DEUTSCHE BUNDESBANK
EUROSYSTEM

Discussion Paper

Deutsche Bundesbank
No 48/2020

Connected funds

Daniel Fricke
Hannes Wilke

Deutsche Bundesbank, Wilhelm-Epstein-Straße 14, 60431 Frankfurt am Main,
Postfach 10 06 02, 60006 Frankfurt am Main

Tel +49 69 9566-0

Please address all orders in writing to: Deutsche Bundesbank,
Press and Public Relations Division, at the above address or via fax +49 69 9566-3077

Internet http://www.bundesbank.de

ISBN 978–3–95729–763–1 (Printversion)
ISBN 978–3–95729–764–8 (Internetversion)

Non-technical summary

Research Question

The connectedness of the financial system can be a source of financial instability. Following the global financial crisis, much research has been devoted to the role of banks, but over recent years the focus has shifted towards non-bank financial intermediaries. In this regard, the investment fund sector is of particular interest, since it exhibits structural liquidity and run risks. There is ample evidence that investment funds' fire sales have persistent price effects, which have real effects on firms whose assets were subject to fire sales. It is therefore important to quantify potential fund sector vulnerabilities and their effects on the broader financial system.

Contribution

We develop a macroprudential stress test for the open-end investment fund sector. We define the fund sector's aggregate vulnerability (AV) as the sum of funds' portfolio losses due to i) funds' common asset liquidations (indirect connectedness) and ii) funds' cross-holdings of fund shares (direct connectedness), standardized by the fund sector's aggregate net assets. By explicitly incorporating funds' cross-holdings, we acknowledge that fund shares make up a growing proportion of funds' asset portfolios. Our unique dataset allows for an in-depth analysis of the broader effects of fund sector vulnerabilities on the wider financial system.

Results

We find that investment funds can amplify losses from a price shock on global securities markets. During the period November 2015 to July 2019, the average AV of the German fund sector is 1.8%. These second round losses due to funds' connectedness can amount to up to 44% of the initial shock. Moreover, we find that the AV displays a strong positive time trend as it increased by up to 140% over our relatively short sample period. Bond funds and mixed funds contribute most to the AV, given their relatively illiquid asset portfolios and high levels of direct connectedness. Our findings suggest that funds' direct connections matter for financial stability. Lastly, we document spillover risks for the broader financial system.

Nichttechnische Zusammenfassung

Fragestellung

Die Vernetzung des Finanzsystems kann Instabilität begünstigen. Seit der globalen Finanzkrise beschäftigt sich die Literatur vorwiegend mit dem Bankensystem, jedoch rückten in den letzten Jahren vermehrt Nicht-Banken-Finanzintermediäre in den Fokus. Von besonderem Interesse sind dabei Investmentfonds, da diese strukturelle Liquiditäts- und Run-Risiken bergen. Die empirische Evidenz zeigt auch, dass Wertpapier-Notverkäufe von Investmentfonds dauerhafte Kursrückgänge nach sich ziehen, welche negative realwirtschaftliche Effekte auf die betroffenen Unternehmen haben. Daher ist es wichtig, mögliche Verwundbarkeiten innerhalb des Fondssektors zu quantifizieren und deren Auswirkungen auf das übrige Finanzsystem abzuschätzen.

Beitrag

Wir entwickeln einen makroprudenziellen Stresstest für den Sektor der Offenen Investmentfonds. Wir definieren die aggregierte Verwundbarkeit (AV) des Fondssektors als die Summe der Portfolioverluste von Investmentfonds, welche aus i) gleichgerichteten Wertpapierverkäufen (indirekte Vernetzung) und ii) dem gegenseitigen Halten von Fondsanteilen (direkte Vernetzung) entstehen, relativ zum aggregierten Nettofondsvermögen des Sektors. Durch die explizite Berücksichtigung direkter Verflechtungen tragen wir dem wachsenden Gewicht von Fondsanteilen in den Fondsportfolios Rechnung. Der verwendete Datensatz erlaubt zudem eine genauere Analyse von Ansteckungsrisiken für das übrige Finanzsystem, die aus der Vernetzung des Fondssektors resultieren.

Ergebnisse

Es zeigt sich, dass Investmentfonds Verluste aus einem Kurseinbruch an den globalen Wertpapiermärkten verstärken können. Im Zeitraum November 2015 bis Juli 2019 beträgt die durchschnittliche AV des deutschen Fondssektors 1,8%; dabei können die Zweitrundenverluste aus der Vernetzung des Fondssektors bis zu 44% des Ausgangsschocks betragen. Zudem finden wir einen positiven Zeittrend in der AV, die im Betrachtungszeitraum einen Anstieg von 140% verzeichnete. Vor allem Anleihe- und Mischfonds tragen zur AV bei, da diese Fondstypen relativ illiquide Wertpapiere halten und stark direkt vernetzt sind. Unsere Ergebnisse verdeutlichen die Wichtigkeit dieser direkten Verbindungen aus Sicht der Finanzstabilität. Zudem bestehen Ansteckungsrisiken für das übrige Finanzsystem.

Deutsche Bundesbank Discussion Paper No 48/2020

Connected Funds*

Daniel Fricke & Hannes Wilke

July 15, 2020

Abstract

Investment funds are highly connected with each other, but also with the broader financial system. In this paper, we quantify potential vulnerabilities arising from funds' connectedness. While previous work exclusively focused on indirect connections (overlapping asset portfolios) between investment funds, we develop a macroprudential stress test that also includes direct connections (cross-holdings of fund shares). In our application for German investment funds, we find that these direct connections are very important from a financial stability perspective. Our main result is that the German fund sector's aggregate vulnerability can be substantial and tends to increase over time, suggesting that the fund sector can amplify adverse developments in global security markets. We also highlight spillover risks to the broader financial system, since fund sector losses would be largely borne by fund investors from the financial sector. Overall, we make an important step towards a more financial-system-wide view on fund sector vulnerabilities.

Keywords: asset management; investment funds; systemic risk; fire sales; liquidity risk; cross-holdings; spillover effects.

JEL classification: G10; G11; G23.

*Contact: Daniel Fricke. Tel.: (+49) 69 9566 1279; email: daniel.fricke@bundesbank.de. Hannes Wilke. Tel.: (+49) 69 9566 7492; email: hannes.wilke@bundesbank.de. We thank seminar participants at the Deutsche Bundesbank and the Halle Institute for Economic Research. The paper especially benefited from valuable comments by Stephan Jank, Corinna Knobloch, Emanuel Mönch, and Benjamin Weigert. The views expressed in this paper represent the authors' personal opinions and do not necessarily reflect the views of the Deutsche Bundesbank or the Eurosystem.

1 Introduction

The connectedness of the financial system can be a source of financial instability. In this regard, much research following the global financial crisis has been devoted to the role of banks (Glasserman and Young (2016)), but over recent years the focus has shifted towards non-bank financial intermediaries (NBFI). In this regard, open-end investment funds have received particular attention given that these tend to be the dominant actors within the NBFI segment and, due to the strong growth since the global financial crisis, the sector's importance within the financial system continues to increase.[1]

Moreover, investment funds exhibit structural liquidity and run risks due to strategic complementarities in the fund-share redemption process (e.g., Goldstein, Jiang, and Ng (2017)): to pay out redeeming investors, fund managers may need to liquidate assets. These asset sales can have a negative impact on market prices, which affects the remaining fund investors. These externalities therefore give rise to first mover advantages[2], suggesting the potential of a negative run-equilibrium with price/illiquidity spirals. In line with recent empirical examples[3], there is substantial evidence that institutional investors' fire sales (and purchases) indeed have persistent effects on asset prices and their co-movement (see, e.g., Coval and Stafford (2007); Manconi, Massa, and Yasuda (2012); Antón and Polk (2014); Chernenko and Sunderam (2020)). Moreover, a growing literature documents that funds' fire sales have real effects on the firms that were subject to such liquidations (Edmans, Goldstein, and Jiang (2012); Hau and Lai (2013)) and even on their peers (Dessaint, Foucault, Fresard, and Matray (2019)). It is therefore important to quantify potential effects of funds' fire sales. More broadly, this paper seeks to quantify vulnerabilities due to the fund sector's connectedness and their impact on the broader financial system.

For this purpose, we develop a macroprudential stress test for the open-end investment fund sector.[4] Our model imposes an abrupt drop of global bond and equity prices (the initial shock), which induces a first round of fund portfolio losses. To capture second round effects triggered by this initial shock, there are three further steps: first, funds suffer losses on their fund holdings (cross-holdings) as the initial shock propagates through the cross-holdings network. Second, funds need to liquidate assets to meet both investor redemptions and their leverage targets. Third, funds' asset liquidations lead to additional asset price drops and thus to further fund portfolio losses. We define the fund sector's aggregate vulnerability (AV) as the sum of funds' second round portfolio losses due to funds' common asset liquidations (indirect connectedness) and cross-holdings (direct connectedness), relative to the aggregated pre-shock total net assets (TNA). As such, the AV measures systemic risks from funds' connectedness and combines information from a number of commonly used macroprudential risk indicators for the fund sector (e.g., funding

[1]See, e.g., Luis de Guindos' speech at the Euro Finance Week in November 2018 (`https://www.ecb.europa.eu/press/key/date/2018/html/ecb.sp181112.en.html`).

[2]A growing body of literature investigates instruments to internalize these externalities, such as swing pricing (see, e.g., Capponi, Glasserman, and Weber (2018); Jin, Kacperczyk, Kahmaran, and Suntheim (2019)). Note that these instruments are slowly becoming available to investment funds in the euro area.

[3]See `https://www.bloomberg.com/news/articles/2019-06-25/six-h2o-funds-lost-almost-eu1-4-billion-on-friday` and `https://www.ft.com/content/a025e93a-0601-11ea-a984-fbbacad9e7dd`.

[4]The Financial Stability Board (2017) recommended that the relevant authorities should develop macroprudential stress tests that quantify the potential effects of fire sales in the investment fund sector.

stability, leverage, and market liquidity). Previous work exclusively focused on fund sector vulnerabilities due to indirect connections between investment funds. In contrast, by explicitly incorporating funds' cross-holdings, our approach acknowledges that the direct connectedness of investment funds tends to increase, which may have important financial stability implications.

We apply the model using a unique dataset on the German investment fund sector, which is the third-largest fund sector in the euro area.[5] We find that, under a scenario of a shock on global bond and equity prices of 4.5% and 14.2% respectively, the average AV during the period November 2015 to July 2019 is 1.8% based on stressed market conditions (1.2% under actual market conditions), corresponding to second round losses of up to 44% of the initial shock. This suggests that the German fund sector may amplify losses on global securities markets. Moreover, the AV displays a strong positive time trend as it increased by up to 140% over our relatively short sample period. We find that much of this increase is 'real' in the sense that the nominal growth of the fund sector accounts for at most 1/3 of this increase. Another key finding is that direct connections between investment funds matter for financial stability, since an average of 65% of the sector's AV is due to funds' cross-holdings. As expected, we find that both bond funds and mixed funds contribute most to the AV, given their relatively illiquid asset portfolios and high levels of direct connectedness (cross-holdings). Lastly, we document spillover risks to the broader financial system. Given that German investment funds are predominantly held by financial intermediaries outside the fund sectors, these actors would bear the vast majority of fund sector losses (on average 75% of the total losses). We find that these spillover risks can be substantial: for example, second round losses of pension funds due to fund sector losses can amount to more than 4% of their fund holdings, which corresponds to second round effects of up to 70% of the initial shock. We should stress that our approach likely underestimates the vulnerability of the financial sector to fund sector losses, since we only include German investment funds in our application.

With regards to the existing literature, our paper makes several important contributions. First, we make an important step towards a fund sector-wide stress test. Previous work typically focused on specific fund types, such as bond funds (e.g., Baranova, Coen, Lowe, Noss, and Silvestri (2017); Cetorelli, Duarte, and Eisenbach (2016)). In contrast, our model application covers around 85% of the German fund sector's total assets as we include the most important fund types in Germany (equity funds, bond funds, mixed funds[6], and funds-of-funds), covering both retail and institutional funds.[7] Second, we make use of the most granular information available on funds' asset portfolios. In contrast, the existing literature typically uses more aggregated information on funds' asset portfolios (e.g., at the asset class level, see Cetorelli et al. (2016)), which heavily overestimates the portfolio overlap within the fund sector (see Fricke and Fricke (2020)). Third,

[5] According to the ECB investment fund balance sheet statistics, the market share of the German fund sector is at 18% (`http://sdw.ecb.europa.eu/reports.do?node=1000003417`).

[6] Mixed securities funds are also referred to as Allocation funds. In contrast to bond and equity funds, mixed funds can invest in a broad range of asset classes. From a financial stability perspective, mixed funds are particularly interesting because they might 'connect' bond and equity funds, in that they could propagate idiosyncratic shocks affecting these two fund types and thus facilitate the comovement between bonds and equities in general. These diversified funds may therefore give rise to socially sub-optimal comovement between these asset classes along the lines of Ibragimov, Jaffee, and Walden (2011).

[7] As of July 2019, institutional funds make up roughly 77% of the German fund sector's total assets.

our model explicitly incorporates cross-holdings between investment funds. This is important because fund shares make up a growing proportion of funds asset portfolios and we shed light on the financial stability implications of the increased direct connectedness within the German fund sector. While direct connections have been studied extensively in the case of banks (e.g., interbank lending networks as discussed Glasserman and Young (2016)), we are the first to take a comparable aspect for investment funds into account. In fact, previous work on cross-holdings between investment funds largely focused on within fund-family cross-holdings.[8] We acknowledge the fact that cross-holdings can also occur between fund-families, which creates an intricate network of direct connections between investment funds. As such, our paper is the first to investigate the financial stability implications of funds' cross-holdings. Lastly, the unique dataset used in this paper allows for a deeper analysis of the effects of investment funds' asset sales on the broader financial system. For example, we quantify the direct portfolio losses of investors from other sectors (such as banks and insurance companies) due to funds' connectedness. Such aspects are important since the existing literature largely focuses on intrasectoral effects. Overall, our paper proposes a more system-wide view on fund sector vulnerabilities.

The remainder of the paper is structured as follows: section 2 presents the model. Section 3 provides information on the empirical data and on the parameter calibration. Section 4 presents and discusses the main results and section 5 concludes.

2 Model

Our model is a substantial extension of the model of Fricke and Fricke (2020), which itself was an extension of the original Greenwood, Landier, and Thesmar (2015) model. The basic steps are as follows (cf. Figure 1):

Step 0: We impose an initial shock on funds' asset portfolios (bonds and equities).

Step 1: The initial portfolio losses lead to further losses due to funds' cross-holdings.

Step 2: Fund managers need to liquidate assets. We incorporate two channels:

a) In response to the initial shock, fund investors redeem some of their fund shares (flow-performance relationship).

b) Fund managers have fixed financial leverage targets. For funds that make use of leverage, additional asset sales may be necessary in order to revert back to the target leverage ratio.

Step 3: Fund managers liquidate a vertical slice of their asset portfolios (pro-rata liquidation), which negatively affects market prices. This leads to:

a) Portfolio losses on bonds and equities of investment funds.

[8] For example, Gaspar, Massa, and Matos (2006) document strategic incentives within fund-families to transfer performance across member funds via directed cross-holdings. Evans, Prado, and Zambrana (2020) find that cross-holdings are more prevalent in fund families that encourage cooperation and that these funds tend to have less volatile cash flows. Bhattacharya, Lee, and Pool (2013) show that affiliated funds-of-funds (who can only invest in other funds within the family) provide an insurance pool to other funds in the family.

b) Portfolio losses on funds' cross-holdings.

We define the fund sector's aggregate vulnerability (AV) as the sum of funds' portfolio losses due to their common asset liquidations (indirect connectedness; Step 3a) and cross-holdings (direct connectedness; Steps 1 and 3b). We normalize the AV by the aggregated pre-shock total net assets (TNA).

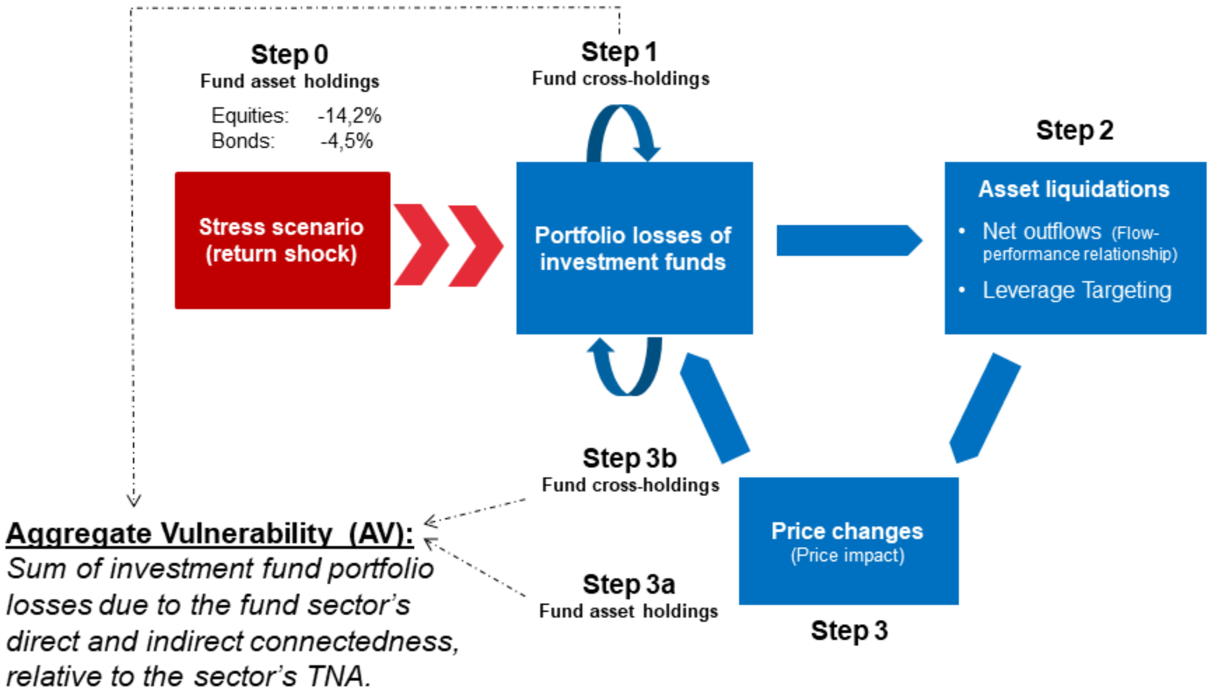


Figure 1: Basic mechanism of the model.

2.1 Details

Before describing the different steps of the model in detail, let us provide the general setup: there are N investment funds and $K+1$ *marketable assets*, where asset $(K+1)$ denotes cash. We think of marketable assets as those assets (bonds and equities) that can be liquidated, even during stressed market conditions. Let $M_{\{N\times(K+1)\}}$ denote the matrix of portfolio weights, where each element $0 \leq M_{i,k} \leq 1$ is the initial weighted share of marketable asset k in fund i's asset portfolio, and $\sum_k M_{i,k} = 1$. Fund i's total investment in marketable assets is equal to $A_i^{\text{MKT}} > 0$.

Funds can also hold *fund shares* in their portfolios and we denote the matrix of funds' cross-holdings as $a_{\{N\times N\}}^{\text{FUND}}$, where element $a_{i,j}^{\text{FUND}} \geq 0$ is the (euro-)amount of shares of fund j in fund i's portfolio. The total amount of fund i's fund holdings are denoted as $A_i^{\text{FUND}} = \sum_j a_{i,j}^{\text{FUND}}$. Here we assume that funds do not liquidate fund shares under distress. Lastly, funds can invest in *non-marketable assets* which will also not be liquidated even under stress.[9] For simplicity, we summarize these non-marketable investments in a single asset with fund i's total investment in this asset being $A_i^{\text{NON}} \geq 0$. Funds are financed by a mix of debt, D_i, and equity (or TNA), E_i.[10] Total assets are thus given by

$$A_{i,i} = A_i^{\text{MKT}} + A_i^{\text{FUND}} + A_i^{\text{NON}} \equiv E_i + D_i,$$

where $A_{\{N\times N\}}$ is a diagonal matrix. We define $B_{\{N\times N\}}$ as the diagonal matrix of pre-shock leverage ratios with $B_{i,i} = D_i/E_i$. Finally, F^{MKT} denotes a $(K+1)$ vector of asset-specific shocks on marketable assets and F^{NON} is a scalar that denotes the initial shock on non-marketable assets. We omit time indices for pre-shock variables.

Step 0: Initial Shock

In matrix notation[11], we obtain funds' original returns on marketable and non-marketable assets as

$$R^{\text{MKT}} = MF^{\text{MKT}}, \tag{1}$$

and

$$R^{\text{NON}} = F^{\text{NON}}. \tag{2}$$

Funds' fund share holdings are not directly affected by the initial shock (we will return to this point in Step 1). The post-shock total marketable assets are

$$A_0^{\text{MKT}} = A^{\text{MKT}}(1 + R^{\text{MKT}}), \tag{3}$$

and

$$A_0^{\text{NON}} = A^{\text{NON}}(1 + R^{\text{NON}}). \tag{4}$$

In the following, we always assume that the initial shock does not lead to negative fund equity and the updated balance sheet identity is

$$A_0 = A^{\text{FUNDS}} + A_0^{\text{MKT}} + A_0^{\text{NON}}, \tag{5}$$

with return on assets

$$R_0^A = \frac{A_0 - A}{A} = w^{\text{MKT}} R^{\text{MKT}} + w^{\text{NON}} R^{\text{NON}}, \tag{6}$$

where $w^{\text{MKT}} = A^{\text{MKT}}/A$ and $w^{\text{NON}} = A^{\text{NON}}/A$ are the initial shares of marketable and non-marketable assets, respectively. The return on equity is equal to

$$R_0^E = \frac{E_0 - E}{E} = (\mathbb{I}_N + B)R_0^A, \tag{7}$$

[9] We comment on the distinction between marketable and non-marketable assets below. Effectively, we use a data-driven approach to categorize individual assets.

[10] Importantly, investment funds' equity is provided by fund investors in exchange for fund shares. Fund equity therefore equals the sum of all issued fund shares, i.e., the fund's TNA. This has major implications for the nature of fund equity, as, in contrast to conventional equity, it can be withdrawn by fund investors on a (mostly) daily basis and is thus runnable like bank deposits.

[11] In the following, unless stated otherwise, subscripts refer to different points in time.

with $\mathbb{I}_N$ being the identity matrix of size $N \times N$. Note that the initial shock also changes the matrix of portfolio weights of individual marketable assets, which we denote as M_0 (post-shock).

Step 1: Impact of Initial Shock via Funds' Cross-Holdings

The initial shock led to a direct loss on funds' asset portfolios. This shock, however, did not directly affect fund shares that are held in funds' portfolios. However, as should be clear from Eq. (7), if a given fund holds shares of other funds in its portfolios, we need to take the losses from Step 0 into account, which involves the fund cross-holdings matrix a^{FUND}.

The total value of a given fund i's fund holdings (after taking the initial shock into account) can be written as:

$$A_{1,i}^{\text{FUND}} = \sum_j a_{i,j}^{\text{FUND}}(1 + R_{1,j}^E). \tag{8}$$

To solve for the unknown R_1^E, we rewrite the previous equation as

$$(A_{1,i}^{\text{FUND}} - A_{0,i}^{\text{FUND}}) = \sum_j a_{i,j}^{\text{FUND}} R_{1,j}^E, \tag{9}$$

which is the additional loss due to fund i holding other funds in its asset portfolio. Hence, we can write the updated return on equity as

$$R_{1,i}^E = \frac{E_{1,i} - E_i}{E_i} = \frac{A_i R_{1,i}^A + (A_{1,i}^{\text{FUND}} - A_{0,i}^{\text{FUND}})}{E_i} = R_{1,i}^E + \frac{\sum_j a_{i,j}^{\text{FUND}} R_{1,j}^E}{E_i}. \tag{10}$$

Hence, through the cross-holdings network, fund i's cross-holdings adjusted return may depend on all other funds' returns.

In matrix notation

$$R_1^E = R_0^E + E^{-1} \times a^{\text{FUND}} R_1^E. \tag{11}$$

Solving for R_1^E, we obtain

$$R_1^E = [\mathbb{I}_N - E^{-1} \times a^{\text{FUND}}]^{-1} R_0^E = \omega^{-1} R_0^E, \tag{12}$$

$$= \underbrace{R_0^E}_{\text{Direct contribution of initial shock}} + \underbrace{\sum_{n=1}^{\infty} (E^{-1} \times a^{\text{FUND}})^n R_0^E}_{\text{Contribution of cross-holdings network}}, \tag{13}$$

which is the return on equity due to the initial shock and the corresponding reduction in the value of fund shares.[12] Note that matrix $\omega = [\mathbb{I}_N - E^{-1} \times a^{\text{FUND}}]$ should be invertible, which is generally the case, even for relatively complex network structures. Also note that, if fund i does not hold any fund shares in its portfolio ($\sum_j a_{i,j} = 0$), Eq. (12) simply

[12] See Miller and Blait (2009, Ch. 2). Note that the functional form of Eq. (12) shares some similarities with the Leontief-inverse in the literature on input-output networks (e.g., Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)).

yields $R^E_{1,i} = R^E_{0,i}$. We denote the updated cross-holdings matrix after Step 1 as a_1^{FUND}. (A similar reasoning will come into play when we look at the losses that arise from funds' common asset liquidations.) The vector of funds' nominal losses due to cross-holdings can be written as:

$$\text{Loss}_1^{\text{CrossHoldings}} = (R_1^E - R_0^E) \times E_0 \tag{14}$$

Note that, while being an immediate effect of the initial shock, these losses due to cross-holdings should be interpreted as a second round effect and thus will be taken into account in our aggregate vulnerability measure below. This is in line with the existing financial contagion literature that quantifies vulnerabilities purely based on mechanical balance sheet interlinkages. For example, Castren and Kavonius (2009) use contingent claims analysis (CCA) to quantify second round losses based on sectoral balance sheet linkages. The within-sector losses from Step 1 are similar in spirit to the CCA approach.

Illustration. Let us provide several examples to illustrate the concept and potential importance of fund cross-holdings.

- **Example 1**. There are $N = 2$ funds, both of equal size (normalized to 1), using zero leverage, and the same initial shock in terms of return-on-equity $R^E_{0,i} = -0.1$ for $i = \{1, 2\}$. Without specifying the details of funds' asset portfolios, fund 1 does not hold shares of fund 2, but fund 2 holds shares of fund 1:

  $$a^{FUND} = \begin{pmatrix} 0 & 0 \\ 0.2 & 0 \end{pmatrix}$$

  Given that fund 1 has no exposure towards fund 2, we can solve this problem by backward induction: we know that $R^E_{1,1} = R^E_{0,1}$. Therefore, we can calculate fund 2's return on equity as follows

  $$R^E_{1,2} = R^E_{0,2} + (-0.1)0.2 = -0.12.$$

  Eq. (12) yields this result directly:

  $$R_1^E = \begin{pmatrix} 1 & 0 \\ 0.2 & 1 \end{pmatrix} \begin{pmatrix} -0.1 \\ -0.1 \end{pmatrix} = \begin{pmatrix} -0.1 \\ -0.12 \end{pmatrix}.$$

  Note that the updated cross-holdings matrix reads as

  $$a_1^{FUND} = \begin{pmatrix} 0 & 0 \\ 0.18 & 0 \end{pmatrix}$$

- **Example 2**. There are $N = 3$ funds, all of equal size, zero leverage and the following initial shocks:

  $$R_0^E = \begin{pmatrix} -0.1 \\ -0.1 \\ -0.2 \end{pmatrix}.$$

  The cross-holdings network has a ring structure as shown in Figure 2. Note that, in contrast to the first example, we cannot solve this case by backward induction since

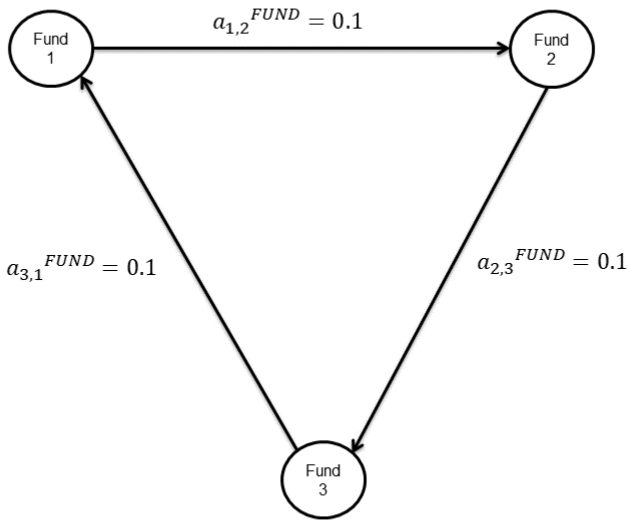


Figure 2: Ring network structure corresponding to Example 2.

funds' returns depend on each other, either directly or indirectly. Using Eq. (12) we obtain the following solution:[13]

$$R_1^E \approx \begin{pmatrix} -0.112 \\ -0.121 \\ -0.211 \end{pmatrix}.$$

- **Example 3**. The final example is based on the actual data on German investment funds' cross-holdings for July 2019. The relevant input variables are taken directly from the data. Here we assume that all funds are being hit equally by the same initial shock ($R_{0,i}^E = -0.1 \; \forall \; i$). The cross-holdings matrix is relatively sparse overall: out of approx. 33 million possible directed links, fewer than 6,000 links exist. (See Figure 8 for a schematic representation of the German investment fund cross-holdings network in 2009/09 and in 2019/07.) The initial shock after taking funds' cross-holdings into account can be much larger than the direct shock, sometimes by a factor of 2 or more, as illustrated in Figure 3. Overall, these results indicate that taking into account funds' cross-holdings is important, even more so since Figure 4

[13] In principle, we could obtain the same solution iteratively. Depending on the size of the network, the iterative solution can be slower or faster than the analytical solution. For example, for the network shown in Figure (12), the results converge to the analytical solution after 30 iterations. In this specific case, the iterative solution takes roughly 3,000 times longer to compute than the analytical solution. As the network gets larger, computing the inverse matrix becomes more and more time-consuming, such that the iterative solution may become relatively more attractive. In our application, we always rely on the analytical solution.

shows that the relative importance of fund shares can be quite large (and growing) for certain fund types.

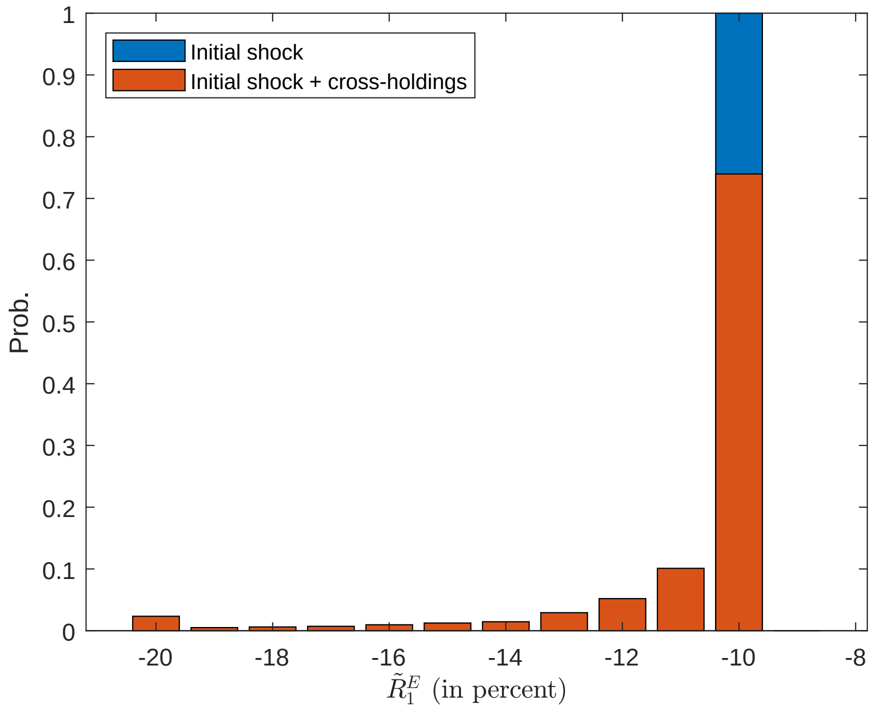


Figure 3: Histogram of a hypothetical initial shock before (in blue) and after (in red) taking into account funds' cross-holdings in 2019/07.

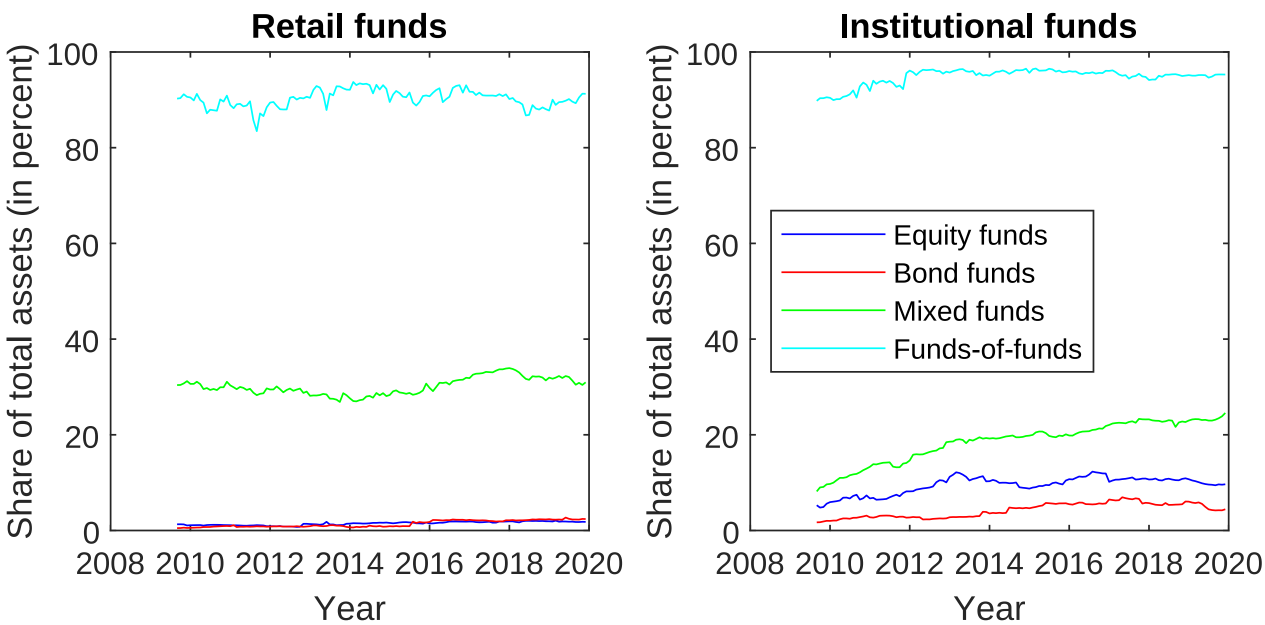


Figure 4: Aggregated portfolio share of fund shares in German investment funds' asset portfolios, by fund type.

Step 2: Asset Liquidations

2a: Flow-Performance Relationship (FPR). In line with the existing fund literature, we assume a positive relationship between lagged fund performances and investor net inflows (see, e.g., Sirri and Tufano (1998); Berk and Green (2004)):

$$\frac{\Delta E_{2a}}{E_1} = \gamma R_1^E, \tag{15}$$

where $\gamma \geq 0$ is the return sensitivity of investor flows. Hence, a negative (positive) performance is followed by a net outflow (net inflow) of fund equity. The fund manager has to liquidate assets in order to make the payments of ΔE_{2a}. Taking net outflows into account, updated equity equals

$$\begin{aligned} E_{2a} &= E_1(1 + \gamma R_1^E), \\ &= \underbrace{A\left([\mathbb{I}_N + B]^{-1} + R_1^A\right)}_{E_1}\left[1 + \gamma(\mathbb{I}_N + B)R_1^A\right]. \end{aligned} \tag{16}$$

Updated total assets are equal to

$$\begin{aligned} A_{2a} &= D + E_{2a}, \\ &= A\left(1 + R_1^A\left[1 + \gamma(\mathbb{I}_N + B)R_1^A\right]\right), \end{aligned} \tag{17}$$

with return on assets

$$R_{2a}^A = \frac{A_{2a} - A}{A} = R_1^A\left[1 + \gamma(\mathbb{I}_N + B)R_1^A\right]. \tag{18}$$

2b: Leverage Targeting (LT). We assume that fund managers target their leverage ratios. This seems reasonable, since fund managers generally need to specify the composition of both their asset and liability side in their sales prospectuses and are unlikely to deviate significantly from these proposed targets. In order to reach the desired level of debt, funds will liquidate additional assets to repay some of their existing debt.

Given that fund managers will have to liquidate an amount ΔE_{2a} due to fund share redemptions after a negative shock, we need to add another leverage targeting component to the total amount to be liquidated. Suppose that the fund targets a leverage ratio of B (which may be equal to zero to begin with), so the desired level of debt would be $D_{2b} = E_{2a} \times B$. Assuming that the fund manager has an adjustment parameter η, with $\eta \geq 0$, we can write the amount to be liquidated due to LT as

$$\Delta D_{2b} = \eta \times (E_{2a}B - D) \tag{19}$$

$$= \eta \times \Big(\underbrace{ABR_1^A}_{\text{LT due to initial shock}} + \underbrace{ABR_1^A\gamma(1 + (\mathbb{I}_N + B)R_1^A)}_{\text{LT due to net outflows}} \Big). \tag{20}$$

Note that $\eta = 1$ corresponds to immediately targeting the desired leverage ratio. (This is the baseline model of interest.) On the other hand, setting $\eta = 0$ yields a case where the fund manager does not target his leverage ratio.

Putting everything together, we obtain

$$\underbrace{\Phi}_{\text{Amount to be liquidated}} = \underbrace{\Delta D_{2b}}_{\text{Leverage targeting}} + \underbrace{\Delta E_{2a}}_{\text{Net outflows}}, \tag{21}$$

$$= \eta ABR_1^A + A\Gamma R_1^A[(\mathbb{I}_N + \eta B) + (\mathbb{I}_N + \eta B)(\mathbb{I}_N + B)R_1^A], \tag{22}$$

where we have replaced the scalar γ by the diagonal matrix $\Gamma_{\{N\times N\}}$ to allow for a fund-specific FPR. Note that for the case of immediate leverage targeting ($\eta = 1$) we obtain

$$\Phi^{\eta=1} = ABR_1^A + A\Gamma R_1^A[(\mathbb{I}_N + B) + (\mathbb{I}_N + B)^2 R_1^A]. \tag{23}$$

Figure 5 shows that $\Phi^{\eta=1}$ is a non-linear function of Γ, B, and R_1^A. (We set $A = 1$ and $\gamma = 0.3$, as a function of B and R_1^A.) The region at the top right of the Figure is undefined, since Eq. (23) is only valid for cases where the initial shock does not completely wipe out a fund's equity.

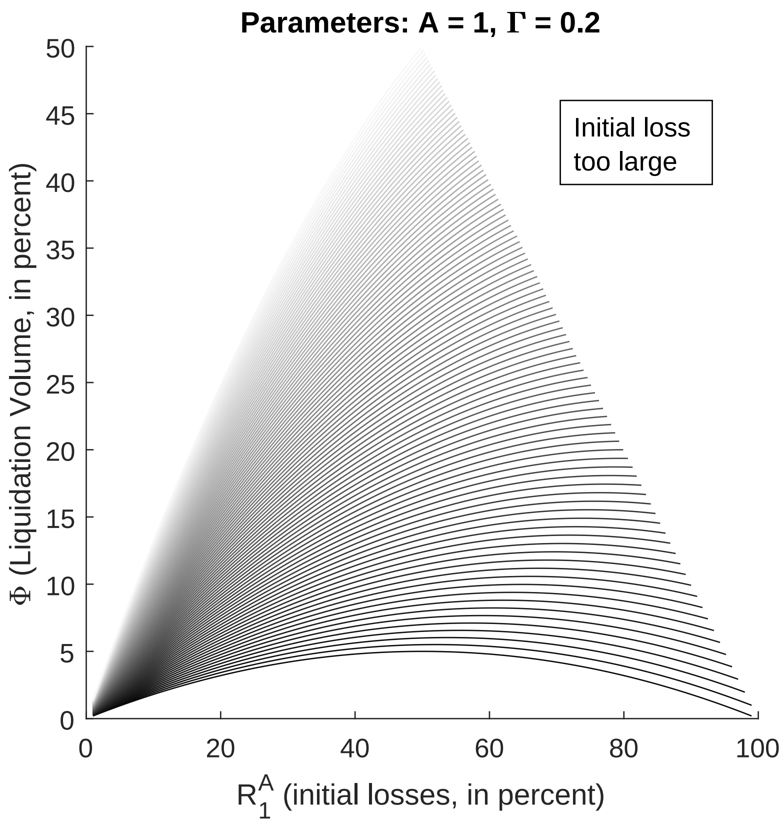


Figure 5: Total amount to be liquidated, $\Phi^{\eta=1}$, as a function of the initial losses (R_1^A). The function is shown for leverage ratios between $B = 0$ (bottom) and $B = 1$ (top).

Asset liquidations. We assume that fund managers liquidate assets proportional to the post-shock portfolio weights (pro-rata liquidation).[14] This is in line with empirical

[14] A similar approach has been used in the recent literature that explores the real effects of funds' fire sales. See, e.g., Edmans et al. (2012); Dessaint et al. (2019). Note that both Greenwood et al. (2015)

evidence that suggests that mutual funds tend to sell assets according to their liquidity pecking order during normal times, but on a pro-rata basis during times of market stress (see, e.g., Jian, Li, and Wang (2016)). In our model, asset liquidations only involve marketable assets (including cash), whereas non-marketable assets (and fund shares) will not be traded even under stress. Hence, the liquidation amounts at the asset level are

$$\phi = M_0' \Phi,$$

which gives a $(K+1)$ vector of total net asset sales of marketable assets by all fund managers.

Step 3: Losses Due to Common Asset Liquidations

3a: Direct Portfolio Losses via Price Impact. We assume that asset sales generate linear price impact

$$F_{3a}^{\text{MKT}} = L\phi = LM_1'\Phi, \tag{24}$$

where $L_{\{(K+1)\times(K+1)\}}$ is the diagonal matrix of price impact ratios, expressed in units of returns per euro of net sales.[15] Since liquidating cash has zero price impact, element $(K+1)$ in matrix L equals to zero by construction, whereas all other diagonal elements will be positive. Using Eq. (24), we can write the return on marketable assets as

$$R_{3a}^{\text{MKT}} = M_1 F_{3a}^{\text{MKT}} = M_1 L {M_1}' \Phi. \tag{25}$$

At the fund level, this involves nominal losses of $A^{\text{MKT}} R_{3a}^{\text{MKT}}$, or normalized by equity prior to asset liquidations

$$R_{3a}^{E} = \frac{A^{\text{MKT}} R_{3a}^{\text{MKT}}}{E_{2b}}. \tag{26}$$

The vector of funds' nominal losses due to fire sales can be written as:

$$\text{Loss}^{\text{FireSales}} = A^{\text{MKT}} \times R_{3a}^{\text{MKT}}. \tag{27}$$

3b: Additional Impact of Losses via Funds' Cross-Holdings. Similar to Step 1, we also need to take funds' cross-holdings into account in order to obtain the total losses due to funds' systemic asset liquidations. Using the same procedure, we obtain

$$R_{3b}^{E} = \underbrace{[\mathbb{I}_N - E_{2b}^{-1} \times a_1^{\text{FUND}}]^{-1}}_{\omega_{2b}^{-1}} R_{3a}^{E}, \tag{28}$$

with a_1^{FUND} being the cross-holdings network matrix after Step 1. The vector of funds' nominal losses from their cross-holdings due to fire sales can be written as:

$$\begin{aligned} \text{Loss}_3^{\text{CrossHoldings}} &= (R_{3b}^{E} - R_{3a}^{E}) \times E_{2b} \\ &= (\omega_{2b}^{-1} - 1) \times \text{Loss}^{\text{FireSales}}. \end{aligned} \tag{29}$$

and Fricke and Fricke (2020) use pre-shock portfolio weights, M, in their modelling approaches. The post-shock portfolio weights are the more natural choice when considering asymmetric initial shocks.

[15] We ensure that asset prices are non-negative and funds can sell at most their marketable assets.

2.2 Measuring Vulnerabilities from Funds' Connectedness

Suppose there is a negative shock on non-marketable assets, $F^{\text{NON}} \in [-1, 0]$, and on marketable assets, $F^{\text{MKT}} = (f_1^{\text{MKT}}, f_2^{\text{MKT}}, \cdots, f_K^{\text{MKT}}, 0)$ with $f_k^{\text{MKT}} \in [-1, 0]\ \forall\ k$. Note that the shock on the market value of cash (element $K+1$) is zero by construction. We summarize this initial shock as $F_1 = \{F^{\text{NON}}, F^{\text{MKT}}\}$.

The total nominal loss due to the initial shock is given by $1_N' A R_0^A$. Using Eqs. (14), (27), and (29), we define the aggregate vulnerability (AV) of the fund sector as follows:

$$AV = \frac{1_N'(\text{Loss}^{\text{FireSales}} + \overbrace{\text{Loss}_1^{\text{CrossHoldings}} + \text{Loss}_3^{\text{CrossHoldings}}}^{\text{Loss}^{\text{CrossHoldings}}})}{\sum_i E_i}. \tag{30}$$

Note that the losses due to cross-holdings (i.e., funds' direct connectedness) consist of a part that comes from the initial shock and a part that comes from funds' common asset liquidations. Overall, the AV quantifies the vulnerability of the fund sector that stems from its connectedness. Note that the overall losses are normalized by the sector's TNA ($\sum_i E_i$) before the initial shock. The AV measures the percentage of aggregate total net assets that would be wiped out by funds' asset liquidations after initial shock F. As shown in Figure 6, the AV shows the expected dependency with regards to the different inputs and, in fact, can be seen as a combined indicator that summarizes information associated from several standard macroprudential risk indicators of investment funds.

Factor		Effect on AV	Intuition
Leverage	↑	↑	With increased leverage more assets need to be liquidated due to the leverage targeting channel.
Flow-Performance Relationship	↑	↑	A stronger relationship between poor past performance and net outflows leads to more fund asset sales after a return shock.
Market liquidity	↓	↑	With lower market liquidity, funds' asset sales will have a stronger price impact.
Indirect Connected-ness	↑	↑	With higher indirect connectedness within the fund sector (portfolio overlap), funds can affect each other more strongly due to their asset sales. Diversification effects may be at work.
Direct Connected-ness	↑	↑	With higher direct connectedness within the fund sector (cross-holdings), losses can propagate more easily through the network. Diversification effects may be at work.

Figure 6: Aggregate vulnerability (AV) and its drivers.

Similar to Greenwood et al. (2015), we wish to decompose the AV into each fund's individual contribution to the whole sector's vulnerability. It turns out that this becomes more complicated due to the non-linearity induced by taking into account funds' cross-holdings. Ideally, our fund-level measure of systemicness (S_i) should capture a given fund's contribution to the AV, i.e., the losses that arise due to the fund's asset sales, where we distinguish between losses due to fire sales and losses due to cross-holdings:

$$S_i = S_i^{\text{FireSales}} + S_i^{\text{CrossHoldings}}, \tag{31}$$

with $AV = \sum_i^N S_i$. Following Fricke and Fricke (2020), the first component is given by:

$$S_i^{\text{FireSales}} = \frac{1_N' A^{\text{MKT}} M_1 L M_1{}' \delta_i \delta_i' \Phi}{\sum_i E_i}, \tag{32}$$

where δ_i is a $(N \times 1)$ vector with all zeros except for the ith element, which is equals 1.

The second component in Eq. (31) is less straightforward, since Eq. (29) gives us fund i's additional losses due to the cross-holdings network, but does not tell us the effect of fund i's network position on *other* funds. Suppose that fund j has additional losses of $\text{Loss}_j^{\text{CrossHoldings}}$ due to its cross-holdings. The question is: how much of these losses are *caused* by fund i? Intuitively this depends on fund i's position in the cross-holdings network (e.g., Alter, Craig, and Raupach (2015)). Fund i's contribution to the total losses should therefore be proportional to its network centrality:

$$S_i^{\text{CrossHoldings}} = \frac{C_i \times (1_N' \text{Loss}^{\text{CrossHoldings}})}{\sum_i E_i}, \tag{33}$$

where C_i is a given network centrality measure (normalized to $\sum_i C_i = 1$). Which network centrality measure should be used? Since the fund-level systemicness will depend on the choice of a specific measure, several aspects need to be considered from an economic perspective:

- Fund i will only **send** losses through the network if it is being held in other funds' portfolio. In other words, fund i is a **sender** if its in-degree is positive ($\sum_j a_{j,i}^{\text{FUND}} > 0$). Note that the in-degree is typically not a choice variable for fund managers, at least in the case of retail funds.

- Fund i will only **receive** losses through the network if it holds other funds in its portfolio. In other words, fund i is a **receiver** if its out-degree is positive ($\sum_j a_{i,j}^{\text{FUND}} > 0$). The out-degree (which funds to hold in its portfolio) is a choice variable for fund managers.

- Fund i is **both a sender and a receiver** if it holds shares of other funds and its own shares are also being held by other funds (i.e. $\sum_j a_{j,i}^{\text{FUND}} > 0, \sum_j a_{i,j}^{\text{FUND}} > 0$). This may lead to losses being amplified through fund i's central position in the network.

- Finally, if fund i is **neither a sender nor a receiver** it is technically not part of the network and therefore does not contribute to losses due to cross-holdings (i. e. $\sum_j a_{j,i}^{\text{FUND}} = \sum_j a_{i,j}^{\text{FUND}} = 0$).

A simple example of a cross-holdings network with the different fund types is shown in Figure 7. As an empirical illustration, Figure 8 shows a schematic representation of the German investment fund cross-holdings network at different points in time: in September 2009 (top panel) cross-holdings within the German fund sector amounted to roughly €56

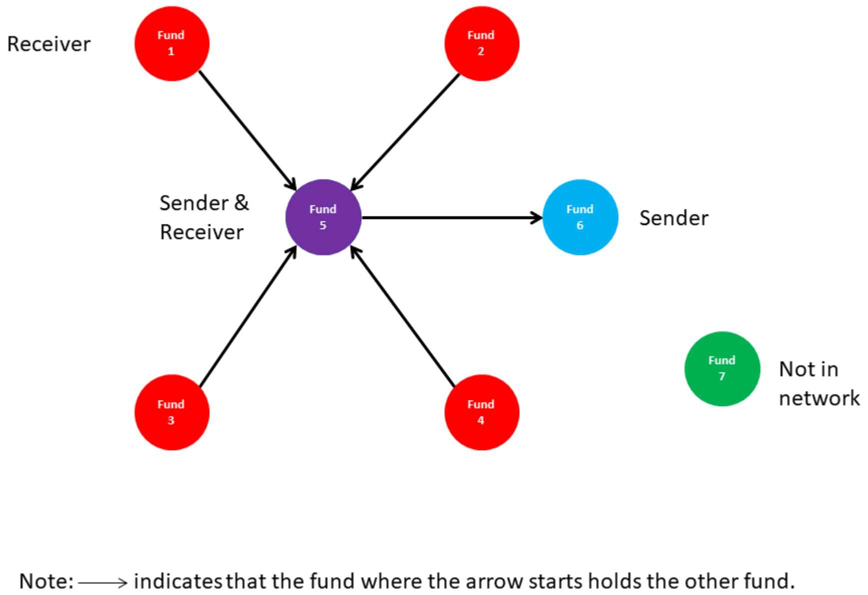


Figure 7: Hypothetical cross-holdings network.

bn, or 5.6% of the fund sector's aggregate TNA. In July 2019 (bottom panel), the total cross-holdings were €272 bn, or 12% of the sector's aggregate TNA. Most importantly, the weight on the direct link from senders to receivers has increased more than five-fold over this period.[16]

Given that systemicness is about the effect of a fund on other funds, the natural centrality measure is given by Eq. (28):

$$C_i = (\omega^{-1} 1_N - 1), \tag{34}$$

which is equivalent to the well-known Katz centrality measure from network theory.[17] Note that C_i is normalized such that funds that are not part of the network will have $C_i = 0$.

[16]Note that previous work largely focused on cross-holdings within fund-families (Gaspar et al. (2006); Bhattacharya et al. (2013); Evans et al. (2020)), while we incorporate also cross-holdings between fund-families. This is important because in terms of the number of connections, within family links make up only between 27% (September 2009) and 37% (July 2019) of the German fund sector's cross-holdings. However, in terms of volume, within family cross-holdings are much more important, making up between 46% (September 2009) and 69% (July 2019) of the sector's cross-holdings.

[17]Katz centrality is related to, but distinct from, eigenvector centrality. See Newman (2010), Ch. 7, for details and Billio, Getmansky, Lo, and Pelizzon (2012) and Diebold and Yilmaz (2014) for related discussions.

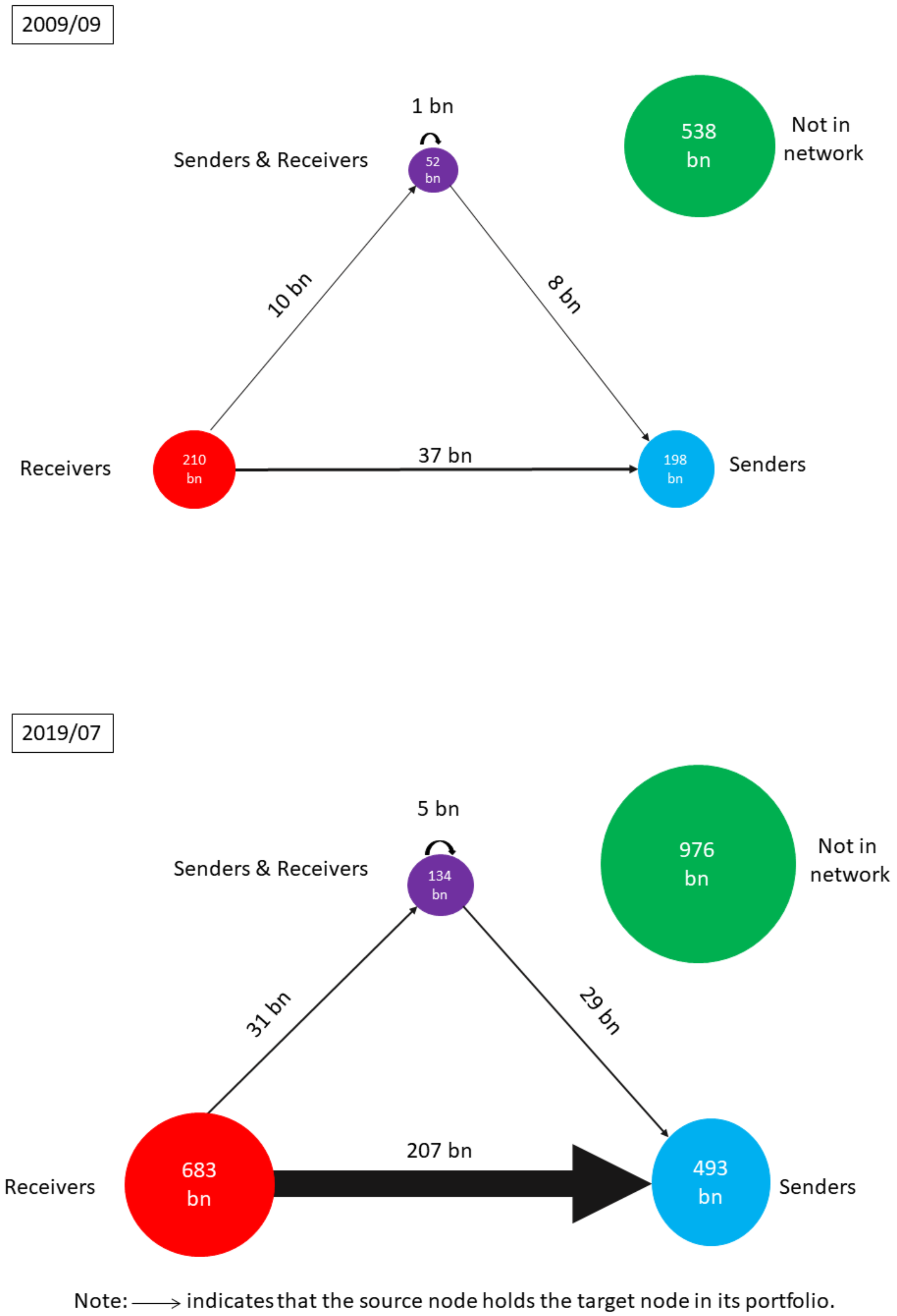


Figure 8: A schematic representation of the German investment fund cross-holdings network in 2009/09 (top panel) and in 2019/07 (bottom panel), respectively. The width of the arrows is proportional to the volume of a directed link; the size of the nodes is proportional to the sum of the TNA of funds within that category (actual numbers written in each node). All values are shown in €billion.

3 Data and Empirical Calibration

We provide the first macroprudential stress test application for the German investment fund sector. Germany is an important domicile for investment funds, hosting the third largest investment fund sector in the euro area. The German fund sector has grown substantially since the global financial crisis. For example, the sector's total assets have more than doubled since September 2009 (cf. Figure 9), amounting to €2.3 trillion in July 2019. The sector's relative importance within the German financial system also continues to increase, as it makes up 14% of the total assets of the German financial system (at the end of 2009, the share was 8%).

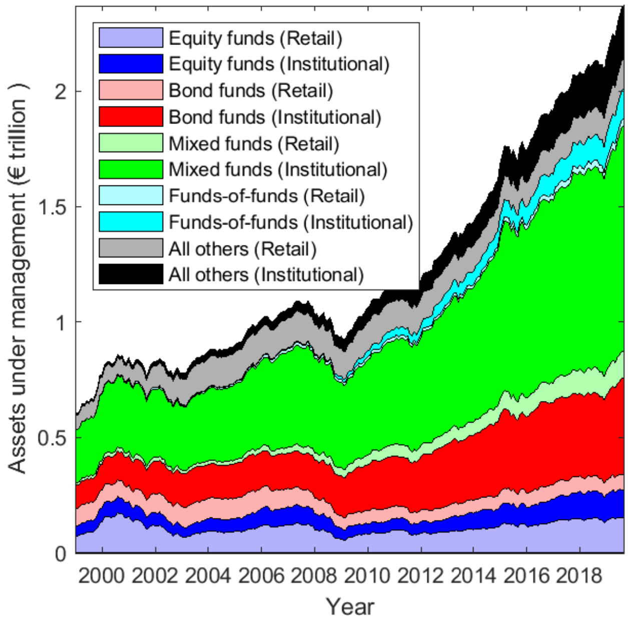


Figure 9: Total assets under management (in € trillion) of the German open-end investment fund sector, broken down by fund type.

By nature, the German fund sector is also highly interconnected within the financial system. For the purpose of illustration, Figure 10 shows the aggregate balance sheet of the sector: on the asset side (left), securities issued by actors from the financial system (including shadow banks, insurance corporations and pension institutions, and monetary financial institutions) make up roughly 50% of funds' investments. On the liability side (right), more than 70% of German funds' TNA are held by actors from the financial system. Hence, dynamics in the fund sector are not independent of the dynamics in the broader financial system, and vice versa.

3.1 Data

Our dataset consists of all open-end equity funds, bond funds, mixed funds, and funds-of-funds reporting to the investment fund statistics (IFS) of the Deutsche Bundesbank. As of July 2019, these fund types cover roughly 87% of the total assets under management

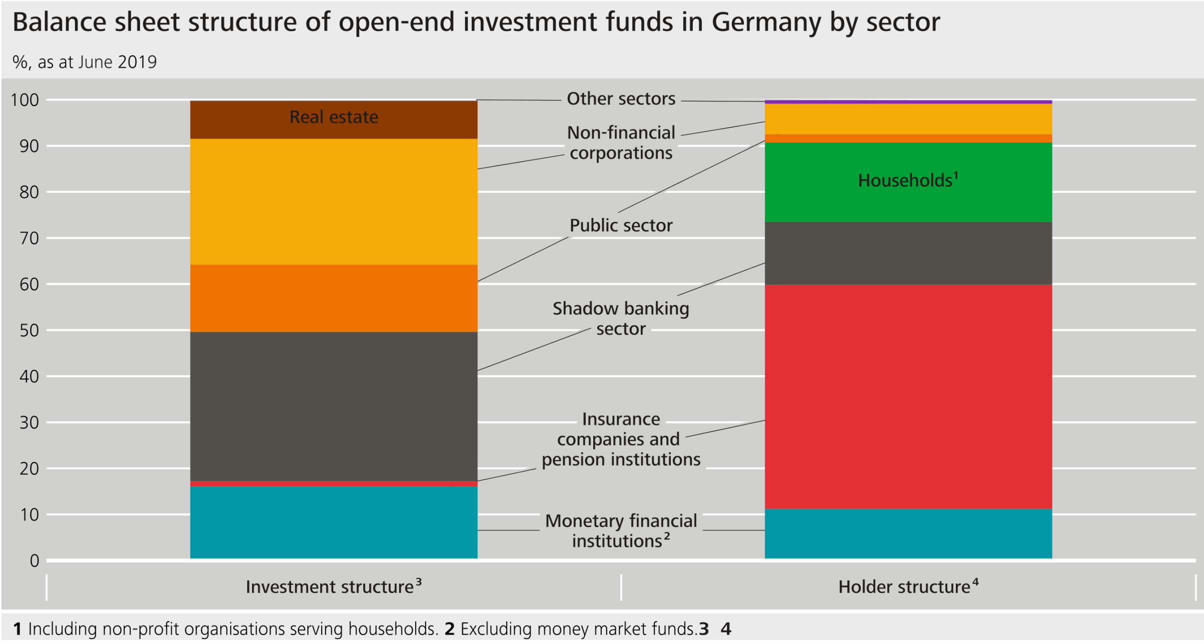


Figure 10: Illustration of the German fund sector's aggregated balance sheet in 2019/06.

of the German investment fund sector (cf. Figure 9). In the following, we use data on individual fund share classes, since the redemption decisions of fund shareholders may depend on share-class specific features.[18] Our stress test sample for the period November 2015 to July 2019 covers a total number of 6,950 unique fund share classes (994 equity funds, 1,261 bond funds, 4,340 mixed funds, and 355 funds-of-funds).

Compared with the U.S., the German investment fund sector is peculiar in the sense that it consists of two very different sub-sectors: first, *Publikumsfonds* are akin to traditional open-ended retail funds which are open to both private and institutional investors. Second, *Spezialfonds* are specialized investment vehicles for institutional investors, which are generally not available to private investors. These institutional funds are typically tailored to the specific needs of a very small number of large investors, such that run risks should be less relevant for these institutional funds. As of July 2019, institutional funds make up roughly 77% of the German fund sector's total assets under management (cf. Figure 9), so it is important to include these funds in the analysis.

In principle, monthly fund-level information is available since April 1993. Also, gran-

[18]We drop exchange traded funds (ETFs) from our sample due to structural differences in their creation/redemption process. While ETFs may be very interesting from a financial stability perspective (see, e.g., Pagano, Serrano, and Zechner (2019) for a review), the main reason for this choice is that ETFs differ structurally from open-end investment funds: ETFs do not allow investors to redeem their fund shares, but rather ETF shares must be traded on secondary markets. As explained by Goldstein et al. (2017), the usual redemption-liquidation mechanism that forms the basis of our model therefore cannot simply be applied to the case of ETFs. For example, estimating the FPR regressions for ETFs would give us the sensitivity of the authorized participant to past performances, not the sensitivity of the actual fund investors. We believe that this exclusion of ETFs is unlikely to lead to a severe underestimation of systemic risks, given that the ETF sector remains rather small compared to traditional open-end investment funds that we are concerned with in our paper. For example, as of July 2019, ETFs make up only 2% of the German fund sector's TNA.

ular holdings data on a fund-month-security level are available from September 2009 onwards. We complement the IFS data with two other datasets: first, we use data from the Securities Holdings Statistics (SHS) to obtain information on the holder structure for each investment fund over time. This information is provided at the sectoral level based on the European System of Accounts (ESA). Second, we use granular information on the individual securities in funds' asset portfolios from the Eurosystem's Centralized Security Database (CSDB). Unfortunately, the CSDB reports information on security-level trading volumes only from November 2015 onwards. This information is crucial, however, to calculate the PriceImpact-parameters (cf. 3.2.3). Therefore, the actual stress-test application will be for the period November 2015 to July 2019.

3.2 Parameter Calibration

In the following, we will first provide details on the two liquidation channels (FPR and LT) and then turn to the estimation of the PriceImpact parameters.

3.2.1 Flow-Performance Relationship (FPR)

Regarding the FPR-liquidation channel, the key parameter is γ, which denotes the sensitivity of fund flows with regards to past returns. An important advantage of the IFS is that investment funds report their inflows and outflows separately for each month, allowing us to directly calculate the relative net flows (Flow) as

$$\text{Flow}_{i,t} = \frac{\text{Inflow}_{i,t} - \text{Outflow}_{i,t}}{\text{TNA}_{i,t-1}}. \tag{35}$$

Using data for the period January 2007 to July 2019, we estimate the following equation based on Fama-MacBeth-regressions:

$$\text{Flow}_{i,t} = a_t + b_t \times \text{Controls}_{i,t} + \boxed{\gamma_t} \times \text{Return}_{i,t-1} + \epsilon_{i,t}.$$

The Fama-MacBeth approach estimates the above relationship separately for each cross-section t and averages these coefficients to provide point estimates. In everything that follows, unless otherwise stated, we use Newey-West standard errors with 4 lags.

Following the literature, we drop individual fund share classes younger than 1 year and/or with TNA below €1 million. We also filter out extreme Flow/Return observations.[19] Table 1 shows the baseline parameter estimates, where we differentiate between the four different fund types, and also between retail and institutional funds.[20] Table 1 shows that the time-average of γ_t is insignificant for institutional funds. This is not surprising given that run risks should be less relevant for these funds. On the other hand, we find significantly positive values for retail funds, ranging between 0.13 (funds-of-funds) and 0.20 (bond funds). Note that, compared with U.S. equity funds (Fricke and Fricke

[19]Following the standard procedure in the literature, we disregard observations with Flows and/or Returns above 200% or below -80%. Our findings are not driven by this particular choice of data filters.

[20]Table A.1 in the Appendix shows the results from an alternative specification based on regressions with time FEs and standard errors clustered by share-class (the specification of Goldstein et al. (2017)). We also experimented with several non-linear specifications, e.g. adding Return^2_{t-1} to the regression. In all cases, we find that these non-linear terms are insignificant.

(2020)), the strength of the relationship is weaker for German investment funds: ceteris paribus, a negative return of -10% in month $t-1$ leads to net outflows of between 1.3% and 2.0% in month t.

Table 1 hides substantial time-variation in the estimated γ parameters both over time and in the cross-section. In fact, one major advantage of the Fama-MacBeth approach is that it lends itself naturally to incorporate time dynamics in the estimated relationship. For the sake of illustration, Figure 11 shows the 36-month rolling window average estimate of γ_t, by fund type. Dotted lines indicate observations that are not significantly larger than zero at the 5% level (based on the standard errors in Table 1). While the results are mostly significant for retail funds, the relationship tends to be insignificant for institutional funds. (We should note that we do not have enough observations for institutional funds-of-funds to estimate the cross-sectional γ_t reliably, so these are treated as zero in everything that follows.) One important exception are institutional bond funds, for which γ is significantly positive from the end of 2016 onwards. In our model application, we will use these dynamic γ parameters based on the 36-month rolling window averages. If a given value is not significantly positive for a given fund type, we will shut down the FPR channel for these funds in a given month t.

A natural question is whether our estimated γ would be different during crisis periods compared to non-crisis periods, since the shock scenario is one where global equity and bond markets are assumed to be under severe stress. In this regard, the existing literature indicates that the flow-performance sensitivity tends to be *lower* during periods of extreme market returns. For example, Franzoni and Schmalz (2017) find that γ is about twice as large during moderate as in extreme states. In other words, if anything, we would expect our approach to overestimate γ by not conditioning on a market state with large negative returns. To show this, we ran the following additional analyses:

- Figure A.1 in the Appendix shows the flow-performance sensitivity, by quintiles of the market return (retail funds only). Specifically, it reports the average of the estimated γ_t, along with 95% confidence intervals, by quintiles of the realization of the market return (proxied by the TNA-weighted average fund return in each category) during the month when the fund performance was measured. The specification replicates the one in the baseline Fama-MacBeth regressions. In order to increase the statistical power of this excercise, this sample includes monthly data for a longer sample period, namely January 1997 to July 2019. The results are very similar to those of Franzoni and Schmalz (2017), namely we find a hump-shaped relationship in all cases. In other words, by conditioning on adverse market states, we would find a weaker flow-performance relationship. (In the case of funds-of-funds, the relationship could even be negative.)

- Table A.2 in the Appendix shows separate Fama-MacBeth regression results for periods with moderate returns versus periods with extreme returns. Again following Franzoni and Schmalz (2017), we define periods with moderate/extreme market returns as those with absolute returns below/above 5% (absolute value). Compared with Figure A1, here we use the monthly return on the European stock market provided by Ken French. The results show that the point estimate of γ tends to indeed be larger during moderate conditions, but the difference may not necessarily be statistically significant. The general picture, however, is in line with the findings

Dep. var.:	Equity funds		Bond funds		Mixed funds		Fund-of-funds	
$Flow_t$	Retail	Inst.	Retail	Inst.	Retail	Inst.	Retail	Inst.
$\mathbf{Return}_{t-1}$	0.175***	0.032	0.200***	0.018	0.160***	0.009	0.128**	-0.174
	(0.028)	(0.036)	(0.046)	(0.029)	(0.024)	(0.013)	(0.051)	(0.274)
$Return_{t-2}$	0.079***	0.005	0.126**	0.053**	0.121***	0.037**	0.069	0.339
	(0.017)	(0.030)	(0.052)	(0.022)	(0.029)	(0.015)	(0.044)	(0.407)
$Return_{t-3}$	0.038	-0.025	0.247***	0.036	0.153***	0.009	0.036	-0.485
	(0.026)	(0.040)	(0.056)	(0.026)	(0.024)	(0.015)	(0.056)	(0.305)
$Return_{t-4}$	0.033*	-0.018	0.163***	0.004	0.075***	0.034***	0.123**	0.190
	(0.019)	(0.043)	(0.047)	(0.024)	(0.025)	(0.011)	(0.052)	(0.287)
$Return_{t-5}$	0.037*	-0.051*	0.064	0.047**	0.031	0.022	0.027	-0.105
	(0.022)	(0.028)	(0.041)	(0.021)	(0.023)	(0.015)	(0.047)	(0.201)
$Return_{t-6}$	0.027	0.006	0.124**	0.007	0.101***	0.030**	-0.057	0.248
	(0.023)	(0.026)	(0.056)	(0.025)	(0.027)	(0.013)	(0.062)	(0.245)
$Return_{t-7}$	0.064***	0.044	0.159***	0.051*	0.033	0.029**	0.057	0.126
	(0.019)	(0.044)	(0.038)	(0.029)	(0.025)	(0.013)	(0.068)	(0.221)
$Return_{t-8}$	0.042*	0.014	0.037	-0.016	0.053**	0.035**	0.058	-0.034
	(0.023)	(0.042)	(0.049)	(0.032)	(0.023)	(0.014)	(0.064)	(0.202)
$Return_{t-9}$	0.025	-0.037	0.012	0.022	0.052	0.040***	0.033	0.141
	(0.022)	(0.032)	(0.048)	(0.025)	(0.032)	(0.010)	(0.074)	(0.219)
$Return_{t-10}$	0.009	0.046	-0.029	0.013	0.031	0.017	-0.024	0.121
	(0.019)	(0.036)	(0.079)	(0.026)	(0.029)	(0.014)	(0.054)	(0.251)
$Return_{t-11}$	-0.005	0.010	0.046	-0.005	0.017	-0.001	0.004	0.123
	(0.020)	(0.054)	(0.040)	(0.019)	(0.029)	(0.011)	(0.048)	(0.196)
$Return_{t-12}$	0.018	-0.028	-0.022	-0.078***	-0.010	-0.037***	-0.084	0.084
	(0.021)	(0.040)	(0.040)	(0.023)	(0.023)	(0.012)	(0.059)	(0.187)
$Flow_{t-1}$	0.099***	0.072***	0.145***	0.059***	0.161***	0.041***	0.104***	0.079
	(0.011)	(0.024)	(0.013)	(0.012)	(0.013)	(0.004)	(0.022)	(0.088)
$Flow_{t-2}$	0.075***	0.075***	0.066***	0.035***	0.097***	0.030***	0.108***	0.088
	(0.012)	(0.024)	(0.010)	(0.007)	(0.009)	(0.003)	(0.024)	(0.187)
$Flow_{t-3}$	0.038***	0.020	0.050***	0.034***	0.080***	0.020***	0.096***	-0.042
	(0.007)	(0.014)	(0.010)	(0.009)	(0.012)	(0.003)	(0.022)	(0.225)
$Flow_{t-4}$	0.053***	0.018	0.031***	0.010	0.077***	0.016***	0.058**	0.364*
	(0.011)	(0.020)	(0.009)	(0.006)	(0.008)	(0.004)	(0.023)	(0.193)
$Flow_{t-5}$	0.040***	0.026*	0.065***	0.024***	0.042***	0.015***	0.028	0.052
	(0.012)	(0.015)	(0.010)	(0.005)	(0.010)	(0.003)	(0.024)	(0.203)
$Flow_{t-6}$	0.011	0.050**	0.023**	0.023***	0.036***	0.008***	0.076***	0.181**
	(0.009)	(0.020)	(0.011)	(0.008)	(0.008)	(0.002)	(0.020)	(0.089)
$Flow_{t-7}$	0.005	0.028	0.041***	0.021**	0.032***	0.007**	0.050**	-0.207
	(0.010)	(0.021)	(0.010)	(0.008)	(0.008)	(0.003)	(0.021)	(0.225)
$Flow_{t-8}$	0.019***	0.034**	0.013	0.006	0.022***	0.010***	0.048**	0.485*
	(0.007)	(0.016)	(0.010)	(0.007)	(0.006)	(0.004)	(0.019)	(0.289)
$Flow_{t-9}$	0.023**	-0.035	0.019**	0.025***	0.013*	0.009***	0.033	-0.344
	(0.009)	(0.023)	(0.008)	(0.008)	(0.008)	(0.003)	(0.022)	(0.414)
$Flow_{t-10}$	-0.000	0.007	0.005	0.018***	0.008	0.007**	-0.019	0.120
	(0.010)	(0.014)	(0.010)	(0.006)	(0.007)	(0.003)	(0.032)	(0.102)
$Flow_{t-11}$	0.013	0.017	0.017*	0.015**	0.024***	0.008***	0.019	0.413
	(0.009)	(0.020)	(0.009)	(0.007)	(0.008)	(0.003)	(0.019)	(0.312)
$Flow_{t-12}$	0.027***	0.017	0.034***	0.038***	0.017***	0.028***	0.068***	0.669
	(0.008)	(0.011)	(0.012)	(0.008)	(0.006)	(0.004)	(0.020)	(0.508)
$\log(TNA_{t-1})$	-0.000	-0.000	-0.001*	-0.000	-0.000	-0.000***	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
$\log(Age_t)$	-0.001*	-0.001	0.001	-0.000	-0.001	-0.001***	-0.001	-0.000
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Fama-MacBeth	✓	✓	✓	✓	✓	✓	✓	✓
Obs.	60,025	25,117	43,510	82,730	88,892	315,174	26,020	9,949
adj. R^2	0.208	0.297	0.242	0.117	0.203	0.035	0.462	0.625

$*$ p<0.1; $**$ p<0.05; ; $***$ p<0.01

Table 1: Flow-performance regressions, based on monthly data using Fama-MacBeth regressions. The model parameter γ is the time-average of the coefficient on $Return_{t-1}$ (Newey-West std. errors with 4 lags in parentheses). *TNA* is a fund's total net assets, *Age* is the fund age in months, and *Flow* is defined in Eq. (35). Monthly data from January 2007 to July 2019.

in Figure A.1.

Overall, these results indeed suggest that, if anything, our current estimation approach likely overestimates the strength of the flow-performance relationship since we do not condition on an adverse market state. As such, the results on the aggregate vulnerability should be seen as a relatively conservative estimate.

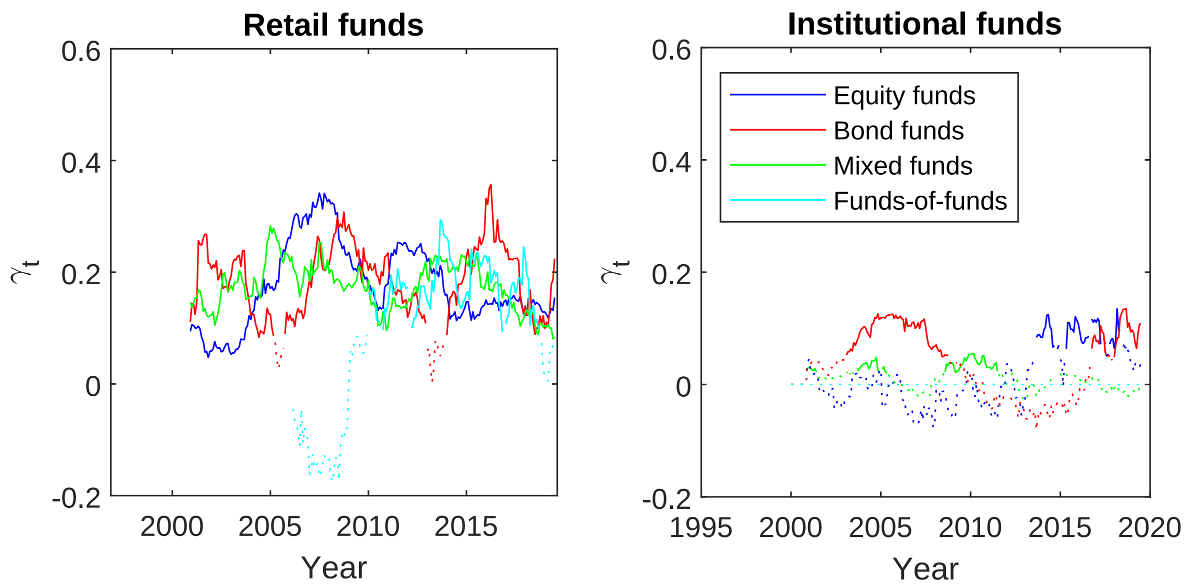


Figure 11: 36-month rolling window average of γ_t over time. Based Fama-MacBeth regressions in Table 1 (dotted lines indicate observations that are not significantly larger than zero at the 5% level, based on the standard errors in Table 1).

For the sake of completeness, Table 2 shows evidence along the lines of Coval and Stafford (2007) that retail funds indeed respond to outflows (inflows) with asset liquidations (purchases).[21] The results are broadly consistent across the different fund categories: funds with the largest net outflows (inflows), tend to reduce (increase) their cash position by 17% to 30% (17% to 34%). These funds also reduce (increase) between 36% and 56% (40% and 59%) of their positions. In other words, funds with large outflows tend to liquidate assets.

3.2.2 Leverage Targeting (LT)

Generally speaking, the financial leverage ratios (defined as B = debt-over-TNA) of German investment funds are rather small. As an illustration, Figure 12 shows the TNA-weighted average leverage ratios over time. Note that, for retail funds the maximum regulatory leverage is $B^{\max} = 0.1$ and for institutional funds $B^{\max} = 0.3$. In both cases, the observed values are substantially smaller.[22]

The LT-liquidation channel can only be relevant for those funds that make use of financial leverage. In the model, we make the assumption that investment funds target

[21] Note that Table 2 is restricted to retail funds only, since the different flow percentiles for institutional funds generally do not contain the same number of observations. This is due to the fact that many institutional funds show zero in- and outflows in most of the sample months.

[22] Figure B.2 in the Appendix shows that the median values are even smaller.

Percentile $Flow_t$	Avg. $Flow_t$	Avg. $Return_{t-1}$	$\%\Delta Cash_t$	New	Increased	Constant Positions	Reduced	Eliminated
Equity funds								
1	-10.43%	0.19%	-27.34%	6.83%	7.94%	27.31%	56.20%	8.55%
2	-1.79%	0.41%	-14.31%	6.72%	12.09%	49.57%	31.62%	6.72%
3	-0.87%	0.50%	-9.54%	6.24%	12.61%	53.84%	27.36%	6.19%
4	-0.52%	0.48%	-1.75%	5.84%	13.46%	55.89%	24.96%	5.69%
5	-0.27%	0.46%	1.49%	6.70%	16.82%	55.07%	22.23%	5.87%
6	-0.08%	0.42%	-0.96%	6.04%	19.25%	54.07%	20.94%	5.73%
7	0.11%	0.34%	2.10%	6.31%	22.28%	50.91%	20.65%	6.15%
8	0.52%	0.51%	6.54%	5.89%	26.07%	49.54%	18.80%	5.59%
9	1.66%	0.63%	14.35%	5.89%	35.58%	41.25%	17.57%	5.60%
10	11.39%	0.88%	28.07%	7.54%	58.90%	25.45%	9.99%	5.66%
Bond funds								
1	-11.91%	-0.06%	-29.71%	7.69%	8.26%	39.54%	42.57%	9.63%
2	-2.44%	-0.02%	-12.17%	4.96%	14.21%	48.89%	30.90%	6.00%
3	-1.18%	0.00%	-6.31%	5.02%	15.50%	53.65%	25.69%	5.17%
4	-0.61%	0.07%	-3.33%	6.33%	15.13%	59.21%	20.56%	5.10%
5	-0.25%	-0.02%	-0.24%	5.59%	16.21%	59.44%	19.41%	4.95%
6	-0.03%	0.07%	1.93%	4.94%	22.25%	52.94%	20.10%	4.71%
7	0.09%	0.02%	1.27%	4.92%	24.51%	50.53%	20.25%	4.71%
8	0.59%	0.10%	5.34%	5.11%	22.98%	53.54%	18.91%	4.57%
9	1.89%	0.00%	9.95%	5.31%	29.09%	49.87%	16.75%	4.29%
10	10.78%	0.21%	34.33%	8.64%	39.55%	42.90%	12.60%	4.95%
Mixed funds								
1	-8.99%	-0.05%	-20.15%	7.11%	8.52%	38.90%	42.89%	9.69%
2	-1.70%	-0.01%	-9.51%	7.79%	12.81%	50.46%	29.92%	6.81%
3	-0.79%	0.05%	-3.97%	6.88%	12.87%	55.96%	24.80%	6.38%
4	-0.34%	0.10%	-0.92%	6.79%	14.53%	59.34%	20.39%	5.73%
5	-0.08%	0.12%	0.81%	6.82%	16.80%	60.83%	16.97%	5.41%
6	0.00%	0.01%	-0.50%	6.06%	18.03%	60.91%	16.01%	5.05%
7	0.14%	0.12%	0.64%	6.00%	18.64%	60.07%	15.94%	5.35%
8	0.63%	0.22%	2.17%	6.24%	22.95%	54.77%	16.81%	5.46%
9	1.70%	0.13%	7.68%	6.47%	30.67%	49.34%	14.57%	5.43%
10	9.59%	0.22%	20.25%	8.98%	45.66%	37.56%	10.82%	5.96%
Funds-of funds								
1	-7.47%	0.09%	-17.19%	7.50%	6.69%	48.74%	36.11%	8.45%
2	-1.32%	0.23%	-7.30%	6.71%	9.04%	61.72%	22.90%	6.34%
3	-0.67%	0.28%	-7.94%	7.56%	9.73%	66.13%	18.15%	5.99%
4	-0.34%	0.35%	-1.10%	5.81%	8.53%	70.36%	15.39%	5.72%
5	-0.12%	0.28%	1.88%	6.30%	9.58%	71.78%	12.66%	5.98%
6	0.04%	0.27%	-0.90%	5.62%	11.77%	72.02%	11.03%	5.18%
7	0.27%	0.24%	2.50%	5.53%	12.87%	72.29%	9.45%	5.39%
8	0.64%	0.32%	6.04%	5.95%	15.73%	70.70%	8.08%	5.49%
9	1.44%	0.38%	8.50%	6.20%	21.99%	64.04%	8.77%	5.21%
10	10.16%	0.34%	16.84%	9.57%	46.96%	37.82%	8.63%	6.59%

Table 2: Funds' asset-level portfolio adjustments as a function of funds' net flows (à la Coval and Stafford (2007)). Analysis includes only retail funds. Monthly data from January 2007 to July 2019.

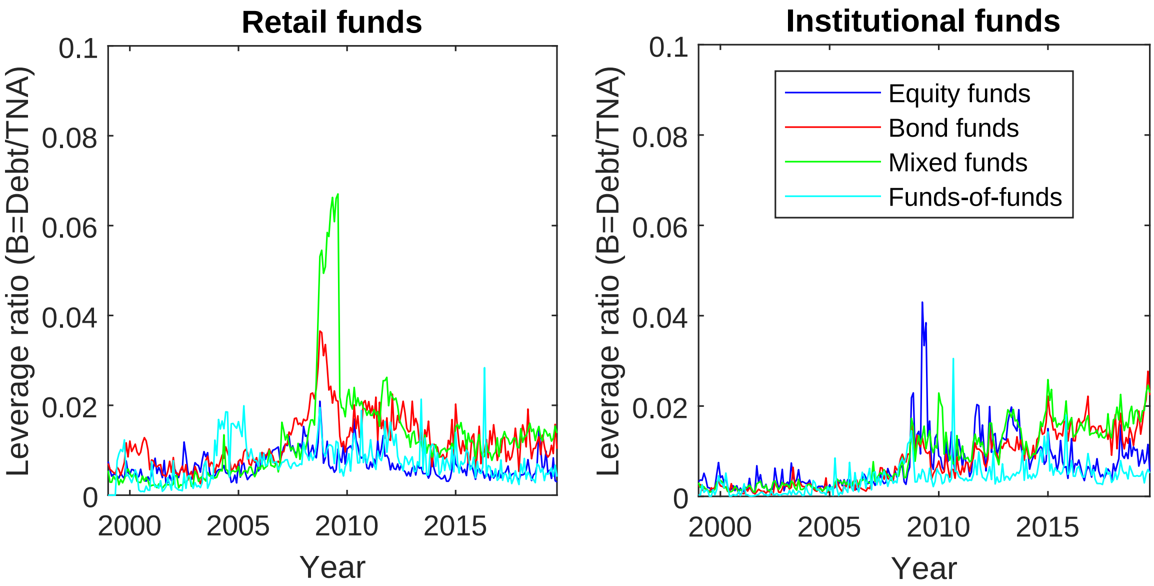


Figure 12: Cross-sectional weighted average leverage ratio over time. Note: maximum regulatory leverage is 0.1 for retail funds and 0.3 for institutional funds.

their financial leverage ratios. To the best of our knowledge, this has not been studied in the literature so far. Following Adrian and Shin (2010), we therefore run the following regression model based on monthly data:

$$\underbrace{\%\Delta \text{Leverage}^{\text{gross}}_{i,t}}_{=\frac{\text{TotalAssets}_{i,t}}{\text{TNA}_{i,t}}} = a + b_t \times \text{Controls}_{i,t-1} + \boxed{\theta_t} \times \log(\text{Leverage}^{\text{gross}}_{i,t-1}) + \epsilon_{i,t}. \tag{36}$$

Note that we restrict ourselves to fund-month observations with $\text{Leverage}^{\text{gross}}_{t-1} > 1$ and estimate parameters based on Fama-MacBeth regressions. (As for the FPR regressions, we show the time-average of each coefficient and use Newey-West standard errors with 4 lags.)

Table 3 shows the results.[23] We find that the estimated θ parameters are significantly negative for all fund types. This is a strong indicator that German investment funds actively manage their leverage ratios to stay close to a given (fund-specific) long-run mean.[24]

[23] These results are robust under alternative specifications. For example, Table B.3 shows the results for a pooled regression, with fund and time FEs. We also performed panel unit-root tests (most importantly, Fisher-type tests that allow for unbalanced panels), all of which strongly reject the presence of a unit-root in all of the panels. In other words, there is strong evidence of leverage being mean-reverting.

[24] The mean-reversion character can be understood by writing (univariate) leverage growth as

$$y_t = a + (\theta + 1)y_{t-1} + \epsilon_t,$$

with $y_t = \log(\text{Leverage}^{\text{gross}}_{i,t})$. Parameter θ can be seen as a measure of the strength of mean-reversion of time series y. Broadly speaking, there are three cases: i) if $\theta = 0$ then leverage follows a random walk (unit root); ii) if $\theta = -1$ then leverage is white-noise; iii) if $-1 > \theta > 0$ then leverage follows an AR(1) process with parameter $(\theta + 1)$. The results in Table 3 point towards case iii). Note that for larger θ (in absolute terms), a given time series shows stronger mean-reversion since the time series tends to stay relatively close to its unconditional mean.

In other words, the assumption that investment fund target their leverage ratios appears plausible. We should also note that all fund types show significantly positive parameters on contemporaneous total asset growth ($\%\Delta\text{TotalAssets}_t$). This suggests that leverage growth of German investment funds is in fact procyclical,[25] such that a fund suffering large losses on its investments would potentially adjust its leverage target downwards. Overall, our leverage targeting approach likely underestimates potential asset sales due to this channel.

Dep. var.: $\%\Delta\text{Leverage}^{\text{gross}}_t$	Equity funds		Bond funds		Mixed funds		Fund-of-funds	
	Retail	Inst.	Retail	Inst.	Retail	Inst.	Retail	Inst.
$\log(\mathbf{Leverage}^{\mathbf{gross}}_{\mathbf{t-1}})$	0.547***	0.691***	0.712***	0.720***	0.926***	0.748***	0.452***	0.883***
	(0.019)	(0.028)	(0.021)	(0.022)	(0.010)	(0.013)	(0.045)	(0.026)
$\%\Delta\text{TotalAssets}_t$	0.021***	0.071***	0.041***	0.103***	0.073***	0.106***	0.058***	0.155***
	(0.002)	(0.009)	(0.005)	(0.008)	(0.007)	(0.007)	(0.009)	(0.017)
Flow_{t-1}	0.000	-0.008**	-0.011***	-0.008***	-0.013***	-0.003	-0.007*	-0.084*
	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.004)	(0.048)
$\log(\text{TotalAssets}_{t-1})$	-0.000***	0.000***	0.000***	0.001***	-0.000	0.001***	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
CashRatio_{t-1}	0.007***	0.009***	0.003	0.006***	0.003**	0.003***	0.007***	0.015**
	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.006)
Fama-MacBeth	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$	$\surd$
Obs.	64,941	22,628	46,603	68,129	103,156	278,891	27,975	9,614
adj. R^2	0.329	0.511	0.540	0.585	0.863	0.601	0.350	0.871

$*$ p<0.1; $**$ p<0.05; $***$ p<0.01

Table 3: Leverage targeting regressions, based on Fama-MacBeth regression (Newey-West std. errors with 4 lags in parentheses). Monthly data from January 2007 to July 2019.

As for the FPR regressions, the results in Table 3 hide time-variation in the estimated θ parameters. Figure 13 shows the 36-month rolling window average estimate of θ_t. Insignificant values that fall within the 5% confidence bands (based on the standard errors in Table 3) are shown as dotted lines. With the exception of institutional funds-of-funds, the estimated parameters are always significantly negative for the period from 2015 onwards. The insignificance for institutional funds-of-funds is likely driven by the fact that the number of observations is rather small for these funds; in fact, we can only estimate the parameters for these funds from 2005 onwards (recall that the regression only includes funds that actually make use of financial leverage). Since the full sample estimates in Table 3 are significantly negative, we switch on the LT channel for all funds that make use of leverage during all months in our model application.

3.2.3 Price Impacts

Having established how much of each individual marketable assets (bonds and equities) the fund sector will liquidate, we need to quantify how strongly prices react to these sales. For this purpose, we use the standard Amihud (2002) ratio as our measure of price impact:

$$\text{PriceImpact}_{k,t} = \frac{|\text{Return}_{k,t}|}{\text{Volume}_{k,t}}, \tag{37}$$

[25]The estimated coefficients are substantially smaller in absolute terms compared with those of Adrian and Shin (2010) for U.S. commercial banks and broker-dealers. This suggests that funds' leverage ratios are less procyclical compared to these types of financial institutions.

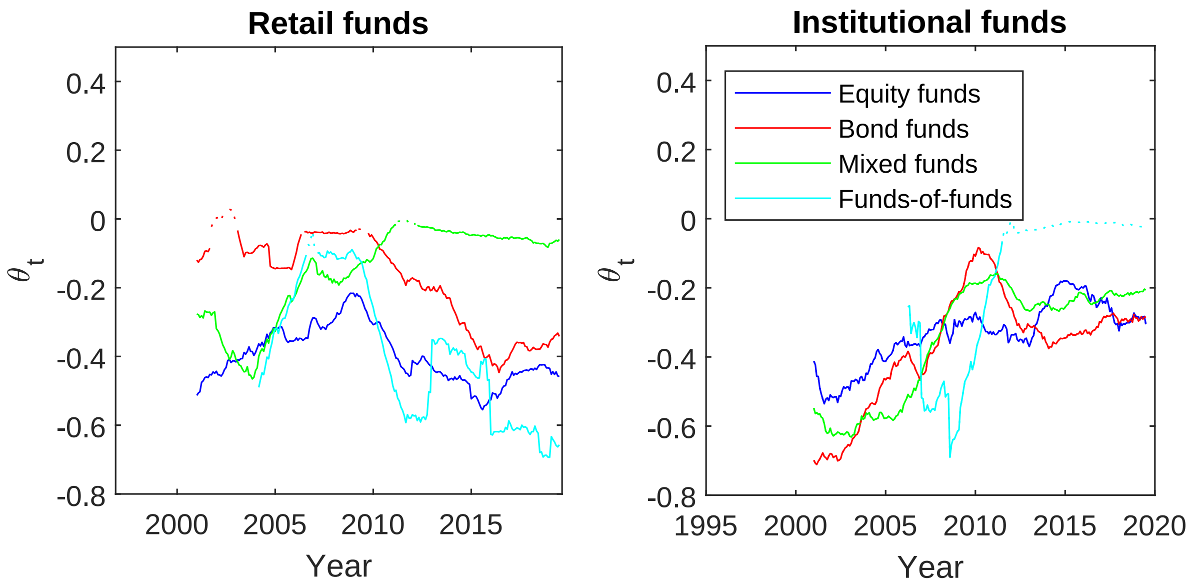


Figure 13: 36-month rolling window average of θ_t over time. Based Fama-MacBeth regressions in Table 3 (dotted lines indicate observations that are insignificant at the 5% level, based on standard errors in Table 3).

which is the absolute return of asset k divided by the nominal trading volume during the same period (based on daily data). The Amihud ratio is quite attractive for our purposes for at least two reasons: first, it only requires information on prices and trading volumes (more on this below); second, given a linear market impact function, we can approximate the expected price drop from funds' fire sales.[26]

In order to calculate PriceImpacts we rely on the CSDB. Unfortunately, the CSDB only has information on trading volumes available from October 2015 onwards, meaning that the PriceImpacts cannot be calculated prior to that.[27] As shown in Table 4, the PriceImpact-coverage is excellent for equities, which are generally exchange-traded: the average coverage (per month) is 87% in terms of the number of equities held by German investment funds. The holdings-weighted coverage is close to 97%. For bonds, the picture is very different: the average PriceImpact-coverage is 1.9% for those bonds that are held by German investment funds (volume-weighted coverage: 6.4%). This is driven by the fact that, for many bonds, there is no information on trading volumes since these tend to be traded over-the-counter.[28]

Compared with previous fire sale stress tests, the number of assets included in our

[26]The latter element is quite important, since other liquidity measures, such as the bid-ask spread, do not allow for this. More specifically, the bid-ask spread could be used as a proxy for the minimum expected price change due to asset liquidations (the price after liquidation should be closer to the bid rather than the ask). However, if funds liquidate large volumes they will consume all of the available liquidity at the best bid and we would need to model the shape of the order book further away from the best bid.

[27]On the other hand, price and return data are generally available from September 2009 onwards. In the future, we may use the estimated parameters to calculate model-implied PriceImpact parameters prior to November 2015.

[28]PriceImpact-coverage for bonds is comparable when using information from the standard market data providers.

PriceImpact-Coverage	Equal-weighted	Holdings-weighted
Equities - raw	86.64%	96.76%
	(3.45%)	(2.69%)
Bonds - raw	1.91%	6.36%
	(0.52%)	(1.95%)
Bonds - model	89.11%	94.62%
	(1.26%)	(0.64%)

Table 4: Average PriceImpact-coverage (std. dev. in parentheses). Monthly data from November 2015 to July 2019.

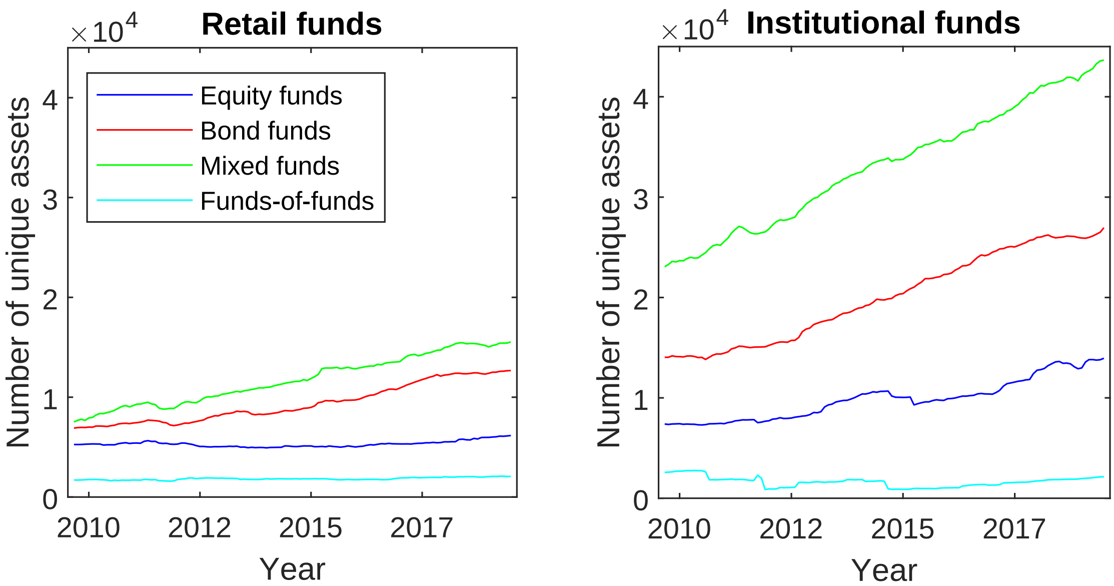


Figure 14: Total number of unique assets (ISINs) held by different fund types.

application is substantially larger due to the fact that we work with the most granular fund portfolios and incorporate more than one fund type (cf. Figure 14). In order to incorporate funds' sales of bonds, we use a simple regression approach that approximates the missing PriceImpact-parameters for bonds. As shown in the last row of Table 4, this method increases the PriceImpact-coverage for bonds to 89% (volume-weighted coverage: around 95%).

Characteristic	Bond-/ issuer-level	Value 0	1	2
Age Group	Bond	≤ 5 yrs.	> 5 yrs.	> 10 yrs.
Maturity Group	Bond	≤ 1 yr.	> 1 yr.	> 5 yrs.
HeldByFunds	Bond	No	Yes	
DevelopedCountry	Issuer	No	Yes	
Sovereign	Issuer	No	Yes	
Financial	Issuer	No	Yes	
HighYield	Bond	$\leq$ 75th perc.	$>$ 75th perc.	
Size Group	Bond	$\leq$ Median	$>$ Median	

Table 5: Characteristics used in the cross-sectional PriceImpact-regression. Time-varying characteristics are computed separately for each cross-section.

For our regression model, we make the identifying assumption that bonds with similar characteristics should also have similar levels of market liquidity (i.e., PriceImpacts).[29] There are different ways of imputing missing Amihud ratios and here we restrict ourselves to a simple linear regression model:

$$\log(\text{PriceImpact}_{k,t}) = \mathbf{b}_t \times \mathbf{X}_{k,t} + \epsilon_{k,t}, \tag{38}$$

which uses data on all bonds for which we can calculate the PriceImpact-parameter at time t while $\mathbf{X}$ includes the observable characteristics reported in Table 5. Note that the set k includes bonds that are being held by German investment funds (corresponding to those in the second line of Table 4) and bonds that are not being held by German investment funds that have non-missing PriceImpacts. Also note that we run the above regression separately for each month t. Based on the estimated coefficients, we can 'predict' the missing PriceImpacts in month t as

$$\log(\widehat{\text{PriceImpact}}_{-k,t}) = \widehat{\mathbf{b}}_t \times \mathbf{X}_{-k,t}, \tag{39}$$

where $-k$ denotes bonds with missing PriceImpacts that are held by German investment funds. With regards to the characteristics $\mathbf{X}$ used in the cross-sectional regressions, we follow the literature and use the characteristics reported in Table 5 (see, e.g., Bao, Pan, and Wang (2011)).

Table 6 summarizes the results: the first column shows regression results based on the Fama-MacBeth approach, the second column shows results from a pooled regression

[29] To identify 'similar' bonds, we follow the literature. Nevertheless, our PriceImpact estimates might over- or underestimate the liquidity of single bonds with missing PriceImpacts at the security level. Within the given cross-section, however, we see no reason for our methodology to systematically over- or underestimate bond liquidity.

Dep. var.: log(PriceImpact)	(1)	(2)	(3)
Age Group	0.151***	0.126***	0.137***
	(0.019)	(0.013)	(0.015)
Maturity Group	0.425***	0.441***	0.445***
	(0.034)	(0.014)	(0.014)
HeldByFunds	0.413***	0.533***	0.522***
	(0.064)	(0.027)	(0.027)
DevelopedCountry	-0.955***	-0.954***	-0.966***
	(0.065)	(0.024)	(0.024)
Sovereign	-1.889***	-1.893***	-1.862***
	(0.068)	(0.032)	(0.032)
Financial	-0.026	-0.036	-0.006
	(0.045)	(0.024)	(0.024)
HighYield	0.310***	0.338***	0.342***
	(0.051)	(0.024)	(0.023)
Size Group	-1.079***	-1.043***	-1.037***
	(0.055)	(0.028)	(0.028)
Fama-MacBeth	√		
Time FEs			√
adj.-R^2	0.265	0.237	0.258
Obs.	46,977	46,977	46,977

$*$ p<0.1; $**$ p<0.05; $***$ p<0.01

Table 6: PriceImpact-regressions (std. errors in parentheses). Monthly data from November 2015 to July 2019.

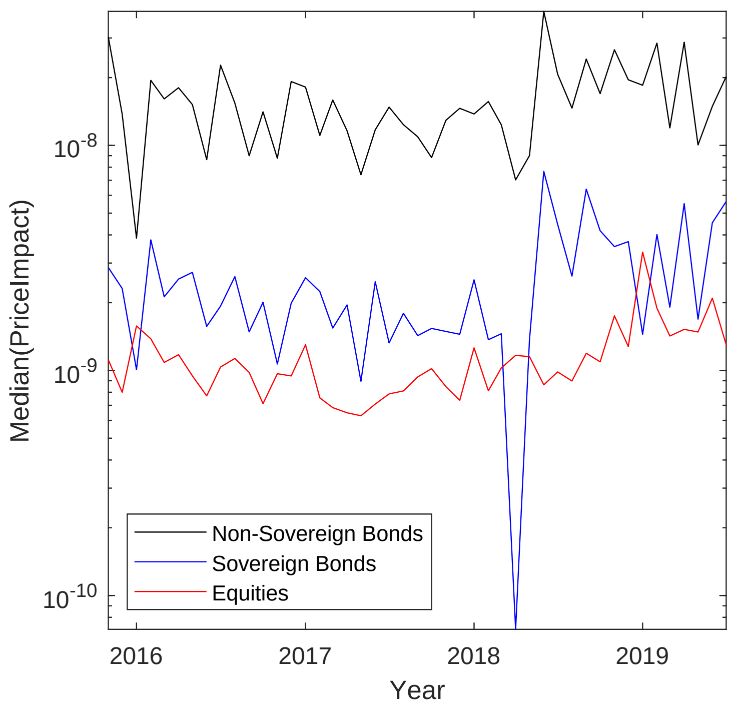


Figure 15: PriceImpact - dynamics over time for equities and bonds.

across all months, and the last column adds time FEs to the pooled regression. The results are broadly in line with those in the literature and the parameters generally show the expected signs: for example, large bonds, sovereign bonds, and bonds from a developed country are more liquid; older bonds, bonds with a long time until maturity, and high-yield bonds tend to be less liquid. We should also mention that the fit of the cross-sectional regressions is relatively good (average adj.-R^2 of 0.26) and the fact that adding time FEs to the regressions hardly improves the R^2 can be seen as an indication that the estimated relationships are rather stable over the sample period.

For the sake of completeness, Figure 15 shows the dynamics of the PriceImpact-parameters over time. The results are as expected: on average, equities tend to be the most liquid instruments, followed by sovereign bonds, whereas non-sovereign bonds (including financial and non-financial corporate bonds) tend to be the least liquid instruments.

4 Vulnerabilities in the German Fund Sector

4.1 Initial Shock Scenario

As discussed in Section 2, our triggering stress event is a sudden shock on the value of investment funds' asset portfolios. Here we assume an abrupt and strong repricing in global bond and equities markets. Of course, such a scenario will be challenging for individual financial intermediaries, but it is also considered relevant by policy makers and regulators from a financial stability perspective given the high asset valuation levels (see e.g. ECB Financial Stability Review in November 2019). This initial shock translates into direct portfolio losses for funds (Step 0) as well as further indirect portfolio losses due to funds' cross-holdings (Step 1). These are followed by funds' asset sales (Step 2), which give rise to additional fund portfolio losses (Step 3).

In order to identify a severe but plausible shock scenario, we use monthly returns from a battery of broad bond and equity market indices for various geographic regions during the period 2000-2018.[30] Since we are interested in severe repricing scenarios, we focus on the lower tail of the historical index return distributions and compute equal-weighted averages of the historical 1%, 2.5% and 5% return percentiles for bond and equity index returns separately (see Panel A of Table 7). As expected, these tend to be much larger in absolute terms for equities compared to bonds. We make a conservative choice and use the 1%-percentiles as our initial shock for both bonds and equities. This amounts to a security-level return shock of -4.48% for bonds and -14.16% for equities. For the sake of comparison, Panel B of Table 7 shows the corresponding percentiles for monthly fund returns and net flows during the same period, based on aggregated data for the different fund types. Consistent with the evidence provided in Panel A, equity funds tend to show the most extreme returns, relative to the other fund types.

[30]Details are available upon request from the authors.

Panel A	Averages of different percentiles (monthly returns, in percent)	
	Bonds	Equities
1%-perc.	**-4.48**	**-14.16**
2.5%-perc.	-2.77	-11.91
5%-perc.	-1.94	-9.22

Panel B	German investment funds (sector-level data).															
	Monthly returns (in percent)								Monthly flows (in percent)							
	Retail				Institutional				Retail				Institutional			
	Equity	Bond	Mixed	FoF	Equity	Bond	Mixed	FoF	Equity	Bond	Mixed	FoF	Equity	Bond	Mixed	FoF
1%-perc.	-8.81	-2.77	-4.15	-3.59	-13.19	-1.80	-4.70	-8.26	-4.85	-0.75	-0.53	-3.69	-2.54	-3.51	-2.60	-1.64
2.5%-perc.	-7.08	-2.30	-3.13	-2.97	-12.16	-1.48	-4.01	-5.86	-3.61	-0.50	-0.32	-0.89	-1.57	-2.47	-1.49	-1.10
5%-perc.	-6.23	-1.88	-2.74	-2.42	-8.92	-1.29	-3.25	-4.87	-1.84	-0.21	-0.15	-0.23	-1.30	-2.04	-1.07	-0.73

Table 7: Equal-weighted averages of different return percentiles for broad bond and equity market indices (Panel A) and German investment fund returns and flows (Panel B), based on aggregated information for different fund types. Sample period: January 2000 - December 2018. Note: FoF refers to funds-of-funds.

4.2 Results

As noted in the previous section, we always allow for time-variation in the FPR-channel (the channel is only relevant for a given fund type in month t if the corresponding 36-month rolling window average of γ_t is positively significant), while the LT-channel is relevant for all fund types during all month (θ_t tends to be significant throughout the application period).[31] For fund managers facing selling pressure, the assumed levels of market liquidity strongly affect our AV measure. In fact, as shown in Figure 15, the estimated level of market liquidity can vary substantially over time, even during our relatively brief sample period.

In the following, we will therefore show separate results for two specifications: in our baseline specification, we take the dynamic PriceImpacts as described in the previous section to account for the observed time-variation. We refer to this specification as the **actual market conditions**. In our alternative specification, we acknowledge that the above specification likely overestimates the level of market liquidity during stress periods (such as large losses on global bond and equity markets). By assumption, fund managers need to liquidate assets in an adverse scenario and it seems reasonable to assume that market liquidity should be under stress as well. In our alternative specification, which we refer to as **stressed market conditions**, we use the 90% percentile of the observed PriceImpact parameter over time for each asset.[32] Note that this approach does not take into account time-variation in market liquidity and should therefore yield relatively less noisy AV estimates.

In what follows, we apply the model separately for each month and impose the same initial shock to bonds and stocks consistently during each month. On average, the initial shock in Step 0 amounts to losses of 6.6% of the sector's TNA (cf. the blue squares in Figure 19).[33] Given that the initial shock is independent of the assumed market conditions, we can directly compare the AVs in the two cases.

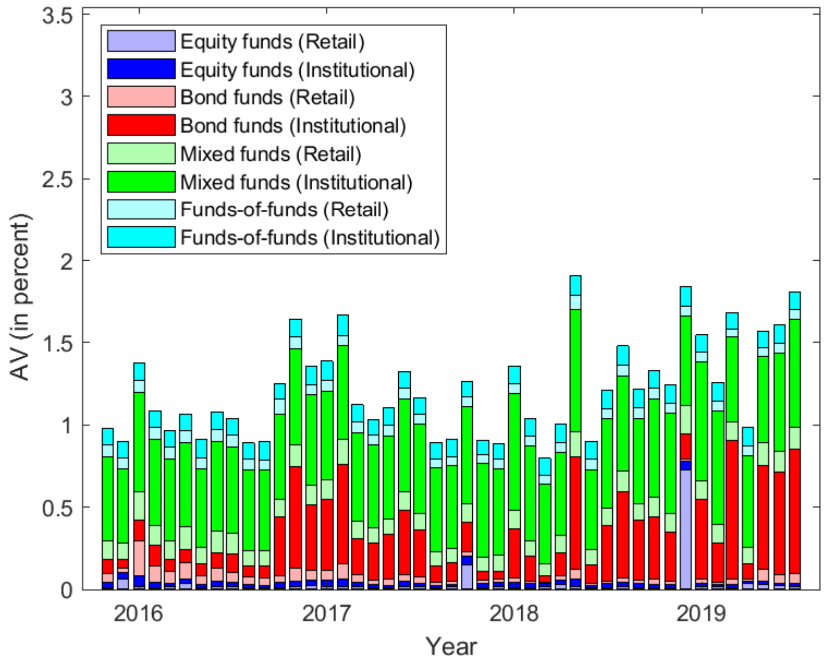
4.2.1 Actual Market Conditions

Aggregate vulnerability over time. Panel (a) of Figure 16 shows the AV of the German fund sector over time. The average AV amounts to 1.2%, but shows substantial time-variation. For example, the AV ranges between 0.8% (March 2018) and 1.9% (May 2018) of the sector's TNA. On average, the AV amounts to losses that are on the order of 18% of the initial shock (ranging between 12% and 28%; cf. Figure 19). Overall, these results indicate that the German fund sector's connectedness may exacerbate an abrupt drop in equity and bond prices, even under market conditions that are not particularly stressed. However, in comparison to similar analyses for the European banking sector

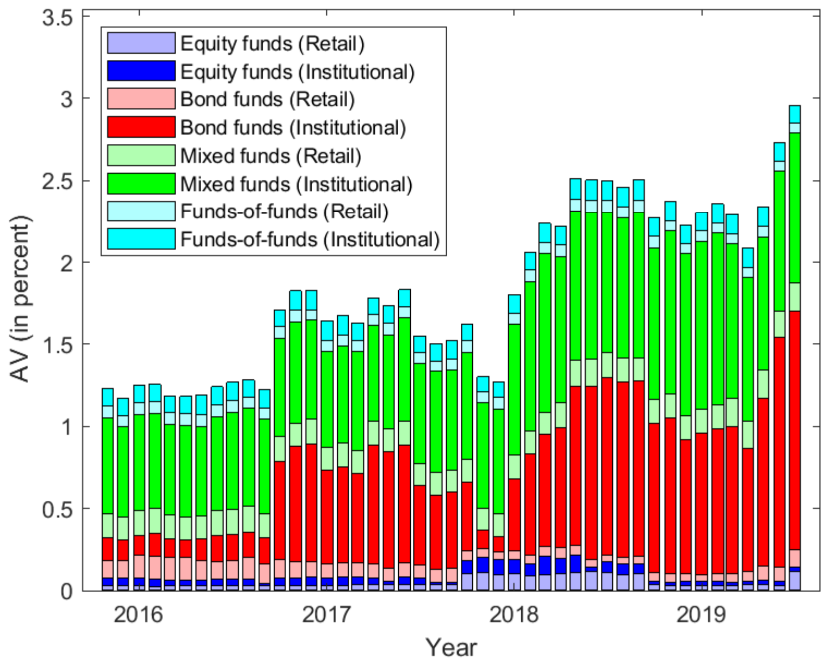
[31] For the sake of completeness, in Appendix E we show results for a constant FPR (based on the estimates in Table 1). This corresponds to the approach of Fricke and Fricke (2020), who assumed that the FPR parameters are time-invariant.

[32] On an asset-by-asset level, the 90% percentile of the PriceImpact parameter is, on average, 3.6 times the median value for each asset.

[33] A larger initial shock would, ceteris paribus, lead to a higher AV since funds would have to sell more securities (cf. Figure 5). In fact, the relationship between the magnitude of the initial shock and the AV is non-linear (cf. Figure 5). For the initial shock imposed in this paper, however, we confirm that doubling the size of the initial shock increases the AV approximately by a factor of 2 as well.



(a) Actual market conditions (dynamic PriceImpacts).



(b) Stressed market conditions (constant PriceImpacts, 90%-perc.).

Figure 16: AV over time. We apply the model separately for each month. The asset-level initial shock is -4.48% for bonds and -14.16% for equities. Contribution by fund type is based on aggregating the fund-level Systemicness measure in Eq. (31).

(as in Greenwood et al. (2015)), these results make the German investment fund sector appear relatively robust.[34]

Note that, despite being relatively noisy, the AV has increased by 80% over our sample period (from 1.0% in November 2015 to 1.8% in July 2019). In order to better understand whether this increase might be driven by the nominal growth of the fund sector, we also calculated an alternative AV under the assumption of constant total assets.[35] Specifically, in our model application, we rescale the nominal value of funds' portfolios to match exactly the total assets in November 2015, as shown in panel (a) of Figure D.3 in the Appendix.[36] As expected, the AV is smaller when we fix the size of the fund sector and the distance with the actual AV increases over the sample period.[37] Nevertheless, even in this case the AV increased by approximately 60% (from 1.0% to 1.6%). Given that all other model inputs are kept as in the baseline application, these results suggest that at most 25% of the AV increase can be attributed to the sector's nominal growth. In other words, the increase in the AV is 'real'.

Panel (a) of Figure 16 also shows the contribution of the different fund types to the overall AV. Unsurprisingly, mixed funds (55% of the total AV) and bond funds (27% of the total AV) are the main contributors to the AV, given their relatively illiquid asset portfolios and high levels of direct connectedness. However, it also becomes clear that other fund types can add substantially to the AV during certain periods. Most strikingly, retail equity funds made up approximately 40% of the sector's AV in December 2018, largely due to their common asset liquidations.[38] During this period, equity markets faced a substantial downward repricing which had a large effect on the PriceImpact parameters (cf. Figure 15). In other words, equity funds' asset sales had a larger effect on asset prices during this period.

Relative importance of the different channels. Which channels contribute most to the overall AV? Based on Eq. (30) we can broadly decompose the AV into losses due to funds' indirect connectedness ($\text{Loss}^{\text{FireSales}}$) and losses due to fund's direct connectedness ($\text{Loss}^{\text{CrossHoldings}}$), where the latter can be split into a component that comes from the initial shock and a component that comes from funds' fire sale losses. Panel (a) of Figure

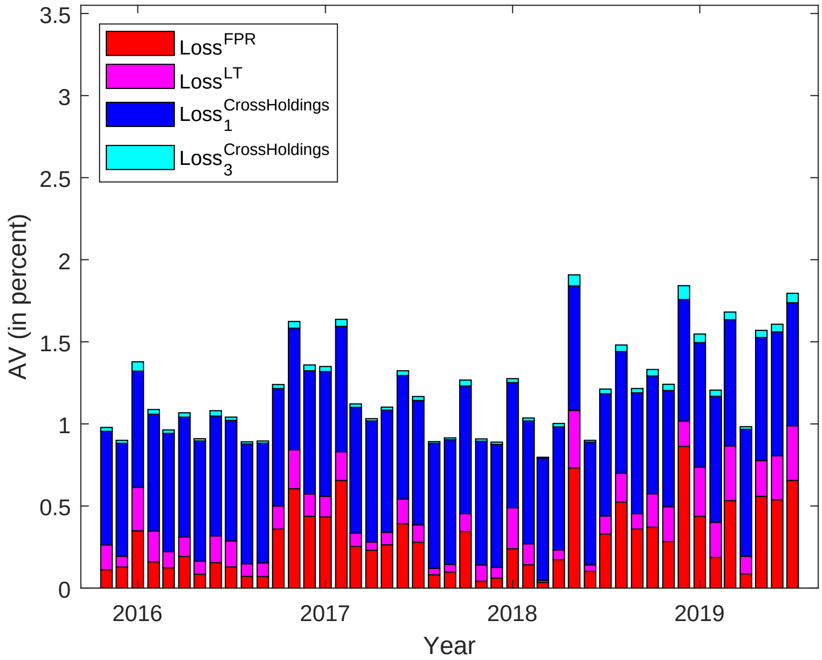
[34]Greenwood et al. (2015) report an AV of 245%, based on a 50% shock on sovereign debt from Greece, Italy, Ireland, Portugal, and Spain. Note that the difference in the AVs of banks and investment funds is strongly driven by differences in their funding models. These differences lead to larger asset sales of banks due to the LT channel and also imply a much smaller denominator for rescaling the AV in Eq. (30). On the other hand, Greenwood et al. (2015) do not incorporate banks' direct connectedness in their model, thus underestimating vulnerabilities from this layer of connectedness.

[35]In addition, we explore the key drivers of the AV in Section C of the Appendix.

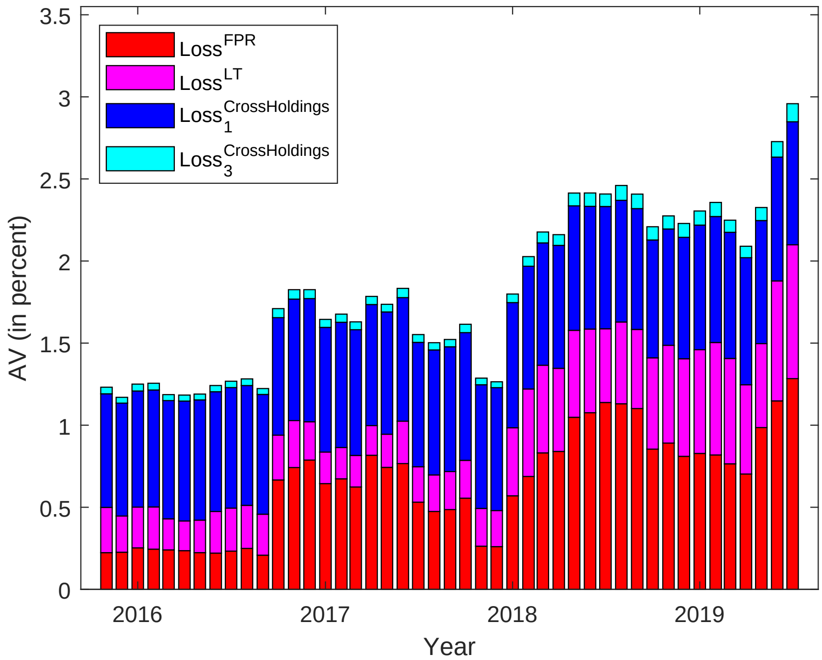
[36]The relationship between the AV and the size of the fund sector is sub-linear. This is because losses from Step 1 remain unaffected by changes in the size of the fund sector. In nominal terms, however, funds will need to liquidate twice as many assets following the initial shock, such that the price drop will be twice as large. In other words, percentage losses due to cross-holdings remain roughly unaffected by the size of the fund sector, while losses due to fire sales become be twice as large. We confirm that this is indeed the case in our sample. On average, doubling the size of the fund sector would increase the AV by a factor of 1.32 (1.45) under actual (stressed) market conditions.

[37]For example, in July 2019, the actual AV is 1.8% and the value with fixed total assets is 1.6%. Therefore, the relative AV difference is 14%, while the relative difference in total assets is 28%.

[38]Note that institutional equity funds added very little compared to retail equity funds, since these funds had to liquidate relatively few assets due to an insignificant FPR (cf. Figure 11).



(a) Actual market conditions (dynamic PriceImpacts).



(b) Stressed market conditions (constant PriceImpacts, 90%-perc.).

Figure 17: AV and the relative contribution of the different channels.

17 shows the relative contribution of these components under actual market conditions. Clearly, the cross-holdings channel tends to dominate, in particular losses from Step 1, with an average contribution of 65% of the estimated AV due to this component. The remainder is largely due to the FPR channel (average contribution of 22%) and the LT channel (11%). This dominance of the cross-holdings channel results from the relatively high liquidity of the underlying bond and equity markets during our sample period, as the fire sale channel and the cross-holdings channel are very asymmetrically affected by changes in market liquidity: while the fire sale channel is driven by liquidity in the underlying securities markets, liquidity has only an indirect effect on the cross-holdings channel (via cross-holding losses due to funds' fire sales, Step 3b). In other words, the picture might look different for highly illiquid periods (see also section 4.2.2). Note that up until the end of 2016, the FPR channel and the LT channel both had roughly the same contribution to the overall AV, which shows that the LT channel can matter despite the relatively low leverage ratios in the German fund sector.[39] This appears to be due to an aggregation effect: while we know that funds generally make relatively little use of financial leverage (cf. Figure 12), aggregating the liquidation amounts due to LT across all funds will lead to a sizable effect on asset prices. This is particularly true for institutional funds, for which the FPR channel tends to be less relevant.

The relative contribution of the cross-holdings channel remains relatively stable over our sample period across all fund types. However, Figure 17 hides substantial variation in losses due to cross-holdings for different fund types. Most importantly, one would expect that funds-of-funds, which generally mainly invest in fund shares, will incur most of their losses via the cross-holdings channel. (Recall that our current modelling framework does not allow funds to liquidate fund shares, but only bonds and equities.) We indeed find evidence along those lines: averaged across all sample fund-months, losses due to cross-holdings made up only around 7.3% of the total losses for equity funds, 5.9% for bond funds, and 29% for the average mixed fund. On the other hand, losses due to cross-holdings make up around 92.3% of the total losses for fund-of-funds. In other words, in the absence of the cross-holdings channel, most funds-of-funds would suffer hardly any losses, despite the fact that their portfolios consist of funds that suffered (potentially substantial) losses themselves. Given that cross-holdings within the German fund sector tend to become more important over time, we anticipate the fund sector's direct connectedness to contribute even more to the overall vulnerability of the sector.

A Closer Look at Fund-Level Indicators. We now take a closer look at the fund-level results. From a macroprudential perspective, it is crucial to identify the most (systemically) important funds. In this regard, we should stress that the results shown in Figures 16 and 17 were obtained by aggregating fund-level Systemicness measure in Eq. (31), which measures how strongly the fund affects other funds due to its direct and indirect connectedness.

[39] We should note that the results in Figure 17 were obtained for the case of $\eta = 1$ (immediate leverage targeting). If we were to switch off the LT channel ($\eta = 0$), the AV would be lowered by the bars corresponding to losses due to leverage targeting Figure 17.

Transition probability (in %)

		Systemicness$_t$										Systemicness$_{t+12}$									
	Decile	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
Panel A	1	80.18	11.53	3.62	2.21	1.16	0.56	0.32	0.20	0.14	0.10	62.88	11.92	5.24	4.16	4.20	4.32	3.04	2.36	1.28	0.60
(Actual)	2	20.49	49.55	20.25	5.41	2.40	1.23	0.43	0.19	0.04	0.02	18.18	40.09	19.00	6.26	4.84	4.84	3.87	1.64	0.89	0.37
	3	7.43	19.33	44.32	19.80	5.54	2.07	1.02	0.32	0.12	0.05	11.28	18.69	32.20	17.51	8.61	5.27	3.41	1.71	0.96	0.37
	4	4.36	5.44	19.76	44.09	18.83	5.08	1.51	0.54	0.31	0.08	7.89	6.93	23.07	28.00	20.41	7.96	3.02	1.40	0.88	0.44
Systemicness$_t$	5	2.01	2.36	5.74	19.28	47.52	18.17	3.52	0.83	0.33	0.24	6.93	4.69	7.68	29.66	24.52	16.39	5.81	2.98	0.60	0.75
	6	0.70	1.00	2.06	4.95	19.13	53.12	16.18	1.82	0.67	0.36	4.61	3.32	3.82	6.99	26.03	31.07	16.01	4.76	2.24	1.15
	7	0.53	0.35	0.89	1.63	3.35	16.82	59.38	14.34	1.97	0.73	4.30	2.08	2.08	2.87	5.09	22.15	38.21	16.49	4.16	2.58
	8	0.39	0.18	0.19	0.57	0.70	1.73	14.91	67.83	11.97	1.54	2.90	1.01	1.59	1.01	2.24	3.11	20.13	48.37	17.16	2.46
	9	0.22	0.06	0.06	0.15	0.34	0.63	1.81	12.36	77.01	7.35	1.72	0.50	0.64	0.64	0.86	1.36	4.37	17.77	58.31	13.83
	10	0.22	0.05	0.03	0.08	0.16	0.29	0.72	1.56	7.46	89.42	1.96	0.15	0.29	0.29	0.29	0.94	2.03	3.41	14.81	75.82
Panel B	1	82.77	10.03	3.24	1.79	0.96	0.53	0.29	0.17	0.12	0.09	63.89	10.80	5.76	4.12	4.40	3.96	3.36	1.76	1.20	0.76
(Stressed)	2	18.14	59.90	15.90	3.17	1.53	0.71	0.36	0.20	0.07	0.02	18.00	40.18	17.48	5.90	5.30	5.00	4.78	2.09	1.12	0.15
	3	6.12	14.99	58.85	15.38	2.65	1.15	0.48	0.17	0.13	0.08	11.35	19.57	30.92	18.82	8.66	4.85	2.76	1.79	0.67	0.60
	4	3.41	3.39	14.54	62.15	13.38	1.81	0.78	0.38	0.11	0.05	6.90	6.61	23.01	30.81	17.97	6.90	3.56	1.86	1.56	0.82
Systemicness$_t$	5	1.74	1.54	2.68	13.11	67.53	11.34	1.25	0.43	0.27	0.12	7.26	4.77	8.14	25.68	27.07	14.23	6.90	3.23	1.76	0.95
	6	0.76	0.75	1.12	1.76	11.59	73.75	8.95	0.78	0.32	0.22	5.38	3.85	3.85	5.60	23.35	36.58	13.38	3.35	2.25	2.40
	7	0.56	0.37	0.54	0.69	1.03	9.10	78.81	7.86	0.69	0.37	4.71	2.78	2.43	3.35	5.42	20.41	38.33	15.99	3.28	3.28
	8	0.37	0.12	0.13	0.29	0.43	0.74	7.98	82.90	6.62	0.42	2.02	1.44	1.59	1.08	2.02	2.82	21.08	51.34	13.94	2.67
	9	0.21	0.04	0.09	0.10	0.20	0.37	0.68	6.73	86.98	4.59	2.00	0.29	0.72	1.07	1.14	2.00	3.43	17.31	61.09	10.94
	10	0.22	0.03	0.06	0.11	0.06	0.16	0.28	0.39	4.71	93.99	1.74	0.22	0.36	0.44	0.58	1.53	1.96	3.12	13.65	76.40

Table 8: Persistence of fund-level Systemicness. The Table shows the transition probability (in percent) of funds in Systemicness-decile x in month t to be in Systemicness-decile y in the future, over the next 1 and 12 months, respectively. Panel A shows the results for the actual market conditions and Panel B for stressed market conditions. Results are pooled across all months (November 2015 to July 2019).

One important question regards the persistence of the fund-level Systemicness indicator. We would expect a high level of persistence, given that the structural features of individual funds (in particular their asset portfolios) tends to be rather persistent over time. The results in Table 8 support this notion and provide evidence that the Systemicness indicator is indeed persistent, particularly so for the extreme cases. For example, after sorting funds into Systemicness-deciles separately for each cross-section t, we find that funds in decile 1 in month t have a probability of 80% to stay in this decile in month $t+1$ (left part of Panel A). For decile 10, the probability is close to 90%. Over 12 months (right part of Panel A) the values are somewhat lower at 63% and 76%, respectively, but still suggest high levels of persistence in funds' Systemicness).

Another important question is whether more systemic funds are also more vulnerable (i.e., suffer large relative second round losses). First evidence in this regard is based on a significant Pearson-correlation between these two measures of 0.18 when pooling across all fund-month observations. This suggests that, on average, funds with larger Systemicness may also incur larger second round losses. In order to take a closer look at funds with large Systemicness, Table 9 shows the probability of funds sorted into Systemicness decile x (rows) to be in Loss decile y (columns) during month t. Panel A shows the average results over each cross-section t. The results are striking: for example, funds with the smallest Systemicness (decile 1) have a 44% probability to also display the smallest losses (decile 1). On the other hand, funds with the highest Systemicness (decile 10) have a 78% probability to also show the largest losses. In other words, funds that are systemic also tend to be vulnerable. Clearly, these are the funds that are particularly relevant from a macroprudential perspective.

Are Funds with higher systemicness more vulnerable? (Probability in %)

		Relative loss$_t$									
	Decile	1	2	3	4	5	6	7	8	9	10
Panel A	1	43.52	12.03	10.63	9.79	8.32	7.15	5.23	2.38	0.73	0.22
(Actual)	2	21.25	16.83	13.35	13.75	12.10	10.06	7.16	3.74	1.36	0.41
	3	18.24	22.04	14.47	11.91	10.47	9.12	7.60	4.03	1.59	0.53
	4	13.54	20.33	17.68	13.90	11.48	9.79	7.68	3.85	1.23	0.51
Systemicness$_t$	5	6.88	12.79	17.15	16.90	15.53	13.17	9.95	5.23	1.83	0.55
	6	2.42	6.98	13.15	15.84	17.72	17.76	14.66	8.24	2.43	0.80
	7	0.71	2.37	6.27	9.60	13.97	18.70	23.96	19.27	3.98	1.16
	8	0.17	0.51	1.69	2.90	5.38	8.63	16.58	36.00	26.71	1.43
	9	0.11	0.20	0.67	1.00	1.86	2.79	4.87	15.72	51.94	20.85
	10	0.01	0.05	0.30	0.45	0.60	1.23	2.48	4.29	12.36	78.23
Panel B	1	42.16	11.44	10.54	9.53	8.34	7.14	5.42	3.42	1.52	0.49
(Stressed)	2	21.79	14.22	13.19	13.55	10.84	9.85	7.66	5.27	2.44	1.19
	3	17.07	19.41	14.79	12.02	10.71	9.65	7.14	5.38	2.80	1.03
	4	13.88	20.42	16.87	13.66	10.58	9.08	7.63	4.54	2.31	1.01
Systemicness$_t$	5	8.17	14.23	15.65	15.71	14.58	12.12	9.11	6.61	2.78	1.05
	6	4.00	8.61	13.18	14.05	16.82	15.56	13.11	8.34	4.56	1.77
	7	0.73	4.12	7.26	10.42	13.93	17.15	21.65	16.55	5.95	2.24
	8	0.09	1.06	2.17	4.38	7.37	11.23	17.60	28.20	24.77	3.12
	9	0.20	0.85	1.16	1.90	2.61	4.05	6.96	18.23	43.32	20.71
	10	0.03	0.27	0.58	1.06	1.65	2.58	3.67	5.26	13.07	71.82

Table 9: This Table shows the probability of funds (in %) that are in Systemicness-decile x to be in Loss-decile y (relative second round loss). Decile 1 (10) corresponds to the smallest (largest) values in absolute terms, respectively. For example, Decile(Systemicness)=10 and Decile(Loss)=10 would be funds whose connectedness has a large effect on other funds *and* that also suffer large losses themselves. Panel A shows the results for the actual market conditions and Panel B for stressed market conditions. Results averaged over the different cross-sections (November 2015 to July 2019).

Spillover effects to the broader financial system. Investment funds are not only connected amongst themselves, but also with other economic sectors. In particular, German investment funds are predominantly held by actors from the financial system (cf. Figure 10). This could make these actors prone to spillover effects triggered by losses within the fund sector.[40] Panel (a) of Figure 18 shows how losses of German investment funds translate into spillover portfolio losses to the respective fund holders. Note that, in contrast to Figures 16 and 17, the Figure reports losses relative to each sector's aggregated fund portfolio TNA. Importantly, these spillover losses only show the second round effects (Steps 1 and 3), not the initial shock (Step 0). (We will comment on the relative magnitude of the second round losses below.)

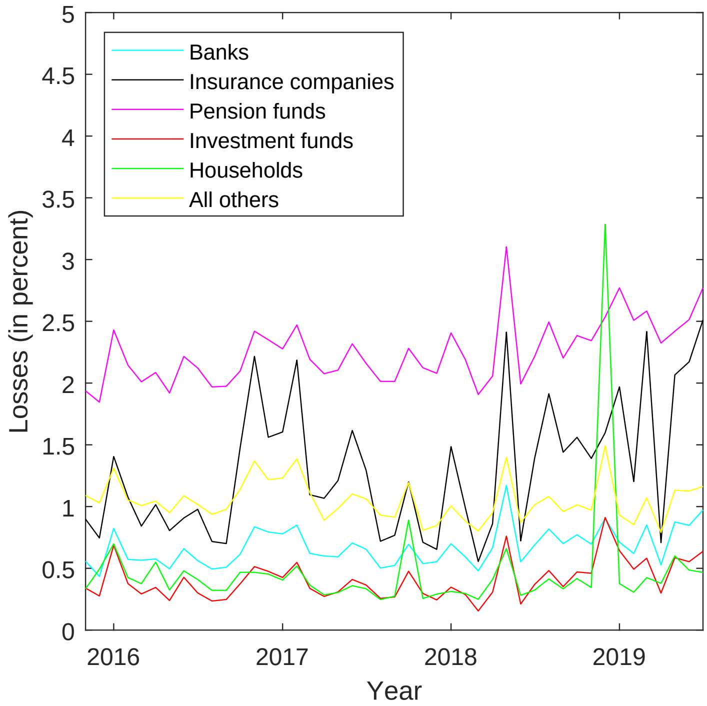
The results indicate that these portfolio losses fluctuate strongly over time and can reach up to 3.3% of a given sector's fund holdings. Pension funds and insurance companies tend to display the largest second round losses (average losses of 2.3% and 1.3% on their fund portfolios, respectively). This is not surprising given that these are the two largest investor groups in German investment funds, particularly so in (institutional) bond funds and mixed funds. The results also indicate that their hypothetical losses increased substantially from the end of 2016 onwards, when the FPR channel became relevant for institutional bond funds. Compared with other sectors, investment funds and households tend to display the smallest losses (average loss of 0.4% and 0.5% on their fund portfolios). However, households' hypothetical losses reached 3.3% in December 2018, since households tend to be the main investors in German retail equity funds, which were the main contributors to the AV during this period (cf. Figure 16). Figure 19 plots the second round losses for the different sectors from Figure 18 against the losses due to the initial shock (Step 0). For the sake of completeness, we also report the AV and initial shock size for the German fund sector as squares (denoted as Total). For example, for pension funds the second round losses can reach up to 50% of the initial shock.

Overall, the results indicate that spillover effects due to funds' connectedness tend to hit fund investor groups asymmetrically and can be substantial, even under non-stressed market conditions. Strikingly, we find that only about 4% of the fund sector losses would actually remain in the fund sector, but more than 75% of the overall losses would be borne by fund investors from the wider financial system. In other words, losses in the fund sector tend to propagate to non-fund financial intermediaries. Future research should therefore take a closer look at intersectoral effects of fund sector vulnerabilities.

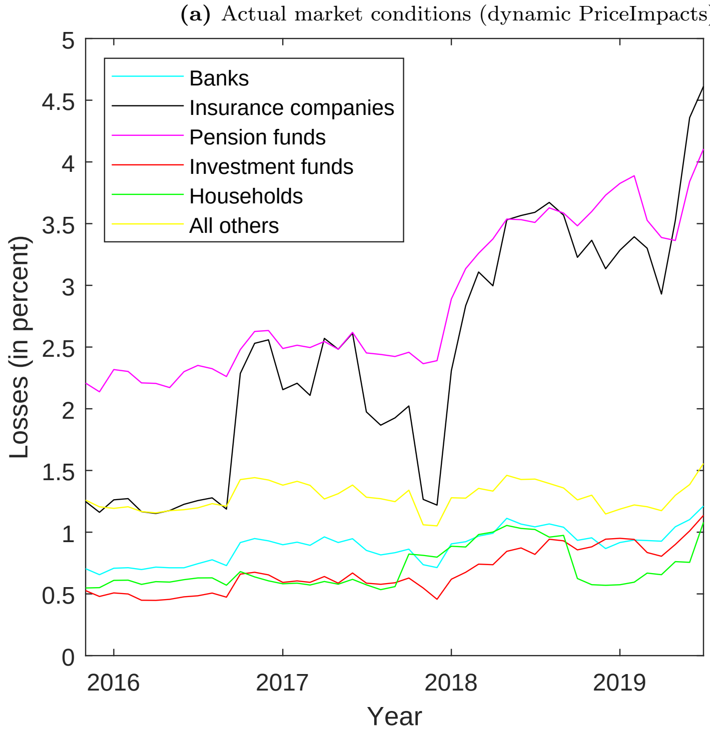
4.2.2 Stressed Market Conditions

Aggregate vulnerability over time. We now turn to the results for stressed market conditions (based on constant PriceImpact parameters at the asset-specific 90% percentile). Panel (b) of Figure 16 shows the AV of the German fund sector over time for this case. Not surprisingly, the AVs are substantially larger under stressed market conditions with an average value of 1.8% (ranging between 1.2% and 3.0%). On average, the AV amounts to losses that are on the order of 28% of the initial shock (ranging between 18% and 44%; cf. Figure 19). This suggests, that the fund sector could amplify losses during

[40] Note that this approach only takes into account losses on German fund shares that are held by these sectors. In future work, we also aim to make use of information on the bond and equity portfolios that are directly held by these sectors and estimate losses on these investments due to funds' asset liquidations.

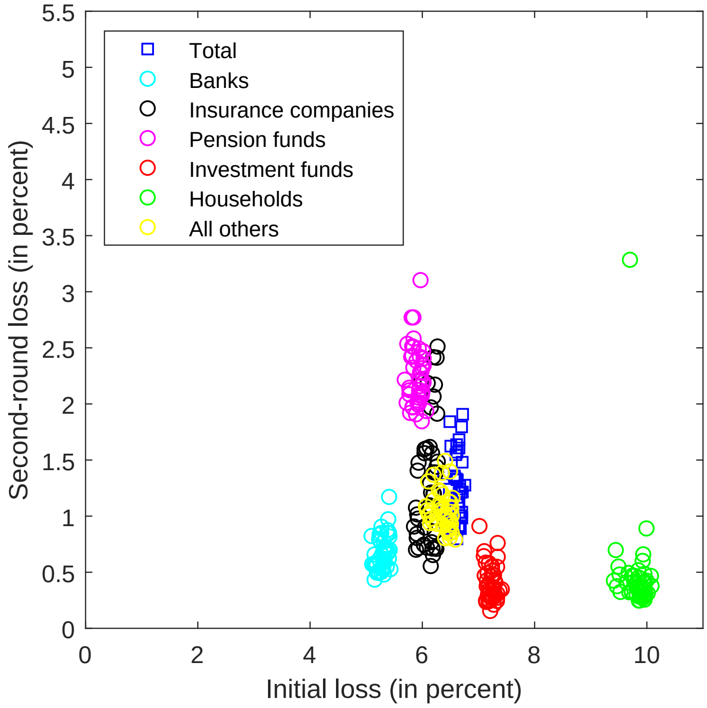


(a) Actual market conditions (dynamic PriceImpacts).

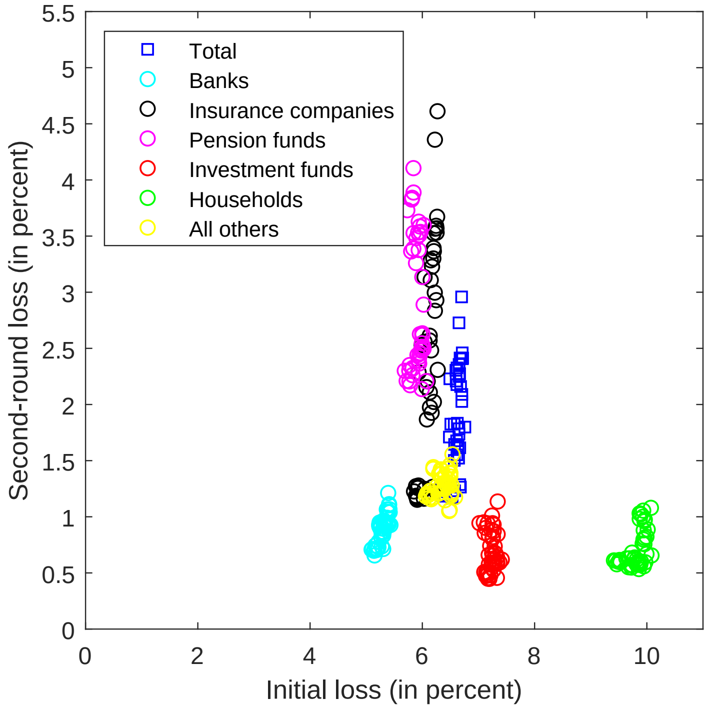


(b) Stressed market conditions (constant PriceImpacts, 90%-perc.).

Figure 18: Second round spillover portfolio losses, by sectors.



(a) Actual market conditions (dynamic PriceImpacts).



(b) Stressed market conditions (constant PriceImpacts, 90%-perc.).

Figure 19: Initial losses versus second round spillover portfolio losses, by sectors.

stressed market conditions more severely.

Note that the AV dynamics display an even stronger time trend, as the AV has increased by 140% (from 1.2% in November 2015 to 3.0% in July 2019). In line with the results under actual market conditions, Panel (b) of Figure D.3 in the Appendix shows that much of this growth is 'real': over the same period, the AV under fixed total assets would have roughly doubled (from 1.2% to 2.5%). In other words, at most 1/3 of the increase in the AV is purely due to the nominal growth of the fund sector.

As before, mixed funds and bond funds remain the chief contributors to the AV (relative contribution of 48% and 37%, respectively), while equity funds and funds-of-funds (relative contribution of 5.4% and 9.8%, respectively) play a much smaller role. Note that from early 2018 onwards, the relative contribution of institutional mixed funds increases, which is largely due to an increased use of financial leverage of these funds (the FPR-channel is switched off for these funds for the full application period, cf. Figures 11 and 12).[41] We find that the large increase in the AV at the end of the sample period is mainly due to an increasing FPR parameter for institutional bond funds and an increasing use of financial leverage for some institutional mixed funds.

Relative importance of the different channels. Panel (b) of Figure 17 shows the relative contribution of the different loss components under stressed market conditions. Given that funds' asset sales now have a stronger impact on market prices, the two fire sale components become more important. In this regard, the average relative contribution of the FPR component to the AV is 33.4% and that of the LT component is 19.7%, thus making up more than half of the overall AV. Losses due to cross-holdings remain important, with losses from Step 1 making up an average of 43.8% of the overall AV. Despite being somewhat lower, losses due to cross-holdings make up 6.2% and 5% of the overall losses of equity and bond funds, respectively. For mixed funds and funds-of-funds, the values are 26.2% and 91.6%, thus indicating that cross-holdings indeed matter from a financial stability perspective. Lastly, we should note that Panel (b) of Figure 17 also neatly illustrates how some of the observed variation in the AV is due to the time-dynamics of the FPR-channel (e.g., the jump in late 2016).

A Closer Look at Fund-Level Indicators. Similar to the results for the actual market conditions, we find that Systemicness is highly persistent (cf. Panel B of Table 8) and that more systemic funds tend to be more vulnerable. For example, the Pearson-correlation between fund-level Systemicness and relative losses is positively significant with a value of 0.18. Moreover, Panel B of Table 9 shows that funds with the highest Systemicness (decile 10) have a 72% probability to also show the largest losses. In other words, funds that are systemic also tend to be vulnerable.

Spillover effects to the broader financial system. In line with the results under actual market conditions, Panel (b) of Figure 18 shows that pension funds and insurance companies would bear the largest spillover losses due to their fund investments (average second round losses of 2.9% and 2.4% on their fund portfolios), with maximum losses

[41] This can be seen even more clearly when comparing the results in Panel (b) of Figure 16 with those in Panel (b) of Figure E.4 in the Appendix, where we use a constant FPR-parameter for all fund types ($\gamma = 0$ for all institutional funds).

reaching above 4%. In fact, much of the time dynamics in the overall AV in Panel (b) of Figure 16 appear to be driven by this set of fund investors. Again, households and investment funds tend to display the smallest losses (both showing average second round losses 0.7% on their fund portfolios). In most cases, however, we see a positive time trend in these hypothetical losses such that spillover effects to the broader financial system appear to become more relevant over time. Figure 19 shows that the second round losses for both pension funds and insurance companies can reach up to 70% of the losses due to the initial shock. Lastly, we again find that only about 4% of the fund sector losses would actually remain in the fund sector, while more than 75% of these losses would have to be borne by non-fund financial intermediaries.

4.3 Discussion

One of our key findings is that both the direct connectedness of investment funds and their pro-cyclical behavior may aggravate financial market stress. The estimated vulnerabilities are due to the fund sector's strong intra- and intersectoral connectedness. From a financial stability perspective, funds' intrasectoral connectedness is important since it facilitates the propagation of shocks through the fund sector. Funds' intersectoral connectedness then has additional effects on fund investors, most importantly the wider financial system.

Our analysis suggests that fund sector vulnerabilities are both driven by direct connections (cross-holdings), but also by indirect connections (portfolio overlap). Depending on the assumed market conditions, the relative importance of these two layers of connections may differ. In particular, direct connections tend to drive the fund sector's vulnerability in times of moderate market conditions. During stressed market conditions, indirect connections tend to matter more since funds' asset sales have larger price effects. In addition, vulnerabilities resulting from direct and indirect fund-level connections are interrelated: as funds' fire sales increase, so do funds direct losses via their cross-holdings. Overall, these findings suggest that funds' cross-holdings must be taken into account to accurately assess fund sector vulnerabilities. In addition, our finding that fund sector losses would largely be borne by non-fund financial intermediaries suggests that a system-wide view on fund sector vulnerabilities is needed.

We should stress that, while our estimated fund sector vulnerabilities can be substantial, we likely underestimate these vulnerabilities. This is for several reasons: first, our sample period is relatively brief and reflects a period with relatively modest market stress. It is therefore possible that the AVs could increase during prolonged periods of market stress. Second, our analysis only takes into account German investment funds. Of course, adding non-German investment funds to the model could increase the potential selling pressure during a stress event. Relatedly, our framework is flexible enough to include a broad variety of financial intermediaries (e.g., banks) to quantify financial sector-wide vulnerabilities. Third, when it comes to spillover losses to the wider financial system, we only discussed losses propagating to different holder groups via direct fund holdings. However, given the results of this paper, second round losses via common asset holdings can be substantial, especially during stressed market conditions. As such, non-fund financial intermediaries would incur additional losses on their asset portfolios, which we did not incorporate in our analysis. Fourth, as noted throughout the paper, our fund sector AV depends on the assumed initial shock. As such, a more severe stress scenario could affect the estimated vulnerabilities.

From a macroprudential policy perspective, two key aspects on the current agenda to limit fund sector vulnerabilities are i) curtailing funds' use of leverage, and ii) assuring that funds' asset portfolios are sufficiently liquid. In particular, proper asset liquidity management practices allow for smooth asset liquidations in the case of large fund investor redemptions. Accordingly, macroprudential policy discussions focused on both leverage limits and liquidity management tools (LMT), most importantly notice periods, redemption gates or swing pricing (see, e.g., Hanouna, Noval, Riley, and Stahel (2015); Financial Stability Board (2017)). The European Systemic Risk Board (2018) recently published recommendations directed towards the European Commission and the European Securities and Markets Authority (ESMA) to reduce risks to financial stability stemming from funds' liquidity transformation and use of leverage. These recommendations include, among other aspects, the introduction of EU-wide harmonized LMTs, a refinement of the already existing guidelines for funds' liquidity stress-testing and limiting measures for (alternative) investment funds' use of leverage. While ESMA already published guidelines for liquidity stress-testing, work on both guidelines for macroprudential leverage limits and the EU-wide harmonization of LMTs is ongoing. For example, it remains unclear whether fund managers would use LMTs adequately and sufficiently in case they were to fear negative signalling effects.[42] However, existing research suggests that swing pricing may be a useful tool for mitigating fund sector vulnerabilities (e.g., Capponi et al. (2018); Jin et al. (2019)). Looking forward, we believe that funds' cross-holdings should deserve further attention as our findings suggest that these matter for financial stability.

5 Conclusions

In this paper, we showed that the connectedness of the German fund sector matters for financial stability. We propose a novel approach to quantify fund sector vulnerabilities to both indirect (portfolio overlap) and direct (cross-holdings) connections between investment funds. In our empirical application, we show that the vulnerability of the German fund sector can be substantial and tends to increase over time. This suggests that the procyclical behavior of German funds could enforce adverse developments in global security markets. Furthermore, we document substantial spillover risks resulting from fund sector vulnerabilities, since the majority of fund sector losses would have to be borne by fund investors from the wider financial system. Of course, all of these results are subject to the assumed stress scenario and estimated vulnerabilities may differ substantially under alternative stress scenarios. Moreover, our stress test application covers a relatively brief sample period with relatively low levels of market stress. As such, the estimated vulnerabilities could be even larger during prolonged periods of stress.

We make an important step towards a system-wide view on fund sector vulnerabilities. Nevertheless, as discussed in our paper, our approach likely underestimates system-wide vulnerabilities, since we only include German investment funds. A natural next step would be to explicitly incorporate funds from other jurisdictions (e.g., Ireland and/or

[42] At the national level, additional LMTs have been introduced in Germany in March 2020, including redemption gates, notice periods, and swing pricing. Single asset managers can now include these in their funds' investment brochures which need to be approved by the German Federal Financial Supervisory Authority (BaFin).

Luxembourg) and additional financial intermediaries (most importantly banks). Given that our model is an extension of the banking fire-sale model of Greenwood et al. (2015), banks could be easily incorporated into the model. Lastly, we should also note that we currently assume that funds only liquidate bonds and equities under stress. In the future, we aim to explicitly incorporate fund share redemptions as a means for funds to obtain liquidity. Based on the network perspective of funds' cross-holdings that we have provided in this paper, it would be interesting to explore how large redemption shocks could propagate through this network. Based on the rich dataset at hand, it would also be possible to validate contagion mechanisms through funds' cross-holdings. Another aspect worth exploring is to what extent the increasing levels of direct connectedness among investment funds may lead to more homogeneous fund performances (see Fricke (2019)). For this purpose, the network perspective taken in this paper should provide a useful framework.

References

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctutations. *Econometrica 80*(5), 1977–2016.

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

Alter, A., B. R. Craig, and P. Raupach (2015). Centrality-based capital allocations. *International Journal of Central Banking 11(3)*, 329–377.

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

Antón, M. and C. Polk (2014). Connected stocks. *Journal of Finance 69*, 1099–1127.

Bao, J., J. Pan, and J. Wang (2011). The illiquidity of corporate bonds. *Journal of Finance 66*, 911–946.

Baranova, Y., J. Coen, P. Lowe, J. Noss, and L. Silvestri (2017). Simulating stress across the financial system: the resilience of corporate bond markets and the role of investment funds. Working Paper 42, Bank of England.

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

Bhattacharya, U., J. Lee, and V. Pool (2013). Conflicting family values in mutual fund families. *Journal of Finance 68*(1), 173–200.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizzon (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics 104*, 535–559.

Capponi, A., P. Glasserman, and M. Weber (2018). Swing Pricing for Mutual Funds: Breaking the Feedback Loop Between Fire Sales and Fund Runs. Working Paper 18-04, Office of Financial Research.

Castren, O. and I. K. Kavonius (2009). Balance sheet interlinkages and macro-financial risk analysis. ECB Working Paper No. 1124/2009.

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

Chernenko, S. and A. Sunderam (2020). Do fire sales create externalities? *Journal of Financial Economics (forthcoming).*

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

Dessaint, O., T. Foucault, L. Fresard, and A. Matray (2019). Noisy stock prices and corporate investment. *Review of Financial Studies 32*(7), 2625–2672.

Diebold, F. X. and K. Yilmaz (2014). On the network topology of variance decompositions: Measuring the connectedness of financial firms. *Journal of Econometrics 182*, 119–134.

Edmans, A., I. Goldstein, and W. Jiang (2012). The real effects of financial markets: The impact of prices on takeovers. *Journal of Finance 67*(3), 933–971.

European Systemic Risk Board (2018). Recommendation on liquidity and leverage risks in investment funds. Policy document.

Evans, R., M. P. Prado, and R. Zambrana (2020). Competition and cooperation in mutual fund families. *Journal of Financial Economics (forthcoming).*

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

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

Fricke, C. and D. Fricke (2020). Vulnerable asset management? The case of mutual funds. *Journal of Financial Stability (forthcoming).*

Fricke, D. (2019). Are specialist funds 'special'? *Financial Management 48*, 441–472.

Gaspar, J.-M., M. Massa, and P. Matos (2006). Favoritism in mutual fund families? evidence on strategic cross-fund subsidization. *Journal of Finance 61*(1), 73–104.

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

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

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

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

Hau, H. and S. Lai (2013). Real effects of stock underpricing. *Journal of Financial Economics 108*, 329–408.

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

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

Jin, D., M. T. Kacperczyk, B. Kahmaran, and F. Suntheim (2019). Swing pricing and fragility in open-end mutual funds. Working Paper 19/227, IMF.

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.

Newman, M. (2010). *Networks - An Introduction*. Oxford University Press.

Pagano, M., A. S. Serrano, and J. Zechner (2019). Can ETFs contribute to systemic risk? Reports of the Advisory Scientific Committee of the ESRB No. 9.

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

Appendix
(Connected Funds)

A Flow-Performance Relationship (FPR)

Dep. var.:	Equity funds		Bond funds		Mixed funds		Fund-of-funds	
$Flow_t$	Retail	Inst.	Retail	Inst.	Retail	Inst.	Retail	Inst.
$Return_{t-1}$	0.121***	0.010	0.191***	0.050	0.050***	0.009	0.053	0.066
	(0.015)	(0.020)	(0.035)	(0.031)	(0.013)	(0.009)	(0.040)	(0.052)
$Return_{t-2}$	0.040***	-0.009	0.023	0.047***	0.063***	0.009	-0.004	-0.019
	(0.013)	(0.017)	(0.030)	(0.014)	(0.012)	(0.007)	(0.029)	(0.055)
$Return_{t-3}$	0.027*	-0.005	0.026	0.021	0.060***	0.012*	-0.021	-0.038
	(0.014)	(0.020)	(0.029)	(0.016)	(0.013)	(0.007)	(0.024)	(0.056)
$Return_{t-4}$	0.014	-0.022	0.000	-0.002	0.051***	0.016**	-0.004	0.136
	(0.013)	(0.020)	(0.026)	(0.011)	(0.011)	(0.008)	(0.026)	(0.133)
$Return_{t-5}$	0.021	-0.025	0.043	0.031**	0.024*	-0.007	0.017	0.071
	(0.014)	(0.025)	(0.029)	(0.013)	(0.012)	(0.008)	(0.021)	(0.044)
$Return_{t-6}$	0.024*	-0.016	0.044	0.000	0.039***	0.004	-0.013	0.122*
	(0.012)	(0.020)	(0.029)	(0.014)	(0.012)	(0.007)	(0.024)	(0.068)
$Return_{t-7}$	0.019	-0.016	0.054**	0.015	0.038***	0.007	0.074***	-0.002
	(0.012)	(0.016)	(0.027)	(0.013)	(0.011)	(0.008)	(0.028)	(0.046)
$Return_{t-8}$	0.017	-0.014	0.031	0.016	0.042***	0.012	-0.038	-0.213**
	(0.013)	(0.036)	(0.031)	(0.012)	(0.013)	(0.007)	(0.023)	(0.106)
$Return_{t-9}$	0.003	-0.009	0.078***	0.005	0.021	0.020***	0.017	0.006
	(0.012)	(0.018)	(0.026)	(0.013)	(0.013)	(0.006)	(0.024)	(0.052)
$Return_{t-10}$	0.009	0.010	-0.006	0.010	0.014	0.019**	-0.041	-0.049
	(0.012)	(0.016)	(0.026)	(0.016)	(0.014)	(0.009)	(0.027)	(0.078)
$Return_{t-11}$	0.027**	0.035	0.088***	0.019	0.030**	0.008	0.040	0.015
	(0.012)	(0.026)	(0.030)	(0.015)	(0.014)	(0.008)	(0.026)	(0.049)
$Return_{t-12}$	0.010	-0.003	-0.024	-0.062***	0.028**	-0.033***	0.017	-0.127**
	(0.012)	(0.018)	(0.029)	(0.018)	(0.012)	(0.009)	(0.028)	(0.052)
$Flow_{t-1}$	0.076***	0.058***	0.123***	0.052***	0.125***	0.035***	0.065***	0.007
	(0.012)	(0.020)	(0.016)	(0.010)	(0.008)	(0.004)	(0.023)	(0.019)
$Flow_{t-2}$	0.051***	0.048***	0.053***	0.033***	0.081***	0.025***	0.083***	0.036**
	(0.009)	(0.018)	(0.011)	(0.006)	(0.008)	(0.003)	(0.019)	(0.017)
$Flow_{t-3}$	0.030***	0.004	0.043***	0.023***	0.061***	0.018***	0.028*	0.038**
	(0.008)	(0.007)	(0.010)	(0.006)	(0.006)	(0.002)	(0.016)	(0.015)
$Flow_{t-4}$	0.043***	0.007	0.037***	0.009*	0.067***	0.015***	0.041	0.001
	(0.007)	(0.009)	(0.012)	(0.005)	(0.007)	(0.003)	(0.026)	(0.010)
$Flow_{t-5}$	0.032***	0.003	0.055***	0.022***	0.045***	0.013***	0.016*	0.022***
	(0.011)	(0.005)	(0.012)	(0.007)	(0.005)	(0.002)	(0.009)	(0.008)
$Flow_{t-6}$	0.009	0.024**	0.009	0.018***	0.031***	0.008***	0.055***	0.015*
	(0.012)	(0.010)	(0.008)	(0.006)	(0.005)	(0.002)	(0.016)	(0.009)
$Flow_{t-7}$	0.003	0.006	0.042***	0.012	0.039***	0.008***	0.033**	0.032
	(0.008)	(0.009)	(0.013)	(0.008)	(0.006)	(0.003)	(0.013)	(0.023)
$Flow_{t-8}$	0.023**	0.013**	0.012	0.010**	0.016***	0.008***	0.051***	0.024
	(0.010)	(0.006)	(0.009)	(0.005)	(0.005)	(0.002)	(0.014)	(0.017)
$Flow_{t-9}$	0.030***	-0.006	0.011	0.022***	0.013**	0.009***	0.016	0.015*
	(0.010)	(0.007)	(0.009)	(0.006)	(0.005)	(0.003)	(0.011)	(0.008)
$Flow_{t-10}$	-0.011	0.013**	-0.001	0.013**	0.009	0.007***	0.006	0.027**
	(0.009)	(0.006)	(0.011)	(0.006)	(0.007)	(0.002)	(0.010)	(0.013)
$Flow_{t-11}$	0.013*	0.011	0.013	0.008	0.025***	0.008***	0.006	0.012
	(0.007)	(0.009)	(0.008)	(0.005)	(0.006)	(0.002)	(0.018)	(0.010)
$Flow_{t-12}$	0.027***	0.025***	0.030***	0.025***	0.015***	0.031***	0.044**	0.047***
	(0.007)	(0.008)	(0.009)	(0.006)	(0.004)	(0.005)	(0.017)	(0.014)
$\log(TNA_{t-1})$	0.000	0.000	-0.000	0.000	-0.000	-0.000**	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\log(Age_t)$	-0.002***	-0.001	0.000	-0.001**	-0.000	-0.001***	-0.002*	-0.003***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Time FEs	√	√	√	√	√	√	√	√
Obs.	60,025	25,117	43,510	82,730	88,892	315,174	26,020	9,949
adj. R^2	0.034	0.018	0.052	0.013	0.076	0.007	0.051	0.049

$*$ p<0.1; $**$ p<0.05; $***$ p<0.01

Table A.1: Flow-performance regressions with time-FEs and standard errors clustered by share-class (as in Goldstein et al. (2017)). Monthly data from January 2007 to July 2019.

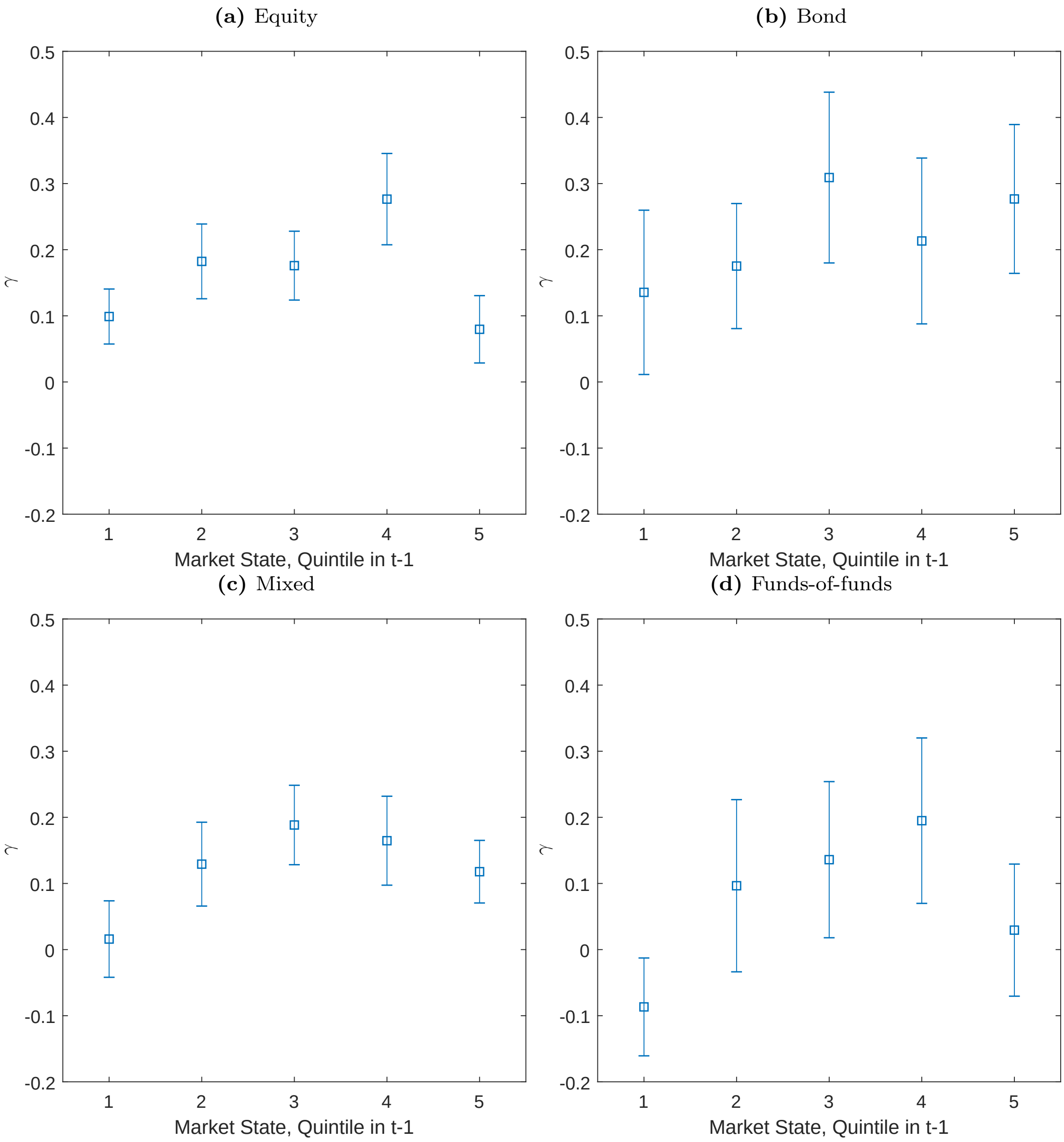


Figure A.1: Flow-performance sensitivity, by quintiles of the market return (retail funds only). Following Franzoni and Schmalz (2017), this Figure reports the average of the estimated γ_t, along with 95% confidence intervals, by quintiles of the realization of the market return (proxied by the TNA-weighted average fund return in each category) during the month when the fund performance was measured. The specification replicates the one in Table 1. In order to increase the statistical power of this excercise, this sample includes monthly data for the period January 1997 to July 2019.

Dep. var.:	Equity funds				Bond funds			
Flow_t	Retail		Inst.		Retail		Inst.	
	Moderate	Extreme	Moderate	Extreme	Moderate	Extreme	Moderate	Extreme
$\textbf{Return}_{t-1}$	0.193***	0.104**	0.065	-0.100	0.202***	0.193**	0.019	0.015
	(0.028)	(0.039)	(0.044)	(0.063)	(0.057)	(0.077)	(0.034)	(0.037)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Flow_{t-1}	0.099***	0.097***	0.070**	0.077*	0.143***	0.155***	0.058***	0.062***
	(0.013)	(0.029)	(0.031)	(0.043)	(0.016)	(0.024)	(0.012)	(0.016)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$\log(\text{TNA}_{t-1})$	-0.000	-0.000	0.000	-0.000	-0.001*	-0.001	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
$\log(\text{Age}_t)$	-0.002**	0.001	-0.001	-0.001	0.000	0.001	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Fama-MacBeth	√	√	√	√	√	√	√	√
Obs.	47,513	12,081	19,960	5,357	35,555	8,658	66,515	16987
adj. R^2	0.205	0.223	0.304	0.271	0.240	0.249	0.127	0.080

	Mixed funds				Funds-of-funds			
	Retail		Inst.		Retail		Inst.	
	Moderate	Extreme	Moderate	Extreme	Moderate	Extreme	Moderate	Extreme
$\textbf{Return}_{t-1}$	0.162***	0.149***	0.007	0.017	0.175***	-0.062	-0.271	0.216
	(0.032)	(0.046)	(0.014)	(0.027)	(0.064)	(0.101)	(0.288)	(0.191)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
Flow_{t-1}	0.164***	0.148***	0.046***	0.022**	0.100***	0.122***	0.032	0.269
	(0.014)	(0.029)	(0.005)	(0.010)	(0.026)	(0.040)	(0.088)	(0.261)
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
$\log(\text{TNA}_{t-1})$	-0.000	-0.001*	-0.000***	-0.000	-0.000	0.000	-0.002	0.003
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)	(0.002)
$\log(\text{Age}_t)$	-0.001*	0.000	-0.001***	0.000	-0.001	0.002	0.001	-0.004
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)	(0.002)	(0.003)
Fama-MacBeth	√	√	√	√	√	√	√	√
Obs.	74,705	15,246	253,715	63,310	20,975	5,219	8,342	1,703
adj. R^2	0.199	0.219	0.035	0.037	0.470	0.427	0.599	0.730

$*$ p<0.1; $**$ p<0.05; $***$ p<0.01

Table A.2: Flow-performance regressions, based on monthly data using Fama-MacBeth regressions. The specification is the same as in Table 1, but differentiates between periods with moderate/extreme market returns (below/above 5% in absolute value). As market return we use the monthly return during month $t-1$ on the European stock market provided by Ken French. Monthly data from January 2007 to July 2019.

B Leverage Targeting

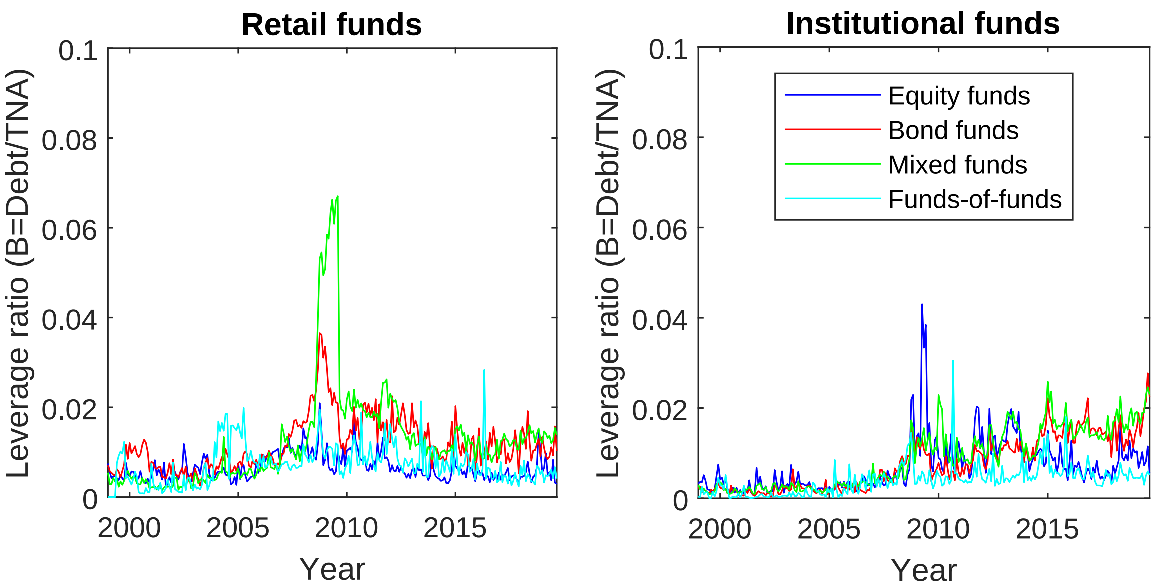


Figure B.2: Cross-sectional median leverage ratio over time. Note: maximum regulatory leverage is 0.1 for retail funds and 0.3 for institutional funds.

Dep. var. $\%\Delta\text{Leverage}_t^{\text{gross}}$	Equity funds Retail	Equity funds Inst.	Bond funds Retail	Bond funds Inst.	Mixed funds Retail	Mixed funds Inst.	Fund-of-funds Retail	Fund-of-funds Inst.
$\log(\textbf{Leverage}_{t-1}^{\text{gross}})$	-0.510***	-0.460***	-0.262***	-0.439***	-0.118***	-0.332***	-0.649***	-0.239***
	(0.034)	(0.042)	(0.025)	(0.034)	(0.011)	(0.013)	(0.028)	(0.039)
$\%\Delta\text{TotalAssets}_t$	0.025***	0.040***	0.048***	0.071***	0.082***	0.117***	0.068***	0.116***
	(0.004)	(0.011)	(0.005)	(0.018)	(0.010)	(0.019)	(0.014)	(0.030)
Flow_{t-1}	0.000	0.001	-0.010***	-0.006***	-0.010***	-0.001	0.002	-0.002
	(0.001)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.005)	(0.004)
$\log(\text{TotalAssets}_{t-1})$	-0.000	0.001	0.002***	0.002***	0.001***	0.001**	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
CashRatio_{t-1}	0.005*	0.010**	0.001	0.001	0.009***	0.003*	0.004	0.003
	(0.003)	(0.004)	(0.006)	(0.003)	(0.003)	(0.002)	(0.005)	(0.005)
Fund FEs	√	√	√	√	√	√	√	√
Time FEs	√	√	√	√	√	√	√	√
Obs.	64,531	22,446	46,346	67,702	102,926	277,138	27,821	9,569
adj. R^2	0.246	0.207	0.156	0.290	0.117	0.169	0.300	0.216

$*$ p<0.1; $**$ p<0.05; $***$ p<0.01

Table B.3: Regression results. Leverage targeting. (robust std. errors in parentheses). Monthly data from January 2007 to July 2019.

C Determinants of the Fund Sector's AV

The fund sector's AV is a combined risk indicator summarizing information from several standard macroprudential risk indicators of investment funds. In this section we provide a first indication about which of these indicators might be major determinants of our AV measure. For this purpose, we are interested in the following linear regression:

$$\Delta \mathrm{AV}_t = a + b \times \Delta X_t, \tag{40}$$

where X_t includes the set of factors that drive the level of the AV (see Figure 6):

- *Leverage* is the weighted cross-sectional average fund leverage,
- *FundingInstability* is the weighted cross-sectional average FPR parameter γ,
- *DirectConnectedness* is funds' aggregated fund holdings relative to their total assets,
- *IndirectConnectedness* is funds' aggregated marketable asset holdings relative to their total assets,
- *MarketIlliquidity* is the portfolio-weighted cross-sectional average PriceImpact parameter,
- we also add *Size* as another control variable, which is the fund sector's total assets.

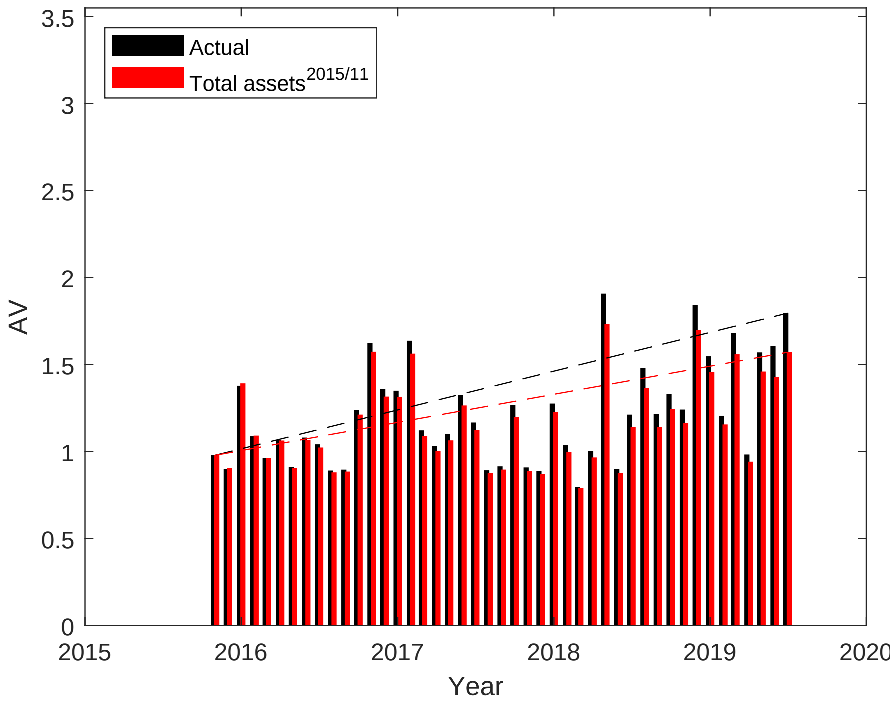
Dep. var.:	Market Conditions	
ΔAV	Actual	Stressed
ΔLeverage	0.302**	0.154***
	(0.123)	(0.049)
ΔFundingInstability	0.312***	0.592***
	(0.027)	(0.056)
ΔDirectConnectedness	4.438***	0.135
	(1.115)	(0.466)
ΔIndirectConnectedness	5.159*	0.306
	(3.074)	(1.275)
ΔMarketIlliquidity	0.311***	0.658
	(0.029)	(0.824)
ΔSize	-2.985*	0.717
	(1.655)	(0.668)
adj.-R^2	0.844	0.802
Obs.	44	44

$*$ p<0.1; $**$ p<0.05; $***$ p<0.01

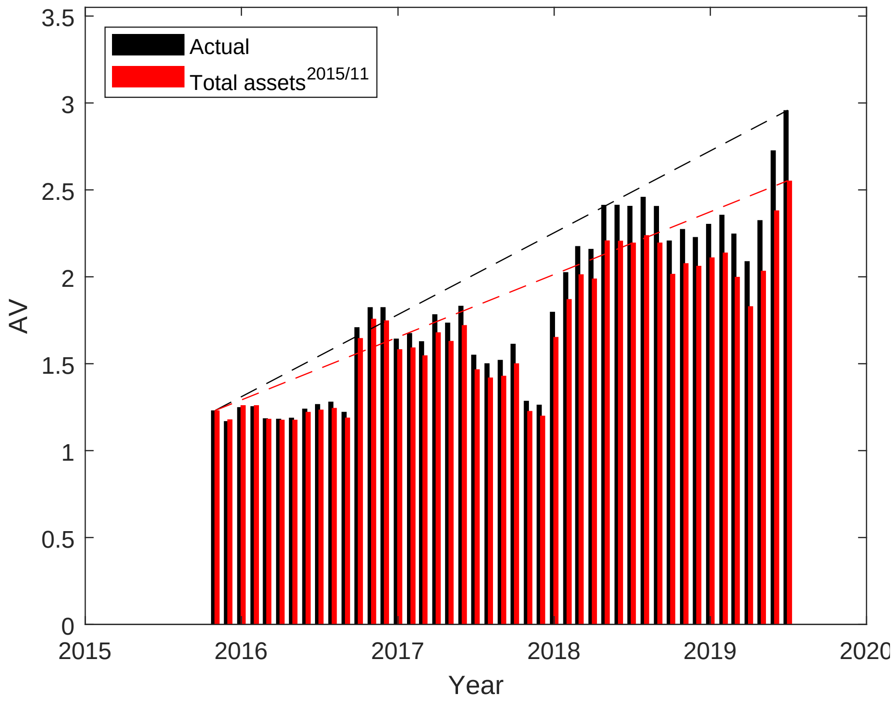
Table C.4: AV determinants for actual and stressed market conditions. Based on linear regressions (std. errors in parentheses). Monthly data from November 2015 to July 2019.

We estimate the linear regression in Equation (40) using monthly log-changes. Table C.4 shows the results. As expected, the model captures a substantial part of the AV variation, given a model fit of more than 80%. Under actual market conditions, the AV is mainly driven by leverage, funding instability, direct connectedness, and market illiquidity. Consistent with the rationale provided in Figure 6, an increase in these underlying factors goes along with an increase in the fund sector's AV. Under stressed market conditions, fund leverage and funding instability are the key drivers of the AV. As expected, market illiquidity no longer plays a role, given that this specification fixes the asset-specific PriceImpacts. This is also the reason why funds' direct connectedness becomes insignificant. We should stress, however, that the two connectedness indicators are imperfect and thus only serve as proxies for the connectedness of the fund sector.

D AV for Constant Total Assets



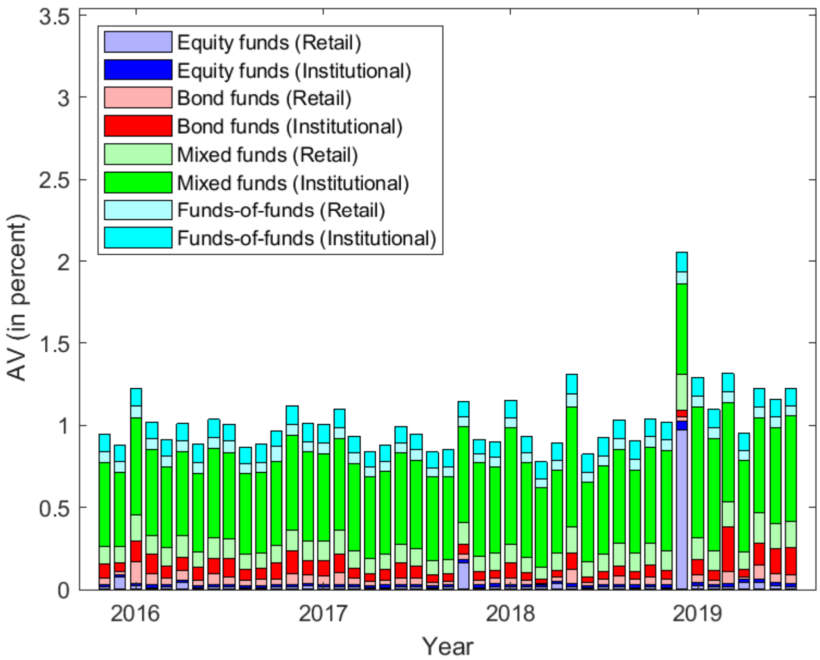
(a) Actual market conditions (dynamic PriceImpacts).



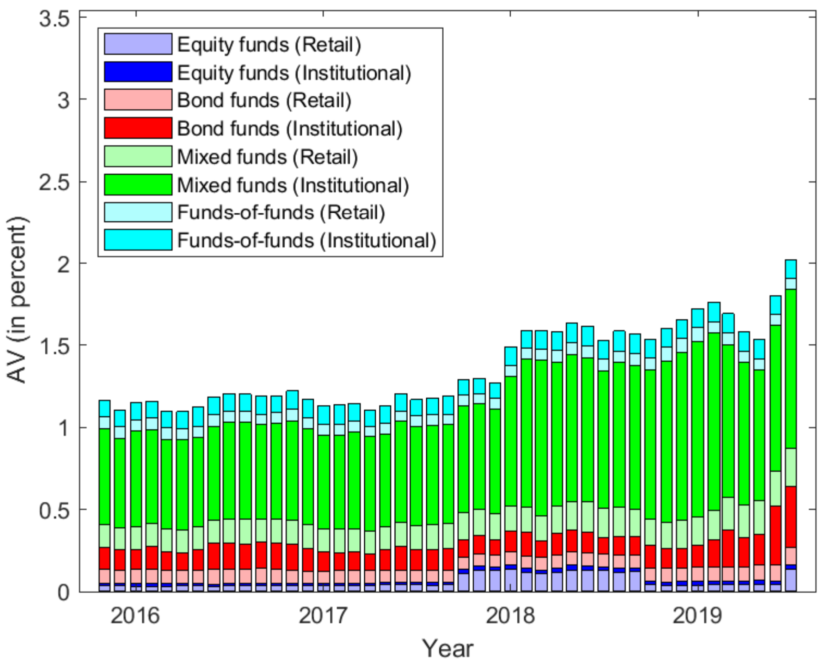
(b) Stressed market conditions (constant PriceImpacts, 90%-perc.).

Figure D.3: AV and time trend under constant aggregate total assets, fixed to the value in November 2015.

E AV for Constant FPR

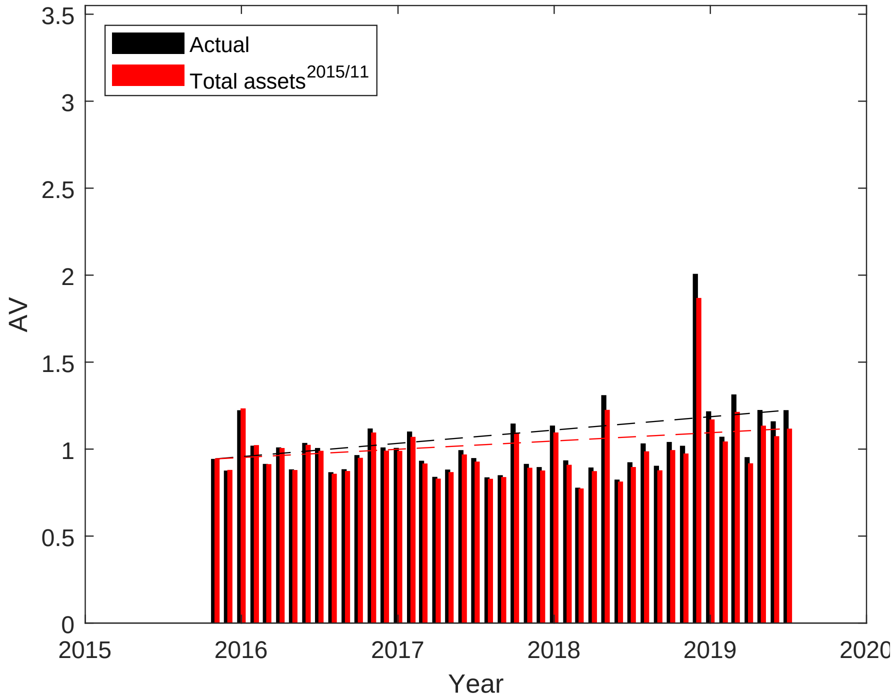


(a) Actual market conditions (dynamic PriceImpacts).

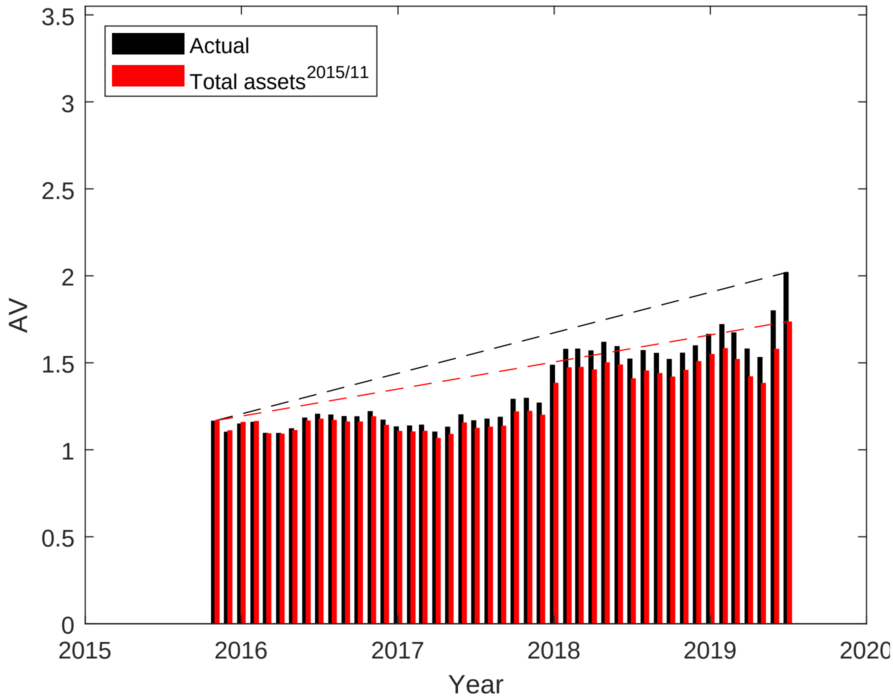


(b) Stressed market conditions (constant PriceImpacts, 90%-perc.).

Figure E.4: AV over time based on constant FPR (point estimates in Table 1). We apply the model separately for each month. The asset-level initial shock is -4.48% for bonds and -14.16% for equities. Contribution by fund type is based on aggregating the fund-level Systemicness measure in Eq. (31).

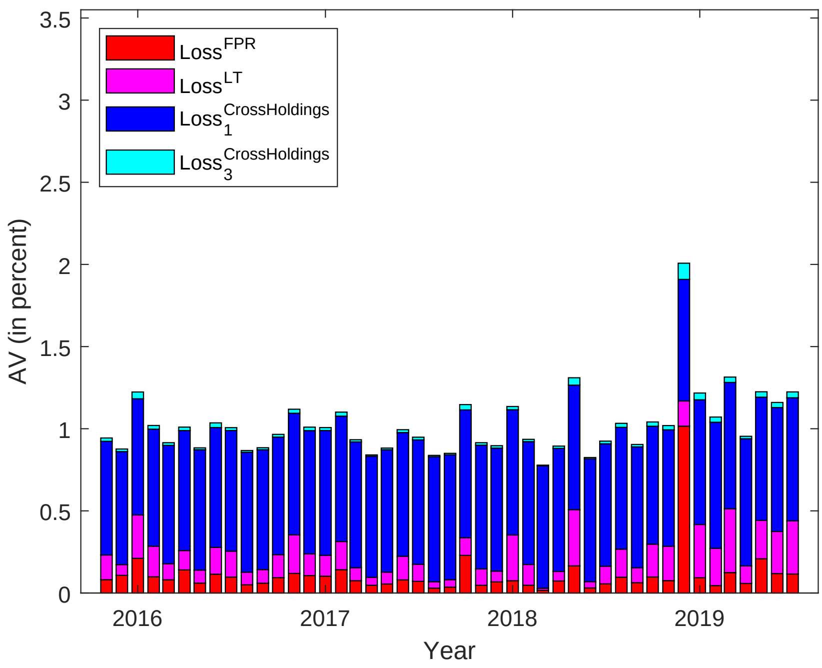


(a) Actual market conditions (dynamic PriceImpacts).

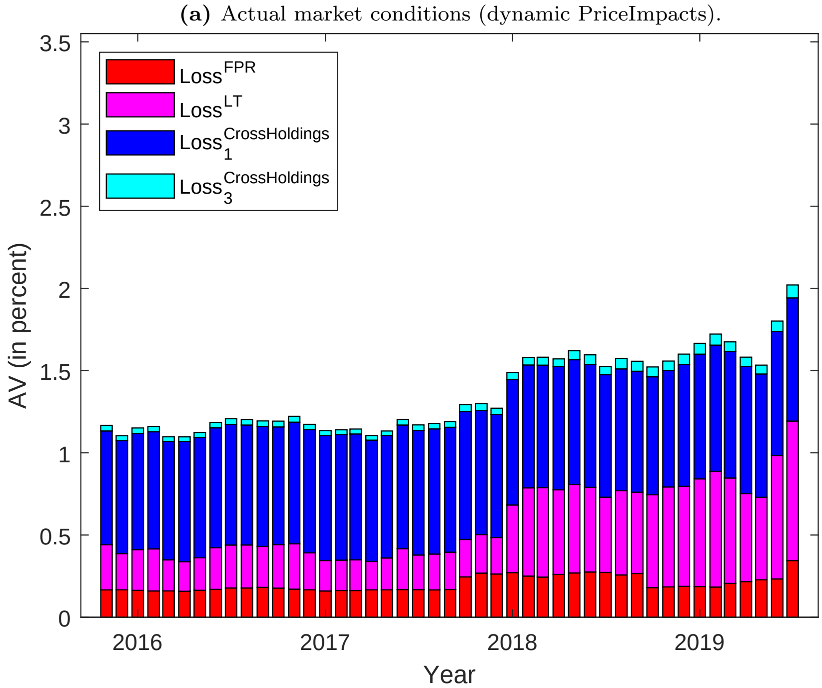


(b) Stressed market conditions (constant PriceImpacts, 90%-perc.).

Figure E.5: AV and time trend under constant aggregate total assets, fixed to the value in November 2015 (constant FPR).



(a) Actual market conditions (dynamic PriceImpacts).



(b) Stressed market conditions (constant PriceImpacts, 90%-perc.).

Figure E.6: Relative contribution of the different channels to the AV (constant FPR).