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Vulnerable Funds?

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Vulnerable Funds?

February 28, 2017

Abstract

There is an active debate on whether asset managers contribute to financial instability. In this paper, we perform a macro-prudential 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, Landier, and Thesmar (2015), where systemic risks can 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 over time. Our main finding is that the system's aggregate vulnerability is generally small and its time dynamics strongly depend on the choice of price impact parameters. 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. Finally, we explore the determinants of individual funds' vulnerability to systemic asset liquidations. Here, we highlight the importance of fund size, diversification levels, and portfolio illiquidity.

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

JEL classification: G10; G11; G23

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 (FSB (2011,2015); OFR (2013); ECB (2014); IMF (2015)). This is particularly true of the global asset management industry which has grown tremendously both in terms of size and importance over the last decades. Figure 1, which is reproduced from BIS (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 might be beneficial in the sense that it provides businesses and households with additional funding channels (BIS (2014)). However, this growth might also entail some risks. 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 steadily over time

(see also ECB (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

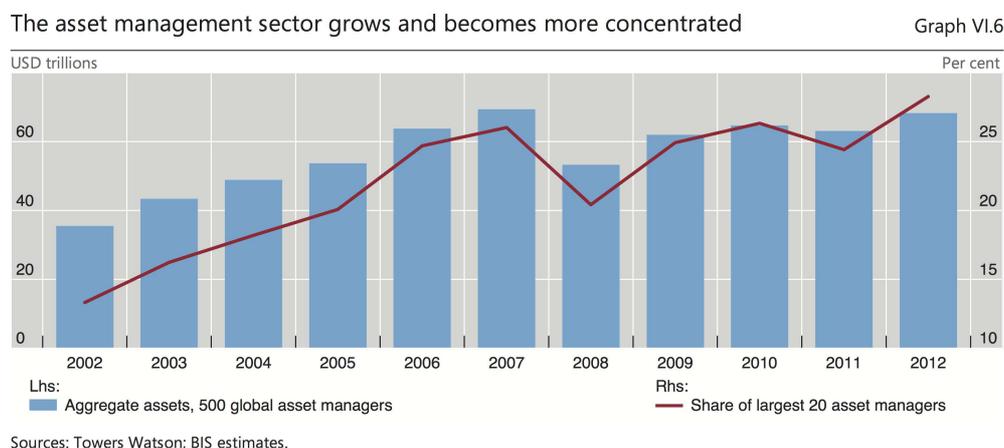


Figure 1: Growth and concentration in the asset management industry. The plot is taken from (2014, p. 115) and shows both the total assets under management for 500 global asset managers and the share of assets held by the 20 largest institutions.

So far, there is no clear consensus whether the investment fund industry, which is by far the most important subset of asset managers, contributes to financial instability. On the one hand, empirical evidence suggests that significant portfolio overlap and correlated trading strategies in the fund industry can indeed have major systemic repercussions. Two prominent examples are the role of portfolio insurers in the market crash of October 1987 and the systemic repercussions of the hedge fund Long Term Capital Management in 1998. On the other hand, leading industry figures argue that investment funds are not a source of systemic risk, mainly because investment funds are subject to tight leverage constraints (see, for example, ICI (2016)). Therefore, there is a general need for regulators and policy makers to understand whether this sector is vulnerable to systemic crises. How to quantify systemicness of funds or the asset management industry is an ongoing debate. The FSB (2015) defines asset liquidation and exposure risk as channels through which stress in the

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

²Portfolio 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 et al. (2014), and Morris and Shin (2014).

fund sector might be propagated. Therefore, the FSB proposed size and leverage as indicators of systemicness in the fund sector. However, Danielsson and Zigrand (2015) advocate focusing on the negative externalities stemming from funds in order to gauge their impact on financial instability.

This paper is the first to quantify the vulnerability of and externalities stemming from the U.S. mutual fund sector to systemic asset liquidations. Specifically, we focus on the economically important set of domestic equity funds. In 2016, this fund type accounted for more than 52% of the sector's asset (see ICI (2016)). The main advantage of restricting ourselves to this particular subset of funds is that we have both detailed data on these funds' stock portfolios 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 macro-prudential 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, Landier, and Thesmar (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 imperfectly illiquid asset markets and funding liquidity being driven by funds' past performances.

The underlying idea of the here developed macroprudential asset manager stress test is rather straightforward: suppose that a leveraged investor experiences a negative asset price shock to his asset portfolio. Assuming that the investor has a fixed leverage target, he will have to liquidate some of his asset holdings in response to a negative shock. This selling pressure will have a negative impact on asset prices, thereby affecting other funds holding similar assets in their portfolios. This can have further knock-on effects on market prices if these funds have to liquidate some of their own asset holdings.

In the Greenwood, Landier, and Thesmar (2015) model, systemic risks are largely driven by leverage - something that makes sense for highly leveraged financial institutions like banks. However, directly applying this model to the mutual fund sector is not likely to be 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 (Sirri and Tufano (1998); Berk and Green (2004)), which means that negative returns will be followed by additional (net)outflows. 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 system's aggregate vulnerability 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 when we keep the price impact parameters constant over time and identical across stocks. 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) mutual funds use little leverage; (2) the flow-performance relationship is weak; and (3) the typical overlap between funds' stock portfolios is strong but relatively far from its maximum value. 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, Landier, and Thesmar (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. We discuss the implications of these findings below. 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.

Our paper mainly adds to the literature on systemic risks in financial networks, first by developing a macroprudential stress-test to gauge systemic risk in the mutual fund sector, and second, by exploring fund characteristics that contribute to systemic risk. To the best of our knowledge, this is the first paper that develops a macro-prudential stress-test for the mutual fund industry.³ Dunne and Shaw (2017) are closest to our work as they relate fund-specific characteristics, such as leverage or usage of derivatives, to their exposure to a tail event in the fund sector (Marginal Expected Shortfall). By contrast, the vast majority of existing work tends to concentrate on systemic risks in the banking system (Allen and Gale (2000); Acemoglu, Ozdaglar, and Tahbaz-Salehi (2015); Glasserman and Young (2016)).

³We are only aware of a blogpost published by the New York Fed (see Cetorelli, Duarte, and Eisenbach (2016)).

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 between banks 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, and Ellul, Jotikasthira, and Lundblad (2011) for corporate bonds), a growing literature is thus looking at the importance of overlapping portfolios as a source of systemic risk (Cifuentes, Ferrucci, and Shin (2005); Wagner (2011); Caccioli et al. (2014); Greenwood, Landier, and Thesmar (2015)). 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, Landier, and Thesmar (2015) that is more relevant for the mutual fund sector. In section 3, we describe our dataset, explain in detail how we calibrate the model parameters, and calculate fund-specific and aggregate vulnerabilities. In section 6, we discuss our main findings, and section 7 concludes.

2. Model

In this section we present an extended version of the model introduced by Greenwood, Landier, and Thesmar (2015). There are N funds (investors) and K assets (investments). Let $\mathbf{M}_{\{N \times K\}}$ 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 . $\mathbf{A}_{\{N \times N\}}$ is the diagonal matrix of funds' assets with $A_{i,i} = E_i + D_i \forall i$. $\mathbf{B}_{\{N \times N\}}$ 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

$$R_1 = \mathbf{M}F_1, \quad (1)$$

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

$$A_1 = A_0(1 + R_1), \quad (2)$$

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

$$E_1 = E_0 + A_0R_1,^4 \quad (3)$$

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

$$D_1 = D_0. \quad (4)$$

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.⁵

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

$$\frac{\Delta E_2}{E_1} = \gamma^E R_1, \quad (5)$$

⁴If 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 the initial shock is small enough to not wipe out the entire equity.

⁵In 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.

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).⁶ Similarly, we can write the change in refinancing power as

$$\Delta D_2 = \gamma^D R_1 D_1 = \gamma^D R_1 D_0, \quad (6)$$

where γ^D is the flow-performance sensitivity parameter of debt, and ΔD_2 is the net inflow in dollars.⁷

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

$$E_2 = E_1(1 + \gamma^E R_1), \quad (7)$$

and

$$D_2 = D_1(1 + \gamma^D R_1). \quad (8)$$

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

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

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.

⁶In 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.

⁷ 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).

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).

For the case of no withdrawal of debt, we would impose $\gamma^D = 0$ and $\gamma^E \neq 0$, whereby $\gamma^E > 0$ would . In this 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 fund 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

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

2.3. Step 3: Leverage Targeting with Fixed Portfolio Weights

In line with Greenwood, Landier, and Thesmar (2015), we assume that funds target their leverage and aim their portfolio weights constant when liquidating (or buying) assets. These two assumptions are quite realistic given that funds need to specify the composition of both their asset and liability side in their sales prospectuses. 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

$$\tilde{\phi} = \underbrace{\gamma^E \mathbf{M}' \mathbf{E}_1 R_1}_{\text{Net inflow of equity}} + \underbrace{\gamma^D \mathbf{M}' \mathbf{D}_1 R_1}_{\text{Net inflow of debt}} + \underbrace{\mathbf{M}' \mathbf{A}_0 \mathbf{B} \tilde{R}_2}_{\text{Leverage targeting}},\tag{13}$$

which gives $(K \times 1)$ vector of net asset purchases by all funds in period 3. The last term in Eq. (13) corresponds to the ϕ in the Greenwood, Landier, and Thesmar (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 $\mathbf{\Gamma}^E_{\{N \times N\}}$ and $\mathbf{\Gamma}^D_{\{N \times N\}}$, where each element $\gamma_{i,i}^E$ and $\gamma_{i,i}^D$ can be fund specific.⁹ With this formulation, we end up with

$$\tilde{\phi} = \mathbf{M}' (\mathbf{\Gamma}^E \mathbf{E}_1 + \mathbf{\Gamma}^D \mathbf{D}_1) R_1 + \mathbf{M}' \mathbf{A}_0 \mathbf{B} \tilde{R}_2, \quad (14)$$

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

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

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

$$F_3 = \mathbf{L} \tilde{\phi}, \quad (16)$$

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

$$\begin{aligned} R_3 &= M F_3 = \mathbf{M} \mathbf{L} \tilde{\phi} \dots \\ &= \mathbf{M} \mathbf{L} \mathbf{M}' \left([\mathbf{\Gamma}^E \mathbf{E}_1 + \mathbf{\Gamma}^D \mathbf{D}_1] R_1 + \mathbf{A}_0 \mathbf{B} \tilde{R}_2 \right). \end{aligned} \quad (17)$$

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 XXX). Hence, liquidating twice as many assets should lead to a price impact that is less than twice the original one.

2.5. Measuring Vulnerability Exposures

Consider what happens after a negative shock, $F_1 = (-f_1, -f_2, \dots, -f_K)$, to asset prices: it translates into dollar shocks to funds' assets given by $\mathbf{A}_1 \mathbf{M} F_1$. The aggregate direct effect

⁹Assuming that the $\mathbf{\Gamma}$ matrices are diagonal implies that we ignore cross-fund correlations in the net inflows.

on all funds' assets is the sum of these values: $1'_N \mathbf{A}_1 \mathbf{M} F_1$. This shock will have additional knock-on effects for individual funds due to investors' fund share redemptions. Funds' net-inflows are equal to $(\mathbf{\Gamma}^E \mathbf{E}_1 + \mathbf{\Gamma}^D \mathbf{D}_1) \mathbf{M} F_1$, 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 $1'_N \mathbf{A}_0$, and normalize by the initial total equity, E_0 ,

$$\tilde{A}V = \frac{1'_N R_3}{E_0} = \frac{1'_N \mathbf{A}_0 \mathbf{M} \mathbf{L} \mathbf{M}' \left([\mathbf{\Gamma}^E \mathbf{E}_1 + \mathbf{\Gamma}^D \mathbf{D}_1] R_1 + \mathbf{A}_0 \mathbf{B} \tilde{R}_2 \right)}{E_0}. \quad (18)$$

$\tilde{A}V$ 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, Landier, and Thesmar (2015), we can decompose aggregate vulnerability into each fund's individual contribution

$$S_i = \frac{1'_N \mathbf{A}_0 \mathbf{M} \mathbf{L} \mathbf{M}' \delta_i \delta_i' \left([\mathbf{\Gamma}^E \mathbf{E}_1 + \mathbf{\Gamma}^D \mathbf{D}_1] R_1 + \mathbf{A}_0 \mathbf{B} \tilde{R}_2 \right)}{E_0}, \quad (19)$$

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

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:

$$IV_i = \frac{\delta_i' \mathbf{A}_0 \mathbf{M} \mathbf{L} \mathbf{M}' \left([\mathbf{\Gamma}^E \mathbf{E}_1 + \mathbf{\Gamma}^D \mathbf{D}_1] R_1 + \mathbf{A}_0 \mathbf{B} \tilde{R}_2 \right)}{E_{i,i}}. \quad (20)$$

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 Funds?

In this section, we apply the 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 portfolios over a relatively long sample period. Moreover, we can match these portfolio holdings with stock-specific information from CRSP, 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 and show how the aggregate vulnerabilities depend on different parameter choices.

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). Portfolio holdings are available at the quarterly level from March 2003 onwards and our final sample comprises 48 quarters between 2003-Q1 and 2014-Q4.¹⁰ In everything that follows, we disregard short positions. Second, we obtain daily stock-specific information from the merged CRSP-Compustat data. The merged 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 'ED'). Note that we do not exclude index funds from our analysis; while this is standard practice in other strands of literature (e.g., in performance analysis only actively managed funds are considered), index funds are subject to the same fire-sale mechanism described above.

The final sample contains 7,914 unique funds and 98,054 fund-quarter observations.

3.2. Estimation of Model Parameters

In the following, we describe in detail how we estimated the necessary model parameters from our dataset.

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

¹⁰Note 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 results to missing).

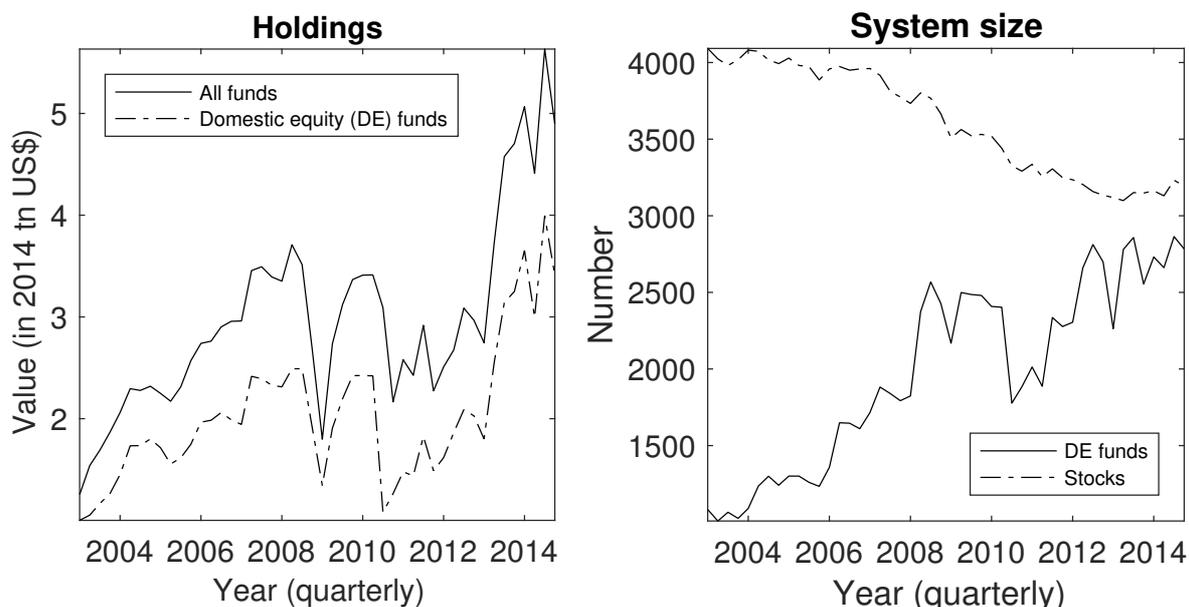


Figure 2: System size. Left: total dollar value of mutual funds' equity holdings over time in 2014 US\$ (trillion). The solid line shows the values when including all funds that report their holdings in the CRSP Mutual Fund Database, and the dashed line shows the values for domestic equity (DE) funds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

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.¹¹ The solid line shows the total volume when including all reported holdings, and the dashed-dotted line shows the values for domestic equity funds (DE) only. Clearly, the system has grown over the sample period, partly because the market value of the asset holdings depends on market prices, which also explains the strong effect of the global financial crisis in Figure 2. The right panel of Figure 2 shows the number of DE funds and the number of active stocks.¹² We see that the number of active funds has increased quite significantly over our sample period, while the number of stocks has been shrinking over time.

As discussed by Greenwood, Landier, and Thesmar (2015), a more concentrated system might be more vulnerable to systemic asset liquidations. Figure 1 above shows 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

¹¹In the following, we adjusted all nominal dollar volumes for inflation.

¹²Active 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.

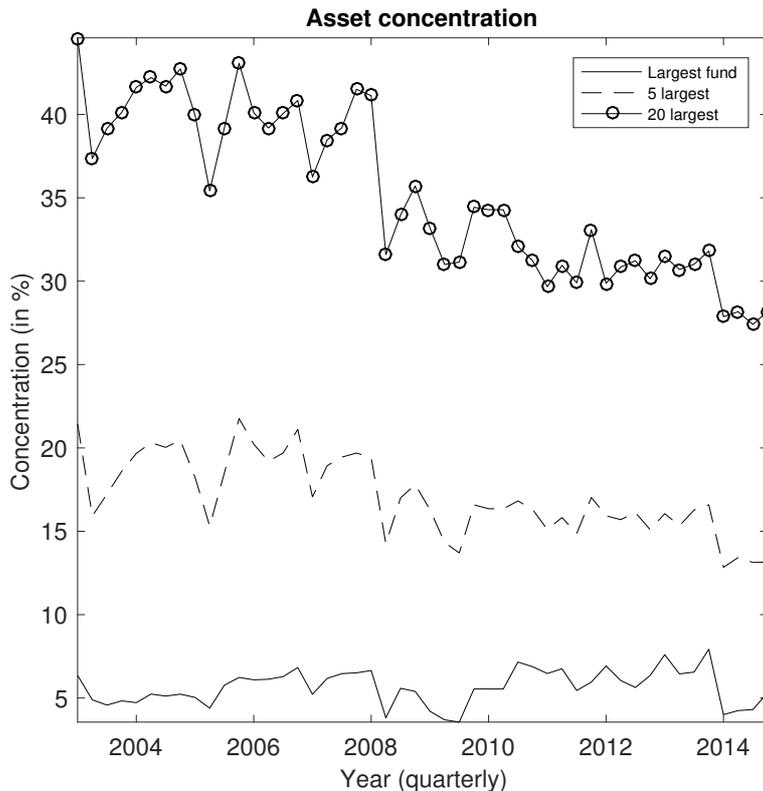


Figure 3: Concentration. Fraction of total holdings held by the largest 1, 5, and 20 fund(s), respectively.

funds considered in this study. Figure 3 shows the size of the largest fund(s) relative to the total size of the system over time. More precisely, we calculate the fraction of total assets held by the largest fund, the 5 largest funds, and the 20 largest funds, respectively. 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 might be driven by the steady growth in Exchange Traded Funds over our sample period. Overall, based on these dynamics alone, we would not expect aggregate vulnerabilities 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, we assume 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, Landier, and Thesmar (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 than banks.

3.2.3. Portfolio Weights

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

Since we observe additional information on the stocks, we also run our model based on more coarse-grained portfolios, say $\mathbf{M}_{\{N \times K^a\}}^a$ with $K^a < K$. In the following, we focus on SIC industry codes (4-digits, 2-digits, and 1-digit).¹⁴ For example, the 4-digit SIC classification defines 1,353 unique industry codes, and each element $M_{i,k}^a$ 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 \mathbf{M}^a will always exceed that of the most granular portfolios \mathbf{M} .

In Greenwood, Landier, and Thesmar (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

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

where $i \neq j$.¹⁵ 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

¹³Note 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.

¹⁴We 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.

¹⁵Other measures of portfolio overlap yield similar results (available upon request from the author).

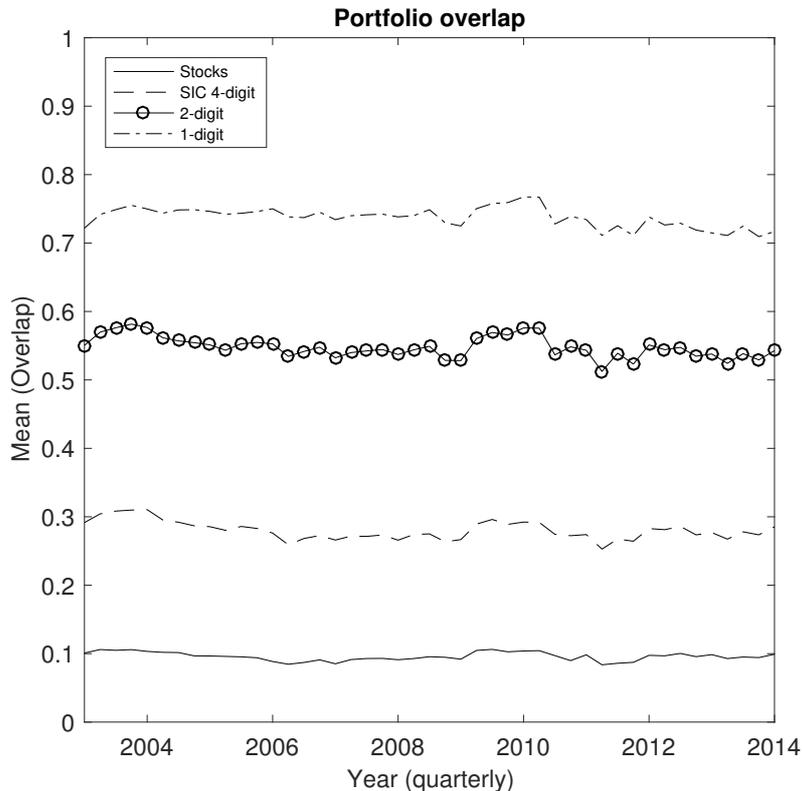


Figure 4: Portfolio overlap. For each quarter we show the cross-sectional average value of Eq. (21) for different aggregation levels. 'Stocks' corresponds to the original holdings reported in the CRSP Mutual Fund Database.

indicating more similar portfolios. If two funds have no assets in common, their overlap is 0; if they hold the exact same portfolios, their overlap is 1.

Figure 4 shows the cross-sectional average overlap over time for different levels of portfolio aggregation.¹⁶ 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 one. With regard to the evolution over time, we do not observe any clear trends in portfolio overlap for either aggregation level. In fact, the values appear to be remarkably stable for all aggregation levels. Hence, an increasing number of active funds and a decreasing number of securities do not necessarily translate into an increasing portfolio overlap. Again, from these figures one

¹⁶The results are largely comparable for other definitions of portfolio overlap.

would not expect an increasing trend in aggregate vulnerability purely due to the dynamics of portfolio overlap.

3.2.4. Price Impact

We apply a data-driven approach for quantifying asset fire-sale price impacts and 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)). Goyenko, Holden, and Trzcinka (2009) have shown that the Amihud-ratio is indeed an adequate proxy for monthly illiquidity conditions.

The Amihud-ratio is simply defined as the daily absolute return over the total dollar volume,

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

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

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

where $D_{k,t}$ is the number of daily observations for stock 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 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) price impact over time, as defined in Eq. (23), on a semi-logarithmic scale. Not surprisingly, the value-weighted average is much smaller since larger stocks are substantially more liquid than smaller stocks. In the Figure, we see that the value-weighted price impact is two orders of magnitude smaller than the equal-weighted price impacts. 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, Landier, and Thesmar (2015): the average values in Figure 5 are 4.77×10^{-6} and 1.11×10^{-8} , respectively.¹⁸

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

¹⁸For the set of large European banks, Greenwood, Landier, and Thesmar (2015) assume a price impact of 10^{-13} for most of their asset classes. The main reason is that Greenwood, Landier, and Thesmar (2015) compute the implied price impact of the complete stock market by aggregating the individual ratios according

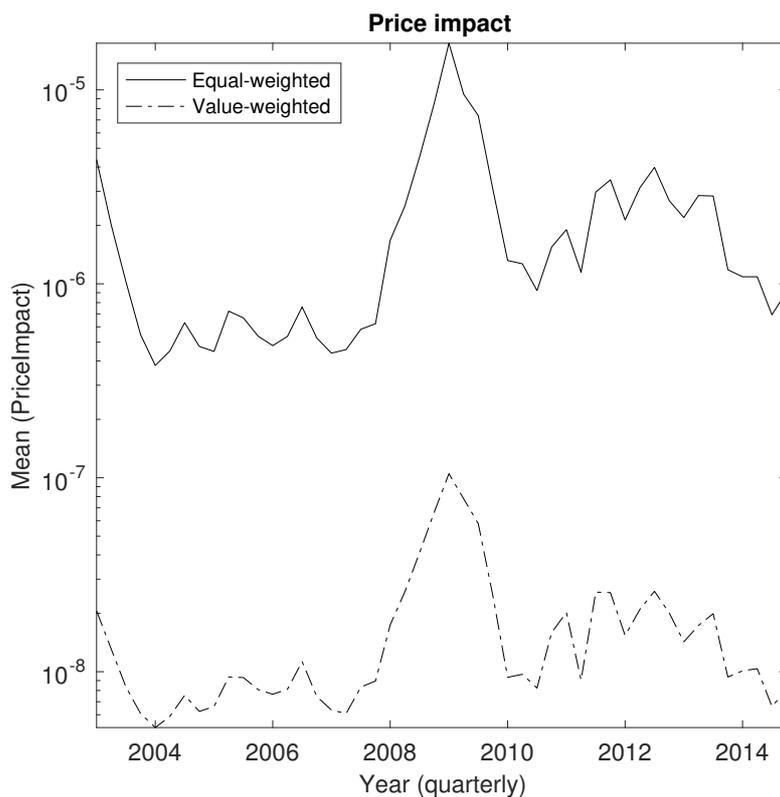


Figure 5: Price impact. For each stock, we calculate the daily Amihud-ratio as $|\text{Return}_{k,t}|/\text{DVolume}_{k,t}$, where $|\text{Return}_{k,t}|$ and $\text{DVolume}_{k,t}$ are the absolute return and the dollar volume of stock k on day t , respectively. We then take the quarterly average of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

We should 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.¹⁹ The estimation equation is

$$\text{Flows}_{i,t} = \alpha + \beta \times \text{Controls}_{i,t} + \gamma^E \times \text{Return}_{i,t-1} + \epsilon_{i,t}, \quad (24)$$

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

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

where TNA are total (net) assets. 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, we use the most simple approach in the following, namely we pool observations for all funds over time and estimate one γ^E for all funds.²⁰ This way, the estimated vulnerabilities in the next section will not be driven by any time dynamics in the flow-performance relationship.

Table 1 shows the results of this exercise, using different control variables and estimation approaches. 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 age, fund size, and fund-/time-FEs to the regressions. Overall, we find that the parameter on $\text{Return}(t-1)$ is always strongly positively significant, but

to $\sum_k (w_k)^2 (\text{Amihud}_k)^2$ (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.

¹⁹The literature has, however, also documented an asymmetry in the relationship: positive returns are followed by different net flows than negative returns (in absolute terms).

²⁰We add further data filters for these regressions: we exclude funds that are less than one year old, and we also drop extreme flow/return observations (above/below +200%/-50%).

Flow-Performance Relationship

	Dependent variable: Flows(t)					
	(1)	(2)	(3)	(4)	(5)	(6)
Return(t-1)	0.0512** (0.0042)	0.0633** (0.0039)	0.0738** (0.0038)	0.1343** (0.0097)	0.1573** (0.0097)	0.3011** (0.0289)
Return(t-2)	-	0.0135** (0.0037)	0.0316** (0.0035)	0.0618** (0.0086)	0.0980** (0.0087)	0.1621** (0.0186)
Return(t-3)	-	0.0139** (0.0039)	0.0307** (0.0038)	0.0260** (0.0096)	0.0631** (0.0094)	0.0703** (0.0235)
Return(t-4)	-	0.0170** (0.0039)	0.0360** (0.0038)	0.0388** (0.0092)	0.0761** (0.0091)	0.0800** (0.0177)
Return(t-5)	-	0.0016 (0.0038)	0.0227** (0.0037)	0.0146 (0.0086)	0.0560** (0.0086)	0.0426 * (0.0191)
Return(t-6)	-	0.0017 (0.0039)	0.0219** (0.0039)	0.0064 (0.0093)	0.0481** (0.0095)	0.0506 * (0.0254)
Return(t-7)	-	0.0021 (0.0038)	0.0166** (0.0037)	0.0223 * (0.0091)	0.0618** (0.0090)	0.0620** (0.0147)
Return(t-8)	-	-0.0023 (0.0038)	0.0096** (0.0037)	0.0023 (0.0089)	0.0421** (0.0089)	0.0515** (0.0162)
Return(t-9)	-	0.0119** (0.0040)	0.0278** (0.0039)	0.0231 * (0.0093)	0.0622** (0.0093)	0.0350** (0.0131)
Return(t-10)	-	-0.0148** (0.0039)	0.0023 (0.0038)	-0.0214 * (0.0093)	0.0196 * (0.0090)	0.0595 (0.0409)
Return(t-11)	-	0.0221** (0.0037)	0.0396** (0.0036)	0.0474** (0.0088)	0.0863** (0.0088)	0.0336 * (0.0158)
Return(t-12)	-	0.0081 * (0.0035)	0.0306** (0.0035)	0.0106 (0.0085)	0.0541** (0.0086)	0.0879 (0.0561)
Flows(t-1)	0.0774** (0.0045)	0.0654** (0.0057)	0.0183** (0.0057)	0.0633** (0.0057)	0.0154** (0.0057)	0.0775** (0.0110)
Flows(t-2)	-	0.0767** (0.0050)	0.0355** (0.0048)	0.0762** (0.0050)	0.0343** (0.0048)	0.0753** (0.0068)
Flows(t-3)	-	0.0563** (0.0048)	0.0215** (0.0047)	0.0563** (0.0048)	0.0206** (0.0047)	0.0152 (0.0442)
Flows(t-4)	-	0.0286** (0.0048)	-0.0024 (0.0047)	0.0288** (0.0048)	-0.0029 (0.0048)	0.0358** (0.0071)
Flows(t-5)	-	0.0484** (0.0047)	0.0204** (0.0046)	0.0483** (0.0047)	0.0198** (0.0046)	0.0364 * (0.0168)
Flows(t-6)	-	0.0376** (0.0047)	0.0129** (0.0046)	0.0376** (0.0047)	0.0127** (0.0046)	0.0148 (0.0185)
Flows(t-7)	-	0.0207** (0.0044)	-0.0014 (0.0043)	0.0213** (0.0044)	-0.0012 (0.0043)	-0.0077 (0.0304)
Flows(t-8)	-	0.0284** (0.0044)	0.0062 (0.0044)	0.0287** (0.0044)	0.0064 (0.0043)	0.0619 (0.0344)
Flows(t-9)	-	0.0277** (0.0044)	0.0086 * (0.0043)	0.0279** (0.0044)	0.0089 * (0.0043)	0.0458 * (0.0194)
Flows(t-10)	-	0.0234** (0.0042)	0.0061 (0.0041)	0.0240** (0.0042)	0.0068 (0.0041)	0.0714 (0.0406)
Flows(t-11)	-	0.0159** (0.0038)	-0.0008 (0.0038)	0.0165** (0.0039)	-0.0001 (0.0038)	0.0181** (0.0050)
Flows(t-12)	-	0.0240** (0.0040)	0.0089 * (0.0039)	0.0242** (0.0040)	0.0093 * (0.0039)	0.0256** (0.0057)
log(1+Age(t-1))	-0.0124** (0.0002)	-0.0030** (0.0002)	-0.0060** (0.0010)	-0.0032** (0.0002)	-0.0050** (0.0017)	0.0034 (0.0041)
log(TNA(t-1))	-0.0010** (0.0001)	-0.0012** (0.0001)	-0.0236** (0.0006)	-0.0012** (0.0001)	-0.0253** (0.0006)	-0.0009 (0.0007)
Fund FE	No	No	Yes	No	Yes	-
Time FE	No	No	No	Yes	Yes	-
Fama-MacBeth	-	-	-	-	-	Yes
adj. R ²	0.024	0.047	0.088	0.052	0.093	0.1573
Obs.	454,570	329,930	329,930	329,930	329,930	329,930

* 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 (robust standard errors in parentheses). The last column shows the results when using Fama-MacBeth regressions, in which case we report the time-series average of cross-sectional regression coefficients and the adjusted R². Age represents the fund age measured in months, TNA is a fund's total net assets, and Flow is defined in Eq. (25).

generally small.²¹ In fact, the maximum value for γ^E is 0.1573 when using pooled OLS. The last column shows the results when using Fama-MacBeth regressions, which yields $\gamma^E = 0.3011$. Also the R^2 is highest in this case. In order to be conservative in the model application, we stick to this value of γ^E in everything that follows.²²

We should stress that this is still a small value: a return of -1% would translate into additional net outflows of only $-1\% \times .3011 \approx -0.30\%$, suggesting that the vulnerability of the system is likely to be small even when including the flow-performance relationship.²³

4. Results: Aggregate Vulnerabilities Over Time

In the following, we consider a shock scenario where we impose an initial shock of -5% on all assets 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:

1. Price impact time-varying and asset-specific.
2. Price impact asset-specific but constant over time.
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 the first scenario: 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

²¹As a robustness check, we split the sample into two subperiods of equal length and find that the parameters on Return(t-1) are largely comparable to the values shown in Table 1.

²²Appendix B contains several robustness checks on the baseline specification in the last column of Table 1. In summary, our estimate of γ^E is robust to these alternative specifications.

²³In the technical Appendix to their blogpost, Cetorelli, Duarte, and Eisenbach (2016) describe a slightly different approach to estimating γ^E : in the first stage, they estimate a 12-month rolling window regression of fund returns on the market return separately for each fund. This gives them an estimate of each fund's excess return ('alpha') over time. In the second stage, they regress each fund's flows against the estimated alpha. We experimented with this approach, finding that it yields a *negative* flow-performance relationship in many cases - this clearly does not make sense. We therefore decided to stick to our approach.

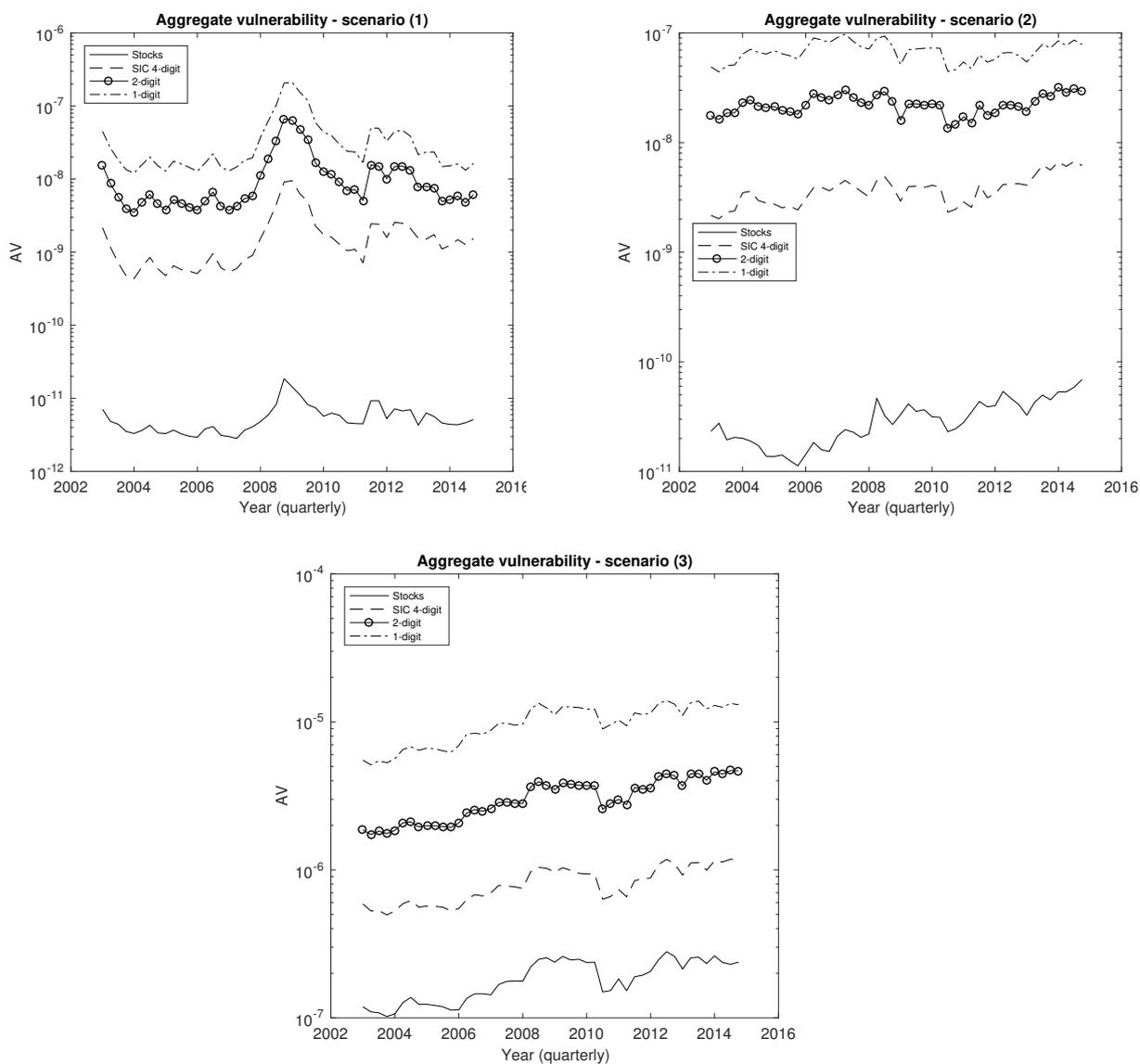


Figure 6: Aggregate vulnerability for the three different price impact scenarios. Top left: scenario 1 (price impact time-dependent and asset-specific). Top right: scenario 2 (price impact asset-specific but constant over time). Bottom: scenario 3 (price impact = 4.77×10^{-6} for all assets/quarters). 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.

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 (see Figure 5). 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.

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

In order to explore how the AVs look 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 are rather flat. In other words, despite the growth of the system, there is no increasing trend in the AVs.

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 dynamic variation 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 over time, but are still small: the maximum AV for this scenario is in the order of 0.001%.

Overall, the results shown in Figure 6 indicate that the aggregate vulnerability of the system is small. Hence, systemic asset liquidations are unlikely to be a major issue for the set of U.S. equity mutual funds. We will discuss this finding in more detail below.

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 (FSB (2016)).

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

$$\log(y_{i,t}) = a_t + \mathbf{b}_t \times \log(\mathbf{X}_{i,t-1}) + \epsilon_{i,t}, \quad (26)$$

where $y_{i,t}$ is the fund-specific vulnerability indicator of interest (systemicness or indirect vulnerability, respectively), \mathbf{X} contains our set of control variables (always using the first lag to alleviate the endogeneity problem), and \mathbf{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 regression parameters following the Fama-MacBeth (1973) methodology, and explore different sets of control variables that allow us to predict fund-specific vulnerabilities. Table 2 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, although considering lagged exogenous variables in the regressions this analysis comes at the cost of an endogeneity bias which hampers inferring any causal relationship between vulnerabilities and these fund-specific characteristics. Second, we aim at mitigating the potential endogeneity issue even further, and 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 2: 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 which go 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, Landier, and Thesmar (2015)). The correlations in Table 2 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)²⁴, and illiquidity (defined as the portfolio-weighted average Amihud-ratio of a fund, Illiq^{Amihud})²⁵:

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

Table 3 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 more systemically important, therefore. 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

²⁴To 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.

²⁵We 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.

Determinants of Fund-Specific Vulnerabilities – Scenario (1)

	Panel A		Panel B		Panel C	
	Full Sample		Full Sample		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(Illiq ^{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)
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(Illiq ^{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 3: The determinants of fund-specific indirect vulnerability (IV₁) and systemicness (S₁), respectively, for scenario 1. Results are based on quarterly data using Fama-MacBeth regressions (robust standard errors in parentheses), including a constant that is omitted from the output. All variables are defined in the main text and in Table 2. 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.

vulnerable and more systemic.²⁶ Overall, these results confirm our model predictions and those of Greenwood, Landier, and Thesmar (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.

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

²⁶We 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.

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, Flows^{6M} , as an additional size proxy. Flows are less deterministic (compared to age) and are likely to capture growth dynamics in the recent past.²⁷

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.²⁸ Not surprisingly, HHI and MeanOverlap are negatively correlated (Pearson correlation of -0.15, see Table 2), 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, Holden, and Trzcinka (2009)). Therefore, we consider the portfolio-weighted relative spread, $\text{Illiq}^{\text{Spread}}$, as an alternative liquidity measure.²⁹

With these alternative measures we then run the following regression

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

Table 3 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 3 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

²⁷Given that flows can take negative values, we do not take logarithms in this case.

²⁸Note 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.

²⁹To be precise, we define the relative spread of stock k in quarter t as $\text{Spread}_{k,t} = \frac{1}{D_{k,t}} \sum \frac{\text{Bid}_{k,d} - \text{Ask}_{k,d}}{(\text{Bid}_{k,d} + \text{Ask}_{k,d})/2}$.

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.

5.2. Additional Robustness Checks

For robustness and in order to expand our examination, we additionally analyse funds' vulnerabilities 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 4 shows the same regression results for *Scenario 2*. The results are largely consistent with those in Table 3 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*.

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, Landier, and Thesmar (2015), and Cetorelli, Duarte, and Eisenbach (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 5 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 vulnerabilities in the fund sector? One would expect that funds with very liquid (illiquid) portfolios will

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(Illiq ^{Amihud} (t-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)
Flows ^{6M} (t-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(Illiq ^{Spread} (t-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 4: The determinants of fund-specific indirect vulnerability (IV₂) and systemicness (S₂), respectively, for scenario 2. Results are based on quarterly data using Fama-MacBeth regressions (robust standard errors in parentheses), including a constant that is omitted from the output. All variables are defined in the main text and in Table 2. 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.

Determinants of Fund-Specific Vulnerabilities – Scenario (3)

	Panel A		Panel B		Panel C	
	Full Sample		Full Sample		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(Illiq ^{Amihud} (t-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)
Flows ^{6M} (t-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(Illiq ^{Spread} (t-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 5: The determinants of fund-specific indirect vulnerability (IV₃) and systemicness (S₃), respectively, for scenario 3. Results are based on quarterly data using Fama-MacBeth regressions (robust standard errors in parentheses), including a constant that is omitted from the output. All variables are defined in the main text and in Table 2. 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.

	Decile (Illiq ^{Amihud})									
	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 6: Correlations between indirect vulnerabilities and systemicness from scenarios 1 and 3, respectively, for different liquidity categories. Decile 1 (10) corresponds to the most liquid (illiquid) funds. All correlations are significant at the 1%-level.

be falsely treated as more illiquid (liquid) than what is observed in the data. We address this question by directly comparing the fund-specific vulnerability measures IV and S of scenario 1 and scenario 3. Table 6 reports the correlations between fund-specific vulnerabilities of scenarios 1 and 3 for different liquidity deciles (based on the Amihud-ratio as a illiquidity indicator). 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. However, the effect of a homogeneous price impact materializes for the most illiquid funds, namely decile 10, where the correlations are 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 Scenarios 1 and 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 6). 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, our model should ideally be applied using time-varying and asset-specific price impacts.

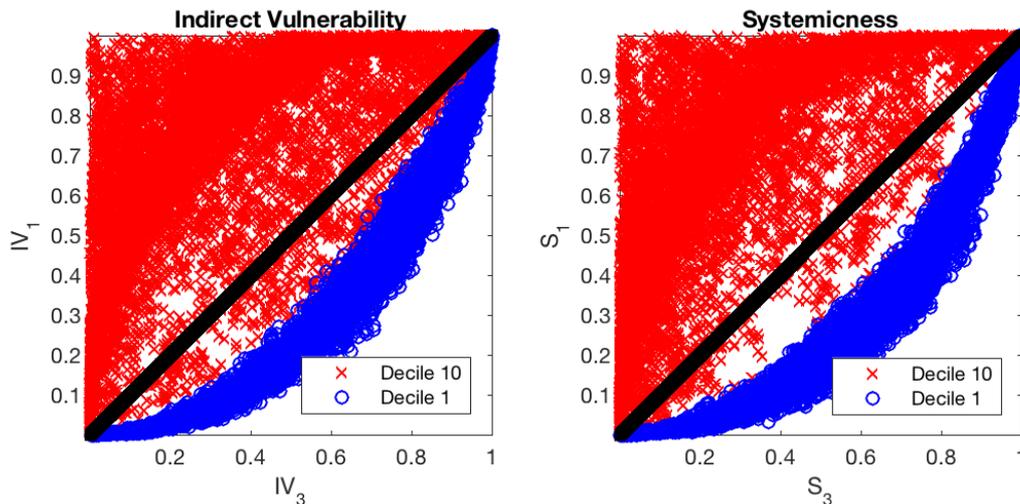


Figure 7: Vulnerability rankings in scenario 1 plotted against those from scenario 3. Left panel: indirect vulnerability. Right panel: systemicness. Both panels show the relative ranking for funds in liquidity Decile 1 (most liquid) and Decile 10 (least liquid), respectively, based on $\text{Illiq}^{\text{Amihud}}$.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

6. Discussion

Implications for future stress tests. Do our findings suggest that the mutual fund sector is robust to systemic crises? The answer would be ‘yes’ if one were interested in the set of 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.³⁰ This seems particularly relevant

³⁰In this case, we would have to approximate funds’ portfolio holdings in other asset categories (e.g., corporate bonds) because these are not directly observed. For this purpose, one could use standard Sharpe-

because other fund types have been growing in importance over time; for example Goldstein, Jiang, and Ng (2016) report that the assets under management of corporate bond mutual funds grew by more than 500% from 2000 to 2013. Fixed income funds held roughly 22% of the system’s assets at the end of 2015 and, together with ETFs, accounted for nearly 60% of net flows into the U.S. asset management sector between January 2014 and September 2016 (see ICI (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. These spill-over effects might be even larger when market liquidity worsens and bond fund flows become more sensitive to fund performance (Goldstein, Jiang, and Ng (2016)).

Nevertheless, even when including these other fund types in our analysis we do not expect dramatically larger aggregate vulnerabilities for at least two reasons: (1) the results of Goldstein, Jiang, and Ng (2016) suggest that the flow-performance relationship is even weaker for bond funds; and (2) bond funds are subject to the same leverage constraints as all other mutual funds. Hence, the order of magnitude of the system’s AVs are likely to be comparable to those reported here.

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 (FSB (2015)). One indicator for assigning systemic relevance is *fund size*, which is readily available and accessible for supervisors in a timely manner (FSB (2015)). Besides size, IMF (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

style regressions, see Kim, White, and Stone (2005). We leave this extension for future research.

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 et al. (2015)), which was followed by FSB recommendations to address the liquidity mismatch in the fund sector in June 2016 (FSB (2016)). 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)).

7. Conclusions

Our paper offers a first attempt to quantify systemic risk in the mutual fund industry. We extended the model of Greenwood, Landier, and Thesmar (2015) by incorporating the well-documented flow-performance relationship for mutual funds. 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. Overall, despite choosing the model parameters in a conservative way, we generally find the system to be robust to systemic shocks. 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, Landier, and Thesmar (2015) for the largest European banks. Overall, these findings 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.

Systemic risk in the mutual fund sector tends to increase with more illiquid fund portfolios. Thus, a clear understanding of funds' liquidity profile is essential for enhancing the corresponding micro- and macroprudential policy tools.

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Appendix A. Robustness: 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 A.8 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.

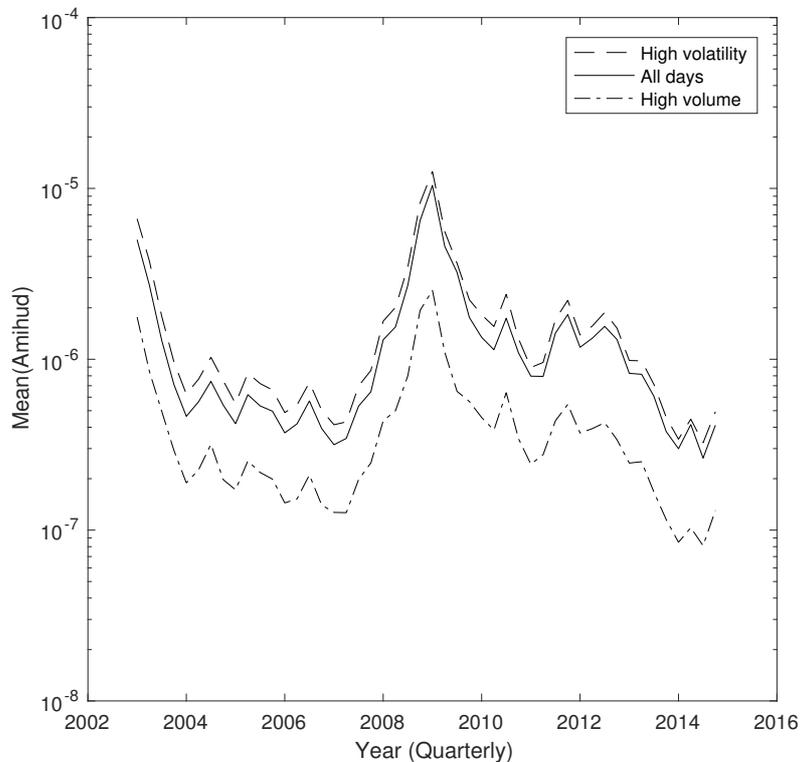


Figure A.8: Price impact for very active periods. In the baseline scenario, we calculate the price impacts as the average values of the daily Amihud ratio for each stock (All Days, as in the main text). We also calculated price impacts using only the most active trading days for each stock: (1) based 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. Note that the y-axis is displayed 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.

Appendix B. Robustness: Flow-Performance Relationship

Table 1 in the main text shows several different specifications for the estimation of the flow-performance relationship. In order to explore the robustness of the baseline specification (i.e., the last column in Table 1), we performed numerous alternative specifications which generally yield very similar results in terms of the estimated γ^E .

In this regard, Table B.7 shows the most important robustness checks (all regressions based on the Fama-MacBeth methodology):

1. Column (1) shows results when using category-adjusted returns. In this case, we take a fund's return and subtract the average return of each fund category (based on CRSP objective codes) separately for each month.
2. Column (2) shows results when using 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. Columns (3-4) show results for large and small funds, respectively. In this case, we use funds' TNA to divide them into above- and below-median size groups.
4. Finally, columns (5-6) show results for high- and low-risk funds, respectively. In this case, we calculate the 6-month rolling-window return standard deviations and divide funds into above- and below-median risk groups.

In summary, the estimates of γ^E for these alternative specifications are always very close to the actual value we used ($\gamma^E = 0.3011$). Hence, the aggregate vulnerabilities will be comparable to the ones presented in the main text.

Flow-Performance Relationship

	Dependent variable: Flows(t)					
	(1) Cat.-adj. Returns	(2) Fam.-adj. Returns	(3) Large Funds	(4) Small Funds	(5) High-Risk Funds	(6) Low-Risk Funds
Return(t-1)	0.2736** (0.0292)	0.2883** (0.0234)	0.2678** (0.0195)	0.2944** (0.0270)	0.2763** (0.0231)	0.3418** (0.0275)
Return(t-2)	0.1734** (0.0190)	0.1450** (0.0218)	0.1704** (0.0185)	0.1469** (0.0213)	0.1266** (0.0190)	0.2585** (0.0301)
Return(t-3)	0.0979** (0.0264)	0.0740** (0.0162)	0.1025** (0.0209)	0.1042** (0.0200)	0.0851** (0.0175)	0.1789** (0.0240)
Return(t-4)	0.1039** (0.0178)	0.0503* (0.0222)	0.0909** (0.0176)	0.0737** (0.0215)	0.0732** (0.0203)	0.1351** (0.0226)
Return(t-5)	0.0710** (0.0191)	0.0402* (0.0196)	0.0565** (0.0202)	0.0532* (0.0217)	0.0392 (0.0204)	0.1293** (0.0251)
Return(t-6)	0.0751** (0.0252)	0.0328 (0.0212)	0.0584** (0.0171)	0.0720** (0.0213)	0.0696** (0.0212)	0.1140** (0.0231)
Return(t-7)	0.1301* (0.0574)	0.0593** (0.0180)	0.0753** (0.0162)	0.0597** (0.0188)	0.0337* (0.0155)	0.1349** (0.0233)
Return(t-8)	0.0756** (0.0167)	0.0458* (0.0182)	0.0390* (0.0157)	0.0672** (0.0211)	0.0435* (0.0181)	0.1074** (0.0231)
Return(t-9)	0.0779* (0.0308)	0.0315* (0.0146)	0.0623** (0.0153)	0.0259 (0.0191)	0.0270 (0.0163)	0.0707** (0.0223)
Return(t-10)	0.0601* (0.0296)	0.0231 (0.0177)	0.0158 (0.0174)	0.0278 (0.0209)	0.0148 (0.0184)	0.0493 (0.0265)
Return(t-11)	0.0523** (0.0150)	0.0219 (0.0172)	0.0299 (0.0174)	0.0362 (0.0222)	0.0264 (0.0183)	0.0552* (0.0212)
Return(t-12)	0.1230* (0.0616)	0.0722 (0.0448)	0.0238 (0.0167)	0.0444* (0.0206)	0.0471* (0.0183)	0.0010 (0.0190)
Flows(t-1)	0.0666** (0.0084)	0.0666** (0.0080)	0.0995** (0.0196)	0.0620** (0.0097)	0.0595** (0.0172)	0.0968** (0.0106)
Flows(t-2)	0.0682** (0.0085)	0.0697** (0.0099)	0.0855** (0.0086)	0.0716** (0.0079)	0.0715** (0.0124)	0.0869** (0.0091)
Flows(t-3)	0.0198 (0.0277)	0.0441** (0.0145)	0.0620** (0.0172)	0.0237 (0.0263)	0.0347 (0.0176)	0.0710** (0.0102)
Flows(t-4)	0.0549** (0.0198)	0.0538** (0.0174)	0.0425** (0.0079)	0.0338** (0.0083)	0.0346** (0.0080)	0.0482** (0.0079)
Flows(t-5)	0.0573** (0.0103)	0.0610** (0.0122)	0.0519** (0.0088)	0.0562** (0.0097)	0.0460** (0.0081)	0.0480** (0.0073)
Flows(t-6)	0.0122 (0.0209)	0.0086 (0.0240)	0.0153 (0.0215)	0.0300** (0.0069)	0.0181 (0.0187)	0.0287** (0.0064)
Flows(t-7)	0.0151 (0.0095)	0.0076 (0.0155)	0.0292** (0.0059)	0.0142 (0.0075)	0.0254* (0.0102)	0.0178** (0.0058)
Flows(t-8)	0.0420* (0.0162)	0.0357* (0.0179)	0.0276** (0.0063)	0.0268** (0.0061)	0.0240** (0.0068)	0.0354** (0.0080)
Flows(t-9)	0.0077 (0.0301)	0.0411** (0.0144)	0.0313** (0.0099)	-0.0034 (0.0291)	0.0225** (0.0067)	0.0360** (0.0101)
Flows(t-10)	0.0482 (0.0292)	0.0502 (0.0281)	0.0148* (0.0074)	0.0611* (0.0291)	0.0326** (0.0124)	0.0262** (0.0070)
Flows(t-11)	0.0166** (0.0048)	0.0161** (0.0048)	0.0204** (0.0065)	0.0186** (0.0067)	0.0167* (0.0066)	0.0164* (0.0063)
Flows(t-12)	0.0241** (0.0065)	0.0226** (0.0065)	0.0360** (0.0078)	0.0283** (0.0080)	0.0335** (0.0081)	0.0158* (0.0063)
log(Age(t-1))	-0.0018 (0.0010)	0.0040 (0.0047)	-0.0026** (0.0004)	-0.0011 (0.0015)	-0.0077 (0.0055)	0.0021 (0.0046)
log(TNA(t-1))	-0.0028* (0.0011)	-0.0015** (0.0003)	-0.0020** (0.0002)	-0.0061** (0.0012)	-0.0092 (0.0072)	-0.0051 (0.0047)
FundFamilySize	-	0.0002 (0.0001)	-	-	-	-
Fama-MacBeth	Yes	Yes	Yes	Yes	Yes	Yes
adj. R ²	0.149	0.151	0.208	0.171	0.182	0.204
Obs.	343,488	343,488	184,177	159,266	171,172	170,307

* p<0.05; ** p<0.01

Table B.7: 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 (robust standard errors in parentheses), as in the main text. Note: FundFamilySize counts the number of funds in a given fund-family.