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Vulnerable asset management? The case of mutual funds

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Non-technical summary

Research Question

There is no clear consensus on whether the asset management industry contributes to financial instability by imposing systemic risk to the financial system. In particular, how to quantify systemicness of funds 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 funds' negative externalities in order to gauge their impact on financial instability. In our model, those externatilities stem from the price impacts generated by the asset liquidations of funds, which affect the market value of other investors' portfolios.

Contribution

This paper contributes to the debate on the systemicness of investment funds by developing a stress test model for mutual funds which we then apply to the set of U.S. equity mutual funds. For this purpose, we extend the Greenwood, Landier, and Thesmar (2015) fire sale model, by incorporating the well-documented flow-performance relationship as an additional funding shock. In our empirical application we quantify both fund-specific and aggregate vulnerabilities to systemic asset liquidations over time.

Results

Our main finding is that mutual funds' aggregate vulnerability to fire-sales is relatively small compared to related studies on the banking sector. This suggests 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 explore the determinants of individual funds' vulnerability to systemic asset liquidations, highlighting the importance of funds' liquidity transformation. Thus, a clear understanding of funds' liquidity profile is essential for enhancing the corresponding micro- and macroprudential policy tools. Therefore, regulators should monitor structural vulnerabilities in the fund sector arising through liquidity transformation.

Nichttechnische Zusammenfassung

Fragestellung

Ob und in welchem Ausmaß der Sektor der Investmentfonds zur Instabilität des Finanzsystems beiträgt, ist eine noch offene Frage. Insbesondere ist die Frage ungeklärt, durch welche Kanäle sich ein Schock im Finanzsektor verbreitet. Ein denkbarer Kanal sind Notverkäufe von Wertpapieren, die ein Fonds tätigen muss, um nach einem Refinanzierungsschock genügend liquide Mittel zu erlangen. Diese Notverkäufe können zu Kursrückgängen bei den entsprechenden Wertpapieren führen und dadurch andere Fonds in Mitleidenschaft ziehen.

Beitrag

Dieses Papier trägt zur Debatte über die Systemrelevanz von Investmentfonds bei, indem ein Stresstestmodell entwickelt wird, bei dem der oben skizzierte Kanal modelliert wird, und dieses anschließend für U.S. amerikanische Aktienfonds angewendet wird. Für diesen Zweck erweitern wir ein Modell für Wertpapiernotverkäufe um die in der Literatur umfassend dokumentierte Beziehung zwischen dem Mittelzufluss zu einem Fonds und dessen Wertentwicklung. In unserer empirischen Studie quantifizieren und analysieren wir sowohl fondsspezifische als auch aggregierte Verwundbarkeiten gegenüber systemischen Wertpapierverkäufen über die Zeit hinweg.

Ergebnisse

Unsere Ergebnisse zeigen, dass die Verwundbarkeiten des Investmentfondssektors durch den oben skizzierten Kanal klein sind. Als eine wesentliche Determinante für fondsspezifische Verwundbarkeiten gegenüber Wertpapierverkäufen erweist sich die von Fonds vorgenommene Liquiditätstransformation. Somit ist ein genaues Verständnis der Liquiditätsprofile der Fonds essentiell für die Verbesserung der entsprechenden mikro- und makroprudenziellen Instrumente.

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Vulnerable Asset Management? The Case of Mutual Funds*

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Abstract

Is the asset management sector a source of financial instability? This paper contributes to the debate by performing a macroprudential stress test in order to quantify systemic risks in the mutual fund sector. For this purpose we include the well-documented flow-performance relationship as an additional funding shock in the model of Greenwood et al. (2015), where systemic risks arise due to funds' fire sales of commonly held assets. Using data on U.S. equity mutual funds for the period 2003-14, we quantify both fund-specific and aggregate vulnerabilities to fire-sales over time. Our main finding is that the funds' aggregate vulnerability according to this propagation mechanism is generally small. We explore the determinants of individual funds' vulnerability to systemic asset liquidations, highlighting the importance of funds' liquidity transformation. 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.

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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, hedge funds, pension funds, and university endowments – 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. This growth highlights the increasing importance of market-based financial intermediation, which offers both new funding opportunities for businesses and households, but might also entail new risks (Bank for International Settlements (2014)). For example, Figure 1 illustrates an increasing trend towards a more concentrated industry: the share of assets held by the 20 largest institutions has grown over time (see also European Central Bank (2014)).[1] 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.[2]

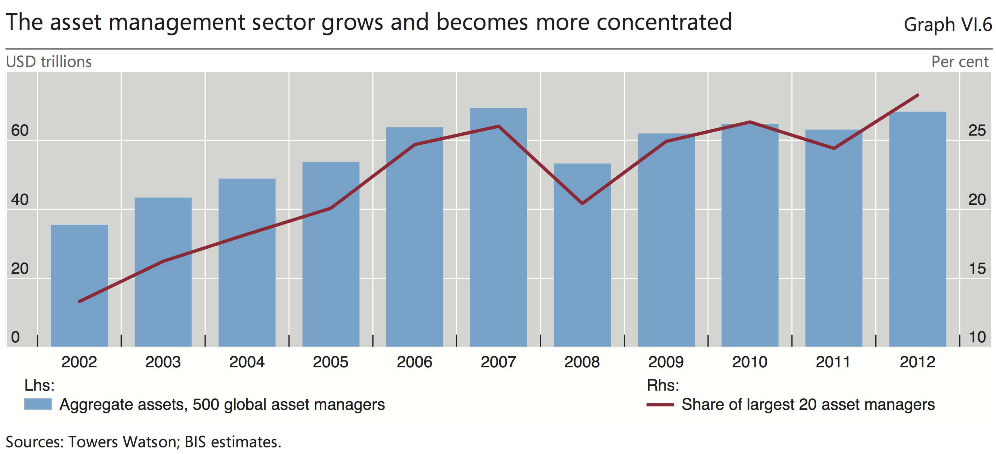

Figure 1: Growth and concentration in the asset management industry. The plot is taken from (Bank for International Settlements, 2014, p. 115) and shows both the total assets under management for 500 global asset managers and the share of assets held by the 20 largest institutions.

So far, there is no clear consensus on whether the asset management industry contributes to financial instability. On the one hand, empirical evidence suggests that sig-

[1]We will see below that we do not necessarily observe a similar trend for the subset of U.S. equity funds which will be the main focus of this study.

[2]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)).

nificant portfolio overlap and correlated trading strategies among institutions can indeed have major systemic repercussions. Two prominent examples are first, the role of portfolio insurers in the market crash of October 1987 and second, 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 are not a source of systemic risks. For example, the Investment Company Institute claims that existing microprudential regulations for investment funds (e.g., leverage and liquidity constraints) are effective in the sense that these were quite robust during the most recent crisis episodes (Investment Company Institute (2016)). However, just because we have not seen any major issues in the recent past does not ensure that we will not see anything in the future. Therefore, there is a general need for regulators and policymakers to understand whether the industry is vulnerable to systemic crises.

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 externatility stems from the price impacts generated by the asset liquidations of leveraged 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 all of the above elements. Specifically, we focus on the economically important subset of U.S. domestic equity mutual funds for the period 2003-14.[3] At the end of 2014, this fund type accounted for more than 52% of the investment industry's total assets (Investment Company Institute (2015)). The main advantage of restricting ourselves to this particular subset of funds is that we have both detailed data on these funds' stock holdings for the period 2003-14, and we can also match the holdings data with stock-specific information (most importantly price impact parameters).

We perform a macroprudential stress test which accounts for both funding liquidity shocks and fire-sale price dynamics, thus including the two key components of stress-tests identified by Greenwood and Thesmar (2011), and Tarullo (2016). The stress test is based on an extension of the model by Greenwood et al. (2015), who proposed a simple model to assess systemic vulnerabilities due to fire sales in the banking sector. In our model, systemic risks can arise due to significant overlap in funds' investment portfolios, coupled with illiquid asset markets and additional funding shocks driven by outflows due to past negative performances. In the Greenwood et al. (2015) model, systemic risks are largely driven by leverage - something that makes sense for highly leveraged financial institutions, such as commercial banks. However, directly applying this model to the mutual fund sector is likely not very informative, mainly because mutual funds generally make very little use of leverage and rely instead on short-term funding by promising daily redeemable fund shares (e.g., Pozen and Hamacher (2011)). Therefore, we extend the model by including the well-documented flow-performance relationship, which means that

[3]Within the asset management industry, mutual funds comprise by far the most important subset of financial institutions. 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)).

negative returns will be followed by additional outflows (Sirri and Tufano (1998); Berk and Green (2004)). Hence, in the extended model, the original fire-sale mechanism could be relevant even in the absence of leverage, and a small initial shock could potentially wipe out significant parts of the fund industry's asset holdings.

The extended model allows us to quantify the vulnerabilities of both the aggregate mutual fund sector and those of individual funds over time. Our main finding is that the mutual funds' aggregate vulnerability according to this propagation mechanism is generally small and its time dynamics strongly depend on the choice of price impact parameters. For example, despite the strong growth of the system over our sample period, we find that aggregate vulnerability only increases over time when we fix the price impact parameters. Even in this case, however, aggregate vulnerabilities are small: in response to a negative shock of -5% on all stocks, the maximum value of aggregate vulnerability (i.e., the fraction of equity wiped out due to the fire-sale mechanism, relative to initial equity) is in the order of less than 0.0001%. We identify three reasons for these very small numbers: (1) the flow-performance relationship is weak; (2) the typical overlap between funds' stock portfolios is relatively low[4]; and (3), mutual funds use little leverage. In particular, the fact that mutual funds are subject to tight leverage constraints leaves us with tiny vulnerabilities in comparison with those reported by Greenwood et al. (2015) for the largest European banks. In summary, 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. Finally, we explore the determinants of individual funds' contribution to systemic asset liquidations. Here, we highlight the importance of fund size, diversification levels, and portfolio illiquidity, and we discuss implications for future stress test designs.

Our paper is one of the first attempts to develop 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). 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

[4]Fricke (2017) performs a detailed analysis of portfolio overlap among U.S. mutual funds using the same dataset. He finds that the observed portfolio overlap is significant relative to randomized versions of mutual funds' portfolios.

(2017); Getmansky, Girardi, Hanley, Nikolava, and Pelizzon (2016)). We add to this literature by using actual data on mutual funds' stock portfolios in order to quantify the sector's vulnerability to systemic asset liquidations over a relatively long sample period.

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) that is more relevant for asset managers. In Section 3, we describe the dataset, explain in detail how we calibrate the model parameters. Section 4 shows aggregate vulnerabilities for different price impact scenarios. Section 5 takes a closer look at fund-specific vulnerabilities, and Section 6 explores the effect of adding heterogeneity in the flow-performance relationship on aggregate vulnerabilities. Section 7 discusses the main findings, and Section 8 concludes.

2 Model

In this section we present an extended version of the model introduced by Greenwood et al. (2015). There are N funds (investors) 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 fund i is financed with a mix of debt, D_i, and equity, E_i. $A_{\{N\times N\}}$ is the diagonal matrix of funds' 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 main steps are as follows:

1. We impose an initial shock on the value of funds' asset holdings.
2. The initial shock will lead investors in mutual funds to withdraw some of their money (flow-performance relationship).
3. Funds have fixed leverage targets and aim to keep their portfolio weights constant.
4. Asset liquidations have price impact.

In the following, we describe these steps in detail.

2.1 Step 1: Initial Shock

In matrix notation, we obtain funds' portfolio returns as

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

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

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

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

$$E_1 = E_0 + A_0R_1, \text{[5]} \tag{3}$$

[5] If the initial shock is large enough, equity could become negative. To avoid 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

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

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

2.2 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 fund performance and net inflows. Hence, negative (positive) fund 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.[6]

The most simple scenario is that net equity inflows (in absolute terms) are a linear function of a fund's realized portfolio return 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 returns are treated symmetrically, whereas empirically there appears to be an asymmetry in the flow-performance relationship (see Sirri and Tufano (1998) for equity funds, and Goldstein, Jiang, and Ng (2016) for bond funds, and Franzoni and Schmalz (2017) for different market states).[7] 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.[8]

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

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

the initial shock is small enough to not wipe out the entire equity.

[6] 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.

[7] In order to keep the model as simple as possible, we stick to the linear relationship in the following. The model can also be written down for more general nonlinear relationships, but this comes at the cost of having to estimate additional model parameters.

[8] 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 withdraw their funds (not roll over the loans), while long-term debt is much more slow-moving, see Gorton and Metrick (2012).

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 have used the fact that $E_0/A_0 = 1/(1+B)$. The fund 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

$$\begin{aligned} \tilde{R}_2 &= \frac{A_2 - A_0}{A_0} \\ &= R_1 \left(1 + \gamma^E \left(R_1 + \frac{1}{1+B}\right) + \gamma^D \frac{B}{1+B}\right). \end{aligned} \tag{10}$$

Hence, all other things equal, $\tilde{R}_2$ will be closer to R_1 for more leveraged firms (higher B), with a weaker flow-performance sensitivity (lower γ^E and γ^D).[9]

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

$$\tilde{R}_2 = R_1 \left(1 + \gamma^E \left(R_1 + \frac{1}{1+B}\right)\right). \tag{11}$$

The relationship between $\tilde{R}_2$ 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 fund without leverage ($B = 0$) and $\gamma^E = 2.5$ will have a $\tilde{R}_2$ 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 funds (higher B amplifies R_1 less strongly) since their equity tranche is relatively small. As we will see below, highly levered funds will, however, liquidate more assets in order to achieve their leverage target (next step).

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

$$\tilde{R}_2 = R_1 \left(1 + \gamma(1 + R_1)\right). \tag{12}$$

2.3 Step 3: Leverage Targeting with Fixed Portfolio Weights

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

[9] If we were to distinguish between short- and long-term debt, see footnote 8, 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.

pro-rata basis during times of market stress (Jian, Li, and Wang (2016)). Given that funds 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 this component to the total amount to be liquidated

$$\underbrace{\tilde{\phi}}_{\text{Amount to be liquidated}} = \underbrace{\gamma^E M' E_1 R_1}_{\text{Net inflow of equity}} + \underbrace{\gamma^D M' D_1 R_1}_{\text{Net inflow of debt}} + \underbrace{M' A_0 B \tilde{R}_2}_{\text{Leverage targeting}} , \tag{13}$$

which gives a $(K \times 1)$ vector of net asset purchases by all funds in period 3. The last term in Eq. (13) corresponds to the ϕ in the Greenwood et al. (2015) model, which we recover when we set $\gamma^D = \gamma^E = 0$. Eq. (13) assumes that both γ^D and γ^E are the same across funds. 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 fund specific.[10] With this formulation, we end up with

$$\tilde{\phi} = M' \left(\Gamma^E E_1 + \Gamma^D D_1\right) R_1 + M' A_0 B \tilde{R}_2, \tag{14}$$

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

$$\tilde{R}_2 = R_1 \circ \left[1_N + \Gamma^E (R_1 + (1+B)^{-1} 1_N) + \Gamma^D B (1+B)^{-1} 1_N\right], \tag{15}$$

where 1_N is an $(N \times 1)$ vector of ones, and $\circ$ denotes element-wise multiplication.

2.4 Step 4: Fire-Sales Generate Price Impact

Asset sales generate a linear price impact

$$F_3 = L\tilde{\phi}, \tag{16}$$

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

$$\begin{aligned} R_3 =& M F_3 = M L \tilde{\phi} \\ =& M L M' \left(\left[\Gamma^E E_1 + \Gamma^D D_1\right] R_1 + A_0 B \tilde{R}_2 \right). \end{aligned} \tag{17}$$

Note that, if anything, the linearity assumption made here likely overestimates the actual price impacts and thus the vulnerability of the system. Empirically, it has been documented that price impact appears to follow a square-root law, i.e., is a concave function (see Engle, Ferstenberg, and Russell (2012)). Hence, liquidating twice as many assets leads to a price impact that is less than twice the original one.

2.5 Measuring Vulnerability Exposures

Consider what happens after a negative shock, $F_1 = (f_1, f_2, \cdots, f_K), \forall f \in \{-1; 0)$, to asset prices: it translates into dollar shocks to funds' assets given by $A_1 M F_1$. The ag-

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

gregate direct effect on all funds' assets is the sum of these values: $1'_N A_1 M F_1$. This shock will have additional knock-on effects for individual funds due to investors' fund share redemptions. Funds' net-inflows are equal to $(\Gamma^E E_1 + \Gamma^D D_1) M F_1$, which we can aggregate as before by multiplying with 1_N. Note that these direct effects do not involve any contagion between funds. The model suggests, however, that funds with similar asset holdings should have similar outflows and similar sensitivities to fund returns.

Using Eq. (17), we can compute the aggregate dollar effect of shock F_1 on fund assets through fire-sales. To do so, we pre-multiply by $1'_N A_0$, and normalize by the initial total equity, E_0,

$$\tilde{AV} = \frac{1'_N A_0 R_3}{E_0} = \frac{1'_N A_0 M L M' \left(\left[\Gamma^E E_1 + \Gamma^D D_1 \right] R_1 + A_0 B \tilde{R}_2 \right)}{E_0}. \tag{18}$$

$\tilde{AV}$ measures the percentage of aggregate fund equity that would be wiped out by funds' asset liquidation in case of a shock of F_1 to asset returns. Similar to Greenwood et al. (2015), we can decompose aggregate vulnerability into each fund's individual contribution

$$S_i = \frac{1'_N A_0 M L M' \delta_i \delta_i' \left(\left[\Gamma^E E_1 + \Gamma^D D_1 \right] R_1 + A_0 B \tilde{R}_2 \right)}{E_0}, \tag{19}$$

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

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

$$IV_i = \frac{\delta_i' A_0 M L M' \left(\left[\Gamma^E E_1 + \Gamma^D D_1 \right] R_1 + A_0 B \tilde{R}_2 \right)}{E_{i,i}}. \tag{20}$$

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

3 Model Application: Vulnerable U.S. Equity Mutual Funds?

In this section, we apply our model to the 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 will explain in detail how we calibrated the model 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 2003-Q1 and 2014-Q4.[11] 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 kept funds with CRSP objective codes starting with 'ED'). In line with the literature, we drop exchange traded funds in everything that follows. On the other hand, we do not exclude index funds from our analysis; while this is standard practice in other strands of literature (e.g., in performance analyses tend to focus on actively managed funds), index funds are subject to the same fire-sale mechanism described above and thus need to be included.

The final sample contains 7,914 unique funds and 98,054 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 in detail the computation of model parameters.

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 2014-Q4 based on the CPI available from the St. Louis Fed) to make them comparable over time.[12] 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 number of active stocks.[13] 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.

[11]Note that there is a structural break in the fund identifiers in CRSP: all fund ID's were replaced with new ones from 2010-Q3 to 2010-Q4. Moreover, there are no holdings data available for 2010-Q4 and, for the sake of simplicity, for this particular quarter we take the portfolio holdings from 2010-Q3 in the analysis below. Alternatively, we could set the 2010-Q4 portfolio holdings equal to the average of the previous and following quarter.

[12]In the following, we adjusted all nominal dollar volumes for inflation.

[13]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.

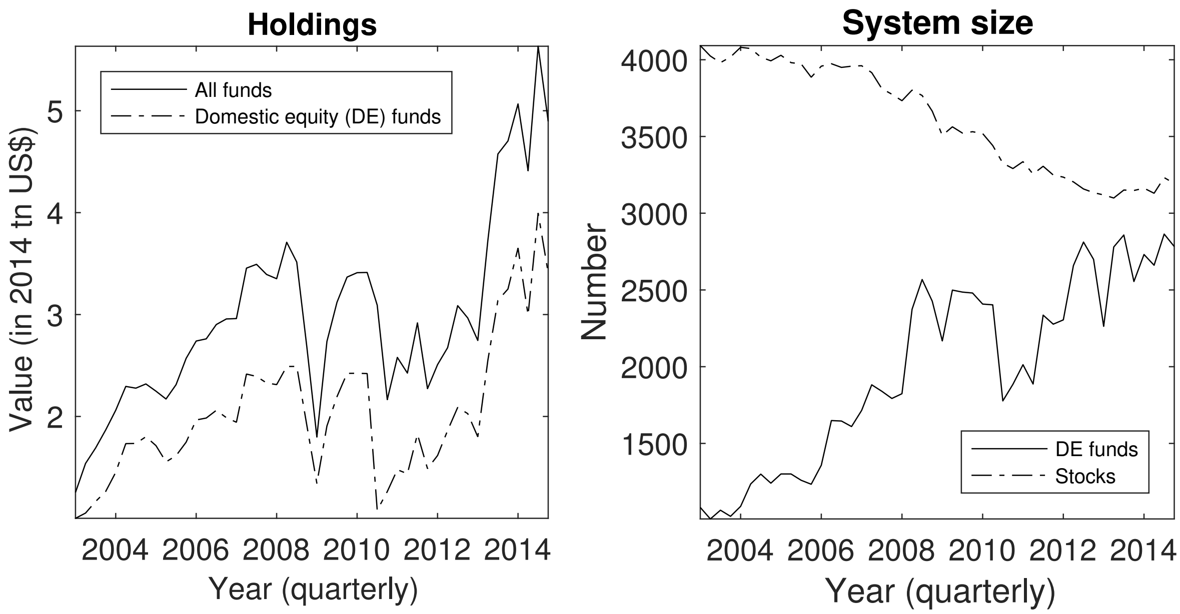

Figure 2: System size. Left: total dollar value of mutual funds' equity holdings over time in 2014 US$ (trillion). The solid line shows the values when including all funds that report their holdings in the CRSP Mutual Fund Database, and the dashed line shows the values for domestic equity (DE) funds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

As discussed by Greenwood et al. (2015), a more concentrated system might be more vulnerable to systemic asset liquidations. Figure 1 showed that the asset holdings of the 500 largest global asset managers have become increasingly concentrated 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

It is well known that 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, p. 28)). 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 $\bar{B} = 0.5$. Unfortunately, our dataset does not include the funding side of funds' balance sheets. Given that we are ultimately interested in the maximum vulnerability of the system (worst case scenario), we assume

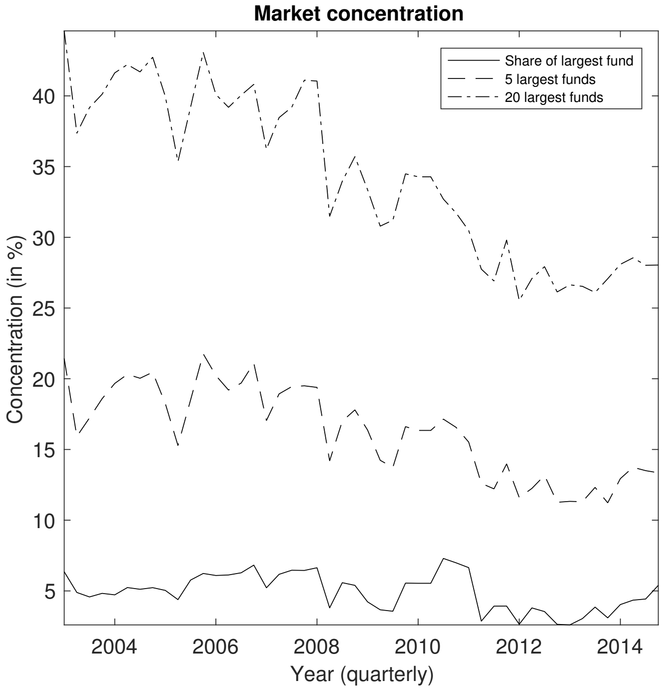

Figure 3: Market concentration. This Figure shows the relative market share of the largest 1, 5, and 20 fund(s) over time, respectively.

that all funds are using maximum leverage of $\bar{B}$. We see this as the most conservative choice, but one should keep in mind that Greenwood et al. (2015) report leverage values exceeding 30 for the largest European banks. Therefore, we expect the mutual fund sector to be much less vulnerable to systemic asset liquidations compared with commercial banks.

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.[14] 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 $M^a_{\{N\times K^a\}}$ with $K^a < K$. In the following, we focus on SIC industry codes (4-digits, 2-digits, and 1-digit).[15] 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, with fewer asset classes, the average overlap between any pair of investors will be higher (see below), meaning that the system's vulnerability for the more granular portfolios M^a will always exceed that of the most granular portfolios M.

[14]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.

[15]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.

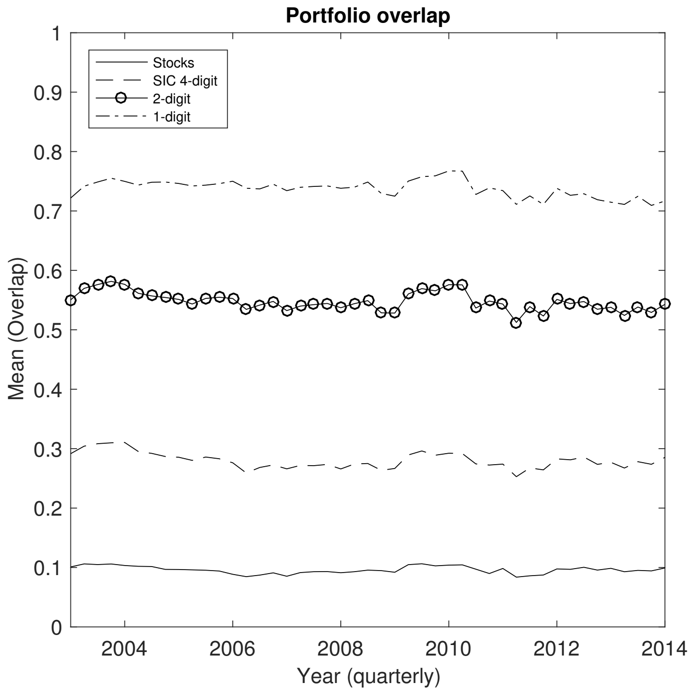

Figure 4: Portfolio overlap. For each quarter we show the cross-sectional average value of Eq. (21) for different aggregation levels. 'Stocks' corresponds to the original holdings reported in the CRSP Mutual Fund Database.

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

$$\text{Overlap}_{i,j} = \frac{\sum_{k=1}^{K} M_{i,k} M_{j,k}}{\sqrt{\sum_{k=1}^{K} (M_{i,k})^2} \times \sqrt{\sum_{k=1}^{K} (M_{j,k})^2}}, \tag{21}$$

where $i \neq j$. Technically, Overlap is defined as the angle between the vectors of portfolio weights between fund i and fund j. 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 regard to the evolution over time, we do not observe any clear trends in portfolio overlap for either aggregation level, but the values appear to be remarkably stable for all aggregation levels.[16] From these numbers one would not expect an increasing trend in aggregate

[16] See Fricke (2017) for a detailed analysis of portfolio overlap among mutual funds.

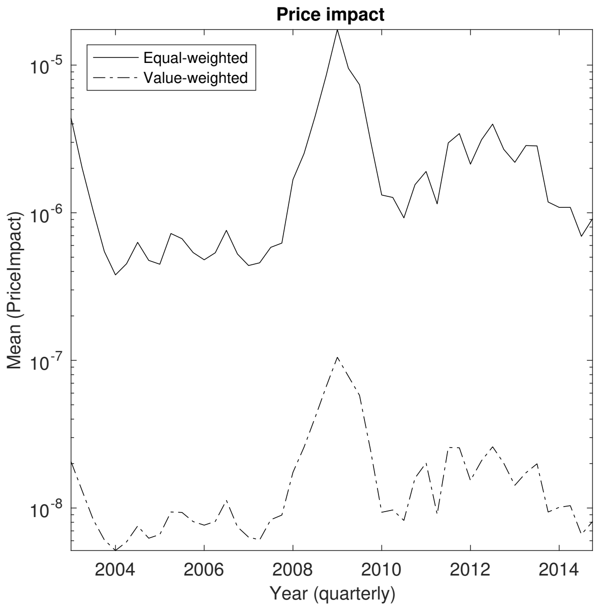

Figure 5: Price impact. For each stock, we calculate the daily Amihud-ratio as $|\text{Return}_{k,t}|/\text{DVolume}_{k,t}$, where $|\text{Return}_{k,t}|$ and $\text{DVolume}_{k,t}$ are the absolute return and the dollar volume of stock k on day t, respectively. We then take the quarterly average of 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.

vulnerability purely due to the dynamics of portfolio overlap.

3.2.4 Price Impact

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

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

$$\text{Amihud}_{k,d} = \frac{|\text{Return}_{k,d}|}{\text{DVolume}_{k,d}}. \tag{22}$$

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

$$\text{PriceImpact}_{k,t} = \frac{1}{D_{k,t}} \sum \text{Amihud}_{k,d}, \tag{23}$$

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). This adjustment then allows us to compare price impacts over time.

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. (23), on a semi-logarithmic scale. 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.[17] Finally, it is worth noting that the typical price impact is several orders of magnitude larger than the values determined by Greenwood et al. (2015): the average values in Figure 5 are 4.77×10^{-6} and 1.11×10^{-8}, respectively.[18]

Note that whenever we aggregate funds' stock portfolios to the SIC industry level, we calculate the price impact of each industry bucket as the weighted average of the individual stocks in that particular bucket.

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

$$\text{Flows}_{i,t} = a + b \times \text{Controls}_{i,t} + \gamma^E \times \text{Return}_{i,t-1} + \epsilon_{i,t}, \tag{24}$$

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

$$\text{Flows}_{i,t} = \frac{\text{TNA}_{i,t} - \text{TNA}_{i,t-1}(1 + \text{Return}_{i,t})}{\text{TNA}_{i,t-1}}, \tag{25}$$

with TNA as total net assets. Given that we think of the stress test happening at relatively short time-scales, we will estimate Eq. (24) using data at the highest available frequency, namely monthly.[19]

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.[20] This way, the estimated

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

[18] For the set of large European banks, Greenwood et al. (2015) assume a price impact of 10^{-13} for most of their asset classes. The main reason is that Greenwood et al. (2015) compute the implied price impact of the complete stock market by aggregating the individual ratios according to $\sum_k (w_k)^2 (Amihud_k)^2$ (see footnote 12 in the working paper version of their article). It is not clear why one should use squared price impacts in the first place, and we rather stick to the raw Amihud value in everything that follows.

[19] 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).

[20] We add further data filters for these regressions: we exclude funds that are less than one year old,

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* 6, 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 et al. (2016)).[21]

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 performed 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.

and we also drop extreme flow/return observations (above/below +200%/-50%).

[21] 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 performed 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. (25).

Robustness: Flow-Performance Relationship

	Dependent variable: Flows(t)							
	(1) Subsample		(2) Index funds		(3) Illiquidity Quartile			
					(Most liquid)			(Least liquid)
	2003-08	2009-14	No	Yes	1	2	3	4
Return(t-1)	0.2951**	0.2521**	0.2578**	0.4396**	0.2089**	0.2822**	0.3235**	0.2498**
	(0.0263)	(0.0487)	(0.0236)	(0.0907)	(0.0428)	(0.0327)	(0.0302)	(0.0371)
Return(t-2)	0.1810**	0.1970**	0.1693**	0.2026*	0.1707**	0.1209**	0.1571**	0.1875**
	(0.0217)	(0.0661)	(0.0154)	(0.0945)	(0.0370)	(0.0364)	(0.0363)	(0.0321)
Return(t-3)	0.1219**	0.0744**	0.0980**	0.0044	0.0664	0.1488**	0.1502**	0.1603**
	(0.0206)	(0.0257)	(0.0208)	(0.0840)	(0.0444)	(0.0377)	(0.0307)	(0.0324)
Return(t-4)	0.0912**	0.0051	0.0926**	0.0299	0.1076*	0.0342	0.0945**	0.1032**
	(0.0202)	(0.0705)	(0.0138)	(0.1013)	(0.0424)	(0.0399)	(0.0281)	(0.0286)
Return(t-5)	0.0558*	0.0783**	0.0696**	-0.0045	0.1431**	0.0840*	0.0890*	0.0718
	(0.0252)	(0.0256)	(0.0144)	(0.0869)	(0.0442)	(0.0376)	(0.0377)	(0.0395)
Return(t-6)	0.0782**	0.1346*	0.0895**	0.0734	0.0648	-0.0175	0.1033**	0.0650*
	(0.0196)	(0.0536)	(0.0165)	(0.0969)	(0.0499)	(0.0388)	(0.0282)	(0.0314)
Return(t-7)	0.0643**	0.0653	0.0879**	-0.1099	0.0581	0.0131	0.0660*	0.0709
	(0.0227)	(0.0422)	(0.0279)	(0.0923)	(0.0395)	(0.0378)	(0.0328)	(0.0374)
Return(t-8)	0.0813**	0.0854*	0.0793**	0.0854	0.0430	0.0279	0.0408	0.0609
	(0.0222)	(0.0399)	(0.0208)	(0.0989)	(0.0447)	(0.0329)	(0.0350)	(0.0385)
Return(t-9)	0.0218	0.1414**	0.0570**	0.0196	0.0620	0.0629	0.0517	0.1220**
	(0.0207)	(0.0434)	(0.0134)	(0.1036)	(0.0407)	(0.0393)	(0.0317)	(0.0435)
Return(t-10)	0.0329	-0.0221	0.0461**	-0.1829*	0.0567	0.0357	0.1024**	0.0668*
	(0.0210)	(0.0673)	(0.0147)	(0.0871)	(0.0446)	(0.0370)	(0.0330)	(0.0269)
Return(t-11)	0.0517*	0.0242	0.0438**	0.0136	0.0604	0.0323	0.0563	0.0309
	(0.0218)	(0.0286)	(0.0125)	(0.1037)	(0.0385)	(0.0374)	(0.0317)	(0.0315)
Return(t-12)	0.0611**	0.0058	0.0363**	0.0526	0.0235	0.0669	0.0356	-0.0202
	(0.0209)	(0.0252)	(0.0129)	(0.0914)	(0.0402)	(0.0372)	(0.0319)	(0.0273)
Flows(t-1)	0.1125**	0.0350*	0.1299**	-0.0778**	0.0345	0.1093**	0.0739**	0.0966**
	(0.0114)	(0.0146)	(0.0101)	(0.0200)	(0.0205)	(0.0173)	(0.0212)	(0.0211)
Flows(t-2)	0.0929**	0.0757**	0.0903**	0.0468*	0.0968**	0.0687**	0.0689**	0.1000**
	(0.0106)	(0.0098)	(0.0084)	(0.0197)	(0.0165)	(0.0205)	(0.0180)	(0.0158)
Flows(t-3)	0.0637**	0.0204	0.0627**	0.0238	0.0900**	0.0919**	0.0594**	0.0634**
	(0.0111)	(0.0356)	(0.0194)	(0.0193)	(0.0145)	(0.0182)	(0.0202)	(0.0125)
Flows(t-4)	0.0501**	0.0143	0.0230	0.0139	0.0250	0.0433*	0.0658**	0.0335*
	(0.0115)	(0.0143)	(0.0195)	(0.0185)	(0.0172)	(0.0182)	(0.0170)	(0.0132)
Flows(t-5)	0.0678**	0.1476	0.0540**	0.0763**	0.0509**	0.0382*	0.0602**	0.0575**
	(0.0096)	(0.1058)	(0.0062)	(0.0185)	(0.0139)	(0.0176)	(0.0179)	(0.0121)
Flows(t-6)	0.0251*	0.0063	0.0457**	0.0306	0.0201	0.0587**	0.0252	0.0398**
	(0.0099)	(0.0384)	(0.0134)	(0.0172)	(0.0285)	(0.0162)	(0.0174)	(0.0127)
Flows(t-7)	0.0237*	0.0931	0.0319**	0.0334*	0.0246	0.0206	0.0299	0.0255*
	(0.0110)	(0.0677)	(0.0114)	(0.0168)	(0.0147)	(0.0142)	(0.0153)	(0.0112)
Flows(t-8)	0.0306**	-0.0103	0.0079	0.0468*	0.0409**	0.0373**	0.0334*	0.0590**
	(0.0095)	(0.0445)	(0.0147)	(0.0191)	(0.0134)	(0.0134)	(0.0132)	(0.0134)
Flows(t-9)	0.0203*	-0.0692	-0.0241	0.0352*	0.0323*	0.0312*	0.0241	0.0189
	(0.0086)	(0.0989)	(0.0471)	(0.0159)	(0.0150)	(0.0136)	(0.0167)	(0.0103)
Flows(t-10)	0.0264**	0.0176	0.0251**	0.0506*	0.0455*	0.0290	0.0308*	0.0166
	(0.0086)	(0.0111)	(0.0059)	(0.0205)	(0.0176)	(0.0148)	(0.0134)	(0.0097)
Flows(t-11)	0.0212**	0.0139	0.0238**	0.0143	0.0281*	0.0091	0.0193	0.0095
	(0.0069)	(0.0078)	(0.0046)	(0.0149)	(0.0138)	(0.0177)	(0.0128)	(0.0109)
Flows(t-12)	0.0286**	0.0334**	0.0198**	0.0604**	0.0404**	0.0354*	0.0259	0.0211**
	(0.0091)	(0.0076)	(0.0047)	(0.0173)	(0.0133)	(0.0144)	(0.0163)	(0.0080)
log(TNA(t-1))	-0.0015**	-0.0107	-0.0056	-0.0030**	-0.0010**	-0.0001	-0.0012**	-0.0011**
	(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
adj. R^2	0.176	0.158	0.175	0.443	0.381	0.436	0.420	0.351
Obs.	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. (25).

Table 2 contains three different exercises:

(1) *Subsamples.* We split the sample into two equal-sized subsamples, where the first subsample covers the years 2003-08, and the second covers 2009-14. 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.[22]

(2) *Index funds.* Index funds have gained increasing 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.[23] 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 6 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. (2016)). 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 6 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 6.

[22] In line with Franzoni and Schmalz (2017), when excluding observations from the global financial crisis period (2008-10) we get a value of $\gamma^E \approx 0.33$ which is slightly larger than the baseline result.

[23] For example, it is common practice in the flow-performance literature to drop index funds from the analysis (e.g., Goldstein et al. (2016))).

4 Results: Aggregate Vulnerabilities Over Time

In the following, we consider a shock scenario where we impose an initial shock of -5% on all stocks[24] and calculate the aggregate vulnerabilities (AV) separately for each quarter. The model parameters are calibrated as defined above, but we will differentiate three scenarios with regard to our choice of the price impact parameters:

- *Scenario 1*: Price impact time-varying and asset-specific.
- *Scenario 2*: Price impact asset-specific but constant over time.
- *Scenario 3*: Homogeneous price impact of 4.77×10^{-6} for all assets in all quarters (the typical value of the equal-weighted average price impact).

We will see that the first two scenarios generate AVs of similar orders of magnitude, and somewhat higher values in the last scenario. Interestingly, we will also see that the time dynamics of the AVs are rather different for the three scenarios.

4.1 *Scenario 1*: Price Impact Time-Varying and Asset-Specific

The top left panel of Figure 6 shows the results for *Scenario 1*: the solid line shows the AV for the most granular portfolios, and the other lines show the results for more aggregated SIC industry portfolios. (Note that the plot is in semi-logarithmic scale.) Not surprisingly, the AVs are significantly smaller for the most granular stock portfolios, since the average portfolio overlap is relatively small in this case (Figure 4). However, the order of magnitude of the AVs is very small in all cases: in response to a negative shock of -5%, we expect a tiny maximum knock-on effect in the order of 0.00001%. When looking at the dynamics over time, we clearly see that in this scenario the AVs are almost purely driven by the dynamics of the price impact. Indeed, the Pearson-correlation between the value-weighted price impacts shown in Figure 5 and the AV is 0.89 for the most granular portfolios and above 0.95 for the industry portfolios.

Lastly, we test whether there is a significant time trend in the AV time series. For this purpose, we regress the quarterly AVs on a constant and a time trend. The results in Table 3 show that the AVs in *Scenario 1* exhibit no significant time trend. In other words, when using time-varying and asset-specific price impacts we do not find that the system has become more vulnerable despite the strong growth in terms of system size.

4.2 *Scenario 2*: Price Impact Asset-Specific (No Time Dynamics)

In order to explore the AVs without time variation in the estimated price impacts, the top right panel of Figure 6 shows the AVs for the case when we set each stock's price impact to its average value over time. The order of magnitude of the estimated AVs is comparable to the ones shown in the left panel for *Scenario 1*. However, in this case, the AVs appear to slowly increase over time. This is confirmed by the trend analysis in Table 3: in this case, the time trend is positive and significant.

[24]Note that the AV scales linearly in the initial shock. In other words, an initial shock of -20% yields an AV which is 4 times that of a -5% shock.

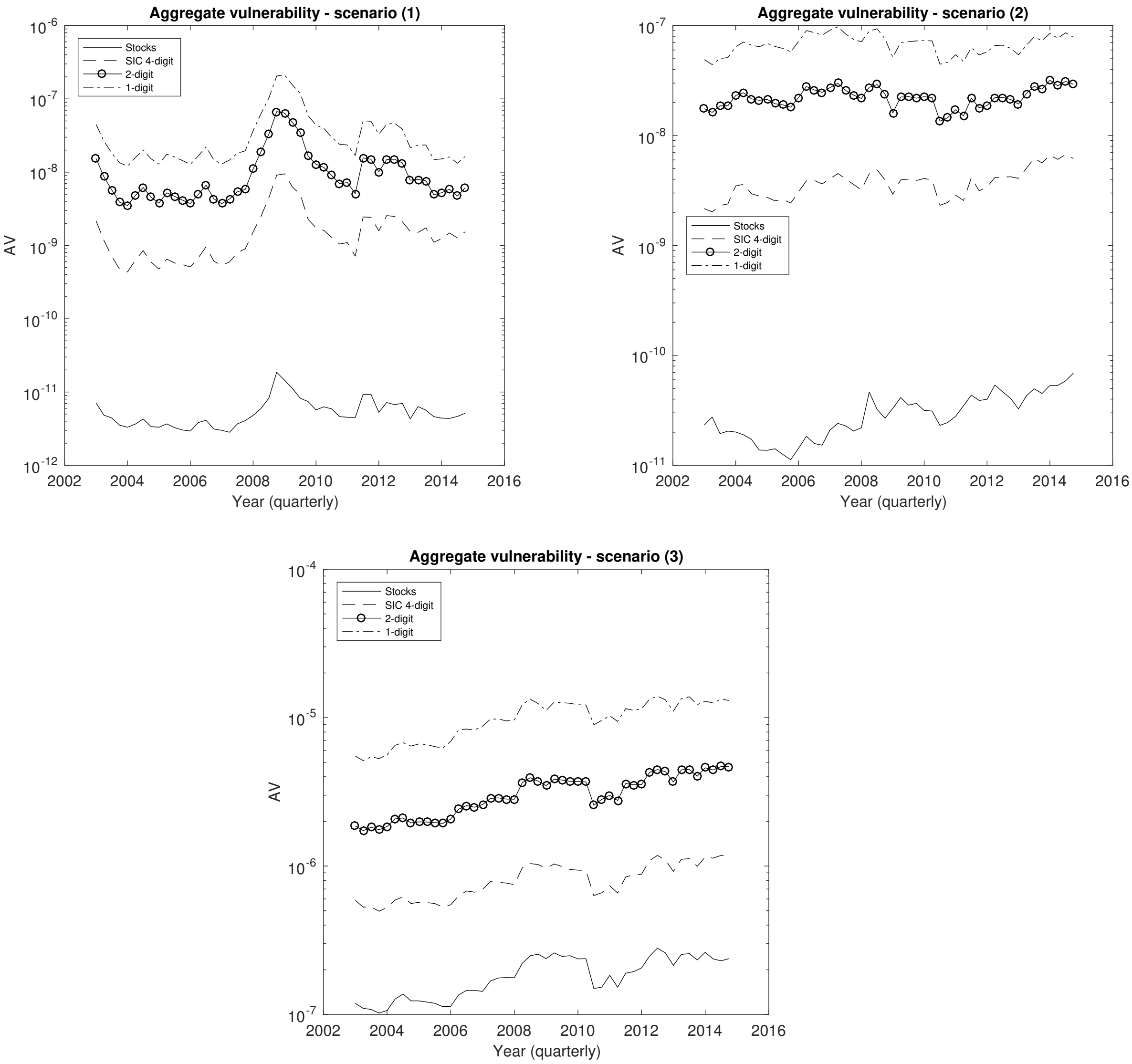

Figure 6: Aggregate vulnerability for the three different price impact scenarios. Top left: *Scenario 1* (price impact time-dependent and asset-specific). Top right: *Scenario 2* (price impact asset-specific but constant over time). Bottom: *Scenario 3* (price impact $= 4.77 \times 10^{-6}$ for all assets/quarters). In all cases, the solid line shows the aggregate vulnerability for the granular stock portfolios; the other lines show the results for the aggregated portfolios (based on SIC industry classifications). Note that the y-axis is displayed in logarithmic scale.

Trend Analysis, AV

	Scenario		
	1	*2*	*3*
Trend	0.0073	0.0363**	0.0274**
Constant	0.6135**	0.4346**	0.8924**
R^2	0.0379	0.7012	0.6472
Obs.	48	48	48

∗ p<0.05; ∗∗ p<0.01

Table 3: Testing for time trends in the aggregate vulnerabilities (AVs) of the U.S. mutual fund industry. This table shows the results from OLS regressions of the AVs on a constant and a time trend for the three scenarios described in the main text. Note: for the sake of comparison, we divide each AV time series by the initial value in 2003-Q1.

4.3 *Scenario 3*: Homogeneous Price Impact (No Time Dynamics)

Finally, we set the same price impact for all assets, thereby ignoring both cross-sectional and time-series variations in the price impacts. The results are shown in the bottom panel of Figure 6. In this case, the estimated AVs are somewhat larger than the first two scenarios, largely because the assumed price impact is the equal-weighted average over the sample period. Moreover, we find that the AVs have increased significantly over time (see Table 3), but are still small: the maximum AV is on the order of 0.001%.

Overall, these results indicate that the aggregate vulnerability of the system is small, irrespective of the scenario under study. 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. On the other hand, the results in Table 3 suggest that the AVs tend to exhibit a positive time trend under the last two scenarios. Hence, the system has not necessarily become more vulnerable over time.

5 A Closer Look at Fund-Specific Vulnerabilities

This section turns to an in-depth analysis of fund-specific vulnerabilities, namely systemicness and indirect vulnerability (see Eqs. (19) and (20)). In particular, we are interested in exploring the determinants of these measures, something that is of utmost importance for regulators and supervisors in formulating a macroprudential framework on asset managers (Financial Stability Board (2017)).

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

$$\log(y_{i,t}) = a_t + b_t \times \log(X_{i,t-1}) + \epsilon_{i,t}, \tag{26}$$

where $y_{i,t}$ is the fund-specific vulnerability indicator of interest (systemicness or indirect vulnerability, respectively), X contains our set of control variables (always using the first lag to alleviate the endogeneity problem), and b is the corresponding parameter vector. Note that we take the logarithm for all variables to adjust for skewness and 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 4 reports the correlations between the variables that will be of interest in the following; interestingly, multicollinearity does not appear to be an issue here, since most correlations are relatively small in absolute terms.

More precisely, the analysis proceeds in three steps: first, we explore to what extent the lagged fund-specific characteristics that appear in the model equations (namely fund size, portfolio illiquidity, and interconnectedness) are able to predict future values of the vulnerability measures. In a way, this can be seen as a simple model validation step. However, despite considering lagged exogenous variables in the regressions, this analysis comes at the cost of an endogeneity bias which hampers inferring any causal relationships between vulnerabilities and these fund-specific characteristics. Second, we therefore replace the model-inherent characteristics from the first step with alternative measures. For example, we approximate fund size by fund age and percentage net-inflows. 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 (Panel A, B, and C).

Variables	IV_1	S_1	IV_2	S_2	IV_3	S_3	Age	$Flows^{6M}$	TNA	HHI	MeanOverlap	$Illiq^{Amihud}$	$Illiq^{Spread}$
Vulnerabilities													
IV_1	1.000												
S_1	-0.162**	1.000											
IV_2	0.601**	-0.141**	1.000										
S_2	-0.153**	0.599**	-0.081**	1.000									
IV_3	0.484**	-0.184**	0.233**	-0.164**	1.000								
S_3	-0.159**	0.493**	-0.132**	0.207**	-0.133**	1.000							
Size													
Age	-0.195**	0.200**	-0.140**	0.155**	-0.143**	0.249**	1.000						
$Flows^{6M}$	0.003	-0.003	0.003	-0.001	0.015**	-0.002	-0.006	1.000					
TNA	-0.075**	0.270**	-0.049**	0.252**	-0.052**	0.273**	0.252**	0.004	1.000				
Interconnectedness													
HHI	0.103**	-0.103**	0.058**	-0.124**	0.178**	-0.019**	0.014**	0.010**	-0.021**	1.000			
MeanOverlap	-0.162**	-0.028**	-0.198**	-0.110**	0.113**	0.328**	0.109**	-0.001	0.095**	-0.149**	1.000		
Illiquidity													
$Illiq^{Amihud}$	0.169**	0.098**	0.054**	0.019**	-0.013**	-0.030**	-0.021**	-0.001	-0.012**	0.009**	-0.078**	1.000	
$Illiq^{Spread}$	0.196**	0.157**	0.123**	0.079**	-0.081**	-0.117**	-0.098**	-0.005	-0.043**	-0.029**	-0.336**	0.614**	1.000

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

Table 4: Correlation matrix. This Table shows the correlation structure of vulnerability measures and fund specific variables. 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 flow over the last 6 months; TNA are the total net assets; HHI is the Hirschmann-Herfindahl-Index of portfolio concentration; MeanOverlap is fund's average portfolio overlap with other fund portfolios; and $Illiq^{Amihud}$ and $Illiq^{Spread}$ is the portfolio-weighted average illiquidity measure of a given fund's portfolio, based on the Amihud-ratio and the quoted relative spread, respectively.

5.1 Towards Understanding Funds' Vulnerabilities (Scenario 1)

In the previous section we calculated aggregate vulnerabilities for three different price impact scenarios. It should be clear that the most relevant case is *Scenario 1*, since it allows for asset- and time-specific price impacts. Hence, we use the results from *Scenario 1* as our baseline scenario and explore the two other cases as a kind of robustness check below.

5.1.1 Step 1: Model-Inherent Measures

The first step is to explore to what extent the fund-specific characteristics going into the model are able to predict future vulnerabilities. According to the model, we expect the following relationship: systemicness increases with a larger fund size or interconnectedness since larger funds should fire-sale 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 larger and more diversified funds should be less vulnerable to other funds' asset liquidations (see Greenwood et al. (2015)). The correlations in Table 4 are in line with this reasoning. More illiquid funds should be both more systemic and vulnerable in general, since illiquid funds have to fire-sale a larger share of their portfolios to meet investors' redemptions and are also likely to suffer more from other funds' asset liquidations.

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)[25], and illiquidity (defined as the portfolio-weighted average Amihud-ratio of a fund, $\text{Illiq}^{\text{Amihud}}$)[26]:

$$\begin{aligned} \log(y_{i,t}) = a_t + b_{1,t} \times \log(\text{TNA}_i(\text{t-1})) + b_{2,t} \times \log(\text{MeanOverlap}_i(\text{t-1})) \\ + b_{3,t} \times \log(\text{Illiq}_i^{Amihud}(\text{t-1})) + \epsilon_{i,t}. \end{aligned} \tag{27}$$

Table 5 Panel A reports the results which are generally as expected: larger funds are less vulnerable to other funds' asset liquidations (lower IV), but contribute more to aggregate vulnerability (higher S) and are therefore systemically more important. 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.[27] Overall, these results confirm our model predictions and those of Greenwood et al. (2015). We should stress that our measure of interconnectedness, MeanOverlap, appears to capture portfolio diversification: funds have high MeanOverlap only if they hold a large number of stocks, and over-weigh widely held stocks at the same time.

[25] 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. (21). At each point in time, MeanOverlap of fund i is then defined as the average Overlap of this particular fund with all other funds.

[26] 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. (23). See Yan (2008) for a similar approach.

[27] We performed several robustness checks. First, we obtain qualitatively similar results when using pooled OLS with time- and fund-FEs (unreported result). Second, we ran the regressions without taking logs of the dependent variables and winsorized the top and bottom 1% of observations, which does not alter our results either.

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))	-0.5832**	0.5898**				
	(0.0541)	(0.0548)				
log(MeanOverlap(t-1))	-0.3409**	0.1676**				
	(0.0606)	(0.0564)				
$\log(\text{Illiq}^{\text{Amihud}}(t-1))$	0.0772**	0.3245**				
	(0.0133)	(0.0143)				
Alternative measures						
log(1+Age(t-1))			-0.9402**	0.9657**	-0.9320**	0.9577**
			(0.0197)	(0.0160)	(0.0237)	(0.0191)
$\text{Flows}^{6M}(t-1)$			-0.6697**	0.4111 *	-0.5889 *	0.3447
			(0.2204)	(0.2000)	(0.2582)	(0.2338)
log(HHI(t-1))			0.4674**	-0.4995**	0.4818**	-0.5074**
			(0.0210)	(0.0132)	(0.0242)	(0.0149)
$\log(\text{Illiq}^{\text{Spread}}(t-1))$			1.0425**	0.6690**	0.9868**	0.5858**
			(0.0370)	(0.0444)	(0.0365)	(0.0413)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
Mean R^2	0.561	0.536	0.281	0.254	0.282	0.255
Obs.	72,872	72,872	59,430	59,430	46,440	46,440

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

Table 5: 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 4. 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.

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 ("alternative measures"). Let us briefly explain how we substitute each of the measures from *Section 5.1.1*.

Size: Fund age turns out as a natural proxy of fund size since older funds tend to be larger (Yan (2008)). The economic intuition behind this link 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 not capture size in general. Therefore, we also include funds' average net inflows over the last 6 months, $\text{Flows}^{6\text{M}}$, as an additional size proxy. Flows are less deterministic (compared to age) and are likely to capture growth dynamics in the recent past.[28]

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. Portfolio concentration is defined as the standard Hirschmann-Herfindahl Index, or HHI.[29] Not surprisingly, HHI and MeanOverlap are negatively correlated (Pearson correlation of -0.15, see Table 4), such that both measures appear to capture some aspects of diversification 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 consider the portfolio-weighted relative spread, $\text{Illiq}^{\text{Spread}}$, as an alternative liquidity measure.[30]

With these alternative measures we then run the following regression

$$\begin{aligned}\log(y_{i,t}) = a_t + b_{1,t} \times \log(\text{Age}_i(\text{t-1})) + b_{2,t} \times \text{Flows}_i^{6\text{M}}(\text{t-1}) + b_{3,t} \times \log(\text{HHI}_i(\text{t-1})) \\ + b_{4,t} \times \log(\text{Illiq}_i^{\text{Spread}}(\text{t-1})) + \epsilon_{i,t}.\end{aligned} \tag{28}$$

Table 5 Panel B shows the results when using these alternative measures. The results are consistent with those shown in Panel A: older funds, with larger percentage flows in the recent past have lower indirect vulnerabilities (IV) and higher systemicness (S). More concentrated funds (higher HHI) have higher IVs and lower systemicness. Finally, more illiquid funds have both higher IVs and higher systemicness.

5.1.3 Step 3: Subsample analysis

Table 5 Panel C addresses concerns that the effect of liquidity on funds' vulnerabilities is due to market liquidity aggravation around the financial crisis (see Figure 5). In order to test whether the fund-specific vulnerabilities are mainly driven by this period, 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 findings are not driven by the financial crisis. In sum, this test does not indicate any potential outlier bias of our sample.

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

[29] Note that the HHI is based on the most granular portfolios, with $\text{HHI}_i = \sum_k (M_{i,k})^2$. We checked that the results are qualitatively similar when using the vulnerabilities from the SIC industry portfolios.

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

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

	Panel A		Panel B		Panel C	
	Full Sample		Full Sample		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))	-0.5678**	0.6004**				
	(0.0544)	(0.0543)				
log(MeanOverlap(t-1))	-0.4484**	0.1180				
	(0.0540)	(0.0624)				
$\log(\text{Illiq}^{\text{Amihud}}(t\text{-}1))$	0.2670**	0.5438**				
	(0.0124)	(0.0193)				
Alternative measures						
log(1+Age(t-1))			-0.9306**	0.9679**	-0.9265**	0.9557**
			(0.0261)	(0.0142)	(0.0318)	(0.0165)
$\text{Flows}^{6M}(t\text{-}1)$			-0.8073**	0.2868	-0.7911**	0.1453
			(0.2271)	(0.2310)	(0.2747)	(0.2580)
log(HHI(t-1))			0.2895**	-0.6805**	0.3091**	-0.6838**
			(0.0253)	(0.0173)	(0.0280)	(0.0206)
$\log(\text{Illiq}^{\text{Spread}}(t\text{-}1))$			1.7760**	1.3971**	1.7743**	1.3788**
			(0.0473)	(0.0754)	(0.0491)	(0.0834)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
Mean R^2	0.551	0.492	0.292	0.279	0.300	0.284
Obs.	72,872	72,872	59,430	59,430	46,440	46,440

∗ $p<0.05$; ∗∗ $p<0.01$

Table 6: 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 4. 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.

5.2 Additional Robustness Checks

For robustness and in order to expand our examination, we additionally analyse funds' vulnerabilites for the other two price impact scenarios. Specifically, we will look at *Scenario 2* (time-fixed, asset-specific price impacts) and *Scenario 3* (equally-weighted average price impact for all assets) in the following.

5.2.1 Results for *Scenario 2* – Price Impact Asset-Specific (No Time Dynamics)

Table 6 shows the same regression results for *Scenario 2*. The results are largely consistent with those in Table 5 both in terms of parameter signs and significance levels. Overall, these results suggest that the first two scenarios tend to give very similar results in terms of which fund-specific characteristics are able to explain funds' vulnerabilities. The only differences are for the systemicness regressions, namely that MeanOverlap is insignificant in Panel A, and Flows are insignificant in Panels B and C. Below we will see that this is not the case for *Scenario 3*.

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))	-0.6095**	0.5823**				
	(0.0584)	(0.0530)				
log(MeanOverlap(t-1))	0.6314**	1.0331**				
	(0.0779)	(0.0428)				
$\log(\text{Illiq}^{\text{Amihud}}(t\text{-}1))$	-0.3138**	-0.1613**				
	(0.0202)	(0.0091)				
Alternative measures						
log(1+Age(t-1))			-0.9214**	1.0051**	-0.9108**	0.9975**
			(0.0160)	(0.0210)	(0.0189)	(0.0255)
$\text{Flows}^{6M}(t\text{-}1)$			-0.4422	0.6450**	-0.3481	0.5832 *
			(0.2397)	(0.2104)	(0.2805)	(0.2496)
log(HHI(t-1))			0.8120**	-0.2502**	0.8070**	-0.2745**
			(0.0152)	(0.0258)	(0.0173)	(0.0285)
$\log(\text{Illiq}^{\text{Spread}}(t\text{-}1))$			-1.8492**	-2.3996**	-1.8034**	-2.3682**
			(0.0844)	(0.0491)	(0.0981)	(0.0551)
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
Mean R^2	0.531	0.655	0.362	0.415	0.366	0.423
Obs.	72,872	72,872	59,430	59,430	46,440	46,440

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

Table 7: 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 4. 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.

5.2.2 Results for *Scenario 3* – Homogeneous Price Impact (No Time Dynamics)

In this case we analyze vulnerability dynamics if the same price impact parameter is assumed for all securities and all time points. As our analysis solely focuses on funds' equity portfolios, *Scenario 3* is comparable to the one proposed by both Greenwood et al. (2015), and Cetorelli et al. (2016) who assign a specific value for the price impact parameter for each asset class. 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. However, it turns out that this approach can be problematic in the sense that it predicts very different vulnerabilities at the micro-level.

Comparing Table 7 with our previous findings reveals that some of the parameter coefficients switch signs. Most importantly, under *Scenario 3*, illiquid funds tend to be both *less* vulnerable and *less* systemic which stands in sharp contrast to model predictions.

How does a homogeneous price impact for all assets affect the estimation of vulnerabilites in the fund sector? One would expect that funds with very liquid (illiquid) portfolios will be treated as more illiquid (liquid) than what is observed in the data. We address

	(Most liquid)				Decile ($Illiq^{Amihud}$)				(Least liquid)	
	1	2	3	4	5	6	7	8	9	10
Corr(IV_1,IV_3)	0.900	0.900	0.895	0.887	0.849	0.791	0.738	0.688	0.636	0.298
Corr(S_1,S_3)	0.908	0.908	0.910	0.906	0.893	0.843	0.771	0.717	0.643	0.378

Table 8: Correlations between indirect vulnerabilities and systemicness from *Scenario 1* and *Scenario 3*, respectively, for different liquidity categories. Decile 1 (10) corresponds to the most liquid (least liquid) funds. All correlations are significant at the 1%-level.

this question by directly comparing the fund-specific vulnerability measures IV and S of Scenario 1 and Scenario 3. Therefore, we sort funds into liquidity deciles with respect to funds' portfolio liquidity (based on the portfolio Amihud-ratio as a fund's illiquidity indicator) and compute correlations between fund-specific vulnerabilities of Scenarios 1 and 3. Table 8 reports these correlations. Vulnerabilities of relatively liquid funds (Decile 1-5) seem to be largely unaffected by considering a homogeneous price impact. For those funds the correlation lies in a narrow band around 0.90. The correlation decreases for more illiquid funds and the effect is strongest for the least liquid funds (Decile 10), where the correlations drop to 0.298 and 0.378, respectively.

Figure 7 provides additional evidence that the most illiquid funds turn out to be both less vulnerable and less systemic if a homogeneous price impact instead of a time-varying asset-specific price impact is assumed (*Scenario 3* instead of *Scenario 1*). Specifically, the Figure plots each fund's rank in terms of its indirect vulnerability (left panel) and systemicness (right panel) in *Scenario 1* and *Scenario 3* against each other, where the ranking is between 0 and 1, where a value of 1 corresponds to the highest vulnerability. We show the results for both the most liquid funds (Decile 1) and the least liquid funds (Decile 10), based on $Illiq^{Amihud}$ (see Table 8). If a homogeneous price impact did not affect fund-specific vulnerabilities, the two scenarios should yield similar rankings and all observations 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 slightly more vulnerable and systemic, since most observations tend to be below the main diagonal. On the other hand, illiquid funds (red crosses) reveal an opposite pattern, since most observations tend to be widespread above the main diagonal. Hence, *Scenario 3* underestimates the vulnerabilities for the least liquid funds and slightly overestimates those for the most liquid funds. In summary, we suggest that the results from *Scenario 3* should be treated with care and, whenever possible, time-varying and asset-specific price impacts should be used.

6 Adding Heterogeneity in the Flow-Performance Relationship

The results presented so far were based on a homogeneous γ^E. Here we explore to what extent adding heterogeneity across different fund types affects the aggregate vulnerabilities. More precisely, we re-applied our model using exactly the same approach as in Section 4 but explored three alternative specifications regarding γ^E discussed in Subsec-

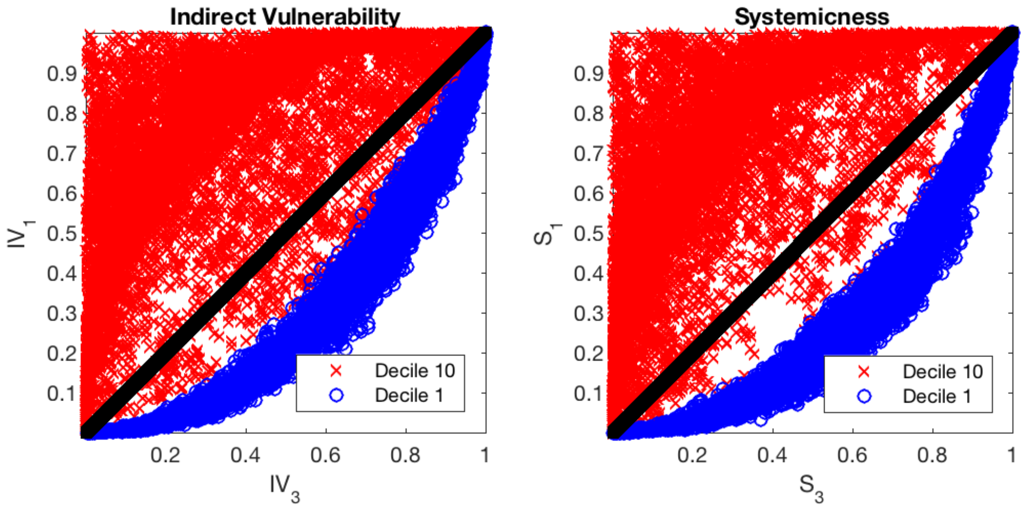

Figure 7: Vulnerability rankings in *Scenario 1* plotted against those from *Scenario 3*. Left panel: indirect vulnerability. Right panel: systemicness. Both panels show the relative ranking for funds in liquidity Decile 1 (most liquid) and Decile 10 (least liquid), respectively, based on $\text{Illiq}^{\text{Amihud}}$. 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.

tion 3.2.5 (see Table 2 in the main text and Table 9 in Appendix B), namely we look at (a) index versus non-index funds; (b) liquid versus illiquid funds; and (c) large versus small funds. In the following, we only show results for *Scenario 1* using the most granular stock portfolios.[31]

Figure 8 shows the AVs for the three different cases, relative to those in the baseline scenario (top left panel of Figure 6). A value larger (smaller) than 1 indicates that the AV in the alternative scenario is larger (smaller) than in the baseline scenario, and thus hints that the system is more (less) risky under this alternative specification. The results are quite remarkable: only for the index/non-index fund scenario do we find that the AVs tend to be larger compared to the baseline specification. In fact, in this case it appears that the relative AV tends to increase over time, suggesting that the growth of index funds

[31]The results are largely comparable for *Scenario 2*, but can be quite different for *Scenario 3*, as one might expect from the results in the previous sections.

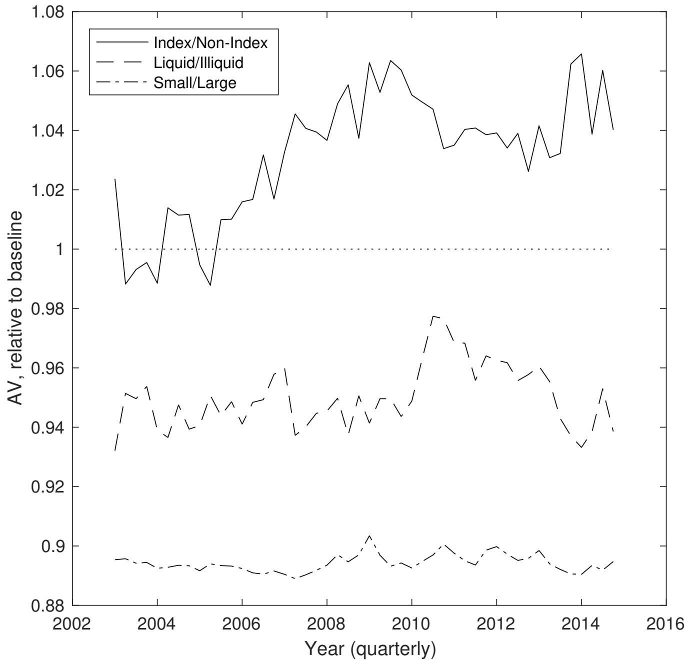

Figure 8: Aggregate vulnerabilities relative to baseline results for *Scenario 1* (as shown in top left panel in Figure 6). Note: 'Index/Non-Index' corresponds to specification (2) in Table 2; 'Liquid/Illiquid' corresponds to specification (3) in Table 2; 'Small/Large' corresponds to specification (3) in Table 9 in Appendix B.

tends to be quite important from a systemic perspective (Malkiel (2013)). In light of our results on portfolio diversification in the previous section, these results seem reasonable. 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.

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. We leave an in-depth analysis of this topic for future research.

7 Discussion

Implications for future stress tests. Do our findings suggest that the mutual fund sector is robust to systemic crises? The answer is 'yes' if we are interested in the set of U.S. domestic equity funds in isolation. However, it is important to keep in mind the main reason why we restricted ourselves to this fund type in this paper, namely that we have accurate information on their stock holdings via the CRSP Mutual Fund Database.

An obvious extension of our analysis would include additional fund types and explore to what extent this might increase the system's vulnerability.[32] Such an extension seems particularly relevant because other fund types have been growing in importance over time,

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

especially corporate and high-yield bond funds (Goldstein et al. (2016); 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. (2016)).

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 investment objective (e.g., emerging markets).

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 larger and more diversified funds appear to be more robust to other funds' deleveraging on average. On the other hand, macroprudential regulators are more concerned with the negative externalities imposed by funds, as proposed for example by Danielsson and Zigrand (2015). In this case, the systemicness (S) measure is the variable of interest. We find that larger, more diversified funds (with higher portfolio overlap) strongly contribute to the vulnerabilities of the overall fund 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.

Lastly, *fund illiquidity* tends to contribute to both funds' own vulnerability and their impact on other funds. Therefore, both micro- and macroprudential regulators should closely monitor the liquidity profile of individual funds. In fact, the SEC released a new set of rules in September 2015 for enhancing liquidity risk management by open-ended funds (see Hanouna, Noval, Riley, and Stahel (2015)), which was followed by FSB recommendations to address the liquidity mismatch in the fund sector in January 2017 (Financial Stability Board (2017)). Other regulators have already recognised 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)).

8 Conclusions

Our paper offers a first attempt to quantify systemic risk among asset managers. For this purpose, we extended the model of Greenwood et al. (2015) by incorporating the well-documented flow-performance relationship. Hence, in response to negative fund returns, investors will withdraw some of their funds, and mutual funds will need to finance these redemptions by liquidating assets.

We then applied the model to the set of U.S. domestic equity mutual funds. Overall, despite calibrating the model parameters to the most adverse scenario, we generally find the system to be robust to systemic asset liquidations. This result is driven by three factors: (1) mutual funds use little leverage; (2) the flow-performance relationship is weak; and (3) the typical overlap between funds' stock portfolios can be quite strong but is generally below the maximum value. In particular the fact that mutual funds are subject to tight leverage constraints makes our estimated vulnerabilities tiny in comparison with those of Greenwood et al. (2015) for the largest European banks. Overall, our findings suggest that systemic risks among mutual funds are unlikely to be a major concern, at least when looking at fire-sale dynamics in the U.S. equity mutual fund sector in isolation.

Lastly, we explored the determinants of individual funds' risk contribution. In this regard, we highlighted 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 the model to a broader set of asset managers.

References

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.

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

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

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).

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. *forthcoming: The Review of Financial Studies 30*(8), 2621–2673.

Fricke, D. (2017). Are specialists 'special'? *SSRN Working Paper*.

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 (2016). Investor flows and fragility in corporate bond funds. *forthcoming: Journal of Financial Economics*.

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.

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.

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

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.

Appendix

A Robustness Checks: Price Impacts

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 9 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.

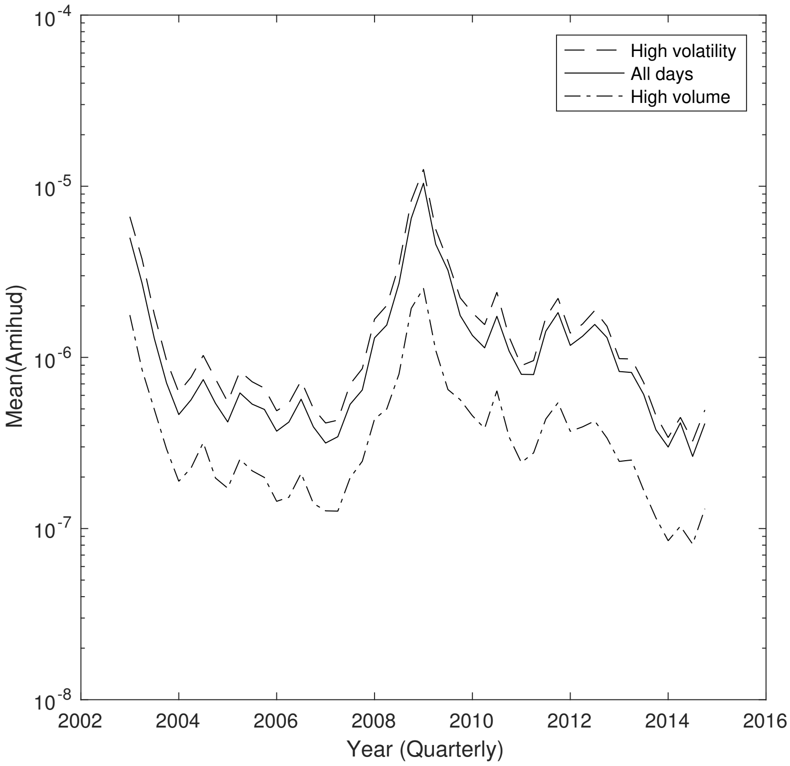

Figure 9: Price impact for very active periods. In the baseline scenario, we calculate the price impacts as the average values of the daily Amihud ratio for each stock (All Days, as in the main text). We also calculated price impacts using only the most active trading days for each stock: (1) based on 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, however, the typical price impacts are comparable to those we used in our main analysis in Scenario 1 in the main text.

B Robustness Checks: 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. (2016) 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.

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.

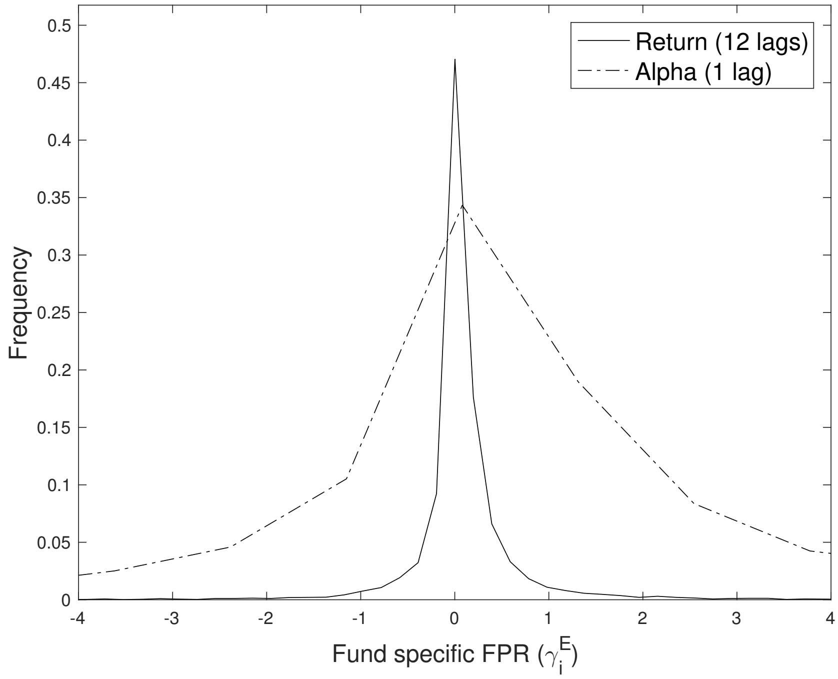

Figure 10: Distribution of fund-specific γ^Es. We estimate the flow-performance relationship separately for each fund using the same control variables as in our main specification. In addition, we also show the distribution when using alphas instead of returns.

B.2 Fund-Specific Flow-Performance Relationship

As another robustness check, we also ran 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 10, 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 10 shows the distribution of the estimated γ parameters in this case. Interestingly, the distribution in 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).