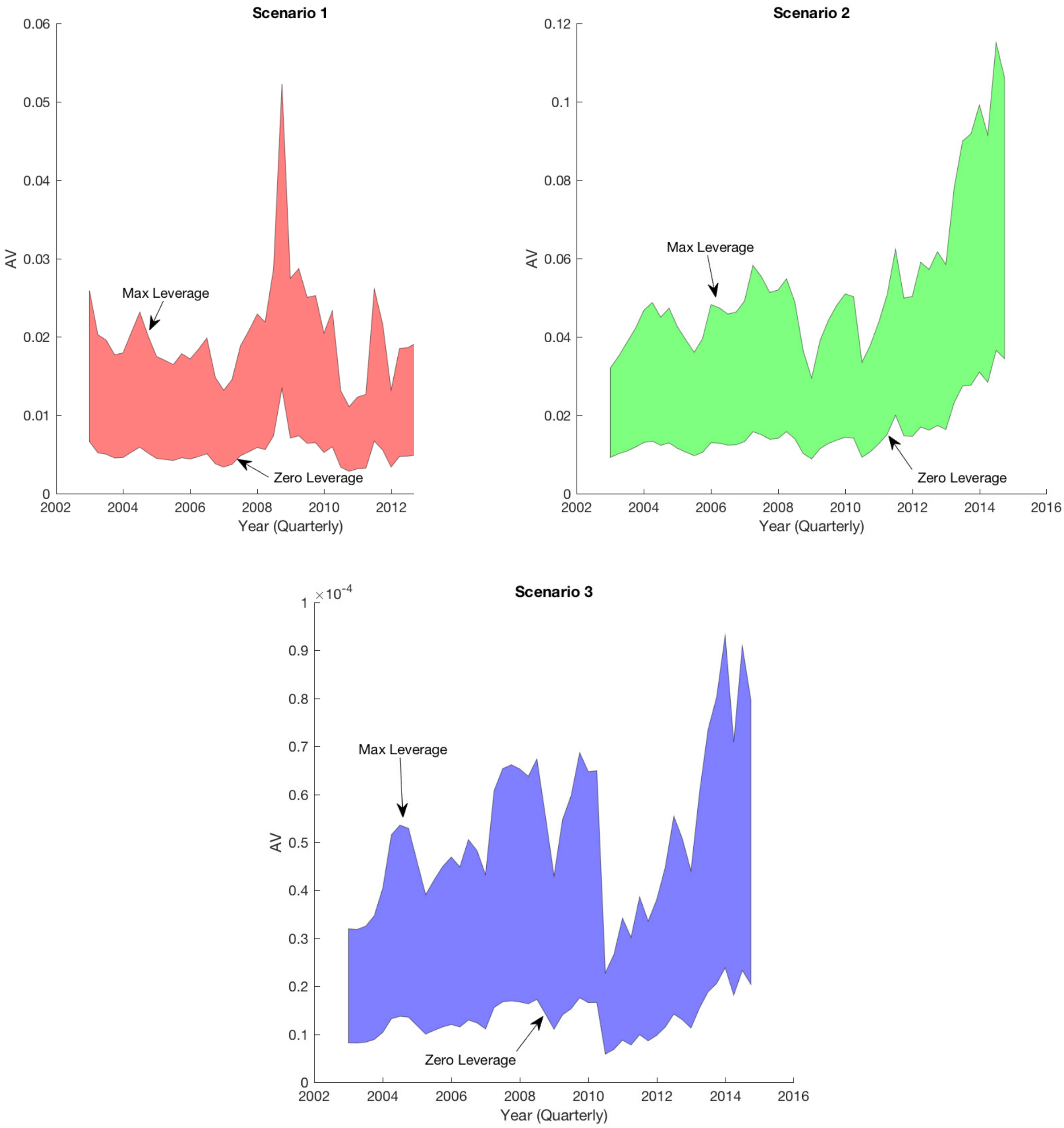

Figure 6: Aggregate vulnerabilities for the three different price impact scenarios. Top left: *Scenario 1* (price impact time-dependent and asset-specific). Top right: *Scenario 2* (price impact constant and asset-specific). Bottom: *Scenario 3* (homogeneous price impact $= 1.57^{-13}$ for all assets/quarters). In all cases, we calculate the AVs when using zero leverage and maximum leverage, respectively, such that the shaded areas show the range of possible AVs.

***Scenario 1*: Price Impact Time-Varying and Asset-Specific.** The top left panel of Figure 6 shows the results for *Scenario 1*: the red shaded area spans the range of possible AVs for varying assumptions on the leverage ratios. With zero leverage, the typical AVs are on the order of 0.5%. With maximum leverage, AVs lie in a range around 2% with the exception of the financial crisis, at which AVs peak at 5% (see Table 3, Panel A).[22]

It turns out that vulnerabilities in the mutual fund sector are smaller than those reported for the banking sector. For example, Greenwood et al. (2015) report AV of 245% (assuming a 50% GIIPS shock[23]). The difference in the systemic risk contribution between asset managers and banks is heavily influenced by differences in their funding models. Banks are well-known to make use of substantial leverage, while mutual funds often use zero leverage. Note that Greenwood et al. (2015) impose a leverage cap on their sample banks (maximum value is winsorized to 30), possibly due to the instability of their results. On the other hand, mutual fund regulations in the U.S. restricts the maximum leverage to 0.5 (see section 3.2.2). Therefore, the amount of fire-sales through leverage targeting (section 2.1.3) is dramatically larger in the banking sector. In addition, while theoretically plausible, mutual funds' fire-sales due to fund share redemptions are also relatively modest due to a weak flow-return-sensitivity. For example, our estimated sensitivities imply that an asset price shock of 5% translates to additional outflows of only 1.35%.

The dynamic of the AVs in *Scenario 1* suggests that they are primarily driven by the dynamics of the price impacts. Indeed, the Pearson-correlation between the value-weighted price impacts shown in Figure 5 and the AVs is 0.67 in this case. Given the absence of a visible time trend in the price impacts, it comes as no surprise that the AVs in *Scenario 1* exhibit no significant time trend. This can be seen from Panel C of Table 3, where we regress the quarterly AVs on a constant and a time trend. In other words, when using time-varying and asset-specific price impact we do not find that the system has become more vulnerable despite the strong growth of the system.

***Scenario 2*: Price Impact Constant and Asset-Specific.** The top right panel of Figure 6 shows the AVs for *Scenario 2*, where we ignore the time variation in the estimated price impacts and simply take the average value for each stock. The AVs of *Scenario 1* differ from those of *Scenario 2* in two ways. First, the magnitude of the AVs is somewhat larger than for *Scenario 1*: with zero leverage, the typical AVs are in the order of 1.5%; with maximum leverage these values are around 5% (see Panel A of Table 3). The maximum values are located around 3.5% and 11.5%, respectively. Given that the average price impact of a given stock will be influenced by the crisis years, these results suggest that in most cases this approach overestimates the actual price impacts and thus the corresponding AVs.[24] Second, the AVs of *Scenario 2* peak at the end of sample rather

[22] Note that the AVs for the two extreme leverage assumptions are perfectly correlated (see Panel B of Table 3). Hence, we will focus on the baseline scenario with zero leverage in the fund-specific analyses below.

[23] The GIIPS shock corresponds to a 50% write-down on sovereign debt from Greece, Italy, Ireland, Portugal, and Spain.

[24] We also experimented with an alternative *Scenario 2b*, where we use the maximum price impacts (rather than the average) for each stock. In this case, the AVs are even larger with average values of 7% (zero leverage) and 18% (max. leverage), respectively.

than during the financial crisis period. When analyzing the time dynamics in more detail, Figure 6 suggests that the AVs have slowly increased over time, which is confirmed by the significantly positive time trend parameter in the trend analysis (see Panel C of Table 3).

***Scenario 3*: Homogeneous Price Impact.** The bottom of Figure 6 shows the AVs when imposing a uniform price impact across all assets and all quarters. In this case, the AVs are very small, with typical values on the order of 10^{-4}. Nevertheless, we still observe that the AVs have significantly increased over time (see Panel C of Table 3 as well), even though the time trend is much weaker than for *Scenario 2*.

Overall, these results indicate that the AV of the system is relatively small in most instances, in particular when comparing the values with those reported by Greenwood et al. (2015) for large European banks.[25] As discussed previously, given that most mutual funds do not make use of any leverage, the somewhat larger values for the case with maximum leverage are likely to be of limited empirical relevance. Hence, systemic asset liquidations are unlikely to be a major issue for the set of U.S. equity mutual funds, at least when looking at this part of the asset management industry in isolation. We will discuss this finding in more detail below. One should keep in mind, however, that the AVs exhibit significantly positive time trends in the last two scenarios. Hence, depending on the choice of price impact parameters, the system may have become more vulnerable over time and might continue to do so in the future.

4.2 Extensions

In the following, we show three extensions of the above baseline analysis: first, we study the linear dependency of the AVs as a function of the initial shock size and the assumed level of market liquidity. Second, we explore to what extent using more coarse-grained stock portfolios has an impact on the estimated AVs. Third, we include heterogeneity in the flow-performance relationship to understand whether our assumption of a homogeneous γ^E affects the AVs. In all cases, for the sake of brevity, we focus on the case of time-varying and asset-specific price impacts (*Scenario 1*) with zero leverage only.

4.2.1 Sensitivity Analysis

In order to assess the dependency of the AV on the size of the initial shock and on the assumed level of market liquidity we perform a sensitivity analysis along these two dimensions. More specifically, we run the model for different sizes of the initial shock (between 0 and 40%) and different multiples of the actual asset-level PriceImpact parameters. With regards to the latter, we look at different "Liquidity Factors" which range between 0.1 and 5, where a value of 1 corresponds to the observed PriceImpacts and a value of 5 to PriceImpacts that are 500% larger than the observed values. The results for Q4 2014 can be found in Figure 7. As expected from the linearity of the model, the AV is roughly linear along these two dimensions. The worst-case scenario (shock size = 40% and Liquidity Factor = 500%) yields an AV of 0.3. This sensitivity analysis reveals that vulnerability of the system is generally modest but can become significant when market liquidity is low

[25] In Appendix C we present an alternative model of mutual fund asset liquidations, which takes a large redemption shock as a starting point.

and shocks are large. Therefore, we see this analysis as an important tool for gauging the resilience of the mutual fund sector to a broader set of adverse stress-test scenarios. With regard to our empirical analysis in the following section, the linearity of the AV means that our results would remain largely unaffected qualitatively. Therefore, for the sake of brevity, we restrict our analyses to the vulnerabilities derived from the baseline scenario.

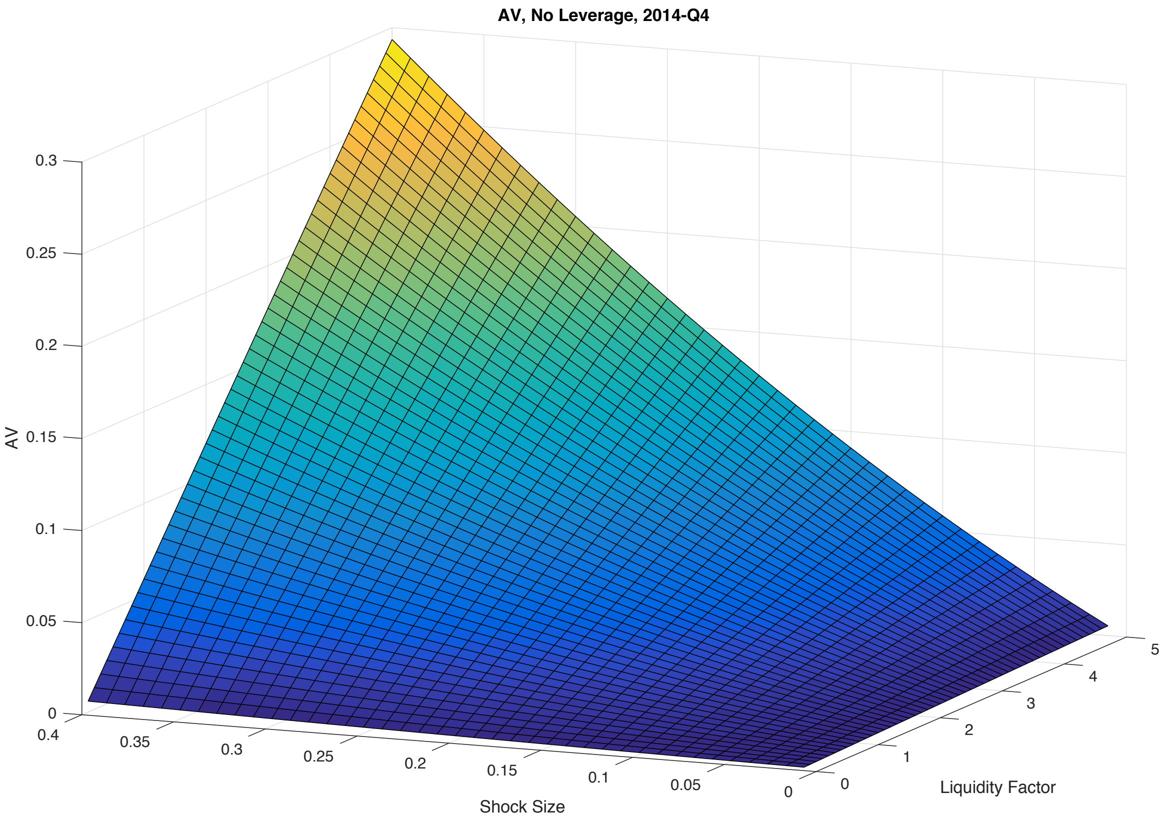

Figure 7: AV as a function of the initial shock and market liquidity in Q4 2014 (Scenario 1). The Amihud ratio is multiplied with the liquidity factor to simulate an aggraviation of market liquidity. Shock size refers to the initial negative market shock.

4.2.2 Portfolios Aggregated to the Industry Level

In our baseline application, we used the most granular stock portfolios, but in many existing applications of fire sale models such detailed information of investor portfolios is not available (e.g., Greenwood et al. (2015); Duarte and Eisenbach (2013); Cont and Schaanning (2017)). For example, in their assessment of vulnerabilities among broker-dealers, Duarte and Eisenbach (2013) collapse their data into 9 major asset classes (such as treasuries, equities, and corporate bonds). Given that we focus on domestic equity funds, the set of asset managers under study invests in one major asset class only. In order to

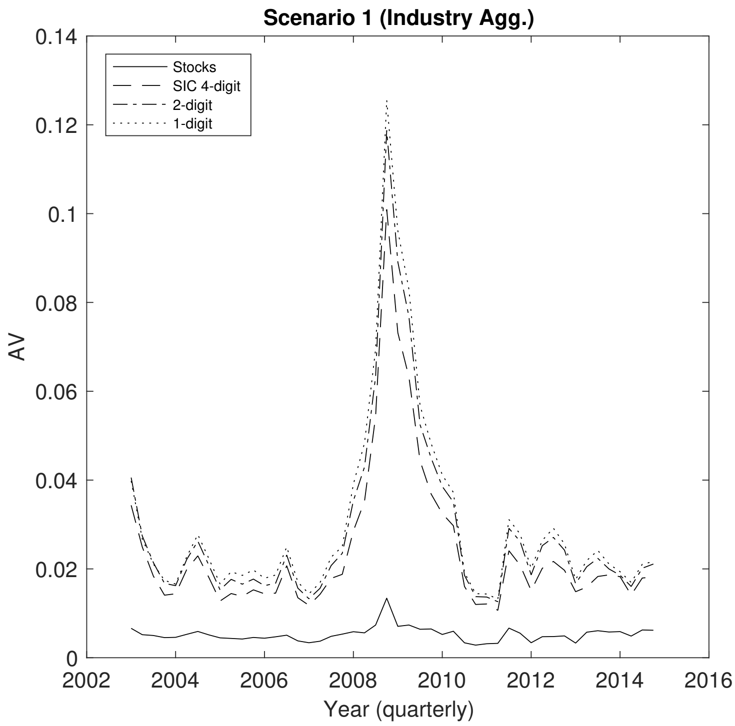

Figure 8: Aggregate vulnerabilities for different industry aggregation levels (based on SIC classifications). Here we show results for *Scenario 1* using the baseline with zero leverage.

explore the effect of using more coarse-grained asset portfolios, we aggregate these to the industry level using different granularity levels of SIC industry codes (4-digits at the most granular level).

Not surprisingly, with fewer asset classes the typical portfolio overlap between mutual funds increases (see Figure 4), which makes it easier for funds to have an impact on others through their asset liquidations. Note that, while we assumed cross-asset price impacts to be zero for the most granular case (the off-diagonal elements of matrix L were all zero), aggregation implicitly includes cross-price impacts between individual assets from the same class. Here the price impact of each industry bucket is defined as the weighted average price impact of the individual stocks in that particular bucket, divided by the number of stocks.[26]

Figure 8 shows the results of this exercise for three different aggregation levels (SIC 4-, 2-, and 1-digit, respectively); for the sake of reference, we also reproduce the AV time series for the most granular stock portfolios from Figure 6. It turns out that, as expected, the AVs tend to increase in the aggregation level and tend to be substantially larger compared

[26] The latter adjustment is important, since the aggregated asset should be more liquid than the individual constituents. In other words, the market depth of an aggregate asset should be larger (see Cont and Schaanning (2017)). Dividing the typical price impact by the number of stocks is the most natural approach under a linear price impact function. An alternative approach would consist of directly calculating the price impacts of the aggregated assets in line with Eq. (25), where we would divide the absolute return of the aggregated asset by the sum of trading volumes of its constituents.

with the baseline results. Interestingly, however, the difference between the AVs of 4-digit and 1-digit codes (consisting of an average of 677 and 10 assets, respectively) is rather small. Overall, the AVs are still relatively small during normal times, but reach values around 10% during the financial crisis, i.e. roughly twice the original shock.

4.2.3 Heterogeneity in Flow-Performance Relationship

In our baseline application we assumed that all funds have the same homogeneous flow-performance relationship.Here we re-apply our model using exactly the same approach as in Section 4 but use four alternative specifications regarding γ^E, some of which were discussed in Subsection 3.2.5 (see Table 2 in the main text and Table 9 in Appendix B):

a) index versus non-index funds,

b) liquid versus illiquid funds,

c) large versus small funds,

d) different combinations of index/non-index funds and institutional/non-institutional funds. We further separate non-index funds by their liquidity profile, since run incentives are more relevant for illiquid funds (see Goldstein et al. (2017)). This results in six different γ^Es which are reported in Table 4 (see Table 11 in Appendix B for details).

Heterogeneity Across Multiple Dimensions			
γ^E	Index	Non-Index	
		Liquid	Illiquid
Inst.	0.255	0.126	0.235
Non-Inst.	0.463	0.339	0.303

Table 4: Estimated γ^E's for different subsets of mutual funds. Full regression results are shown in Table 11 in Appendix B.

Figure 9: Aggregate vulnerabilities relative to baseline results for *Scenario 1* (as shown in top left panel in Figure 6). Note: 'Index/Non-Index' corresponds to specification (2) in Table 2; 'Liquid/Illiquid' corresponds to specification (3) in Table 2; 'Small/Large' corresponds to specification (3) in Table 9 in Appendix B. 'Index/Non-Index (Liquid/illiquid + Inst./Non-Inst)' corresponds to the distinction in Table 4.

Figure 9 shows the AVs for the four different cases, relative to those in the baseline scenario (as in the top left panel of Figure 6). A value larger (smaller) than 1 indicates that the AV under the new approach is larger (smaller) than in our baseline. The results are quite remarkable: in almost all cases – with the exception of the index/non-index fund scenario – the resulting AVs tend to be *smaller* compared to the baseline specification. In fact, when distinguishing between index/non-index funds it appears that the relative AV tends to increase over time, suggesting that the growth of index funds tends to be quite important from a systemic perspective (Malkiel (2013)). On the other hand, when allowing for differences between funds' with different portfolio liquidity or different sizes, the AVs are generally significantly smaller than in the baseline scenario. Lastly, when allowing for multiple sources of heterogeneity (combining index/non-index and institutional/non-institutional), the resulting AVs are slightly more volatile, but largely comparable to those for the liquid/illiquid case. In summary, these results show that adding heterogeneity across different fund types in terms of the flow-performance relationship does not necessarily lead to a more vulnerable system.

Variables	IV_1	S_1	IV_2	S_2	IV_3	S_3	Age	$Flows^{6M}$	TNA	Concentration	MeanOverlap	$Illiq^{Amihud}$	$Illiq^{RelSpread}$
Vulnerabilities													
IV_1	1.000												
S_1	0.053**	1.000											
IV_2	0.318**	-0.031**	1.000										
S_2	0.037**	0.785**	0.130**	1.000									
IV_3	-0.289**	0.064**	-0.344**	0.011**	1.000								
S_3	-0.047**	0.862**	-0.069**	0.679**	0.173**	1.000							
Size													
Age	-0.022**	0.225**	-0.003	0.201**	0.142**	0.195**	1.000						
$Flows^{6M}$	-0.005	-0.003	-0.001	-0.002	0.011**	-0.002	-0.008*	1.000					
TNA	-0.028**	0.596**	-0.019**	0.449**	0.083**	0.573**	0.252**	0.006	1.000				
Interconnectedness													
Concentration	-0.070**	-0.060**	-0.096**	-0.076**	0.161**	-0.031**	0.014**	0.012**	-0.022**	1.000			
MeanOverlap	-0.356**	0.116**	-0.413**	0.044**	0.767**	0.204**	0.109**	-0.001	0.096**	-0.149**	1.000		
Illiquidity													
$Illiq^{Amihud}$	0.502**	-0.001	0.062**	-0.009**	-0.111**	-0.019**	-0.032**	-0.001	-0.018**	0.005	-0.123**	1.000	
$Illiq^{RelSpread}$	0.635**	0.014**	0.120**	-0.016**	-0.338**	-0.052**	-0.099**	-0.008*	-0.043**	-0.023**	-0.332**	0.679**	1.000

* $p<0.05$, ** $p<0.01$

Table 5: Correlation matrix between fund-specific vulnerabilities and fund characteristics. IV_i (S_i) measures funds' indirect vulnerability to asset fire sales (systemicness) according to the three different price impact scenarios. Age represents the fund age measured in month; $Flows^{6M}$ is the average net percentage flow over the previous 6 months; TNA are the total net assets; Concentration is the portfolio concentration index of Kacperczyk et al. (2005); MeanOverlap is the fund's average portfolio overlap with all other funds; $Illiq^{Amihud}$ and $Illiq^{Spread}$ are the portfolio-weighted average illiquidity measures of a given fund's portfolio, based on the Amihud-ratio and the quoted relative spread, respectively.

5 A Closer Look at Fund-Specific Vulnerabilities

This section explores the determinants of the two fund-specific vulnerability indicators, namely systemicness S and indirect vulnerability IV (see Eqs. (21) and (22)). Identifying such determinants is of utmost importance when formulating a macroprudential regulatory framework for asset managers (Financial Stability Board (2017)).

Generally speaking, we are interested in the following cross-sectional regressions

$$\log(y_{i,t}) = a_t + b_t \times \log(X_{i,t-1}) + \epsilon_{i,t}, \tag{28}$$

where $y_{i,t}$ is the fund-specific vulnerability indicator of interest (S or IV, respectively) based on the case of zero leverage[27], X contains our set of control variables (always using the first lag to alleviate the endogeneity problem), and b is the corresponding parameter vector. A log-transformation is applied to each variable to adjust for skewness and to mitigate the effect of extreme observations. In everything that follows, we estimate parameters following the Fama and MacBeth (1973) methodology, and explore different sets of control variables that allow us to predict fund-specific vulnerabilities. Table 5 reports the correlations between the variables that will be of interest in the following; multicollinearity is not an issue, since correlations are relatively small in absolute terms.

The analysis proceeds in three steps: first, we explore to what extent the (lagged) fund-specific characteristics that appear in the model equations are able to predict future values of the vulnerability measures. In a way, this can be seen as a simple model validation step and we acknowledge that this analysis, despite using lagged exogenous variables, suffers from a potential endogeneity bias, hampering the identification of causal relationships between vulnerabilities and these fund-specific characteristics. Second, to address a possible endogeneity bias, model-inherent fund characteristics are replaced with alternative measures. For example, we approximate fund size using fund age and net flows. We find that the regression results are qualitatively very similar to the ones from the first step, such that our analysis indeed uncovers the determinants of fund-specific vulnerabilities. Third, we address concerns on a potential outlier bias related to the market liquidity aggravation around the financial crisis (see Figure 5) and explore the robustness of our findings by conducting a subsample analysis that excludes observations from the 2008-09 period. In line with this three-step analysis, the following regression tables will consist of three panels each (Panels A, B, and C).

5.1 Towards Understanding Funds' Vulnerabilities (Scenario 1)

Here, we explore fund characteristics which determine individual funds' vulnerability to systemic asset liquidations, highlighting the importance of size and portfolio illiquidity. Again, *Scenario 1* is our starting point and serves as the benchmark, since it allows for asset and time-specific price impacts. We explore the two other scenarios afterwards.

[27]As shown in Table 3 above, despite showing different levels, aggregate vulnerabilities are (nearly) perfectly correlated when comparing the cases with zero leverage and with maximum leverage for each of the three scenarios under study here. Not surprisingly, this is also true for the fund-specific indicators. Hence, all of the results shown below are practically identical when looking at the case of maximum leverage, since the differences in levels are fully absorbed by the intercepts in our regressions.

5.1.1 Step 1: Model-Inherent Measures

The first step is to explore to what extent the fund-specific characteristics serving as inputs in our stress testing model are able to predict future vulnerabilities. Our model suggests the following relationships: systemicness increases with a larger fund size or interconnectedness since larger funds should sell more assets, and a higher interconnectedness means that those funds sell assets that are held by many other funds as well. The reverse should be true for indirect vulnerability, since more diversified funds should be less vulnerable to other funds' asset liquidations. The correlations in Table 5 are in line with this reasoning. As mentioned in Greenwood et al. (2015), the relationship between fund size and indirect vulnerability is not clear. In our case, Table 5 shows a small negative correlation between IV and TNA. Lastly, more illiquid funds should be both more systemic and vulnerable in general, since illiquid funds have to sell a larger share of their portfolios to meet investors' redemptions and are also likely to suffer more from other funds' asset liquidations. Of course, we would also expect leverage to have a strong impact on both systemicness and indirect vulnerability. Given that in our model application there is no cross-sectional variation in leverage (zero or maximum leverage, respectively), we cannot include it in the regressions below.

The first set of regressions, therefore, uses only three control variables, namely fund size (defined as TNA), interconnectedness (defined as a fund's average portfolio overlap with all other funds, MeanOverlap)[28], and illiquidity (defined as the portfolio-weighted average Amihud-ratio of a fund, $\text{Illiq}^{\text{Amihud}}$)[29]:

$$\begin{aligned}\log(y_{i,t}) = a_t + b_{1,t} \times \log(\text{TNA}_i(\text{t-1})) + b_{2,t} \times \log(\text{MeanOverlap}_i(\text{t-1})) \\ + b_{3,t} \times \log(\text{Illiq}_i^{Amihud}(\text{t-1})) + \epsilon_{i,t}.\end{aligned} \tag{29}$$

The results are shown in Panel A of Table 6 and in line with expectations stated above: first, larger funds contribute more to aggregate vulnerability and are therefore more systemically important. Interestingly, larger funds also show significantly higher IVs and are therefore more vulnerable to other funds' asset liquidations (lower IV). Second, more connected funds exhibit lower IV (likely due to the benefits of diversification) but contribute to a larger extent to the sector's asset fire sales (higher S). Finally, illiquid funds are both more vulnerable and more systemic. Overall, these results are in line with our discussion above and with those of Greenwood et al. (2015).

5.1.2 Step 2: Alternative Measures

In order to overcome endogeneity concerns, the second step is to regress vulnerabilities on variables that are not directly included in the model (what we call "alternative measures"). Those variables are direct substitutes for the model-inherent variables discussed in section 5.1.1. Let us briefly explain how we substitute each of the exogenous variables from Panel A of Table 6.

[28] To be precise, for each quarter we calculate this fund-specific portfolio overlap as follows: for each pair of funds, we calculate their portfolio overlap according to Eq. (23). At each point in time, MeanOverlap of fund i is then defined as the average Overlap of this particular fund with all other funds.

[29] We calculate the illiquidity of fund i in quarter t as $\sum_k M_{i,k}\text{PriceImpact}_{k,t}$, where $\text{PriceImpact}_{k,t}$ is defined in Eq. (25). See Yan (2008) for a similar approach.

Determinants of Fund-Specific Vulnerabilities (*Scenario 1*)

	Panel A Full Sample		Panel B Full Sample		Panel C No Crisis	
	log(IV_1)	log(S_1)	log(IV_1)	log(S_1)	log(IV_1)	log(S_1)
Model-inherent measures						
log(TNA(t-1))	0.0156**	0.6222**				
	(0.0017)	(0.0573)				
log(MeanOverlap(t-1))	-0.0705**	0.2030**				
	(0.0046)	(0.0401)				
log($\text{Illiq}^{\text{Amihud}}$(t-1))	0.1128**	0.1352**				
	(0.0052)	(0.0100)				
Alternative measures						
log(1+Age(t-1))			0.0280**	1.0289**	0.0290**	1.0211**
			(0.0009)	(0.0161)	(0.0009)	(0.0193)
Flows^{6M}(t-1)			-0.0033	0.3069 *	-0.0016	0.3200 *
			(0.0069)	(0.1245)	(0.0083)	(0.1483)
log(Concentration(t-1))			0.0057**	-0.4376**	0.0057**	-0.4344**
			(0.0017)	(0.0112)	(0.0017)	(0.0135)
log($\text{Illiq}^{\text{RelSpread}}$(t-1))			0.5147**	0.2036**	0.4566**	0.1388**
			(0.0276)	(0.0360)	(0.0239)	(0.0356)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
Mean R^2	0.652	0.539	0.605	0.236	0.572	0.234
Obs.	72,688	72,688	67,556	67,556	52,479	52,479

$*$ p<0.05; $**$ p<0.01

Table 6: The determinants of fund-specific indirect vulnerability (IV_1) and systemicness (S_1), respectively, for *Scenario 1*. Results are based on quarterly data using Fama-MacBeth regressions (Newey-West standard errors in parentheses), including a constant that is omitted from the output. All variables are defined in the main text and in Table 5. Panels A and B cover the full sample period from 2003-14 and Panel C reports results of the subsample without the financial crisis period 2008-09.

Size. Fund age is the natural proxy of fund size since older funds tend to be larger (Yan (2008)). The economic intuition is that older funds were able to expand their assets under management over a longer period of time compared to younger funds. However, fund age might also capture aspects that are not size related. Therefore, we also include funds' average net flows over the previous 6 months, Flows^{6M}, as an additional size proxy. Flows are less deterministic (compared to age) and are likely to capture growth dynamics in the recent past.[30]

Interconnectedness. Portfolio concentration is considered as an inverse proxy for interconnectedness as a highly diversified fund might have at least some common asset holdings with other funds. Here we define Concentration as the portfolio concentration index of Kacperczyk et al. (2005) for a given fund i at a specific point in time as

$$\text{Concentration}_i = \sum_k (M_{i,k} - \bar{M}_k)^2,$$

where $\bar{M}_k$ is the weight of asset k in the market portfolio.[31] Not surprisingly, Concentration and MeanOverlap are negatively correlated (Pearson correlation of -0.15, see Table 5), such that both measures appear to capture certain aspects of concentration or interconnectedness, respectively.

Illiquidity. An asset's relative spread tends to better capture asset illiquidity, while the Amihud-ratio is more related to price impact (see Goyenko et al. (2009)). Therefore, we use the portfolio-weighted relative spread, $\text{Illiq}^{\text{RelSpread}}$, as an alternative liquidity measure.[32]

With these alternative measures we then run the following regression

$$\begin{aligned}\log(y_{i,t}) = a_t + b_{1,t} \times \log(\text{Age}_i(\text{t-1})) + b_{2,t} \times \text{Flows}_i^{6M}(\text{t-1}) + b_{3,t} \times \log(\text{HHI}_i(\text{t-1})) \\ +b_{4,t} \times \log(\text{Illiq}_i^{\text{RelSpread}}(\text{t-1})) + \epsilon_{i,t}.\end{aligned} \tag{30}$$

The results in Panel B of Table 6 generally consistent with those in Panel A: larger (and older funds) are both more vulnerable and systemically important. More concentrated funds are more vulnerable but less systemically important. Finally, more illiquid funds have both higher IVs and higher systemicness.

5.1.3 Step 3: Subsample analysis

As a last step, Panel C of Table 6 addresses concerns that the effect of liquidity on funds' vulnerabilities is mainly driven by the market liquidity aggravation around the financial crisis (see Figure 5). For this purpose, we run the same Fama-MacBeth regressions as in the previous step but exclude all observations during the crisis years 2008-09. This subsample analysis delivers nearly identical regression parameters and suggests that our

[30] Given that flows can take negative values, we do not take logarithms in this case.

[31] In order to be consistent with our calculation of *MeanOverlap*, we compute the portfolio concentration index on basis of deviations from the market portfolio at the security level. This deviates from Kacperczyk et al. (2005) who define the portfolio concentration index for 1-digit industry portfolios. We checked that defining Concentration based on funds' industry portfolios yields similar qualitative results.

[32] To be precise, we define the relative spread of stock k in quarter t as:
$\text{RelSpread}_{k,t} = \frac{1}{D_{k,t}} \sum \frac{Bid_{k,d} - Ask_{k,d}}{(Bid_{k,d} + Ask_{k,d})/2}$.

Determinants of Fund-Specific Vulnerabilities (*Scenario 2*)

	Panel A Full Sample		Panel B Full Sample		Panel C No Crisis	
	$\log(IV_2)$	$\log(S_2)$	$\log(IV_2)$	$\log(S_2)$	$\log(IV_2)$	$\log(S_2)$
Model-inherent measures						
log(TNA(t-1))	0.0255**	0.6321**				
	(0.0016)	(0.0568)				
log(MeanOverlap(t-1))	-0.1645**	0.1091**				
	(0.0080)	(0.0394)				
$\log(\mathrm{Illiq}^{\mathrm{Amihud}}(t\text{-}1))$	0.2400**	0.2624**				
	(0.0074)	(0.0116)				
Alternative measures						
log(1+Age(t-1))			0.0388**	0.9974**	0.0388**	0.9877**
			(0.0054)	(0.0126)	(0.0065)	(0.0146)
$\mathrm{Flows}^{6M}(t\text{-}1)$			-0.0277	0.3096 *	-0.0430	0.3071 *
			(0.0289)	(0.1304)	(0.0313)	(0.1496)
log(Concentration(t-1))			0.0192	-0.4238**	0.0134	-0.4263**
			(0.0105)	(0.0193)	(0.0126)	(0.0236)
$\log(\mathrm{Illiq}^{\mathrm{RelSpread}}(t\text{-}1))$			1.0732**	0.7593**	1.0643**	0.7435**
			(0.0379)	(0.0503)	(0.0409)	(0.0562)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
Mean R^2	0.469	0.509	0.422	0.226	0.435	0.223
Obs.	72,688	72,688	67,556	67,556	52,479	52,479

$*$ p<0.05; $**$ p<0.01

Table 7: The determinants of fund-specific indirect vulnerability (IV_2) and systemicness (S_2), respectively, for *Scenario 2*. Results are based on quarterly data using Fama-MacBeth regressions (Newey-West standard errors in parentheses), including a constant that is omitted from the output. All variables are defined in the main text and in Table 5. Panels A and B cover the full sample period from 2003-14 and Panel C reports results of the subsample without the financial crisis period 2008-09.

findings are not driven by the financial crisis.

5.2 Additional Robustness Checks

Let us now briefly turn to the regression results for *Scenarios 2* and *3*.

5.2.1 Results for *Scenario 2* – Price Impact Constant and Asset-Specific

Table 7 shows the results for *Scenario 2*. The results are largely consistent with those in Table 6 both in terms of parameter signs and significance levels. Overall, these results suggest that the first two scenarios, despite showing different time dynamics in terms of the aggregate vulnerabilities, tend to give very similar results.

5.2.2 Results for *Scenario 3* – Homogeneous Price Impact

Table 8 shows the regression results for *Scenario 3*. It turns out that these results are quite different from those presented for the other two scenarios. For example, some of the parameters switch signs. Most importantly, under *Scenario 3*, illiquid funds tend to be

Determinants of Fund-Specific Vulnerabilities (*Scenario 3*)

	Panel A Full Sample		Panel B Full Sample		Panel C No Crisis	
	$\log(IV_3)$	$\log(S_3)$	$\log(IV_3)$	$\log(S_3)$	$\log(IV_3)$	$\log(S_3)$
Model-inherent measures						
log(TNA(t-1))	-0.0139**	0.5927**				
	(0.0029)	(0.0529)				
log(MeanOverlap(t-1))	0.9711**	1.2447**				
	(0.0152)	(0.0275)				
$\log(\text{Illiq}^{\text{Amihud}}(\text{t-1}))$	-0.2912**	-0.2688**				
	(0.0070)	(0.0076)				
log(1+Age(t-1))			0.0376**	0.9963**	0.0357**	0.9846**
			(0.0041)	(0.0189)	(0.0049)	(0.0227)
$\text{Flows}^{6M}(\text{t-1})$			-0.0175	0.3198 *	-0.0262	0.3239 *
			(0.0241)	(0.1225)	(0.0275)	(0.1454)
log(Concentration(t-1))			0.0030	-0.4399**	0.0134	-0.4263**
			(0.0148)	(0.0138)	(0.0174)	(0.0155)
$\log(\text{Illiq}^{\text{RelSpread}}(\text{t-1}))$			-2.5460**	-2.8600**	-2.4781**	-2.7989**
			(0.0820)	(0.0726)	(0.0933)	(0.0818)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
Mean R^2	0.837	0.712	0.719	0.495	0.737	0.503
Obs.	72,688	72,688	67,556	67,556	52,479	52,479

$*$ p<0.05; $**$ p<0.01

Table 8: The determinants of fund-specific indirect vulnerability (IV_3) and systemicness (S_3), respectively, for *Scenario 3*. Results are based on quarterly data using Fama-MacBeth regressions (Newey-West standard errors in parentheses), including a constant that is omitted from the output. All variables are defined in the main text and in Table 5. Panels A and B cover the full sample period from 2003-14 and Panel C reports results of the subsample without the financial crisis period 2008-09.

both *less* vulnerable and *less* systemic, which is against economic intuition.[33]

As our analysis solely focuses on funds' equity portfolios, *Scenario 3* is closest to the applications Greenwood et al. (2015) and Cetorelli et al. (2016), where a specific homogeneous price impact parameter is assigned to an entire asset class. While this seems like a reasonable approach in the absence of detailed information on asset liquidity and price impact parameters are derived from regulatory guidelines, such as Basel III, our analysis reveals that this can be problematic in the sense that the model yields very different vulnerabilities at the micro-level.

Let us take a closer look at how *Scenario 3* affects the estimated fund-specific vulnerabilities. Given the assumption of a homogeneous price impact parameter, we effectively treat funds with very liquid (illiquid) portfolios as being more illiquid (liquid) than what they should be. To illustrate the effect of this point on both IV and S, Figure 10 plots each fund's relative rank in terms of its indirect vulnerability (left panel) and systemicness (right panel) in *Scenario 1* and *Scenario 3* against each other. For a given measure, the ranking is between 0 and 1 (least and most vulnerable/systemic, respectively). We show the results for both the most liquid funds (Decile 1) and the least liquid funds

[33]Note that Tables 6-8 all use exactly the same exogenous variables, with the two illiquidity measures being the *actual* portfolio illiquidity observed in the data (not the homogeneous value that would arise in the stress test model application).

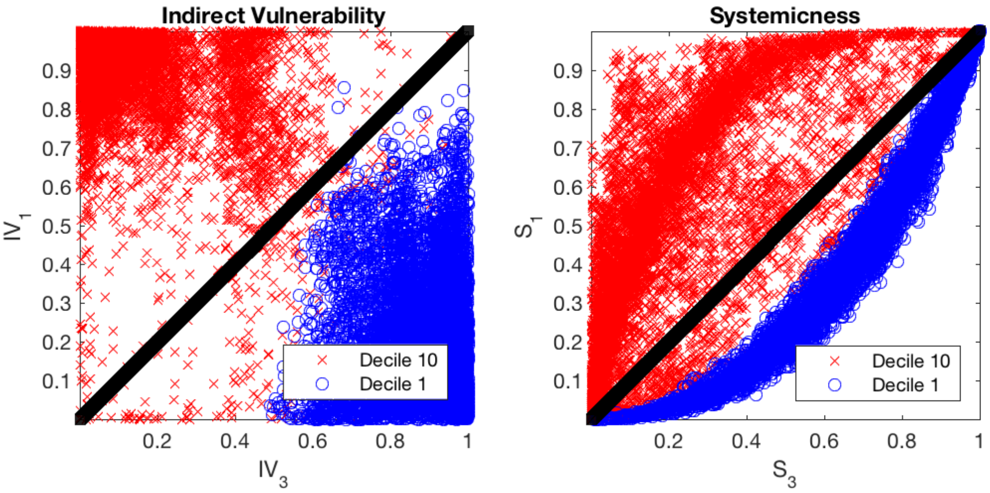

Figure 10: Vulnerability rankings in *Scenario 1* plotted against those from *Scenario 3*. Left panel: indirect vulnerability. Right panel: systemicness. Both panels show the relative ranking for funds in liquidity Decile 1 (most liquid) and Decile 10 (least liquid), respectively, based on $\text{Illiq}^{\text{Amihud}}$. For the sake of reference, the solid line shows the 45 degree line. Note: ranks are between 0 and 1, with higher values corresponding to higher vulnerabilities.

(Decile 10), based on the observed $\text{Illiq}^{\text{Amihud}}$. If a homogeneous price impact did not affect fund-specific vulnerabilities, the two scenarios should yield similar rankings and all observations would lie on the main diagonal (solid black line). It turns out that the rankings are quite different for the two sets of funds under study here: liquid funds (blue dots) tend to be much more vulnerable (and slightly more systemic), since almost all observations are below the main diagonal. The reverse is true for the most illiquid funds (red crosses). Hence, *Scenario 3* underestimates the vulnerabilities for the least liquid funds and overestimates those for the most liquid funds.

In summary, we propose that *Scenario 3* should be treated with care and, whenever possible, time-varying and asset-specific price impacts should be used in the application of stress testing models.

6 Discussion

Implications for future stress tests. Do our findings suggest that the mutual fund sector is relatively robust to systemic asset liquidations? The answer tends to be 'yes' if we are interested in the set of U.S. domestic equity funds in isolation, at least during periods of relatively high market liquidity. However, it is important to keep in mind that we restricted ourselves to this relatively liquid fund type for two reasons: first, domestic equity funds constitute an economically meaningful subset of the U.S. asset management industry. Second, this fund type is well-studied in the literature, largely because the CRSP Mutual Fund Database provides accurate information on these funds' asset holdings and the corresponding price impacts. Therefore, our analysis is an obvious first step in the quantification of systemic risks among asset managers.

An obvious extension of our analysis would include additional fund types and explore to what extent this might further increase the system's vulnerability.[34] Such an extension seems particularly relevant because other fund types have been growing in importance over time, especially corporate and high-yield bond funds (Goldstein et al. (2017); Cetorelli et al. (2016)). Assuming that a typical fixed income fund holds at least some stocks in its portfolio (and vice versa for equity funds), shocks that originate in one asset class would spread to other asset classes. Therefore, we would expect higher vulnerabilities when including these additional fund types. As pointed out by Cetorelli et al. (2016), these spill-over effects might be even larger when market liquidity worsens and bond fund flows become more sensitive to fund performance (see Goldstein et al. (2017)).

Policy implications. Our paper contributes to the ongoing discussion about systemic risk in the asset management sector, especially to the SIFI designation of Non-Bank Non-Insurer entities (Financial Stability Board (2015)). One indicator for assigning systemic relevance is *fund size*, which is readily available and accessible for supervisors in a timely manner (Financial Stability Board (2015)). Besides size, International Monetary Fund (2015) suggests considering funds' *investment style* as a further indicator, which might be proxied by a fund's portfolio diversification and liquidity profile.

Our analysis reveals ambiguous effects of *fund size* and *investment style* on vulnerabilities in the fund sector. In fact, micro- and macroprudential regulators might draw opposite conclusions from our results. On the one hand, microprudential supervisors are mainly concerned with the resilience of individual funds to market-wide shocks, which we capture to a certain extent with our indirect vulnerability (IV) measure. It turns out that smaller and more concentrated funds appear to be more robust to other funds' asset liquidations. On the other hand, macroprudential regulators would be more concerned with the negative externalities imposed by funds, as proposed for example by Danielsson and Zigrand (2015). In this case, systemicness (S) is the variable of interest and we find that larger, more diversified funds strongly contribute to the aggregate vulnerability of the sector. This finding relates to the model of diversification disasters by Ibragimov, Jaffee, and Walden (2011), where financial intermediaries increase systemic risks by attempting to reduce their exposure to idiosyncratic risks.

Fund illiquidity tends to contribute to both funds' own vulnerability and their impact on other funds. Therefore, both micro- and macroprudential regulators should closely

[34] As these data are not covered by the CRSP Mutual Fund Database, we leave this extension for future research.

monitor the liquidity profile of individual funds. This proposal is in line with a new set of SEC rules for enhancing liquidity risk management by open-ended funds (see Hanouna, Noval, Riley, and Stahel (2015)), and FSB recommendations to address the liquidity mismatch in the fund sector (Financial Stability Board (2017)). Other regulators have already recognized the need to monitor the liquidity profiles of individual institutions. For example, the Liquidity Coverage Ratio (LCR) has become an important metric for banking regulators, and there is an active academic debate on how to measure the liquidity profile of individual institutions (Brunnermeier, Gorton, and Krishnamurthy (2012); Krishnamurthy, Bai, and Weymuller (2016)).

Swing pricing is a potential element which can help to mitigate vulnerabilities in the mutual fund sector (Securities and Exchange Commission (2018); Capponi, Glasserman, and Weber (2018)). The basic idea of swing pricing is to levy redeeming investors for their redemption-induced transaction costs due to asset liquidations. Hence, swing pricing can possibly reduce existing first-mover advantages, particularly so for more illiquid funds (see Goldstein et al. (2017)). In this context, the SEC recently allowed funds to use swing pricing as a further liquidity risk management tool (Securities and Exchange Commission (2018)). In this regard, Capponi et al. (2018) point out that an adequate design of swing pricing likely depends on the amount of fire-sale losses that should be accounted for from a macropudential perspective. In this context, our fund-level indicators (vulnerability and systemicness) could serve as inputs for macroprudential extentions of swing pricing models.

7 Conclusions

Our paper proposes a macroprudential stress test for asset managers. For this purpose, we extended the model of Greenwood et al. (2015) by incorporating the well-documented flow-performance relationship. We then applied the model to the set of U.S. domestic equity mutual funds. Overall, we generally find that the system in isolation is relatively robust to systemic asset liquidations, at least when market liquidity is not too low. This result is largely driven by the fact that mutual funds tend to use little leverage compared with commercial banks and broker-dealers. Lastly, we also explored the determinants of individual funds' vulnerabilities, highlighting the importance of fund size, diversification levels, and portfolio illiquidity. Thus, a clear understanding of funds' liquidity profile is essential for enhancing the corresponding micro- and macroprudential policy tools.

Moving forward, we see various interesting avenues for future research. Most importantly, we aim to apply our model to a broader set of asset managers. In addition, we believe it is of utmost importance to combine stress tests for bank and non-bank financial institutions in order to understand repercussions and interconnections between different parts of the financial system. Our model is general enough to accommodate a variety of financial institutions with different regulatory constraints and potentially different behavioral rules.

References

Acharya, V. V., D. Gale, and T. Yorulmazer (2011). Rollover risk and market freezes. *The Journal of Finance 66*(4), 1177–1209.

Adrian, T. and H. S. Shin (2010). Liquidity and leverage. *Journal of Financial Intermediation 19*(3), 418–437.

Almazan, A., K. Brown, M. Carlson, and D. Chapman (2004). Why constrain your mutual fund manager? *Journal of Financial Economics 73(2)*, 289–321.

Amihud, Y. (2002). Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Bank for International Settlements (2014). 84th Annual Report.

Bauguess, S. W. (2017). Market fragility and interconnectedness in the asset management industry. Keynote Address - Buy-Side Risk USA 2017 Conference ("Market Fragility and Interconnectedness in the Asset Management Industry"), June 20, 2017.

Berk, J. B. and R. Green (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy 112*, 1269–1295.

Boguth, O. and M. Simutin (2017). Leverage constraints and asset prices: Insights from mutual fund risk taking. *Journal of Financial Economics forthcoming*.

Brennan, M., S.-W. Huh, and A. Subrahmanyam (2013). An analysis of the amihud illiquidity premium. *Review of Asset Pricing Studies 3*, 133–176.

Brunnermeier, M., G. Gorton, and A. Krishnamurthy (2012). Risk topography. *NBER Macroeconomics Annual 26*, 149–176.

Caccioli, F., M. Shrestha, C. Moore, and J. Farmer (2014). Analysis of financial contagion due to overlapping portfolios. *Journal of Banking and Finance 46*, 233–245.

Capponi, A., P. Glasserman, and M. Weber (2018). Swing pricing for mutual funds: Breaking the feedback loop between fire sales and fund redemptions. *Office of Financial Research Research Paper No. 18-04*.

Cetorelli, N., F. Duarte, and T. Eisenbach (2016). Are asset managers vulnerable to fire sales? Blogpost Liberty Street Economics (February 18, 2016).

Chen, Q., I. Goldstein, and W. Jiang (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics 97*(2), 239 – 262.

Cifuentes, R., G. Ferrucci, and H. Shin (2005). Liquidity risk and contagion. *Journal of the European Economic Association 3*(2/3), 556–566.

Cont, R. and E. Schaanning (2017). Fire sales, indirect contagion and systemic stress testing. *SSRN Working Paper*.

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

Cremers, K. J. M. and A. Petajisto (2009). How active is your fund manager? A new measure that predicts performance. *The Review of Financial Studies 22*(9), 3329–3365.

Danielsson, J. and J.-P. Zigrand (2015). Are asset managers systemically important? Voxeu.org - Opinion Piece (August 05, 2015).

Duarte, F. and T. Eisenbach (2013). Fire-sale spillovers and systemic risk. Federal Reserve Bank of New York Staff Reports, number 645.

Dunne, P. and F. Shaw (2017). Investment fund risk: The tale in the tails. Working Paper, Bank of Ireland.

Ellul, A., C. Jotikasthira, and C. Lundblad (2011). Regulatory pressure and fire sales in the corporate bond market. *Journal of Financial Economics 101*, 596–620.

Engle, R., R. Ferstenberg, and J. Russell (2012). Measuring and modeling execution cost and risk (digest summary). *Journal of Portfolio Management 38*(2), 14–18.

European Central Bank (2014). Structural and systemic risk features of Euro Area investment funds. Financial Stability Review.

Fama, E. and J. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy 81*, 607–636.

Feroli, M., A. K. Kashyap, K. Schoenholtz, and H. S. Shin (2014). Market tantrums and monetary policy. Report for the 2014 US monetary policy forum.

Financial Stability Board (2011). FSB Recommendations to Strengthen Oversight and Regulation of Shadow Banking. Recommendations of the Financial Stability Board. Policy document.

Financial Stability Board (2015). Assessment methodologies for identifying Non-Bank Non-Insurer Global Systemically Important Financial Institutions. Consultative document.

Financial Stability Board (2017). Policy recommendations to address structural vulnerabilities from asset management activities. Policy document.

Franzoni, F. and M. C. Schmalz (2017). Fund flows and market states. *The Review of Financial Studies 30*(8), 2621–2673.

Fricke, D. (2017). Are specialist funds "special"? *forthcoming: Financial Management*.

Getmansky, M., G. Girardi, K. W. Hanley, S. Nikolava, and L. Pelizzon (2016). Portfolio similarity and asset liquidation in the insurance industry. *SSRN Working Paper*.

Glasserman, P. and H. Young (2015). How likely is contagion in financial networks? *Journal of Banking and Finance 50*, 383–399.

Glasserman, P. and H. Young (2016). Contagion in financial networks. *Journal of Economic Literature 54*(3), 779–831.

Goldstein, I., H. Jiang, and D. Ng (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics 126*(3), 592–613.

Gorton, G. and A. Metrick (2012). Securitized banking and the run on repo. *Journal of Financial Economics 104*, 425–451.

Goyenko, R. Y., C. W. Holden, and C. Trzcinka (2009). Do liquidity measures measure liquidity? *Journal of Financial Economics 92*, 153–181.

Greenwood, R., A. Landier, and D. Thesmar (2015). Vulnerable banks. *Journal of Financial Economics 115*, 471–485.

Greenwood, R. and D. Thesmar (2011). Stock price fragility. *Journal of Financial Economics 102*, 471–490.

Hanouna, P., J. Noval, T. Riley, and C. Stahel (2015). Liquidity and flows of U.S. mutual funds. SEC staff white paper.

Ibragimov, R., D. Jaffee, and J. Walden (2011). Diversification disasters. *Journal of Financial Economics 99*, 333–348.

International Monetary Fund (2015). Global financial stability review. Technical report.

Investment Company Institute (2015). ICI 2015 fact book. Technical report.

Investment Company Institute (2016). ICI 2016 fact book. Technical report.

Jian, H., D. Li, and A. Wang (2016). Dynamic liquidity management by corporate bond mutual funds. Technical report.

Kacperczyk, M., C. Sialm, and L. Zheng (2005). On the industry concentration of actively managed equity mutual funds. *Journal of Finance 60*, 1983–2011.

Krishnamurthy, A., J. Bai, and C.-H. Weymuller (2016). Measuring liquidity mismatch in the banking sector. NBER Working Paper 22729.

Malkiel, B. G. (2013). Asset management fees and the growth of finance. *Journal of Economic Perspectives 27*(2), 97–108.

Manconi, A., M. Massa, and A. Yasuda (2012). The role of institutional investors in propagating the crisis of 2007–2008. *Journal of Financial Economics 104*(3), 491 – 518.

Office of Financial Research (2013). Asset management and financial stability. Technical report.

Pozen, R. and T. Hamacher (2011). *The Fund Industry - How Your Money is Managed* (2^{nd} edition ed.). Wiley.

Pulvino, T. C. (1998). Do fire sales exist? An empirical investigation of commercial aircraft transactions. *Journal of Finance 53*, 939–978.

Securities and Exchange Commission (2018). Investment Company Swing Pricing.

Sirri, E. R. and P. Tufano (1998). Costly search and mutual fund flows. *Journal of Finance 53*, 1589–1622.

Spiegel, M. and H. Zhang (2013). Mutual fund risk and market share-adjusted fund flows. *Journal of Financial Economics 108*, 506–528.

Tarullo, D. K. (2016). Next steps in the evolution of stress testing. Remarks at the Yale University School of Management Leaders Forum (September 26, 2016).

Wagner, W. (2011). Systemic liquidation risk and the diversity-diversification trade-off. *Journal of Finance 66*, 1141–1175.

Yan, X. (2008). Liquidity, investment style, and the relation between fund size and fund performance. *Journal of Financial and Quantitative Analysis 43*, 741–767.

Internet Appendix

A Price Impacts During Active/Volatile Trading Periods

The price impacts shown in Figure 5 are likely to be representative of the typical market conditions in a given quarter. More precisely, in the baseline scenario, we calculate the price impacts as the average values of the daily Amihud ratio for each stock. In order to explore to what extent one would expect even larger price impacts during very active periods, Figure 11 shows the results for: (1) trading days with above-median volatility for each stock within a given quarter; and (2) the same for trading days with above-median trading volumes for each stock within a given quarter.

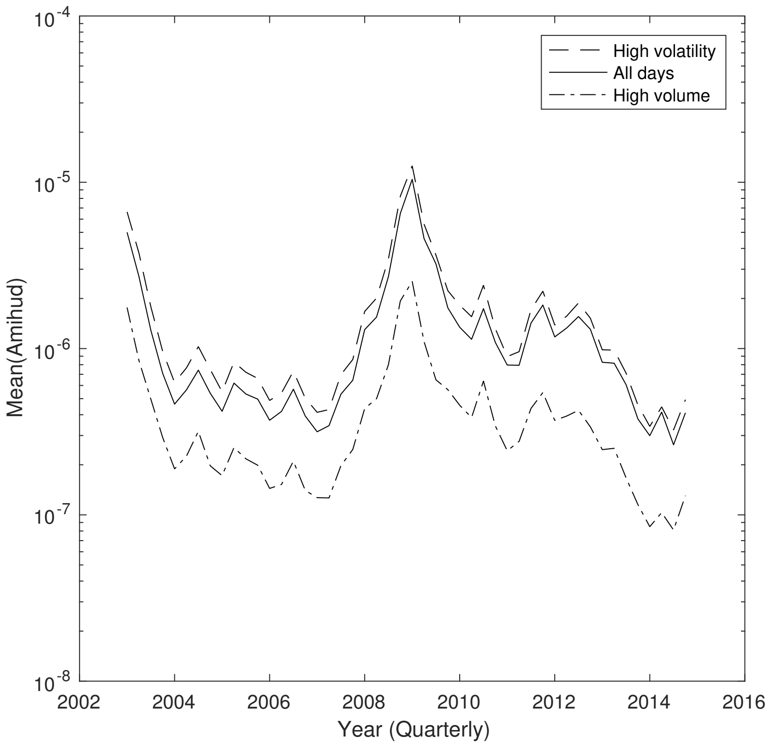

Figure 11: Price impacts for very active periods. In the baseline scenario, we calculate the price impacts as the average values of the daily Amihud ratio for each stock (All Days, as in the main text). We also calculated price impacts using only the most active trading days for each stock: (1) based on daily trading volumes in a quarter; (2) based on absolute returns in a given quarter. We then take the quarterly average of these daily values separately for each stock. Dollar-trading volumes are adjusted for inflation. For each quarter, we show the cross-sectional equal-weighted average values. (y-axis in logarithmic scale).

Interestingly, the results go in opposite directions: price impacts are slightly larger (smaller) for high volatility (trading volume) days. This indicates that high-volume days do not coincide with high-volatility days in general. Overall, the typical price impacts are comparable to those we used in our main analysis in Scenario 1 in the main text.

B Flow-Performance Relationship

B.1 Pooled Regressions

Table 1 in the main text shows several different specifications for the estimation of the flow-performance relationship, most importantly the baseline specification using the Fama-MacBeth methodology. In addition to the results shown in Table 2, here we report additional robustness checks which generally yield very similar results in terms of the estimated parameter γ^E. In this regard, Table 9 shows the most important robustness checks:

(1) *Style-adjusted returns.* In this case, we take a fund's return and subtract the average return of each fund category (based on CRSP obective codes) separately for each month.

(2) *Fund family-adjusted returns.* In this case, we take a fund's return and subtract the average return of funds' from the same fund family (CRSP management company code) separately for each month, if the fund is member of a fund family.

(3) *Size.* Here we separate the sample into large and small funds, respectively, based funds' TNA to (above- and below-median size groups).

(4) *Flow Volatility.* Goldstein et al. (2017) find that more illiquid funds tend to display a stronger flow-performance relationship. In addition to the liquid/illiquid funds estimation in the main text, it seems natural to also estimate the relationship for funds with different levels of funding fragility. Here we separate the sample into funds with high and low levels of flow volatility (above- and below-median funds), using the 6-month rolling-window flow standard deviations.

(5) *Return Volatility.* Franzoni and Schmalz (2017) find that funds with higher return volatility display a weaker flow-performance relationship. Hence, we also estimate the relationship for funds with different levels of return volatility. Similar to the previous case, we separate the sample into funds with high and low levels of return volatility (above- and below-median funds), using the 6-month rolling-window return standard deviations.

Flows might also be influenced by large return variations, especially during crisis periods. To test this hypothesis we extend the baseline flow-performance regression by including dummy variables that are meant to capture fund-month observations with extreme returns. Adding the different dummies to the regressions allows us to check to what extent extreme fund-level returns might lead to higher netflows. Here we calculate two sets of dummy variables: the first set compares a given fund's lagged return with its own lagged 6-month rolling window return standard deviation ($\sigma_{i,t-1}^{6M}$)[35]

$$\mathrm{D}_{i,t}^{\text{abs,fund-level}} = \begin{cases} 1 & \text{if abs(Return(t-1))} > 2 \times \sigma_{i,t-1}^{6M} \\ 0 & \text{else.} \end{cases}$$

In order to specifically focus on extreme negative returns, we also calculated another dummy

$$\mathrm{D}_{i,t}^{\text{neg,fund-level}} = \begin{cases} 1 & \text{if Return(t-1)} < -2 \times \sigma_{i,t-1}^{6M} \\ 0 & \text{else.} \end{cases}$$

For the sake of robustness, we also analyze if the average fund sector return variation affects fund flows. In this case, we define two additioal dummies which compare fund-level returns with the lagged 6-month rolling window return standard deviation of the average fund return ($\sigma_{\text{mkt},t-1}^{\text{6M}}$), denoted as $\mathrm{D}^{\text{abs,mkt}}$ and $\mathrm{D}^{\text{neg,mkt}}$, respectively.
Table 10 reports the results. The estimated γ^{E}s are generally within the confidence bands of the original baseline estimator from Table 1. In other words, the strength of the flow-performance relationship does not change significantly for these alternative specifications. If anything, given that the parameters on the different dummy variables are generally positive (or insignificant), large lagged returns tend to be followed by rather muted outflows. This suggests that the baseline specification we have chosen in the paper will tend to overestimate rather than underestimate the vulnerability of the system.

Lastly, Table 11 shows the full regression results corresponding to the ones shown in Table 4 in the main text.

[35]Given that the average fund return is approximately zero, adding the rolling-window average returns to the dummy construction is immaterial for the reported results.

Flow-Performance Relationship

	Dependent variable: Flows(t)								
	(1)	(2)	(3)		(4)		(5)		
	Style	Fam.-adj.	Fund size		Flow vola		Return vola		
	Returns	Returns	Small	Large	Low	High	Low	High	
Return(t-1)	0.3225**	0.3405 **	0.3234**	0.2411**	0.0667**	0.4305**	0.3158**	0.2884**	
	(0.0244)	(0.0484)	(0.0274)	(0.0172)	(0.0037)	(0.0291)	(0.0264)	(0.0225)	
Return(t-2)	0.1966**	0.1375 **	0.1705**	0.1536**	0.0452**	0.2243**	0.2337**	0.1378**	
	(0.0210)	(0.0234)	(0.0258)	(0.0165)	(0.0033)	(0.0284)	(0.0299)	(0.0232)	
Return(t-3)	0.1202**	0.0366	0.1053**	0.1130**	0.0343**	0.1348**	0.1744**	0.0901**	
	(0.0211)	(0.0384)	(0.0242)	(0.0211)	(0.0031)	(0.0245)	(0.0234)	(0.0203)	
Return(t-4)	0.0823 *	0.0551 **	0.0818**	0.0862**	0.0183**	0.1109**	0.1378**	0.0842**	
	(0.0405)	(0.0192)	(0.0226)	(0.0147)	(0.0029)	(0.0268)	(0.0229)	(0.0205)	
Return(t-5)	0.0990**	0.0764 *	0.0774**	0.0538**	0.0079**	0.0859**	0.1570**	0.0522 *	
	(0.0189)	(0.0326)	(0.0245)	(0.0198)	(0.0030)	(0.0268)	(0.0269)	(0.0213)	
Return(t-6)	0.1195**	0.1058 *	0.1085**	0.0528**	0.0096**	0.1035**	0.1143**	0.0569 *	
	(0.0192)	(0.0411)	(0.0238)	(0.0140)	(0.0036)	(0.0237)	(0.0233)	(0.0218)	
Return(t-7)	0.0844**	0.1088	0.0441	0.0618**	0.0058	0.0594 *	0.1126**	0.0188	
	(0.0227)	(0.0768)	(0.0234)	(0.0138)	(0.0029)	(0.0263)	(0.0241)	(0.0196)	
Return(t-8)	0.0896**	0.0701 **	0.0772**	0.0505**	0.0167	0.0874**	0.0944**	0.0679**	
	(0.0185)	(0.0229)	(0.0260)	(0.0149)	(0.0103)	(0.0272)	(0.0238)	(0.0220)	
Return(t-9)	0.0783**	0.0622 **	0.0598 *	0.0630**	0.0067 *	0.0772**	0.0738**	0.0850**	
	(0.0177)	(0.0193)	(0.0244)	(0.0135)	(0.0029)	(0.0256)	(0.0224)	(0.0323)	
Return(t-10)	0.0648**	0.0474 *	0.0530	0.0324 *	0.0142	0.0395	0.0507	0.0313	
	(0.0181)	(0.0223)	(0.0279)	(0.0147)	(0.0074)	(0.0281)	(0.0285)	(0.0259)	
Return(t-11)	0.0472**	0.0374	0.0363	0.0348 *	0.0101**	0.0472	0.0663**	0.0388	
	(0.0172)	(0.0220)	(0.0243)	(0.0158)	(0.0030)	(0.0277)	(0.0228)	(0.0211)	
Return(t-12)	0.1074 *	0.0715	0.0350	0.0348 *	-0.0002	0.0649 *	-0.0031	0.0412	
	(0.0453)	(0.0389)	(0.0234)	(0.0142)	(0.0028)	(0.0287)	(0.0200)	(0.0213)	
Flows(t-1)	0.0764**	0.0907 **	0.0631**	0.1332**	0.2803**	0.0686**	0.1145**	0.0492**	
	(0.0099)	(0.0167)	(0.0112)	(0.0179)	(0.0057)	(0.0102)	(0.0125)	(0.0118)	
Flows(t-2)	0.0734**	0.0889 **	0.0861**	0.0930**	0.1910**	0.0769**	0.0921**	0.0815**	
	(0.0106)	(0.0073)	(0.0088)	(0.0088)	(0.0051)	(0.0072)	(0.0094)	(0.0099)	
Flows(t-3)	0.0310	0.0386 *	0.0178	0.0661**	0.1554**	0.0103	0.0707**	0.0243	
	(0.0205)	(0.0187)	(0.0270)	(0.0150)	(0.0049)	(0.0326)	(0.0156)	(0.0281)	
Flows(t-4)	0.0557**	0.0287 *	0.0343**	0.0519**	0.1161**	0.0335**	0.0559**	0.0568 *	
	(0.0191)	(0.0137)	(0.0085)	(0.0083)	(0.0037)	(0.0072)	(0.0086)	(0.0236)	
Flows(t-5)	0.0684**	0.0695 **	0.0561**	0.0526**	0.1002**	0.0504**	0.0497**	0.0542**	
	(0.0145)	(0.0144)	(0.0079)	(0.0093)	(0.0041)	(0.0062)	(0.0078)	(0.0085)	
Flows(t-6)	0.0142	0.0147	0.0400**	0.0232	0.0047**	0.0364**	0.0298**	0.0130	
	(0.0206)	(0.0205)	(0.0105)	(0.0179)	(0.0011)	(0.0081)	(0.0069)	(0.0284)	
Flows(t-7)	0.0151	0.0508	0.0218 *	0.0261**	0.0050**	0.0267**	0.0231**	0.0271 *	
	(0.0115)	(0.0270)	(0.0086)	(0.0058)	(0.0018)	(0.0082)	(0.0065)	(0.0109)	
Flows(t-8)	0.0417**	0.0317 **	0.0317**	0.0319**	0.0052**	0.0332**	0.0427**	0.0262**	
	(0.0120)	(0.0058)	(0.0066)	(0.0067)	(0.0011)	(0.0074)	(0.0101)	(0.0076)	
Flows(t-9)	-0.0080	-0.0170	-0.0087	0.0296**	0.0066	0.0378**	0.0347**	0.0265**	
	(0.0478)	(0.0468)	(0.0478)	(0.0105)	(0.0038)	(0.0123)	(0.0111)	(0.0073)	
Flows(t-10)	0.0236**	0.0344 **	0.0306**	0.0327 *	0.0065	0.0295**	0.0271**	0.0250**	
	(0.0069)	(0.0096)	(0.0066)	(0.0138)	(0.0037)	(0.0067)	(0.0073)	(0.0077)	
Flows(t-11)	0.0181**	0.0171 **	0.0174 *	0.0267**	0.0022 *	0.0073	0.0171 *	0.0188 *	
	(0.0051)	(0.0051)	(0.0068)	(0.0068)	(0.0009)	(0.0142)	(0.0066)	(0.0072)	
Flows(t-12)	0.0263**	0.0286 **	0.0402**	0.0216**	0.0031	0.0328**	0.0200**	0.0443**	
	(0.0066)	(0.0057)	(0.0110)	(0.0059)	(0.0019)	(0.0070)	(0.0071)	(0.0129)	
log(TNA(t-1))	-0.0058	-0.0057	-0.0089**	-0.0023**	-0.0003	-0.0040**	-0.0009**	-0.0043	
	(0.0033)	(0.0033)	(0.0033)	(0.0003)	(0.0002)	(0.0011)	(0.0003)	(0.0024)	
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
adj. R^2	0.163	0.165	0.191	0.224	0.686	0.164	0.211	0.203	
Obs.	306,570	306,570	143,184	163,386	158,677	147,893	151,900	154,669	

$*$ p<0.05; $**$ p<0.01

Table 9: Additional robustness checks, flow-performance relationship. This Table shows the results of the flow-performance regressions, with γ^E being the parameter on Return(t-1). All regressions based on monthly data using Fama-MacBeth regressions (Newey-West standard errors in parentheses), as in the main text.

Flow-Performance Relationship

	$\sigma^{6M}_{i,t-1}$ abs	$\sigma^{6M}_{i,t-1}$ neg	$\sigma^{6M}_{mkt,t-1}$ abs	$\sigma^{6M}_{mkt,t-1}$ neg
Return(t-1)	0.3178**	0.3176**	0.2456**	0.2730**
	(0.0334)	(0.0326)	(0.0467)	(0.0461)
Return(t-2)	0.1520**	0.1527**	0.1608**	0.1609**
	(0.0208)	(0.0208)	(0.0193)	(0.0192)
Return(t-3)	0.1173**	0.1190**	0.1102**	0.1107**
	(0.0222)	(0.0221)	(0.0177)	(0.0180)
Return(t-4)	0.0423	0.0434	0.0323	0.0323
	(0.0439)	(0.0437)	(0.0489)	(0.0489)
Return(t-5)	0.0673**	0.0700**	0.1227 *	0.1184 *
	(0.0178)	(0.0181)	(0.0551)	(0.0551)
Return(t-6)	0.0935**	0.0975**	0.1162**	0.1165**
	(0.0197)	(0.0193)	(0.0387)	(0.0386)
Return(t-7)	0.0365	0.0398	0.0576**	0.0604**
	(0.0219)	(0.0217)	(0.0178)	(0.0175)
Return(t-8)	0.0626**	0.0634**	0.0764**	0.0805**
	(0.0197)	(0.0196)	(0.0188)	(0.0186)
Return(t-9)	0.0827**	0.0810**	0.0630**	0.0596**
	(0.0267)	(0.0267)	(0.0169)	(0.0167)
Return(t-10)	0.0259	0.0276	0.0270	0.0273
	(0.0198)	(0.0199)	(0.0212)	(0.0210)
Return(t-11)	0.0378 *	0.0389 *	0.0898	0.0918
	(0.0176)	(0.0176)	(0.0510)	(0.0509)
Return(t-12)	0.0364 *	0.0361 *	0.0382 *	0.0397 *
	(0.0164)	(0.0163)	(0.0163)	(0.0161)
Flows(t-1)	0.0741**	0.0739**	0.0696**	0.0695**
	(0.0090)	(0.0090)	(0.0086)	(0.0086)
Flows(t-2)	0.0776**	0.0774**	0.0798**	0.0802**
	(0.0093)	(0.0093)	(0.0080)	(0.0080)
Flows(t-3)	0.0190	0.0188	0.0107	0.0106
	(0.0288)	(0.0288)	(0.0356)	(0.0356)
Flows(t-4)	0.0602**	0.0600**	0.0565**	0.0563**
	(0.0224)	(0.0224)	(0.0193)	(0.0193)
Flows(t-5)	0.0553**	0.0552**	0.0553**	0.0554**
	(0.0062)	(0.0062)	(0.0062)	(0.0062)
Flows(t-6)	0.0096	0.0091	0.0151	0.0151
	(0.0250)	(0.0250)	(0.0196)	(0.0196)
Flows(t-7)	0.0224**	0.0229**	0.0238**	0.0240**
	(0.0070)	(0.0071)	(0.0066)	(0.0066)
Flows(t-8)	0.0616 *	0.0620 *	0.0625 *	0.0630 *
	(0.0301)	(0.0301)	(0.0313)	(0.0313)
Flows(t-9)	-0.0020	-0.0021	0.0051	0.0051
	(0.0496)	(0.0496)	(0.0526)	(0.0526)
Flows(t-10)	0.0247**	0.0248**	0.0263**	0.0255**
	(0.0058)	(0.0058)	(0.0054)	(0.0054)
Flows(t-11)	0.0182**	0.0183**	0.0187**	0.0190**
	(0.0051)	(0.0051)	(0.0051)	(0.0051)
Flows(t-12)	0.0304**	0.0305**	0.0303**	0.0303**
	(0.0058)	(0.0059)	(0.0058)	(0.0058)
log(TNA(t-1))	-0.0057	-0.0057	-0.0058	-0.0058
	(0.0033)	(0.0033)	(0.0033)	(0.0033)
$D(\sigma^{6m}_{t-1})$	0.0003	0.0012	0.0074**	0.0156 *
	(0.0025)	(0.0070)	(0.0025)	(0.0069)
Fama-MacBeth	Yes	Yes	Yes	Yes
adj. R^2	0.168	0.169	0.169	0.170
Obs.	306570	306570	306570	306570

$*$ $p<0.05$; $**$ $p<0.01$

Table 10: Flow-performance regressions for volatile markets. This Table shows the results of the flow-performance regressions which additionally control for nonlinear flow behavior during volatile markets by including dummy variables. Dummy variables take a value of one if the fund return is more than two standard deviations above the 6-month return average. γ^E represents the parameter on Return(t-1). All regressions based on monthly data using Fama-MacBeth regressions (Newey-West standard errors in parentheses), as in the main text.

Flow-Performance Relationship

	Dependent variable: Flows(t)					
	(1)		(2)			
	Index		Non-Index			
	Inst.	Non-Inst.	Inst.		Non-Inst.	
			Liquid	Illiquid	Liquid	Illiquid
Return(t-1)	0.2557	0.4627 **	0.1260**	0.2347**	0.3393**	0.3026**
	(0.1430)	(0.1109)	(0.0301)	(0.0297)	(0.0337)	(0.0359)
Return(t-2)	0.6026**	0.1405	0.1160**	0.1982**	0.1233**	0.1761**
	(0.2132)	(0.1284)	(0.0327)	(0.0281)	(0.0357)	(0.0291)
Return(t-3)	0.1501	0.0589	0.1482**	0.1387**	0.1237**	0.1242**
	(0.1979)	(0.1310)	(0.0283)	(0.0347)	(0.0337)	(0.0272)
Return(t-4)	0.3271	-0.0058	0.0645 *	0.0590	0.0572	0.1189**
	(0.1794)	(0.1404)	(0.0289)	(0.0326)	(0.0367)	(0.0315)
Return(t-5)	0.2081	-0.0349	0.1544**	0.0668 *	0.0519	0.0345
	(0.1525)	(0.1155)	(0.0294)	(0.0309)	(0.0408)	(0.0262)
Return(t-6)	0.3300	-0.0862	0.0696 *	0.1066**	0.0186	0.0428
	(0.1677)	(0.1288)	(0.0290)	(0.0307)	(0.0404)	(0.0263)
Return(t-7)	-0.0101	-0.0853	0.0690 *	0.1412**	0.0136	0.0437
	(0.1721)	(0.1469)	(0.0280)	(0.0259)	(0.0322)	(0.0289)
Return(t-8)	0.0596	0.2225	0.0474	0.0529 *	0.0599	0.0692
	(0.1708)	(0.1664)	(0.0290)	(0.0258)	(0.0317)	(0.0388)
Return(t-9)	-0.0003	0.0860	0.0101	0.1198**	0.0214	0.0515
	(0.1657)	(0.1548)	(0.0311)	(0.0296)	(0.0321)	(0.0310)
Return(t-10)	-0.2015	-0.3388 *	0.0534	0.0969**	0.0962**	0.0389
	(0.1670)	(0.1461)	(0.0323)	(0.0305)	(0.0336)	(0.0305)
Return(t-11)	0.3032 *	-0.1176	0.0666 *	0.0653 *	0.0061	0.0537
	(0.1476)	(0.1603)	(0.0296)	(0.0254)	(0.0316)	(0.0283)
Return(t-12)	0.1184	-0.0188	0.0307	0.0338	0.0625 *	0.0269
	(0.1613)	(0.1480)	(0.0279)	(0.0277)	(0.0314)	(0.0268)
Flows(t-1)	0.1276**	-0.1385 **	0.1171**	0.1138**	0.1338**	0.1638**
	(0.0351)	(0.0273)	(0.0195)	(0.0221)	(0.0195)	(0.0266)
Flows(t-2)	0.0822**	0.0330	0.1117**	0.0721**	0.0664**	0.0717**
	(0.0310)	(0.0252)	(0.0125)	(0.0133)	(0.0218)	(0.0200)
Flows(t-3)	0.0673**	0.0134	0.0933**	0.1006**	0.0954**	0.0525**
	(0.0216)	(0.0259)	(0.0108)	(0.0121)	(0.0212)	(0.0159)
Flows(t-4)	0.0653**	-0.0141	0.0527**	0.0585**	0.0203	0.0515**
	(0.0248)	(0.0259)	(0.0125)	(0.0098)	(0.0195)	(0.0176)
Flows(t-5)	0.0789**	0.1074 **	0.0639**	0.0721**	0.0624**	0.0431 *
	(0.0247)	(0.0278)	(0.0137)	(0.0106)	(0.0151)	(0.0186)
Flows(t-6)	0.0603	0.0344	0.0415**	0.0376**	0.0394 *	0.0111
	(0.0336)	(0.0235)	(0.0105)	(0.0118)	(0.0178)	(0.0172)
Flows(t-7)	0.0606 *	0.0411	0.0552**	0.0266**	0.0216	0.0215
	(0.0268)	(0.0249)	(0.0093)	(0.0096)	(0.0174)	(0.0131)
Flows(t-8)	0.0343	0.0341	0.0292**	0.0424**	0.0154	0.0460**
	(0.0319)	(0.0239)	(0.0094)	(0.0126)	(0.0177)	(0.0136)
Flows(t-9)	0.0130	0.0381	0.0057	0.0311 *	0.0428**	0.0219
	(0.0169)	(0.0224)	(0.0125)	(0.0120)	(0.0163)	(0.0146)
Flows(t-10)	0.0173	0.0697 *	0.0299 *	0.0348**	0.0597**	0.0070
	(0.0192)	(0.0310)	(0.0116)	(0.0083)	(0.0205)	(0.0113)
Flows(t-11)	0.0158	0.0058	0.0193 *	0.0068	-0.0091	0.0280
	(0.0192)	(0.0246)	(0.0092)	(0.0075)	(0.0152)	(0.0152)
Flows(t-12)	0.0285	0.0634 *	0.0091	0.0228**	0.0422**	0.0189
	(0.0180)	(0.0264)	(0.0084)	(0.0077)	(0.0149)	(0.0150)
	(0.0173)	(0.0084)	(0.0077)	(0.0149)	(0.0150)	
log(TNA(t-1))	-0.0007	-0.0041 **	-0.0006**	-0.0018**	-0.0011**	-0.0008 *
	(0.0005)	(0.0007)	(0.0002)	(0.0005)	(0.0002)	(0.0004)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
adj. R^2	0.512	0.592	0.311	0.329	0.450	0.391
Obs.	14180	20222	34,831	34,622	29,207	29,434

$*$ p<0.05; $**$ p<0.01

Table 11: Adding further heterogeneity in the flow-performance relationship. This Table shows the results of the flow-performance regressions, with γ^E being the parameter on Return(t-1). All regressions based on monthly data using Fama-MacBeth regressions (Newey-West standard errors in parentheses), as in the main text.

B.2 Fund-Specific Flow-Performance Relationship

As another robustness check, we also run the following flow-performance regressions

$$\text{Flows}_{i,t} = a_i + b_i \times \text{Controls}_{i,t} + \gamma_i^E \times \text{Return}_{i,t-1} + \epsilon_{i,t}$$

separately for each fund, using the same controls as in our main specification (specifically 12 lags of flows and returns).

The results can be found in Figure 12, where we show the distribution of the fund-specific γ parameters. The solid line gives the results for our baseline case, showing that the distribution is quite broad with a large number of negative values. While the typical estimate is positive (mean = 0.08; median = 0.03), these values are rather noisy (std. dev. = 0.77) and substantially smaller than those used in the model application.

Lastly, we also used a similar approach as Cetorelli et al. (2016) in their blogpost

$$\text{Flows}_{i,t} = a_i + b_i \times \text{Controls}_{i,t} + \gamma_i^E \times \text{Alpha}_{i,t-1} + \epsilon_{i,t}$$

where Alpha is the intercept of a one-factor model regression using a moving window of 12 months, separately for each month. The dashed-dotted line in Figure 12 shows the distribution of the estimated γ parameters in this case. Interestingly, the distribution is even broader compared to the previous case, yielding a non-negligible number of observations exceeding 4 in absolute terms. Again the typical estimate is positive (mean = 0.64; median = 0.39), but even noisier than before (std. dev. = 5.63).

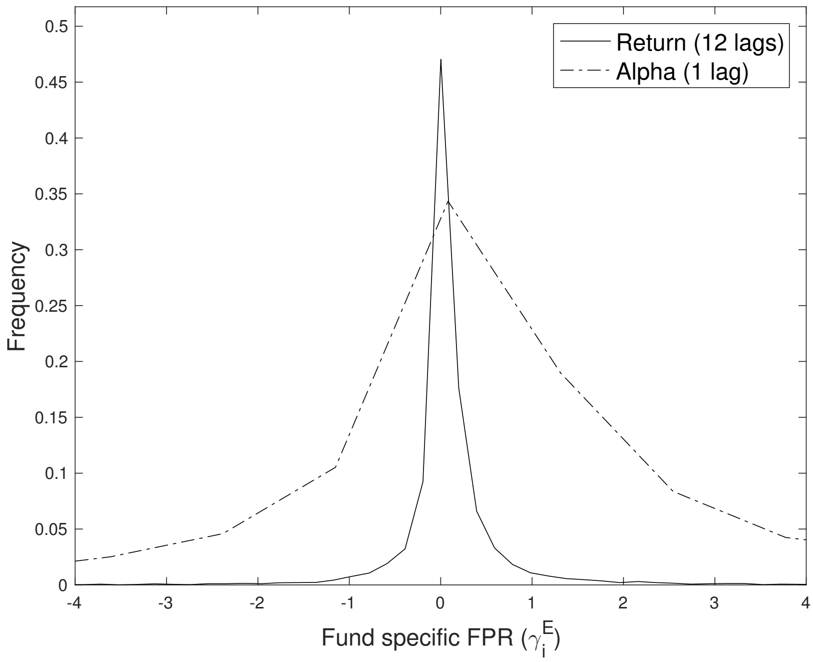

Figure 12: Distribution of fund-specific γ^Es. We estimate the flow-performance relationship (FPR) separately for each fund using the same control variables as in our main specification. In addition, we also show the distribution when using alphas instead of returns.

C Initial Redemption Shock

Given the modest AV levels in our baseline model application, we also explored alternative approaches. Let us briefly describe a simple model that uses the following steps:

1. **Initial redemption shock.** Rather than imposing an initial shock on asset prices, we assume that all mutual funds' observe redemptions of κE_0, with $1 > \kappa \geq 0$.

2. **Leverage targetting.** As in the baseline model, funds can have a leverage target (which may be equal to zero). Hence, in the general case funds will liquidate additional assets to revert to their original leverage target. Adding this to the values from the previous step, a given fund will liquidate a total amount of κA_0 assets, irrespective of the value of B.

3. **Asset liquidation proportional to portfolio weights.** As in the baseline model, we assume that funds' liquidate their assets proportional to their portfolio weights. Hence, the amount to be liquidated per asset is $\phi = \kappa M' A_0$, which results in a market impact of $F = L\phi$. Given the portfolio holdings matrix M, we can calculate each fund's corresponding return as

$$R = MF = \kappa MLM'A_0.$$

This allows us to obtain an equivalent definition of the aggregate vulnerabilities in this simplified model:

$$AV = \frac{1'_N A_0 R}{E_0}. \tag{31}$$

In our application, we again compare the two different cases of $B = 0$ and $B = \bar{B} = 0.5$. Here we assume a homogeneous initial redemption shock of $\kappa = -0.05$ for all mutual funds.[36] Furthermore, we use time-varying and stock-specific price impacts (as in *Scenario 1* in the main text).

The yellow area in Figure 13 shows the corresponding AVs; for the sake of comparison, the red area reproduces the AVs for the baseline model (see top left Panel of Figure 6 in the main text). It turns out that these values are somewhat larger than in the baseline model, but yield identical time dynamics. Generally speaking, however, the resulting values are still relatively modest given that redemptions of 5% constitute a reasonably large initial shock.

[36] In our sample, net flows of -5% roughly correspond to the 5%-percentile of the monthly/quarterly flows of U.S. domestic equity mutual funds.

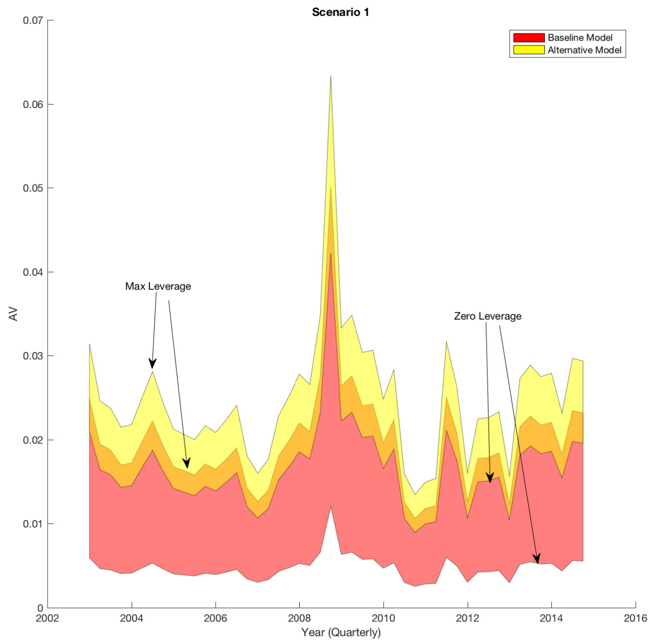

Figure 13: AVs over time in response to initial redemption shock of $\kappa = -0.05$ (based on alternative model in Appendix C) are shown in yellow. Price impacts as in Scenario 1. We also reproduce the AVs from the baseline model in red (as shown in top left panel of Figure 6 in the main text).

D Nonlinear Flow-Performance Relationship

Our baseline FPR-specification assumes a linear relationship between flows and lagged returns. Here we present several analyses which, in line with the existing literature, show that conditioning on negative returns/allowing for a nonlinear FPR would lead to lower AVs in general given that equity fund flows are less responsive to negative returns.

D.1 Flow-Performance Relationship for Negative Returns

Here we test for an asymmetric response of fund flows to negative and positive returns, respectively. Chen et al. (2010) and Goldstein et al. (2017) document a convex relationship between flows and returns for equity funds meaning that flows less sensitive to negative returns compared with positive returns. Following the approach of Goldstein et al. (2017), we test for this possibility by conditioning the γ^E-parameter on negative returns and including a dummy variable for lagged negative returns (D(Return(t-1)<0)) and an interaction term (Return(t-1)×D(Return(t-1)<0)) as additional control variables in our baseline Fama-MacBeth regressions. Given the above-mentionend convexity of the flow-performance relationship, we expect a smaller (rather than a larger) return sensitivity parameter compared to our baseline scenario.
Table 12 reports the results for the full sample and for the crisis period, respectively. In both cases the estimated parameter on Return(t-1) becomes larger. However, as expected

from the convex flow-performance relationship, the parameters on the interaction terms show that this result is driven by positive rather than negative returns: the estimated γ^E, conditioned on negative returns ($0.5344 - 0.4524 = 0.0820$), is substantially lower than our baseline estimate (0.2748). Hence, if anything, the AVs reported in the main part of the paper are again biased upwards rather than downwards. More precisely, if we were to use the estimated γ^E conditioned on negative returns, the linearity of our stress test model implies that the corresponding AVs would be less than 1/3 of the reported values.

D.2 Nonlinear Flow-Performance Relationship

To capture potential nonlinearities in the flow-performance relationship we added Return(t-1) raised to powers 2, 3, ... as additional explanatory variable(s) to the baseline regression. It turns out that only a power of 2 seems relevant, whereas higher powers are insignificant in all specifications (unreported result). In this regard, the second column of Table 13 shows the flow-performance regressions when adding Return(t-1)^2 as explanatory variable. The positive coefficient indicates that large returns (positive or negative) tend to increase net-inflows (Flows) while leaving the γ^E coefficient largely unaffected. In order to allow for asymmetry between squared negative and positive returns (as an indicator for return volatility due to losses/gains), the last column in Table 13 uses a standard linear-piecewise (LP) regression approach. The results show that the nonlinearity is purely driven by positive returns since the coefficient on Return(t-1)^2 is insignificant for negative returns. As an illustration, Figure 14 compares the estimated Flows as a function of Return(t-1) for different specifications. The results for the LP regression (which has the highest adjusted R^2) are in line with the empirically documented convexity of the flow-performance relationship for equity funds (Goldstein et al. (2017)). As for the previous subsection, the model-generated AVs would be lower when allowing for a nonlinear flow-performance relationship.

Flow-Performance Relationship

	Baseline 2003-14	2003-14	Crisis 2008-09
Return(t-1)	0.2748**	0.4664**	0.5344 **
	(0.0268)	(0.0597)	(0.0656)
Return(t-2)	0.1885**	0.1933**	0.2061 **
	(0.0330)	(0.0330)	(0.0376)
Return(t-3)	0.0996**	0.1088**	0.1118 **
	(0.0164)	(0.0167)	(0.0187)
Return(t-4)	0.0507	0.0591	0.0513
	(0.0349)	(0.0351)	(0.0405)
Return(t-5)	0.0664**	0.0652**	0.0821 **
	(0.0179)	(0.0181)	(0.0201)
Return(t-6)	0.1047**	0.1047**	0.1202 **
	(0.0273)	(0.0272)	(0.0311)
Return(t-7)	0.0647**	0.0723**	0.0827 **
	(0.0231)	(0.0222)	(0.0247)
Return(t-8)	0.0832**	0.0874**	0.0849 **
	(0.0221)	(0.0214)	(0.0245)
Return(t-9)	0.0780**	0.0771**	0.0775 **
	(0.0237)	(0.0238)	(0.0271)
Return(t-10)	0.0070	0.0094	0.0101
	(0.0335)	(0.0334)	(0.0385)
Return(t-11)	0.0387 *	0.0484**	0.0408 *
	(0.0177)	(0.0178)	(0.0193)
Return(t-12)	0.0351 *	0.0406 *	0.0397 *
	(0.0164)	(0.0165)	(0.0184)
Flows(t-1)	0.0760**	0.0748**	0.0646 **
	(0.0098)	(0.0098)	(0.0103)
Flows(t-2)	0.0848**	0.0850**	0.0813 **
	(0.0073)	(0.0072)	(0.0072)
Flows(t-3)	0.0433 *	0.0432 *	0.0369
	(0.0178)	(0.0177)	(0.0203)
Flows(t-4)	0.0332**	0.0333**	0.0340 **
	(0.0092)	(0.0092)	(0.0105)
Flows(t-5)	0.1053 *	0.1053 *	0.1117
	(0.0500)	(0.0500)	(0.0582)
Flows(t-6)	0.0162	0.0164	0.0218
	(0.0187)	(0.0187)	(0.0217)
Flows(t-7)	0.0564	0.0559	0.0588
	(0.0324)	(0.0324)	(0.0377)
Flows(t-8)	0.0114	0.0114	0.0117
	(0.0215)	(0.0215)	(0.0250)
Flows(t-9)	-0.0218	-0.0226	-0.0267
	(0.0467)	(0.0468)	(0.0546)
Flows(t-10)	0.0223**	0.0218**	0.0198 *
	(0.0069)	(0.0069)	(0.0076)
Flows(t-11)	0.0178**	0.0186**	0.0162 **
	(0.0052)	(0.0052)	(0.0056)
Flows(t-12)	0.0309**	0.0311**	0.0307 **
	(0.0060)	(0.0059)	(0.0066)
log(TNA(t-1))	-0.0058	-0.0058	-0.0064
	(0.0033)	(0.0033)	(0.0039)
D(Return(t-1)<0)		-0.0052 *	-0.0021
		(0.0024)	(0.0024)
Return(t-1)×D(Return(t-1)<0)		-0.4112**	-0.4524 **
		(0.0849)	(0.0953)
Fama-MacBeth	Yes	Yes	Yes
adj. R^2	0.168	0.172	0.175
Obs.	306,570	306,570	270,655

$*$ $p<0.05$; $**$ $p<0.01$

Table 12: Flow-performance regressions. The first column reproduces the baseline specification from the main part of the paper, columns two and three show results for an enhanced model in the spirit of Goldstein et al. (2017) that include dummy/interaction terms for negative lagged returns for the full sample and the crisis period, respectively. All regressions based on monthly data using the Fama-MacBeth methodology (Newey-West standard errors in parentheses).

Flow-Performance Relationship

	Baseline	Non-lin.	Non-lin. LP
Return(t-1)	0.2748**	0.2820**	0.2496 **
	(0.0268)	(0.0365)	(0.0420)
Return(t-2)	0.1885**	0.1956**	0.1946 **
	(0.0330)	(0.0331)	(0.0330)
Return(t-3)	0.0996**	0.1129**	0.1105 **
	(0.0164)	(0.0166)	(0.0169)
Return(t-4)	0.0507	0.0522	0.0522
	(0.0349)	(0.0353)	(0.0351)
Return(t-5)	0.0664**	0.0718**	0.0718 **
	(0.0179)	(0.0183)	(0.0180)
Return(t-6)	0.1047**	0.1058**	0.1080 **
	(0.0273)	(0.0267)	(0.0267)
Return(t-7)	0.0647**	0.0753**	0.0739 **
	(0.0231)	(0.0223)	(0.0221)
Return(t-8)	0.0832**	0.0922**	0.0884 **
	(0.0221)	(0.0211)	(0.0211)
Return(t-9)	0.0780**	0.0802**	0.0794 **
	(0.0237)	(0.0238)	(0.0239)
Return(t-10)	0.0070	0.0065	0.0065
	(0.0335)	(0.0335)	(0.0334)
Return(t-11)	0.0387 *	0.0428 *	0.0458 *
	(0.0177)	(0.0181)	(0.0178)
Return(t-12)	0.0351 *	0.0435**	0.0391 *
	(0.0164)	(0.0166)	(0.0168)
Flows(t-1)	0.0760**	0.0748**	0.0750 **
	(0.0098)	(0.0098)	(0.0097)
Flows(t-2)	0.0848**	0.0843**	0.0846 **
	(0.0073)	(0.0072)	(0.0072)
Flows(t-3)	0.0433 *	0.0428 *	0.0427 *
	(0.0178)	(0.0178)	(0.0177)
Flows(t-4)	0.0332**	0.0331**	0.0331 **
	(0.0092)	(0.0092)	(0.0092)
Flows(t-5)	0.1053 *	0.1054 *	0.1051 *
	(0.0500)	(0.0500)	(0.0500)
Flows(t-6)	0.0162	0.0162	0.0164
	(0.0187)	(0.0187)	(0.0188)
Flows(t-7)	0.0564	0.0564	0.0563
	(0.0324)	(0.0324)	(0.0324)
Flows(t-8)	0.0114	0.0114	0.0111
	(0.0215)	(0.0215)	(0.0215)
Flows(t-9)	-0.0218	-0.0225	-0.0223
	(0.0467)	(0.0467)	(0.0467)
Flows(t-10)	0.0223**	0.0218**	0.0221 **
	(0.0069)	(0.0069)	(0.0070)
Flows(t-11)	0.0178**	0.0184**	0.0185 **
	(0.0052)	(0.0052)	(0.0052)
Flows(t-12)	0.0309**	0.0308**	0.0309 **
	(0.0060)	(0.0059)	(0.0059)
log(TNA(t-1))	-0.0058	-0.0057	-0.0057
	(0.0033)	(0.0033)	(0.0033)
Return(t-1)^2		1.8305**	
		(0.3478)	
Return(t-1)$^2 \times$D(Return(t-1)<0)			1.1678
			(0.9019)
Return(t-1)$^2 \times$D(Return(t-1)>0)			3.3900 **
			(1.0757)
Fama-MacBeth	Yes	Yes	Yes
adj. R^2	0.168	0.171	0.174
Obs.	306,570	306,570	306,570

$*$ p<0.05; $**$ p<0.01

Table 13: Flow-performance regressions. The first column reproduces the baseline specification from the main part of the paper, column two shows results for an enhanced model, column three shows a piecewise linear specification that distinguishes between negative and positive returns, respectively. All regressions based on monthly data using the Fama-MacBeth methodology.

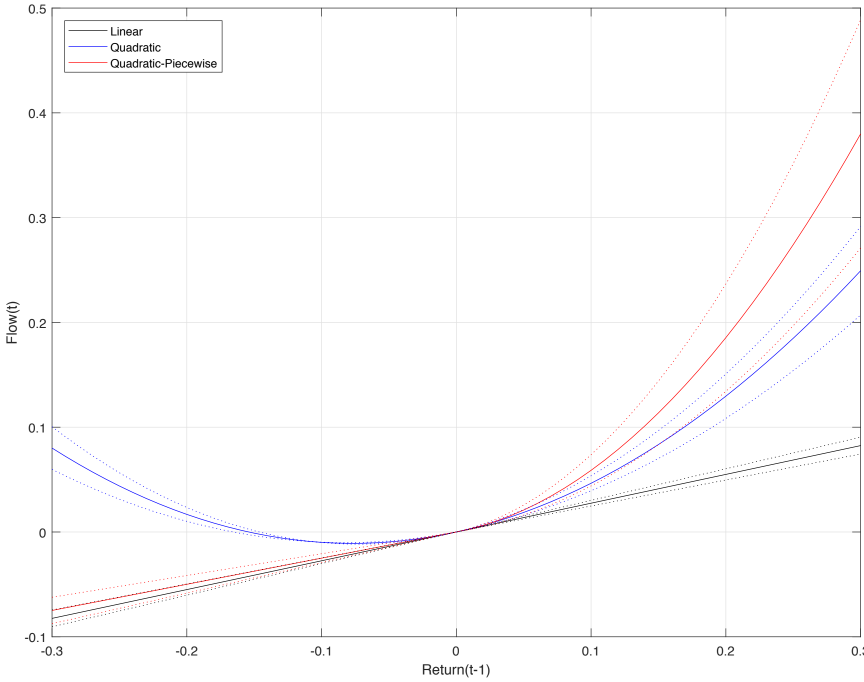

Figure 14: Estimated flow-performance relationship, as shown in Table 13, for the baseline linear model (black line; dotted lines show std. errors) and the extended model which includes the quadratic return (blue line). We also show the extended linear-piecewise model which estimates separate parameters for squared positive and negative returns (red line).