Who creates and who bears flow externalities in mutual funds?

November 18, 2021

Abstract

Using a unique dataset on the sectoral ownership structure of euro area equity mutual funds, we study how different investor groups contribute to the negative externality on performance resulting from large outflows. Investment funds, as holders of mutual funds, are the main contributors to the flow externality. Insurers and households, in particular less financially-sophisticated ones, are the main receivers. These differences are due to investment funds reacting more strongly on past fund performance and displaying a more pro-cyclical investment behavior compared to households and insurers. Our results raise concerns regarding consumer protection and financial stability due to the trading activity of short-term oriented investors.

Keywords: asset management; mutual funds; externalities; contagion; performance.

JEL classification: G10; G11; G23.

1 Introduction

Investors in open-ended mutual funds can redeem their shares on any given day at the fund's closing net asset value. While this mechanism provides redeeming fund investors with liquidity, in specific circumstances it creates a negative externality for investors remaining in the fund: when faced with large outflows, fund managers may need to liquidate parts of their asset portfolios, which results in downward pressure on these assets' market prices (e.g., Coval and Stafford, 2007; Manconi, Massa, and Yasuda, 2012; Antón and Polk, 2014). Since fund managers typically spread the corresponding portfolio adjustments over multiple business days following the redemption, the corresponding portfolio losses induced by redeeming investors are borne by those investors remaining in the fund (Jin, Kacperczyk, Kahraman, and Suntheim, 2021). These flow-induced externalities give rise to first-mover advantages and run risks in mutual funds. Prior work provides robust evidence on the existence of negative externalities from large outflows in mutual funds (Edelen, 1999; Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017).[1] What has not yet been studied, however, is which investors create and which investors bear the flow externality. Our paper seeks to fill this gap.

Studying this question requires information on the ownership structure of mutual funds, which has been unavailable so far.[2] In this paper we use a unique dataset on the sectoral ownership structure of mutual funds in the euro area. In particular, we merge information from Morningstar with the Eurosystem's sectoral Securities Holdings Statistics (SHS-S), which provides quarterly mutual fund holdings from the most relevant economic sectors, such as households, insurers, investment funds, pension funds, banks and non-financial corporations (see e.g., Koijen, Koulischer, Nguyen, and Yogo, 2021). This rich information allows us to study behavioral heterogeneities not only between

[1]This paper focuses on within-fund externalities. A different strand of the literature explores fire sale externalities across funds with similar asset portfolios (Chernenko and Sunderam (2020); Falato, Hortacsu, Li, and Shin (2020)).

[2]An important exception is Jin et al. (2021), which draws on information on investors' holdings of UK bond funds categorized into retail and institutional investors. Our paper complements this study by analyzing distinct heterogeneities among institutional investor sectors.

households and institutional investors but also within the group of institutional investors.[3]

We develop an empirical framework to quantify each sector's net externality on fund-level when large outflows occur. The intuition is as follows: how much a sector contributes to the fund-level externality is equal to its relative share of a fund's large outflows. How much a sector absorbs of the externality is equal to its relative holdings share after the outflows occurred. To assess whether a sector – on net – originates or receives the flow externality over and beyond what is to be expected we compare it against the null hypothesis that assumes a uniform flow behavior across all investor sectors. We show that if all sectors redeemed their fund shares proportional to their holdings, the net externality of each sector, defined as the difference between the externality received and the externality originated, is zero. We test the estimated net externality of each investor sector against this null hypothesis. Furthermore, the empirical framework provides a network perspective on the flow externality that highlights how different sectors affect each other through their redemption patterns. Our methodology accounts for differences in holdings overlap across sectors and for the possibility that the degree to which flows can be anticipated may vary across sectors.

Within our framework, we study the net externality of different investor sectors in relatively illiquid equity mutual funds (small-/mid-cap holdings in the top 25% across the full sample) that experience large outflows (quarterly net outflows of more than 10% of their total net assets, TNA). For these funds we estimate an overall flow externality of –45 bps on their performance in the following quarter. We find that investment funds are the main drivers of this flow externality. The fund sector originates a flow externality of –15 bps and receives only –4 bps. This results in an statistically significant net externality (received minus originated) of +11 bps by the investment fund sector. In other words, investment funds are net originators of the flow externality in mutual funds. Interestingly,

[3]Such detailed sector-level ownership information provides several advantages compared to prior work typically relying on more coarse-grained fund classifications that mainly distinguish retail from institutional funds. These approaches may understate differences if the actual ownership structure of a share class is not fully aligned with its classification (retail/institutional). Indeed, our granular ownership data reveals that even some retail share classes are in fact predominantly held by institutional investors.

the investment fund sector's fund holdings are not primarily due to the category of funds of funds, but rather due to conventional funds that may also invest in mutual funds (Fricke and Wilke, 2020). Furthermore, mainly institutional funds invest in other mutual funds.[4] This justifies viewing externalities from the investment fund sector as externalities from institutional investors. In any case, our results show that a cascading structure of fund ownership, namely funds holding other funds' shares, increases flow externalities.

The main receivers of the flow externality are households and insurers. Representing the largest holder group, households originate –22 bps of the externality, but absorb even –30 bps. Consequently, their net externality amounts to –8 bps, which is also statistically significantly different from zero. Our network analysis corroborates strong linkages between investment funds and households: 44% of the excess externality originating from investment funds is absorbed by the household sector. Interestingly, insurers, the second largest holder group, also tend to be at the receiving end of the flow externality. They originate only –3 bps of the externality, but receive –6 bps. Even though their net externality of –3 bps is not statistically significant, the economic magnitude is sizable. In relative terms, the amount of externality originated by insurers is only half of what would be expected dependent on their holdings share. Comparing insurers and investment funds also highlights important behavioral heterogeneities within the group of institutional investors: even though insurers and investment funds display roughly similar aggregate mutual fund holdings, investment funds' contribution to the flow externality is about five times larger than the contribution of insurers (–15 bps versus –3 bps).

In further analyses we study why households and insurers over-proportionally absorb the flow externality in mutual funds. First, we decompose households' contribution to the flow externality according to households' level of financial sophistication. For this purpose, we exploit that funds' minimum investment amounts acts as an entry barrier for less-wealthy households, which have been documented to be less financially sophisticated (Campbell, 2006; Calvet, Campbell, and Sodini, 2007, 2009a,b). We find that only in share

[4]For further information, see Figure IA.1 in the Internet Appendix.

classes with a low minimum investment amount households are net externality receivers, suggesting that lack of financial sophistication places large parts of the household sector at the receiving end of the flow externality. We also explore whether conflicts of interest in insurer-affiliated asset management companies might explain the trading behavior of the insurance sector. However, even in unaffiliated funds, insurers tend to be net receivers of the flow externality. This suggests that their generally longer investment horizon (Gaspar, Massa, and Matos, 2005; Becker and Ivashina, 2015; Timmer, 2018) explains the fact that insurers are net receivers of the negative flow externality.

Indeed, we find striking differences in the trading behavior across sectors. Investment funds – the main originators of the flow externality – are rather short-term investors, reshuffling their fund holdings very actively. Moreover, they exhibit a strong and concave flow-performance relationship. The investment fund sector displays particularly large redemptions during market distress periods, such as the COVID-19 market crash, when funds' portfolio liquidity tends to be low and, hence, flow externalities tend to be large. In contrast, households and insurers – the main receivers of the flow externality – tend to act much more long-term oriented, since they exhibit a significantly lower portfolio turnover. Both sectors' flow-performance relationship is weaker and convex in shape. They show considerably less cyclical flow behavior and their outflows were limited even during the COVID-19 episode.

Lastly, the holdings data reveals a novel stylized fact regarding institutional investors' preferences. Unlike direct investments of institutional investors, which are tilted towards large and liquid stocks (Gompers and Metrick, 2001; Ferreira and Matos, 2008), their indirect investments through mutual funds are tilted towards relatively illiquid stocks. This is especially so for investment funds, which seem to value other funds' knowledge on certain small-cap segments and their liquidity transformation services.

Taken together, our findings raise consumer protection and financial stability concerns regarding open-ended mutual funds. While their open-ended structure caters to the liquidity preferences of certain institutional investors, this liquidity is actually involuntarily provided by investors remaining in mutual funds when large outflows occur. Our study shows that retail investors, in particular less financially sophisticated households, provide this liquidity, since they absorb most of the flow externality created by investment funds. To add insult to injury, households pay substantially higher fees compared to investment funds. Moreover, financial stability issues may arise due to the fact that investment funds' fund redemptions exert pressure on insurers fund investments, especially so during crisis times.

Our paper contributes to several streams of the literature. First and foremost, our paper adds to the literature on fund flow externalities (e.g., Chen et al. (2010); Goldstein et al. (2017)). While it has been acknowledged that the ownership structure of funds may be an important determinant of fund-level externalities, our paper is the first to take an investor-sector-specific perspective on flow externalities. In line with the existence of clientèle effects, we find substantial heterogeneity between different investor sectors' net externality contributions. Notably, our paper is the first to take a network perspective on fund flow externalities. Especially, we can identify the share of one investor sector's externality received that is due to the flows of another sector. Hereby, we add to a large literature on contagion in economic (Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi, 2012) and financial networks (Elliott, Golub, and Jackson, 2014; Acemoglu, Ozdaglar, and Tahbaz-Salehi, 2015).

More broadly, our paper adds to the literature on the role of investment horizons in financial markets. Much work has been devoted to the question of how corporate governance depends on a company's ownership structure and whether higher ownership by short-term investors is harmful for long-term performance (Froot, Perold, and Stein, 1992; Graham, Harvey, and Rajgopal, 2005; Gaspar et al., 2005; Giannetti and Yu, 2021). We contribute to this literature by showing that the trading activity of (short-term oriented) investment funds in mutual funds is harmful to (longer-term oriented) investors like insurers. In line with previous work (Timmer, 2018), we document substantial cross-sectional variation in the trading behavior of different institutional sectors. Given their relatively short-term liabilities, investment funds trade their fund shares more actively and behave much more pro-cyclical compared to other more longer-term oriented investors. These behavioral differences shed light on why certain investor sectors originate or absorb more externalities than others.

Lastly, our paper adds to the literature on structural vulnerabilities in the fund sector (Coval and Stafford (2007); Chernenko and Sunderam (2020); Falato et al. (2020)). In particular, Fricke and Wilke (2020) document an increasing trend of investment funds to invest into other funds' shares and show that this development may amplify fire sale losses within the fund sector. In line with this literature, we find that investment funds constitute a relatively sophisticated investor sector that tends to react rather pro-cyclically and drives a large part of the estimated flow externalities. In addition, a growing body of literature investigates instruments to internalize these externalities, such as swing pricing (Capponi, Glasserman, and Weber (2020); Jin et al. (2021)). While these instruments are only slowly becoming available to funds in the euro area, our findings suggest that investment funds as fund investors should be an important target for such pricing rules.

2 Data and variable construction

2.1 Data sources

For our empirical analysis we merge a broad array of fund characteristics from Morningstar with the Eurosystem's Securities Holdings Statistics by Sector (SHS-S), which provides investors' securities holdings as reported by euro area custodians.

We start with Morningstar's universe of equity mutual funds domiciled and available-for-sale in the euro area that fall under the harmonized EU regulatory framework (Undertakings for the Collective Investment in Transferable Securities, UCITS). We focus on actively-managed funds, i.e., we exclude index funds and exchange-traded funds. We also exclude fund-of-funds, sector funds, and emerging market funds. We drop observations with missing total net assets (TNA), return, or expense ratio and observations with falsely reported (i.e., negative) or implausibly large expense ratios. Following the literature, we apply several standard data filters. To mitigate incubation bias, we drop funds younger than two years and also drop all observations prior to a fund reaching a TNA of five million Euros for the first time (Franzoni and Schmalz (2017)). We apply the TNA reversal filter of Pastor, Stambaugh, and Taylor (2013). We conduct our analyses at different aggregation levels, i.e., at the fund level and/or at the share class level. When working with fund-level data, we aggregate information that varies across share classes (e.g., expense ratios) using TNA-weighted averages.

We merge the Morningstar data with share class (ISIN) level holdings data from the SHS-S which provides information about investors' fund holdings reported by euro area custodians. The SHS-S data are available at the quarterly frequency from 2013:Q4 onwards and the sectoral classification is based on the European System of Accounts (ESA) 2010. We focus on the main investor sectors of our sample funds, namely *households* (ESA Codes S 14 and S 15), *investment funds* (S 124), *insurers* (S 128), *pension funds* (S 129), *banks* (S 122) and *non-financial companies* (S 11). We aggregate smaller investor sectors in a category labeled as *others*. Since fund shares may be held at custodians outside the euro area, we define a residual investor sector labeled *foreign* (Koijen et al., 2021). We treat investment funds as an institutional sector throughout the paper, since mainly institutional funds invest in other mutual funds.[5]

Our final sample covers 27 quarters over the period 2013:Q4 up until 2020:Q2. For the merged Morningstar/SHS-S dataset, we ensure a high matching quality between the TNA reported by Morningstar and the total holdings reported in the SHS-S. Specifically, we drop fund-quarter observations where the SHS-S holdings exceed the Morningstar TNA by more than 5%. Moreover, we focus on funds that are sufficiently covered in terms of their holdings information. Many funds that are both domiciled and available-for-sale in the euro area are also marketed to investors outside the euro area, particularly so for certain offshore domiciles such as Ireland and Luxembourg. In such cases, SHS-S coverage might

[5]For further information, see Figure IA.1 in the Internet Appendix.

be lower as offshore investors might hold their securities at offshore custodians (which do not report into the SHS-S). To this end, we drop funds for which the reported SHS-S holdings are below 75% of the TNA in Morningstar on average across the full sample.[6]

The final dataset comprises 7,722 share classes managed in 2,597 funds and a total number of 45,643 fund-quarter (114,949 share class-quarter) observations. Table 1 reports the number of funds and share classes for our sample as well as the aggregate TNA by domicile and country available-for-sale as of December 2019, i.e. before the COVID-19 market crash. Overall, the funds in our sample manage 502 bn EUR as of December 2019. Looking at Panel A, Luxembourg, Germany and France represent by far the three largest domiciles in our sample both in terms of TNA and number of funds. Panel B provides a breakdown by country available-for-sale and shows that the distribution across countries is much more balanced and in line with country size. Note that there is a substantial share of funds (in terms of TNA, 242 bn EUR out of 502 bn EUR) that are also available-for-sale in at least one country outside the euro area.

2.2 Variable definitions

We now introduce the key variables used throughout the paper. Our dataset contains funds' detailed ownership structure at quarterly frequency which allows us to expand the standard formula for implied fund flows (e.g. Sirri and Tufano, 1998) and calculate the implied flows of different investor sectors within the same fund. Specifically, we calculate investor sector i's Euro net flows in fund f during quarter t as follows:

$$EuroFlows_{t,f,i} = \mathrm{TNA}_{t,f,i} - \mathrm{TNA}_{t-1,f,i}\left(1 + \mathrm{Return}_{t,f}\right), \tag{1}$$

where we denote $EuroFlows_{t,f,i}$ as investor sector i's Euro net flows in fund f during quarter t, $TNA_{t,f,i}$ as investor sector i's total euro holdings in fund f in quarter t, and $\mathrm{Return}_{t,f}$ as the fund's return. Naturally, summing over all investor sectors i gives the

[6]This corresponds to excluding funds where to the residual sector *foreign* holds more than 25% of the TNA in Morningstar on average across the full sample.

fund's overall implied flows: $\text{EuroFlows}_{t,f} = \sum_i^K \text{EuroFlows}_{t,f,i}$

We standardize sector-specific fund flows based on two different approaches to generate relative sector-specific flows. The first approach standardizes the $EuroFlows$ of investor sector i using the lagged total TNA of fund f:

$$RelFlows^a_{t,f,i} = \frac{\text{EuroFlows}_{t,f,i}}{\text{TNA}_{t-1,f}}. \tag{2}$$

$RelFlows^a_{t,f,i}$ measures the relative importance of each investor sector's flows to the fund. Note that these sector-specific relative flows sum up to the total relative flows of the fund:

$$RelFlows_{f,t} = \sum_i^K \text{RelFlows}^a_{t,f,i} = \frac{\text{EuroFlows}_{t,f}}{\text{TNA}_{t-1,f}}. \tag{3}$$

The second approach standardizes sector-specific flows using each investor sector's lagged holdings in fund f:

$$RelFlows^b_{t,f,i} = \frac{\text{EuroFlows}_{t,f,i}}{\text{TNA}_{t-1,f,i}}, \tag{4}$$

where $RelFlows^b_{t,f,i}$ measures how strongly investor sector i increases or decreases its own position in a specific fund. Substituting Eq. (2) into Eq. (4) gives us the relationship between the two relative flow measures:

$$RelFlows^a_{t,f,i} = RelFlows^b_{t,f,i} \left(\frac{TNA_{t-1,f,i}}{TNA_{t-1,f}} \right). \tag{5}$$

This relationship is useful to understand how flow contributions would behave under the null hypothesis of uniform flow behavior across all investor sectors. If all investor sectors displayed exactly the same percentage flows, relative to their own TNA, we can write $\text{RelFlows}^b_{t,f,1} = \text{RelFlows}^b_{t,f,2} = (...) = \text{RelFlows}^b_{t,f,K} = \text{RelFlows}_{f,t}$. Under this null hypothesis, the relative importance of each sector's flows to the fund, $RelFlows^a_{t,f,i}$, only depends on the sector's (lagged) relative ownership share: $TNA_{t-1,f,i}/TNA_{t-1,f}$.

To mitigate the influence of large outliers it is common practice in the literature to winsorize flow variables. In order to ensure that the aggregation in Eq. (3) holds exactly, we refrain from winsorization. Instead, we truncate $RelFlows$ and $RelFlows^a$ for all investor sectors whenever a fund's $RelFlows$ fall in the 1st or 99th percentile. Additionally, we winsorize each investor sector's $RelFlows^b$ separately at the 1%/99% level since standardizing by a sector's lagged holdings can result in very extreme values, particularly for smaller sectors.

When measuring fund performance we employ benchmark-adjusted returns. As noted by Pastor et al. (2013), this index-based adjustment may adjust fund style and risk more precisely than the commonly used factor adjustments. In particular, Cremers, Petajisto, and Zitzewitz (2013) recommend using index-based benchmarks and find that such benchmarks better explain the cross section of mutual fund returns. Specifically, we define fund performance $Alpha$ the following way:

$$Alpha_{t,f} = \text{Return}_{t,f} - \beta_f \times \text{Benchmark}_{t,f}, \tag{6}$$

where $Return_{t,f}$ is a fund f's realized (net) return in quarter t, $Benchmark_{t,f}$ is the quarterly return of the index portfolio selected for each fund category by Morningstar, and β_f is a fund's benchmark beta which we estimate at monthly frequency over 36 months.

Table A.1 in the Data Appendix provides an overview of all variables used in this paper, including further standard control variables, which we do not discuss here for the sake of brevity. Table 2 reports summary statistics for various key fund and share class characteristics.

3 Descriptive statistics on investors' holdings and flows

3.1 Aggregate holdings and flows

Panel A of Figure 1 shows the aggregated ownership structure of our sample funds over time. Households represent the largest investor sector, holding on average 36% of aggregate mutual fund assets. In terms of holdings, they are followed by insurers (23%), investment funds (20%), and foreign investors (12%). Banks, non-financial corporations, pension funds, and other institutional investors play only a minor role in our sample of funds. Panel B of Figure 1 shows investors' contributions to aggregate fund flows over time. Looking at the market crash following the onset of the COVID-19 pandemic already provides interesting insights into differences in flow behavior across investor sectors: while all investor sectors redeemed fund shares during the first quarter of 2020, with overall net outflows of –2.75%, investment funds account for almost half of these outflows (–1.34 pp). This is remarkable given that investment funds are only the third largest investor sector. On the other hand, households and insurers redeemed their fund shares less than proportionally during the crisis period, accounting for –0.86 and –0.12 pp, respectively. This is only a very first indication that investor sectors contribute very differently to funds' overall flows. We will study differences in the redemption patterns across investor sectors more rigorously in Section 4.2, where we also account for the fact that investor sectors may differ in their preferences regarding mutual fund characteristics, such as investment objective or portfolio liquidity.

3.2 Investors' preferences for fund characteristics

In Figure 2 we analyze the ownership structure of mutual funds in the cross-section, focusing on selected characteristics. We provide the ownership shares by investor sector, averaged over time. Looking at the breakdown by share class type in Panel A, institutional investor sectors, in particular investment funds (47.2%) dominate the institutional share classes; as expected, households play only a minor role (5.7%) in institutional share classes. On the other hand, retail share classes have a more mixed ownership structure. Households are the largest single investor sector in retail share classes (41.4%). However, when aggregating all institutional investor sectors, these make up an even larger share (46.9%) in retail share classes. This share would be even larger if we were to assume that the remaining share (11.7%) held by foreign investors is also institutional. Hence, relying on a retail/institutional share class classification is prone to understate true differences between retail and institutional investors.

The ownership breakdown by minimum investment amount in Panel B reveals that households are the main investor sector in share classes without minimum investment (49.2%), while their share shrinks as the minimum investment required increases. Reversely, investment funds and foreign investors hold only a small share in share classes with low minimum investment while their share rises as the minimum investment amount increases. Surprisingly, this is not the case for insurers. Similar to households they hold relatively large shares in share classes with no or low minimum investment amounts. While for households a high minimum investment certainly poses an entry barrier, this explanation is less plausible for insurers.

It is well-known that fund fees differ substantially in the cross-section. For example, Schmidt, Timmermann, and Wermers (2016) document that institutional share classes tend to charge significantly lower fees compared to retail-oriented ones. Our sample allows us to assess how the differences in mutual fund ownership translate into differences in fund fees charged across investor sectors. The bottom left panel of Figure 2 provides the ownership structure across expense ratio quartiles. While the less costly share classes (in the bottom quartile) are mainly held by institutional investors, in particular by investment funds, households are primarily invested in share classes with relatively high expense ratios. Consistent with the observations regarding share class type and minimum investment amount, insurers also invest in rather costly share classes.[7]

Finally, we explore sectoral preferences regarding mutual fund holdings, specifically the share of small-to-mid-cap holdings as a proxy for portfolio liquidity. The bottom right figure shows that households are strongly invested in rather liquid large-cap oriented funds. In contrast, institutional investors – in particular investment funds – hold larger shares in rather illiquid funds with a high share of small-to-mid-cap holdings. This

[7]These differences in expense ratios do not only hold across funds, but also *within* funds, as we show in Table IA.2 of the Internet Appendix where we perform OLS and WLS regressions, including fund-time fixed effects.

observation is particularly interesting in the light of the extant literature, which shows that institutional investors have preferences for large and liquid stocks when holding stocks directly (Gompers and Metrick, 2001; Ferreira and Matos, 2008). The indirect holdings of institutions, on the contrary, are tilted towards illiquid stocks, apparently because the open-ended structure of mutual funds caters to the liquidity preference of institutional investors.

Table 3 provides further details and statistical tests on differential preferences across sectors. For each quarter and investor type we compute the weighted average of a fund/share class characteristic based on the investor types' quarterly holdings. For each characteristic we report in the first line the time-series average of the respective investor sector. In the second line we report the difference in means relative to the household sector, in the third line we report t-statistics for the difference in means test based on Newey-West standard errors in parentheses (with the number of lags based on Newey-West's optimal lag-selection algorithm). Households direct only 2% of their fund investments into institutional share classes. Not surprisingly, this share is significantly larger for institutional investor sectors, notably investment funds (33%) and pension funds (51%). Economically speaking, insurers' share in institutional share classes is rather low with only 9%. Institutional and foreign investors hold share classes with load fees less often than households, with the exception of insurers. The weighted average minimum investment amount is for all institutional investors significantly higher than for households. However, for insurers the difference is economically smaller. Households pay the highest fund fees, amounting to 1.64% per year. The lowest average expense ratio is achieved by pension funds and investment funds (1.25% and 1.19% p.a.). Again, insurers pay relatively high expenses with an average weighted expense ratio of 1.53%, which is only 0.10% lower than that of households. Moreover, households and institutional investors also differ along various characteristics at the fund level: compared to institutional investors, households tend to invest in larger, older, and more liquid funds (as measured by their ratio of small-to-mid-cap holdings).

Overall, the descriptive statistics show significant differences in preferences between households and institutional investors when investing in mutual funds. Moreover, our descriptive analysis also reveals substantial heterogeneity between different types of institutional fund investors – differences seem to be especially pronounced between investment funds and insurers.

3.3 Investors' contributions to mutual fund flows

In section 3.1 we already highlighted that – over time – the different investor sectors contributed very differently to mutual funds' overall net flows. In this section we deepen our analysis and shed light on how much each investor sector contributes to the overall net flows from and to mutual funds and contrast it with their holdings share in mutual funds. Based on the decomposition of overall flows into sector-specific flows in Eq. (3), we measure the relative importance of each sector to overall flows using Shapley value regressions (Shapley, 1954; Joseph, 2019). Specifically, we run a pooled regression of the overall fund flow $\text{RelFlows}_{f,t}$ on all flows $\text{RelFlows}^{a}_{t,f,i}$ of all sectors i. The Shapley value, similar to a variance decomposition, measures how much a particular investor sector contributes to the overall variation of fund flows. The main advantage of Shapley values over a variance decomposition is that Shapley values are non-negative and thus more intuitive to interpret.[8]

The results from these Shapley value regressions are shown in Figure 3, which plots the variance contributions to flows against the average relative size of each investor sector. As highlighted in Section 2.2, under the null hypothesis of uniform flow behavior across investor sectors, the relative flow contribution of each sector should only depend on the sector's relative ownership share. Hence, if all investor sectors were to display the same behavior, all variance contributions should lie on the main diagonal of the plot.

[8]We confirm that the results in this subsection are robust to using a standard variance decomposition. For example, we find a correlation of 0.995 between the point estimates in the top panel of Figure 3 and standard variance contributions across the different investor sectors. We obtain standard errors for the estimated Shapley values using a bootstrapping approach with re-sampling over 1,000 repetitions.

The observed values, however, lie far off the main diagonal. Among the three largest investor sectors – households, investment funds and insurers – both households and insurers contribute less than proportionally to overall flow variation, while investment funds contribute more than proportionally. The latter is particularly striking and again underlines the heterogeneity existent within the institutional investor space: even though investment funds' mutual fund holdings are slightly smaller than those of insurers, they contribute to flow variation about twice as much as insurers. While investment funds' fund investments are only about half the size of households' fund investments (21% versus 38%), both sectors have a similarly large effect on the overall flows (each close to 30%). As shown in the separate zoom-in in the top panel, smaller investor sectors (including foreign investors, pension funds, banks, and non-financial institutions), also tend to contribute more than proportional to the overall flows, but their economic importance in terms of their TNA share is relatively small. In the bottom panels we split the sample into inflows and outflows. The graphs show that imbalances in variance contributions to mutual fund flows is particularly pronounced for outflows, where investment funds show a variance contribution of 37% compared to only 22% for households and 15% for insurers.

Based on the observation that imbalances in flow contributions are particularly large for outflows, we study extreme outflows in more detail. Specifically, we sort fund outflows into deciles and compute the value-weighted flow contributions in each decile. Figure 4 shows that fund net outflows can be substantial, as funds in the bottom decile of the outflow distribution face net outflows amounting to nearly –20% of their lagged TNA. Investment funds particularly contribute to these extreme outflows: in the lowest outflow decile investment funds' redemptions cause 42% of funds' overall outflows. Households and insurers, on the other hand, only account for 17% and 20%, respectively.

Overall, these results provide a first indication that investment funds' redemptions, rather than those of households or insurers, are a likely driver of the negative flow externalities in mutual funds.

4 Decomposing fund flow externalities

In this section we develop an empirical framework to directly measure how much each sector contributes to and absorbs from the flow externality in mutual funds. Such a direct measurement is crucial since imbalances in flow contributions alone are not a sufficient condition for imbalances in externality contributions. There are two main reasons why: first, different investor groups need to have sufficient overlap in holdings to affect each other by means of their flows, i.e. investor groups have to meet each other within the same funds. Second, the degree to which flows can be anticipated may vary across investor groups. For example, an investor sector may largely contribute to fund outflows but fund managers better anticipate flows by this sector, resulting in fewer negative externalities. Our methodology accounts for both aspects since we measure the externality contributions directly where they occur, namely at the fund level. While different share classes of a fund cater to different investor clientèles with regard to fees, minimum investment amount or currency, all share classes within the same fund are effectively claims on the same asset portfolio. Hence, large outflows in one share class affect investors in other share classes since the fund manager performs the portfolio adjustments at the fund level.

4.1 Empirical framework

For the set of funds that experience large outflows in period $t-1$ ($\text{Outflows}_{t-1,f} = 1$), where large outflows will be defined by a certain cutoff, we compute the following excess performance measure:

$$\widetilde{Alpha}_{t,f} = \text{Alpha}_{t,f} - \widehat{\text{Alpha}}_{t,f} \tag{7}$$

where $\text{Alpha}_{t,f}$ is defined in Eq. (6) as the observed performance of funds with large outflows and $\widehat{\text{Alpha}}_{t,f}$ is the fitted value of performance based on a regression, which includes various fund characteristics including past performance and expenses. In other words, for funds experiencing large outflows, $\widetilde{\text{Alpha}}_{t,f}$ measures their subsequent excess (under-)performance beyond what is predicted by past performance, expenses and other fund control variables. Following the literature (Chen et al., 2010), we refer to $\widetilde{\text{Alpha}}_{t,f}$ as the estimated flow externality in mutual funds. Averaging over all f, t observations with large outflows yields the expected conditional flow externality: $\textit{Externality} = \frac{1}{n}\sum_{t,f}\widetilde{\text{Alpha}}_{t,f}$, where n is the total number of observations with $\text{Outflows}_{t-1,f} = 1$.

Based on the flow externality in Eq. (7), we can now decompose it along the two directions of interest. First, the degree to which a given investor sector contributes to the negative flow externality and, second, the degree to which a given investor sector absorbs the negative flow externality.

Starting with the contribution to the overall flow externality, investor sector i's contribution is proportional to its relative contribution to the observed large outflows. We therefore propose the following measure:

$$\textit{Externality}_i^{\text{generated}} = \frac{1}{n}\sum_{f,t}\underbrace{\left(\frac{\text{EuroFlows}_{t-1,f,i}}{\text{EuroFlows}_{t-1,f}}\right)}_{w_{t-1,f,i}^{\text{generated}}}\times\widetilde{\text{Alpha}}_{t,f}, \tag{8}$$

where $w_{t-1,f,i}^{\text{generated}}$ is the share of sector i's Euro flow relative to the overall Euro flows within a given fund. The externality generated by the flows of sector i quantifies how much investor sector i's flows contribute to the estimated flow externality. Summing over all investor sectors gives overall flow externality ($\sum_i \textit{Externality}_i^{\text{generated}} = \textit{Externality}$).

Next, we study the degree to which investors bear losses due to the negative flow externality. Generally, all investors who remain in the fund throughout quarter t would absorb the flow externality. Hence, the externality *received* by investor sector i in fund f in quarter t is proportional to the sector's relative TNA share:

$$\textit{Externality}_i^{\text{received}} = \frac{1}{n}\sum_{f,t}\underbrace{\left(\frac{\text{TNA}_{t-1,f,i}}{\text{TNA}_{t-1,f}}\right)}_{w_{t-1,f,i}^{\text{received}}}\times\widetilde{\text{Alpha}}_{t,f}. \tag{9}$$

Note that since flows are assumed to take place at the end of each quarter, TNA shares are computed using the values at the end of quarter $t-1$. The externality received by sector i quantifies the losses investor sector i has to bear due to the estimated flow externality. Again, summing over all investor sectors gives the overall fund-level externality ($\sum_i \textit{Externality}_i^{\text{received}} = \textit{Externality}$). We define a sector's *net externality* as the difference between the losses generated and absorbed by that sector (generated minus received, $\textit{Externality}_i^{\text{generated}} - \textit{Externality}_i^{\text{received}}$). Positive (negative) values indicate that a given sector is a net generator (absorber) of the flow externality in mutual funds.

Naturally, one would assume that larger investor sectors (in terms of their TNA share) would also contribute more to the flow externality. At the same time, larger investor sectors would also absorb more of the externality. To assess whether investor sector i contributes (absorbs) over and beyond what is to be expected from its relative size in a given fund, we also calculate sectors' hypothetical externality contributions (absorptions). As laid out in Section 2.2, our null hypothesis is based on the assumption that all investor sectors redeem their mutual fund shares in an equal manner (i. e., proportional to their fund holdings). Under this null hypothesis, investor sector i's contribution to the flow externality would depend on its TNA share *prior* to the occurrence of the large outflows:

$$\textit{Externality}_i^{\text{H0}} = \frac{1}{n} \sum_{f,t} \underbrace{\left(\frac{\text{TNA}_{t-2,f,i}}{\text{TNA}_{t-2,f}} \right)}_{w^{\text{H0}}_{t-2,f,i}} \times \widetilde{\text{Alpha}}_{t,f}. \tag{10}$$

Since all investor sectors redeem proportionally under the null, TNA shares do not change from $t-2$ to $t-1$. Hence, Eq. (10) also describes the amount of externality absorbed by each investor sector under the null hypothesis.

We define ($\textit{Externality}_i^{\text{generated}}$ - $\textit{Externality}_i^{\text{H0}}$) as the *excess externality originated* by investor sector i, which measures whether the sector's flows contributed more strongly to the fund-level externality than what would be expected under the null of uniform flow behavior. Similarly, we define ($\textit{Externality}_i^{\text{received}}$ - $\textit{Externality}_i^{\text{H0}}$) as the *excess externality received* from investor sector i, which measures whether the sector absorbed more of the flow externality than what would be expected under the null of uniform outflow behavior. In terms of excess externality, this is a zero-sum game: if one investor sector originates (receives) more of the flow externality than expected, another sector must originate (receive) less. Hence, it holds that the sum of excess externality over all investor sectors is zero:

$$\sum_i (\mathit{Externality}_i^{\text{generated}} - \mathit{Externality}_i^{\text{H0}}) = \sum_i (\mathit{Externality}_i^{\text{received}} - \mathit{Externality}_i^{\text{H0}}) = 0.$$

Importantly, our framework also allows us to take a network perspective on the estimated flow externality. How investor sector i affects investor sector j depends on their potentially different outflow behavior and also on how connected they are with each other through common ownership in mutual funds. To study this question, we simultaneously decompose the externality along both dimensions – received and originated. Specifically, the following relationship tells us how much a given investor sector i drives the externality received by investor sector j in fund f:

$$\mathit{Externality}_{i \to j} = \frac{1}{n} \sum_{f,t} w_{t-1,f,i}^{\text{generated}} \times w_{t-1,f,j}^{\text{received}} \times \widetilde{\text{Alpha}}_{t,f}. \tag{11}$$

Summing over all originating sectors i gives the externality received by sector j: $\sum_i \mathit{Externality}_{j \to i} = \mathit{Externality}_j^{\text{received}}$. Summing over all receiving sectors j gives the externality originated by sector i: $\sum_j \mathit{Externality}_{j \to i} = \mathit{Externality}_i^{\text{generated}}$. Summing over all originating and receiving sectors i, j gives the overall flow externality: $\sum_{ij} \mathit{Externality}_{j \to i} = \mathit{Externality}$. Note that investor sector i can only affect investor sector j when the two sectors share at least some investments in the same funds.

As before, we can also compute an externality network under the null hypothesis of uniform flow behavior:

$$\mathit{Externality}_{i \to j}^{\text{H0}} = \frac{1}{n} \sum_{f,t} w_{t-2,f,i}^{\text{H0}} \times w_{t-2,f,j}^{\text{H0}} \times \widetilde{\text{Alpha}}_{t,f}, \tag{12}$$

where $w_{t-2,f,j}^{\text{H0}}$ is weight based on investor sector j's TNA share *prior* to the occurrence of the large outflows as defined in Eq. (10). We define $(\mathit{Externality}_{i \to j} - \mathit{Externality}_{i \to j}^{\text{H0}})$ as the network excess externality, which measures whether the flow externality originating from sector i to sector j is stronger than what would be expected under the null of uniform flow behavior. As before, the sum of all excess externalities is zero ($\sum_{ij}(Externality_{i \to j} - Externality^{\mathrm{H0}}_{i \to j}) = 0$).

4.2 Results

Table 4 shows the results of our externality decomposition as laid out in the previous subsection. Consistent with previous work, which documents flow externalities in mutual funds to be large in relatively illiquid funds, we focus on funds with small-to-mid-cap holdings in the top quartile across the full sample. When these funds experience large outflows of more than 10% per quarter, we estimate an average flow externality of –45 bps on their performance in the following quarter.[9] We see this estimate as a lower bound, since the cumulative effect of fund managers' flow-driven trading is likely to have stronger effects at higher than quarterly frequencies (e.g., Falato et al. (2020)).

Households, are at the receiving end of the flow externality. Representing the largest investor sector, households originate an externality of –22 bps, but absorb an externality of –30 bps. Hence, their net externality amounts to –8 bps, which is also statistically significant. In other words, households receive 8 bps *more* of the externality than expected under the null. This negative net externality can be decomposed in two parts: first, households redeem less strongly than expected under the null (+7 bps); second, households receive more of the externality than expected under the null (–1 bps), with the latter being of course a result of the former. Since households do not redeem their fund shares as aggressively as other investor sectors, their relative share in funds with large outflows increases, resulting in a higher exposure to the negative flow externality.

Insurers, the second largest investor sector, are also at the receiving end of the flow

[9] For the sake of completeness, Table IA.1 in the Internet Appendix reports regression results for a regression of fund performance on a dummy for large outflows and further fund controls (as in Chen et al. (2010)). While we find no significant externality in liquid funds, the externality of illiquid funds amounts to approximately –45 bps, which corresponds closely to the total values shown in Table 4.

externality. They originate only –3 bps of the externality and absorb –6 bps. Their net externality of –3 bps is mainly driven by the fact that insurers redeem considerably less in absolute terms than what we would expect from their relative holdings share (–5 bps). Even though the difference is not statistically significant, the economic magnitude is sizable, since insurers originate only around 50% of the externality that would be expected due to their portfolio share in the mutual funds of interest.

Investment funds, on the other hand, represent the largest net originator of the flow externality: the sector originates –15 bps and receives –4bps. Their net externality of +11 bps is highly statistically significant, which suggests that this sector originates 11 bps *more* of the externality than what it absorbs. Notably, compared to the null hypothesis (–6 bps), investments funds contribute more than twice as strongly and receive only half the externality. Overall, the net flow externality of investment funds amounts to 11 bps, which means that

Turning to the other investor sectors, we find that foreign investors and non-financials are net receivers of the flow externality (–3.6 and –1.4 bps, respectively). The remaining investor sectors tend to be net originators of the flow externality. Interestingly, banks tend to be neutral, displaying a net externality close to zero. However, for all of these sectors the net externality is insignificant.

We next analyze how each investor sector affects the other investor sectors through its outflows. In our framework two investor sectors can only affect each other via their flows if they are invested in the same funds. Despite the fact that institutional and retail investors show differential preferences for fund and share class characteristics (see Section 3.2), we find that their portfolio overlap is sizable, in particular at the fund level. For example, at the share class level, investment funds and households share roughly 65% of their fund investments in the same share classes. At the fund level, this overlap reaches close to 80%.[10] Based on Eq. (11), Panel A of Figure 5 plots a heat map of the flow externality decomposition across both directions. Each column shows how the contribution of a

[10]See Figure IA.2 in the Internet Appendix.

specific investor sector is distributed among the receiving investor sectors. Each row shows from which investor groups a specific investor sector receives the flow externality. Column (row) sums correspond to the externality originator (receiver) values reported in Table 4. Summing over all rows and columns yields the overall externality of –45 bps.

Due to the fact that households represent the largest investor sector in mutual funds, much of the flow externality (–16.1 bps) is originated from and absorbed by the household sector. Additionally, households are heavily affected by outflows from investment funds and receive a flow externality of –7.4 bps. This flow externality of investment funds on households is economically sizable, in particular when compared to insurers, which are of similar size, but impose an externality of only –2.2 bps on households. Moreover, investment funds impose a large externality both on themselves (–4 bps) and on insurers (–1.9 bps).

To account for differences in size of the investor sectors, Panel B of Figure 5 shows a heat map of the excess externality network. This being a zero sum game, summing excess externalities over all rows and columns in the matrix yields zero. Looking at the upper left corner, we see that the negative externality households impose on themselves in Panel A is actually 2.9 bps higher than what would be expected under the null of uniform outflow behavior for the given holder structure. The first column shows that households in general are generating a marginally positive excess externality on most other investors. Turning to the second column, we observe that insurers generate no sizable excess externality on households (–0.3 bps). The excess externality of insurers on themselves is positive (1.4 bps). Column 3 reports how the negative flow externality of investment funds is distributed among receiving sectors. The results show that households are absorbing a large part (–4.0 bps) of the excess externality originating from investment funds. Investment funds themselves, insurers and foreign investors are the other main receivers of investment funds' excess flow externality (–1.9 bps, –1.4 bps and –1.5 bps, respectively).

Overall the analysis identifies investment funds as the main drivers of the flow externality in mutual funds. In contrast, households and insurers, are mainly at the receiving end.[11] Note that our results not only highlight marked differences between retail and institutional investors but also between large institutional investor groups, especially investment funds and insurers: even though insurers and investment funds display roughly similar aggregate mutual fund holdings, investment funds' contribution to the flow externality is about five times larger than the contribution of insurers (–15 bps versus –3 bps). Our results carry financial stability implications since within-fund contagion effects are particularly relevant when investment funds and insurers meet each other in the same funds. Our findings are in line with the findings of Fricke and Wilke (2020), who showed that the increasing tendency of investment funds to invest into other funds has the potential to amplify existing fire sale vulnerabilities in the fund sector.

4.3 A closer look at households and insurers

We now want to gain a better understanding for the underlying reasons why certain sectors are at the receiving end of the flow externality in mutual funds. First, we look at households, which are by far the main receivers of the externality. We hypothesize that – besides the large size of their fund holdings – households' lack of financial sophistication is the reason why they absorb large parts of the flow externality. To test this hypothesis, we decompose the flow externality within the household sector according to investor sophistication, using the share class-specific minimum investment amount as proxy. The minimum investment amount acts as an entry barrier for less wealthy households, which tend to be less financially sophisticated (e.g., Campbell, 2006; Calvet et al., 2007, 2009a,b). Consistent with this rationale, we define more sophisticated households as those invested in share classes with a minimum investment amount of 10.000 EUR or more.

[11]Our main findings are also present before the 2020 stock market crash following the outbreak of the COVID-19 pandemic. Table IA.3 repeats the analysis of Table 4 but it excludes observations of the year 2020. The overall externality in this sample period is –26 bps. Investment funds are the main source of the externality (net externality: +8 bps) and households the main receivers (net externality: –8 bps). Insurers are still net receivers but their net externality reduces to below –1 bps. This finding suggests that insurers absorb flow externalities especially in times of market distress.

Panel A of Table 5 shows the externality decomposition for the two sub-sectors within the household sector. Consistent with the financial sophistication hypothesis, we find that the vast majority of the flow externality is absorbed by less sophisticated households in share classes with a low minimum investment amount. These households receive –22 bps flow externality, but only originate –15 bps flow externality, which amounts to a statistically significant difference of –7 bps net externality. In contrast, for households invested in share classes with high minimum investment amount the externality received and the externality originated nearly balance out: these more sophisticated households receive –7 bps and originate –6 bps of the externality, the difference being insignificant.

Insurers are also at the receiving end of the flow externality, albeit their net externality of –3 bps is statistically insignificant. Especially, insurers tend to originate less *and* absorb more of the externality than expected based on the size of their fund holdings. A possible explanation for this lies in the fact that several asset management companies are affiliated with large insurers in Europe. Similar to the literature on bank-affiliated mutual funds (Golez and Marin, 2015; Gil-Bazo, Hoffmann, and Mayordomo, 2020), conflicts of interest may arise in such a setting. Specifically, we hypothesize that insurers investing into affiliated mutual funds tend to support these funds in the event of large outflows by offsetting inflows. To test this hypothesis, one would ideally use data at the insurer level. Due to the lack of such data, we pursue a second-best approach at the sector level. In particular, we classify asset management companies as insurer-affiliated, if their ultimate parent belongs to the insurance sector.[12]

Panel B of Table 5 shows the externality decomposition for insurers in insurer-affiliated and unaffiliated funds. For insurer-affiliated funds we find a positive, but insignificant out-externality, pointing in the hypothesized direction. That is, for large outflows insurers' fund flows seem – to some extent – to provide a positive externality offsetting other investor sectors' outflows. The lack of finding statistically significant evidence for insurer

[12] Using this approach, insurer-affiliated sector holdings include holdings from the associated insurance company but can also potentially include holdings from unrelated third party insurance companies. Therefore, supporting inflows to stressed funds from the affiliated insurers may be diluted by noise.

support to insurer-affiliated funds may well be due to the measurement of affiliation at the sector level. Nevertheless, there are other important insights to gain from this exercise. Turning to unaffiliated funds, we see that conflicts of interest are not the entire explanation for the observed trading behavior of insurers. Even in unaffiliated funds, insurers – unlike investment funds – tend to be net receivers and not originators of the flow externality.

5 Characterizing differences in trading behavior across sectors

In this section we aim to better understand the differences in investment behavior across investor sectors. Specifically, we look at different investor sector's trading behavior and the procyclicality of their fund flows. Lastly, we take a closer look at the COVID-19 induced stress episode in the first half of 2020 to further uncover behavioral differences during periods of severe market stress.

5.1 Portfolio turnover and investment procyclicality

We start our analysis in Table 6, where we disentangle the time-series variation and the cross-sectional variation of investors' flows to mutual funds. First, we study the question how much investor sectors reshuffle their holdings in mutual funds in a given quarter. Our approach applies the commonly used portfolio turnover measure (Gaspar et al., 2005; Giannetti and Yu, 2021) at the investor sector level. Specifically, we define a sector's portfolio turnover as the minimum of its aggregate purchases or sales in a quarter, divided by a sector's average holdings during that period:

$$Turnover_{t,i} = min(Sales_{t,i}, Purchases_{t,i})/(1/2(TNA_{t-1,i} + TNA_{t,i})).$$

Taking the minimum of purchases and sales in a quarter ensures that systematic in- or outflows of an investor sector are not incorporated into the turnover measure. In other words, the turnover measure purely focuses on reshuffling in the cross-section, leaving aside any aggregate time-series variation of flows. Note that the turnover measure is not measured at the individual investor level, but rather at the *investor sector* level. The actual turnover ratios of individual investors belonging to a sector of investors are likely to be higher since the sale of one investor may be compensated by the purchase of another investor within the same investor sector. Nevertheless, the turnover measure provides a first assessment for the trading activity of each investor sector.

In Panel A of Table 6, we report the average investor sector turnover in our sample period. The average quarterly turnover of households amounts to 2.9%, which is relatively low, compared to the turnover of other investor sectors. In fact, for most other investor sectors turnover is substantially and significantly larger. Except for insurers, turnover by institutional investors is more than twice as large as the turnover of households. For investment funds we compute a turnover ratio of 6.6%, but also smaller investor sectors, such as pension funds, banks and non-financial institutions, display comparable turnover ratios. The portfolio changes of these smaller sectors may simply carry less weight in the overall flow externality. Among the institutional investors, only insurers are less actively reshuffling their holdings in funds. Their turnover ratio is only half a percentage point larger than that of households, amounting to 3.4%. Overall, our findings regarding the portfolio reshuffling of investors line up well with their externality contributions.

Next, we analyze investors' investment behavior over time. Previous literature has documented a positive contemporaneous correlation of aggregate mutual fund flows and market returns (Warther, 1995; Edelen and Warner, 2001; Jank, 2012). Motivated by this observation, we study which investor sectors' flows are more related to the state of the market. We compute aggregate quarterly net flows for each investor sector and regress this time series on (1) the aggregate market return, and (2) the VIX volatility index as a measure for market uncertainty. We test for the equality of slope coefficients across investor sectors using the simultaneous covariance matrix of the obtained estimates.

Panel B of Table 6 shows the co-movement of investors' flows with the return of developed stock markets provided by Ken French. For most investor sectors we only find a weak positive association of flows with the market return, which may be due to the fact that our dataset is at the quarterly frequency. However, investment funds' flows to mutual funds exhibit a strong positive correlation with market returns. Their slope coefficient is statistically different from zero and more than twice as large as that of households. Moreover, market returns explain 46.4% of investment funds' fund flows over time. On the other hand, insurers trading behavior displays no significant co-movement with the market. Panel C of Table 6 analyses the correlation of investors' flows with market uncertainty, which we measure by the VIX. Compared to households, investment funds show significantly larger redemptions during volatile market conditions. Relatively stronger outflows during uncertain market conditions are also found for pension funds and banks. In contrast, households and insurers exhibit no sizable VIX exposure, both economically and statistically.

In summary, this section documents distinct differences in portfolio turnover and investment procyclicality between the main originators and receivers of the flow externality. The investment fund sector – the main originator of the flow externality – very actively reshuffles its fund holdings and strongly withdraws its money from mutual funds during periods of market distress and during periods of high market uncertainty. Thus, the investment fund sector displays particularly large redemptions when liquidity is low and, hence, flow externalities are large. In contrast, insurers and households – the main receivers of the flow externality – show no significant cyclical flow behavior and their portfolio turnover is significantly lower than the turnover of the investment fund sector. The next two subsections dive further into these behavioral differences.

5.2 Flow-performance relationship

Much research has been devoted to the question on how fund investors respond to past performance, the so-called flow-performance relationship (Ippolito, 1992; Sirri and Tufano, 1998; Chevalier and Ellison, 1999; Goldstein et al., 2017). We now analyze whether and how investor sectors differ in terms of their flow sensitivity to past performance.

Following the methodology developed by Robinson (1988) and applied by Chevalier and Ellison (1999), we start by semi-parametric estimates of the flow performance sensitivities of different investor sectors:

$$\text{RelFlows}^b_{t,f,i} = f(\text{AlphaRank}_{t-1,f}) + b \times X_{t-1,f} + \mu_t + \epsilon_{t,f,i}, \tag{13}$$

where $\text{RelFlows}^b_{t,f,i}$ are flows of investor sector i standardized by their lagged holdings in fund f, $\text{AlphaRank}_{t-1,f}$ is the percentile rank of fund performance over the past 24 months (cumulated Alpha) and ranges between 0 and 1. We use RelFlows^b in the flow-performance regressions since it allows for a comparison across investor sectors. As derived in Section 2, under the null hypothesis of a uniform flow behavior, all investor sectors should display the same percentage flows relative to their own TNA. $X_{t-1,f}$ is a vector of control variables, which includes lagged fund flows, fund age, fund size, fund family size, expense ratio, a dummy for funds with load fees and both aggregate Morningstar Category flows as well as fund family flows. Finally, μ_t are time fixed effects. We run this semi-parametric estimation separately for the different investor sectors.

Figure 6 plots the relationship between flows and past performance for the three main investor sectors of interest, namely households, insurers, and investment funds.[13] The graph reveals strong differences in how these investor sectors react to past performance. For households we observe the well-known convex flow performance relationship: while there are some inflows to well-performing funds, the flow-performance relationship is essentially flat for poorly-performing funds. The flow-performance sensitivity of insurers is steeper than that of households, but the relationship is still convex. This fact shows that even among sophisticated institutional investors a convex flow-performance relationship can exist. On the other hand, investment funds respond very differently to past

[13]We focus on the major sectors for two reasons: first, we want to avoid clutter. Second, the variation of RelFlows^b is more extreme for smaller investor sectors leading to very noisy estimates in a semi-parametric approach. In the parametric regression we again include all investor sectors.

performance, since their flow-performance relationship is much steeper and concave. In summary, it is mainly investment funds that display strong outflows from poorly performing funds, but not households or insurers. We now provide further evidence on these differences and their statistical significance in a parametric regression framework.

We employ the following regression specification to jointly estimate the flow-performance sensitivities of all investor sectors:

$$\text{RelFlows}^b_{t,f,i} = \sum_i^K \gamma^i I(Inv. = i) \times \text{AlphaRank}_{t-1,f} + b \times X_{t-1,f} + \mu_t + \epsilon_{t,f,i}, \tag{14}$$

The dependent variable $\text{RelFlows}^b_{t,f,i}$, *AlphaRank* and control variables are defined as before, but we now interact past fund performance, $\text{AlphaRank}_{t-1,f}$, with a dummy variable for each investor sector. Specifically, $I(Inv. = i)$ equals 1 if $\text{RelFlows}^b_{t,f,i}$ are from investor sector i and it is zero otherwise. Hence, the coefficient γ^i measures the flow-performance sensitivity of investor sector i relative to a reference sector, which we define as the household sector. Estimating the flow-performance relationship in a three-dimensional panel (fund×investor sector×quarter) also allows us to control for time-varying fund unobservables that may spuriously influence our results. Instead of controlling for fund characteristics that also influence flows we simply include fund-time-fixed effects in Eq. (14). Within the same fund and at the same time, the model measures investors' differential response to past performance. Hence, this saturated regression model addresses endogeneity concerns regarding existing differences in the holding structure of the investor sectors.

To capture potential non-linearities in the flow-performance sensitivity we also run a piecewise-linear regression, which estimates separate slopes for observations above and below the median of past performance. We run the following regression model:

$$\begin{aligned} \text{RelFlows}^b_{t,f,i} = &\sum_i^K \gamma^i_{Low} I(Inv. = i) \times \text{AlphaRankLow}_{t-1,f} + \\ &\sum_i^K \gamma^i_{High} I(Inv. = i) \times \text{AlphaRankHigh}_{t-1,f} + b \times X_{t-1,f} + \epsilon_{t,f,i}. \end{aligned} \tag{15}$$

where $AlphaRankLow = AlphaRank$ and $AlphaRankHigh = max(0, AlphaRank - 0.5)$. The breakpoint of the piecewise linear regression is set at a performance rank of 0.5, which corresponds to the median. Hence, $AlphaRankLow$ and $AlphaRankHigh$ provide the marginal effect of an increase in performance on investor flows below and above median fund performance, respectively. Again, we run a saturated regression which includes fund-time-fixed effects $\mu_{f,t}$ instead of time-fixed effects μ_t and the vector of fund-level controls $X_{t-1,f}$.

Panel A of Table 7 shows results for the regression model specified in Equations (14). Looking at the linear model shown in Panel A, households – the benchmark sector – show a statistically significant and positive flow-performance sensitivity. The estimates suggest that an increase from the worst to the best performing fund ($\Delta AlphaRank = 1$) increases net flows of households by 4.44 percentage points. Looking at the interaction term $AlphaRank \times investment\ funds$ of (additional) 4.99, we see that investment funds' sensitivity to past performance is more than twice as large. The interaction term $AlphaRank \times Insurers$ of 3.13 suggests that also insurers have a stronger flow-performance sensitivity than households, but they do not react as strongly as investment funds. Moreover, the results show that also non-financial corporations and the diverse sector of other investors react more strongly to past performance than households. All these results are robust to including fund-time fixed effects in our second specification. In this saturated model the baseline effect of households' flow-performance sensitivity is absorbed in the fixed effects, but the results show that investment funds and insurers react more strongly to past performance.

Panel B of Table 7 shows the results for the piecewise linear model in (15). For the benchmark sector of households, the results are in line with a convex flow-performance sensitivity. Below the median performance rank, their sensitivity is 1.23, which is indistinguishable from zero. Above the median their sensitivity amounts to 6.38, which is statistically significant at all conventional levels. In contrast, investment funds exhibit a concave flow-performance relationship. In particular, we observe investment funds very actively redeeming shares of poorly performing mutual funds. Their flow-performance sensitivity below the median is 7.9 percentage points larger than that of households. Insurers, on the other hand, exhibit a convex flow-performance sensitivity that is even more pronounced at the upper end than that of households. Below median insurers' sensitivity to past performance is statistically and economically non-different from that of households. Above median, on the other hand, their flow performance sensitivity is considerably larger, in particular in the saturated regression model, which yields a statistically significant differential effect of 9.43 percentage points.

In summary, investment funds – the main originators of the flow externality – exhibit a strong flow sensitivity to past performance, in particular in the low-performance segment of our sample funds. Households and insurers – the main receivers of the flow externality – exhibit a clear convex flow-performance sensitivity. These patterns are in line with our finding that, within the same fund, investment funds react much more strongly to past poor performance and thus disproportionally hurt investor sectors that trade less actively.

5.3 Outflows during the COVID-19 stress episode

Lastly, we study the flow behavior of different investor sectors in times of severe market stress. The outbreak of the COVID-19 pandemic provides a large exogenous shock that heavily impacted global financial markets – with global bond and stock markets facing extreme volatility levels and steep price declines. As can be seen from Figure 1, our sample funds experienced sizable aggregate outflows of –2.75% during first quarter of 2020, which is in line with the dynamics for both U.S. equity and bond funds (Falato, Goldstein, and Hortacsu, 2021; Pastor and Vorsatz, 2020). As noted in Section 3, the contributions of different investor sectors to these aggregate outflows differ substantially. In this section, we study their flow behavior during times of marked financial distress in more detail.

As the crisis unfolded rapidly during March 2020, we conduct the following analyses at the daily frequency. We begin by identifying share classes which are predominately held by a specific investor sector prior to the crisis. Specifically, an investor sector is flagged as the major owner of a given share class if it holds more than 75% of that share class' issued shares by the end of 2019:Q4. Again, we focus on the three largest investor sectors, namely households, insurers and investment funds. By the end of 2019, these three investor sectors are major owners of 998 (households), 469 (investment funds) and 320 (insurers) share classes, respectively, amounting to around 41% of all share classes in our sample. We trace daily flows in these share classes throughout the first half of 2020.

Figure 7 shows TNA-weighted cumulative daily net flows for the three different major owner sectors. During the acute market stress period between 24th February 2020 and 23rd March 2020 (shaded red area), all three investor sectors redeemed some ot their fund investments, but there is substantial variation across sectors. Investment funds redeemed close to 2% of their holdings in the market crash period. In contrast, both households and insurers redeemed only a relatively small share of their fund holdings (less than 1% of their fund holdings). The latter two sectors reinvest also relatively swiftly after the market crash, whereas investment funds even continued to withdraw their money. Up until the end of June 2020, fund-owned share classes displayed net flows amounting to up to –2.3% of their net assets, whereas insurer- and household-owned share classes received cumulative net flows of 0.8% and 0.6%, respectively.[14]

To study these behavioral differences more formally, we perform cross-sectional regressions of daily cumulative net flows from the beginning of the crisis on dummy variables for the respective share class' major owner sector:

$$CumRelFlows_{s,f,H} = \beta_0 + \beta_1 \times I(\text{Insur.})_s + \beta_2 \times I(\text{Inv. funds})_s + \mu_f + \epsilon_{s,f,H}, \tag{16}$$

with index s as share class identifier, index f the identifier, and H the horizon, i.e., the number of trading days over which net flows are cumulated. To gain insight into the time structure of fund investors' COVID-related flows, we run the cross-sectional regression specified in (16) over different horizons H including the 1–5, 10, 20, 40 and 60 consecutive

[14]The results shown in Figure 7 are also robust to alternative specifications of share class level major ownership. See Figure IA.3 in the Internet Appendix.

trading days starting from 24th February 2020. $I(\text{Insur.})_s$ and $I(\text{Inv. funds})_s$ are dummy variables that indicate major ownership of insurers or investment funds, respectively. Household-owned share classes serve as the reference sector. We also include fund fixed effects μ_f in the regression to control for unobserved heterogeneity across funds.

Table 8, Panel A shows the OLS estimation results. During the first 20 trading days (24 February to 23 March 2020), which corresponds to the most acute period of market turmoil, households show net flows of -0.79%. Investment funds have significantly more outflows during this time, amounting to a total net flow of -0.79% -1.48% $= -2.27\%$. In contrast, insurers show no significantly larger outflows during the market crash compared with households. Also note that outflows from fund-owned share classes significantly exceed those from share classes held by the other investor sectors already ten trading days after the pandemic hit financial markets. During the following recovery period, share classes owned by insurers or households no longer display significant negative cumulative flows, while cumulative outflows from fund-owned share classes get even more pronounced.

Table 8, Panel B shows estimation results when including fund fixed effects. As before, investment funds redeemed significantly more fund shares than households during the market crash period (–2.49% versus –0.34%). Within the same fund, insurer-owned share classes also face significantly outflows, however, they are still not as pronounced as those of investment funds (–2.07%). We should note, however, that the number of observations is relatively small because of singletons dropping out due to the inclusion of fund fixed effects. During the market recovery period we observe prolonged outflows from investment funds but a reversal pattern for insurers.

Overall, our high-frequency analysis highlights important differences in investor sectors' redemption patterns during times of severe financial turmoil. Once again, our results flag different redemption behavior between retail and institutional investors but – what we consider even more important – also between different institutional investors (i. e., investment funds and insurers). Different from households, investment funds react to market distress instantaneously – i.e. at day two of the crisis (see Table 8) – and redeem large amounts of their fund shares during a very short period of time (see Figure 7). Compared to insurers (and households), investment funds' fund redemptions are larger in size, more volatile and much more persistent.

6 Conclusions

Prior work provides robust evidence on flow-induced negative externalities in open-ended mutual funds. This paper develops an empirical framework to quantify how severely these negative effects impact the diverse investor groups invested into mutual funds. At the fund-quarter level, our framework reveals how much each investor sector contributes to and absorbs from the negative externality emanating from fund investors' large outflows.

Drawing upon granular information on funds' dynamic ownership structure, we find that investment funds are the main drivers of negative flow externalities in euro area equity mutual funds. In stark contrast, households and insurers are at the receiving end of these externalities. Comparing insurers to investment funds also uncovers important behavioral differences within the group of institutional investors: even though insurers and investment funds display roughly similar aggregate mutual fund holdings, investment funds' contribution to the flow externality is more than five times larger than the contribution of insurers.

Our findings highlight negative effects arising from the trading activity of short-term institutional investors. Our results are consistent with the existence of clientèle effects in mutual funds and reveal potential spillover risks that can arise whenever different investor groups meet in the same fund. Financial stability issues might arise as investment funds' fund share redemptions exert pressure on insurers' and households' fund returns. We believe that the behavioral heterogeneities across different institutional sectors, as presented in this paper, deserve further attention. This is even more important in light of the ongoing attempts to mitigate structural vulnerabilities in the mutual fund sector. To what extent instruments to internalize flow externalities in mutual funds have the potential to also reduce the procyclicality of the trading behavior of some investor sectors remains an important question. Moreover, our study raises consumer-protection concerns. Households, which pay substantially higher fund fees compared to institutional investors, bear most of the flow externality in mutual funds.

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7 Tables and figures

Table 1: Sample by domicile and country available for sale

Table 1 presents number of share classes, the number of funds, and the total net assets (TNAs) across domicile (Panel A) and country available for sale (Panel B) as of December 2019. The sample consists of actively-managed equity mutual funds available for sale and domiciled in the Euro area, which are covered sufficiently in both Morningstar and the Securities Holdings Statistics by Sector. In Panel A five out of the 19 euro area countries are not fund domiciles in our sample due to the data filters applied. In Panel B aggregation over countries is not meaningful since funds are available for sale im multiple countries. Non-euro-area provides the number of share classes, funds, and their TNA, which are available for sale in at least one country outside the Euro area.

Country	# share classes	# funds	TNA (EUR, millions)
Panel A: By domicile			
Austria	245	87	9080
Belgium	309	79	23,288
Finland	80	31	5,805
France	1,418	573	127,755
Germany	388	231	135,618
Greece	6	3	82
Ireland	170	42	9,841
Italy	70	34	11,926
Latvia	3	3	13
Lithuania	1	1	4
Luxembourg	2,427	527	147,265
Netherlands	20	13	5,970
Portugal	9	8	212
Spain	348	185	25,096
Total	5,494	1,817	501,955
Panel B: By country available for sale			
Austria	1,786	545	215,864
Belgium	1,285	361	109,124
Cyprus	63	14	9,791
Estonia	10	5	1,238
Finland	810	207	75,079
France	3,008	941	253,150
Germany	2,426	812	289,310
Greece	215	55	21,317
Ireland	514	131	74,439
Italy	1,476	422	164,411
Latvia	10	6	298
Lithuania	9	4	289
Luxembourg	2,832	650	221,580
Malta	26	10	4,881
Netherlands	1,153	298	100,450
Portugal	451	152	42,029
Slovakia	218	81	20,660
Slovenia	23	14	2596
Spain	1,844	552	167,248
Non-euro-area	2,409	564	242,622

Table 2: Summary statistics

Table 2 reports summary statistics for various share class and fund characteristics of our sample mutual funds. Summary statistics are computed at the share class level and include the number of observations, mean, standard deviation (SD), and the 10th – 90th percentiles. The sample period is 2013:Q4–2020:Q2.

					Percentiles				
Variable	Unit	Obs.	Mean	SD	10th	25th	50th	75th	90th
Institutional share class	(0/1)	114,949	0.16	0.37	0.00	0.00	0.00	0.00	1.00
Load fees	(0/1)	112,972	0.76	0.42	0.00	1.00	1.00	1.00	1.00
Minimum investment	EUR, thousands	104,430	873.1	8891.0	0.0	0.0	0.0	5.0	1000.0
Expense ratio	(%, p.a.)	114,949	1.57	0.68	0.74	1.13	1.55	1.93	2.35
Fund size	EUR, millions	114,949	355.8	844.6	17.4	45.6	135.4	370.6	824.6
Fund age	years	114,949	14.2	9.0	3.6	6.8	13.5	19.3	25.4
Share small/mid cap stocks	(%)	106,419	34.0	27.1	7.2	13.5	24.9	47.2	83.4
Alpha	(%)	107,216	-0.33	3.08	-3.65	-1.82	-0.36	1.17	3.08
Relative net flow	(%)	103,553	3.7	35.2	-12.6	-4.3	-0.3	2.8	16.2

Table 3:
Fund characteristics by investor sector

Table 3 reports the time-series averages of weighted mean fund and share class characteristics of different investor sectors. For each quarter and investor sector we compute the TNA-weighted average of a fund/share class characteristic based on the investor types' quarterly holdings. For each characteristic we report in the first line the time-series average of the respective investor sector. In the second line we report the difference in means relative to the household sector, in the third line we report t-statistics for the difference in means test based on Newey-West standard errors in parentheses. The sample period is 2013:Q4–2020:Q2. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Households	Insurers	Investment funds	Foreign	Pension funds	Banks	Non-financials	Others
Institutional share class	0.02	0.09	0.33	0.17	0.51	0.31	0.13	0.32
		0.07***	0.31***	0.15***	0.49***	0.29***	0.11***	0.30***
		(7.06)	(12.59)	(43.07)	(36.81)	(9.28)	(9.09)	(10.94)
Load fees	0.85	0.92	0.75	0.78	0.64	0.71	0.79	0.77
		0.07***	-0.10***	-0.06***	-0.21***	-0.14***	-0.06***	-0.08***
		(7.00)	(-3.95)	(-7.81)	(-6.15)	(-4.47)	(-3.46)	(-7.40)
log(Minimum investment)	10.87	12.92	14.18	14.57	13.38	14.14	12.66	13.41
		2.05***	3.31***	3.70***	2.51***	3.28***	1.80***	2.55***
		(12.26)	(25.49)	(9.05)	(6.97)	(18.60)	(9.13)	(27.97)
Expense ratio (%, p.a.)	1.64	1.53	1.25	1.46	1.19	1.43	1.60	1.33
		-0.10***	-0.39***	-0.18***	-0.45***	-0.21***	-0.04**	-0.31***
		(-9.97)	(-13.80)	(-19.71)	(-28.11)	(-3.63)	(-2.42)	(-7.42)
log(Fund TNA)	7.98	7.42	6.93	7.28	6.83	7.53	7.40	7.02
		-0.56***	-1.05***	-0.70***	-1.15***	-0.46***	-0.58***	-0.96***
		(-9.07)	(-9.80)	(-7.62)	(-15.51)	(-11.82)	(-6.53)	(-9.33)
Age (years)	22.59	22.59	14.46	18.01	14.98	15.38	16.40	15.04
		0.00	-8.13***	-4.59***	-7.61***	-7.22***	-6.19***	-7.55***
		(-0.01)	(-13.26)	(-5.89)	(-8.53)	(-8.73)	(-18.74)	(-9.50)
Share of small/mid-cap stocks	22.49	25.93	29.20	30.26	24.37	29.47	30.52	31.15
		3.44***	6.72***	7.78***	1.88*	6.99***	8.04***	8.67***
		(9.15)	(49.73)	(10.90)	(1.92)	(16.60)	(10.02)	(21.40)

Table 4:
Fund flow externality decomposition

Table 4 decomposes the flow externality in mutual across holder sectors. Column (1) shows the total externality (quarterly return, in basis points) arising from large redemptions at the end of the previous quarter (RelFlows $\leq$ -10%) in illiquid funds (share of micro, small, and mid-cap stocks is in the top 25 percent of funds), Columns (2)-(9) report the decomposition across different sectors. Externality^{generated} shows how much each sector contributes to the externality, Externality^{received} shows how much of the externality each sector absorbs, Externality^{H0} shows how much each sector would contribute/absorb under the null hypothesis of uniform outflow behavior (i.e. all sectors withdraw money proportional to their TNA shares). (Externality^{received} - Externality^{generated}) reports the net externality of each sector, (Externality^{generated} - Externality^{H0}) reports the excess externality originated by each sector, and (Externality^{received} - Externality^{H0}) reports the excess externality received by each sector. We report t-statistics based on standard errors clustered at the fund level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2013:Q4–2020:Q2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Households	Insurers	Investment funds	Foreign	Pension funds	Banks	Non-financials	Others
Externality^{generated}	-44.92	-22.21***	-2.71	-15.07**	1.84	-1.38	-1.37	-2.50	-1.52
		(-2.79)	(-0.65)	(-2.52)	(0.48)	(-0.73)	(-0.68)	(-1.10)	(-0.46)
Externality^{received}	-44.92	-29.78***	-5.92	-3.88	-1.62	-0.04	-1.34	-3.93**	1.61
		(-3.82)	(-1.54)	(-0.84)	(-0.97)	(-0.16)	(-1.02)	(-1.98)	(1.08)
Externality^{H0}	-44.92	-28.92***	-5.25	-6.00	-1.06	-0.22	-1.18	-3.65*	1.36
		(-3.75)	(-1.40)	(-1.32)	(-0.62)	(-0.58)	(-0.96)	(-1.91)	(0.79)
Externality^{received} - Externality^{generated}	0.00	-7.57**	-3.21	11.19***	-3.46	1.33	0.03	-1.43	3.13
		(-2.06)	(-1.12)	(2.66)	(-0.98)	(0.71)	(0.01)	(-0.75)	(0.95)
Externality^{generated} - Externality^{H0}	0.00	6.71**	2.54	-9.07***	2.90	-1.15	-0.18	1.15	-2.88
		(2.16)	(1.05)	(-2.63)	(0.97)	(-0.72)	(-0.11)	(0.73)	(-1.12)
Externality^{received} - Externality^{H0}	0.00	-0.86	-0.67	2.12**	-0.57	0.18	-0.16	-0.29	0.25
		(-1.39)	(-1.38)	(2.40)	(-0.98)	(0.63)	(-0.51)	(-0.85)	(0.30)
Obs.	722								

Table 5:
Externality decomposition within the household and insurer sectors

This table repeats the externality decomposition of Table 4 for sub-samples within households (Panel A) and insurers (Panel B). In Panel A we split the household sector according to holdings in share classes with a low (< 10.000 EUR) and high ($\geq$ 10.000 EUR) minimum investment amount. In Panel B we split the insurer sector according to holdings in fund families which are (or are not) associated with insurers. Externality^{generated} shows how much each sector contributes to the externality, Externality^{received} shows how much of the externality each sector absorbs, Externality^{H0} shows how much each sector would contribute/absorb under the null hypothesis of uniform outflow behavior (i.e. all sectors withdraw money proportional to their TNA shares). (Externality^{received} - Externality^{generated}) reports the net externality of each sector, (Externality^{generated} - Externality^{H0}) reports the excess externality originated by each sector, and (Externality^{received} - Externality^{H0}) reports the excess externality received by each sector. Differences in the number of observations arise due to missing values with respect to the conditioning variables. We report t-statistics based on standard errors clustered at the fund level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. The sample period is 2013:Q4–2020:Q2.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Households			**Panel B: Insurers**		
		Minimum investment amount			Insurer-associated fund family	
	All	Low	High	All	Yes	No
Externality^{generated}	-22.06***	-15.24**	-6.20**	-2.93	0.80	-3.73
	(-2.67)	(-2.07)	(-2.04)	(-0.69)	(0.48)	(-0.95)
Externality^{received}	-30.34***	-22.37***	-7.30**	-7.29*	-0.30	-6.99*
	(-3.76)	(-3.18)	(-2.28)	(-1.83)	(-0.20)	(-1.89)
Externality^{H0}	-29.42***	-21.38***	-7.20**	-6.51*	0.08	-6.58*
	(-3.69)	(-3.08)	(-2.31)	(-1.68)	(0.05)	(-1.82)
Externality^{received} - Externality^{generated}	-8.28**	-7.13*	-1.10	-4.36	-1.10	-3.26
	(-2.21)	(-1.94)	(-0.66)	(-1.51)	(-0.83)	(-1.27)
Externality^{generated} - Externality^{H0}	7.36**	6.13**	0.99	3.58	0.72	2.86
	(2.32)	(1.99)	(0.73)	(1.48)	(0.63)	(1.34)
Externality^{received} - Externality^{H0}	-0.92	-1.00	-0.10	-0.78	-0.38*	-0.41
	(-1.45)	(-1.52)	(-0.31)	(-1.55)	(-1.84)	(-0.88)
Obs.	695			663		

Table 6: Investor turnover and investment procyclicality
In Panel A we report the trading sectors' sectors' quarterly portfolio turnover. Sector turnover is defined as the minimum of sectors' aggregate purchases or sales in a quarter, divided by average sector holdings during that period (in %). We report the average sector turnover in the sample period in the first row. In the next row the table shows the difference in turnover between a specific sector, column (j) and the household sector, column (1), along with the respective t-value below. In Panel B and C we measure the co-movement of investors' aggregate flows and states of the market. We regress a sector's aggregate flows relative to their past TNA holdings (in %) on the return of developed stock markets provided by Ken French (Panel B) and the average quarterly VIX volatility index (Panel C). All regressions include a constant which we omit for brevity. The sample period is 2013:Q4–2020:Q2. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Households	Insurers	Investment funds	Foreign	Pension funds	Banks	Non-financials	Others
Panel A: Sector turnover								
Turnover	2.91	3.40	6.63	7.87	6.44	8.40	6.80	7.67
$\Delta(j) - (1)$		0.49*	3.72***	4.95***	3.53***	5.49***	3.89***	4.75***
		(1.98)	(13.17)	(12.52)	(5.89)	(11.41)	(6.97)	(7.93)

Panel B: Aggregate sector flows and the market

	Dependent variable: Aggregate sector flows (in percent of lagged TNA)							
Market	0.08**	0.02	0.18***	0.03	0.12	0.20*	0.02	-0.06
	(2.31)	(0.89)	(4.38)	(0.48)	(1.04)	(1.79)	(0.28)	(-0.69)
R^2	23.0	1.1	46.4	0.7	5.1	11.7	0.1	1.1
$\Delta(j) - (1)$	–	-0.06*	0.10*	-0.05	0.04	0.11	-0.06	-0.14
		(-2.02)	(1.73)	(-0.76)	(0.32)	(0.99)	(-0.89)	(-1.51)

Panel C: Aggregate sector flows and the VIX

	Dependent variable: Aggregate sector flows (in percent of lagged TNA)							
VIX	-0.04	0.02	-0.16	-0.01	-0.33***	-0.40***	0.03	0.05
	(-0.49)	(0.64)	(-1.38)	(-0.09)	(-4.15)	(-3.36)	(0.45)	(0.41)
R^2	2.2	0.4	17.6	0.0	20.3	24.4	0.2	0.3
$\Delta(j) - (1)$	–	0.05	-0.12**	0.03	-0.29***	-0.36***	0.07	0.08
		(0.79)	(-2.22)	(0.39)	(-4.26)	(-5.09)	(0.83)	(0.86)

Table 7:
Flow-performance relationship of different investor sectors
Table 7, Panel A shows the linear flow-performance relationship regression described in Equation (14). The dependent variable is $\text{RelFlows}^{b}_{t,f,i}$, which are investor sectors' fund flows standardized by their lagged TNA. The main independent variable is *AlphaRank*, which is the percentile rank (ranging from 0 - 1) of fund alpha measured over the past 24 months. We interact *AlphaRank* with a dummy for each investor sector, where households serve as the reference sector. Fund-level controls, which are omitted for brevity, include lagged fund flows, fund age, fund size, fund family size, expense ratio, a dummy for fund with load fees and aggregate Morningstar Category and fund family flows. Specification (1) includes fund-level controls and time fixed effects, specification (2) includes fund-time fixed effects, where all fund-level controls are absorbed. Panel B shows the result for piecewise linear flow-performance relationship regression described in Equation (15) with a single knot at the median fund performance (i.e., $AlphaRank = 0.5$) *AlphaRank low* (*AlphaRank high*) provides the flow-performance sensitivity below (above) median fund performance. The sample period is 2013:Q4–2020:Q2. We report t-statistics based on standard errors clustered at the fund level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

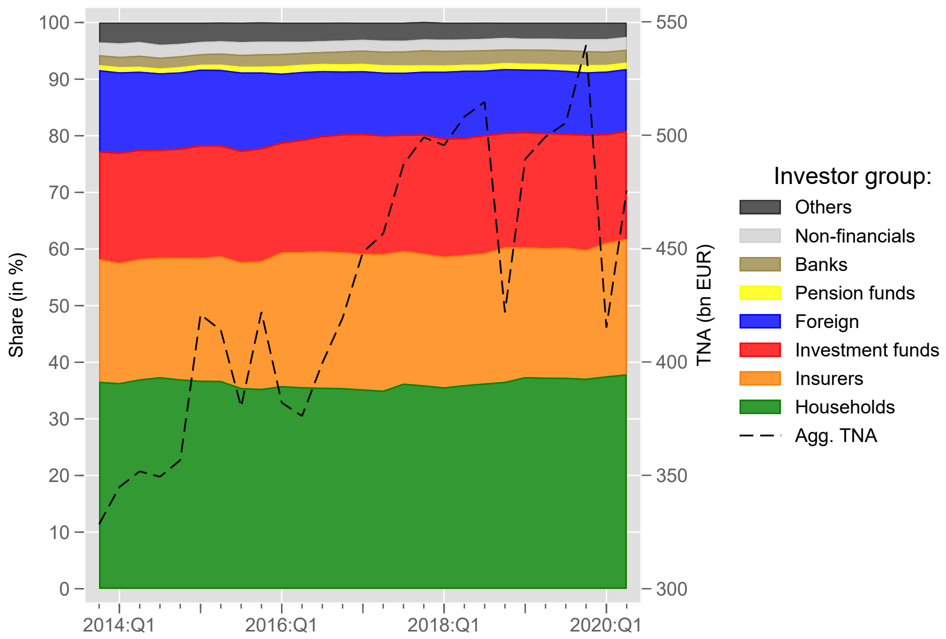
	(1)		(2)	
Panel A: Linear specification				
	Dependent variable: $\text{RelFlows}^{b}_{t,f,i}$			
Alpha rank	4.51***	(8.01)	–	
Alpha rank × Investment funds	4.97***	(3.96)	5.25***	(3.39)
Alpha rank × Insurance companies	3.11***	(3.07)	3.91***	(3.17)
Alpha rank × Pension funds	-1.67	(-0.59)	0.47	(0.13)
Alpha rank × Banks	1.73	(0.27)	-0.28	(-0.04)
Alpha rank × Non-financials	2.42***	(2.84)	2.92***	(3.04)
Alpha rank × Foreign	-2.56	(-0.69)	-1.93	(-0.52)
Alpha rank × Others	7.50***	(4.14)	7.07***	(3.75)
Fund-level controls	Yes		–	
Time fixed effects	Yes		–	
Fund×time fixed effects	No		Yes	
R^2	1.401		19.57	
Within R^2	1.34		1.17	
Obs.	181.392		181.122	

	(1)		(2)	
Panel B: Piecewise-linear specification				
	Dependent variable: $\text{RelFlows}^b_{t,f,i}$			
Alpha rank low	1.32	(1.30)	–	
Alpha rank high	6.33***	(3.44)		
Alpha rank low × Investment funds	7.82***	(2.85)	8.20**	(2.33)
Alpha rank high × Investment funds	-5.71	(-1.17)	-5.42	(-0.90)
Alpha rank low × Insurance companies	0.65	(0.32)	-1.02	(-0.39)
Alpha rank high × Insurance companies	4.66	(1.21)	9.60**	(2.01)
Alpha rank low × Pension funds	5.68	(0.77)	12.22	(1.34)
Alpha rank high × Pension funds	-13.78	(-1.10)	-20.65	(-1.36)
Alpha rank low × Banks	-1.05	(-0.07)	-6.33	(-0.43)
Alpha rank high × Banks	5.15	(0.20)	11.67	(0.45)
Alpha rank low × Non-financials	-0.33	(-0.18)	0.99	(0.46)
Alpha rank high × Non-financials	5.39	(1.57)	3.81	(0.95)
Alpha rank low × Foreign	1.55	(0.18)	0.64	(0.07)
Alpha rank high × Foreign	-8.21	(-0.52)	-5.10	(-0.33)
Alpha rank low × Other	0.75	(0.20)	0.34	(0.09)
Alpha rank high × Other	13.12*	(1.94)	13.17*	(1.87)
Fund-level controls	Yes		–	
Time fixed effects	Yes		–	
Fund×time fixed effects	No		Yes	
R^2	1.1		19.57	
Within R^2	1.35		1.17	
Obs.	181.392		181.122	

Table 8:
Redemption behavior of major sectors during the COVID-19 market crash
Table 8 shows the result for the cross-sectional regressions described in Eq. (16). The dependent variable is $CumRelFlows_{s,f,H}$, which is cumulative net flow of fund f's share class s over horizon H. An investor group is defined as the major owner of a share-class, if it holds shares worth more than 75% of the share-class TNA. Explanatory variables are dummy variables for the respective investor sectors, where households serve as reference sector. Columns show coefficients estimated for flows cumulated over horizons of 1-5, 10, 20, 40 and 60 consecutive trading days. The reported coefficients are WLS estimates, meaning that observations are weighted by the relative net asset share. The sample period is 24th February 2020 until June 2020. We report t-values based on standard errors clustered at the fund level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Market crash period (24th February - March 23, 2020)								
Horizon H =	1 day	2 days	3 days	4 days	5 days	10 days	20 days	40 days	60 days
	Dependent variable: $CumRelFlows_{s,f,H}$								
Panel A: OLS									
Investment Funds	-0.02	-0.09***	-0.09*	-0.09	-0.10	-0.41***	-1.48***	-2.23***	-2.82***
	(-1.34)	(-2.75)	(-1.74)	(-1.47)	(-1.22)	(-2.60)	(-3.89)	(-5.34)	(-5.67)
Insurers	-0.02	0.01	0.06	0.04	0.05	-0.02	0.23	0.15	0.15
	(-1.29)	(0.22)	(1.39)	(0.79)	(0.74)	(-0.17)	(0.93)	(0.40)	(0.33)
Constant	0.01	-0.03**	-0.11***	-0.17***	-0.25***	-0.33***	-0.79***	-0.32	-0.03
	(0.92)	(-2.15)	(-4.42)	(-4.89)	(-5.45)	(-4.72)	(-5.04)	(-1.53)	(-0.09)
R^2	0.00	0.01	0.01	0.00	0.00	0.01	0.03	0.03	0.04
Within R^2	0.00	0.01	0.01	0.00	0.00	0.01	0.03	0.03	0.04
# share classes	1,627	1,624	1,623	1,618	1,616	1,611	1,594	1,563	1,537
# Funds	1,010	1,009	1,009	1,007	1,006	1,006	1,001	990	981
Fund FE	No	No	No	No	No	No	No	No	No
Panel B: Fund fixed effects									
Investment Funds	-0.05	-0.18***	-0.27***	-0.30**	-0.46***	-1.13***	-2.49***	-3.26***	-3.54***
	(-1.11)	(-2.60)	(-2.72)	(-2.38)	(-3.19)	(-4.03)	(-3.38)	(-4.74)	(-4.94)
Insurers	-0.11	-0.28*	-0.37**	-0.52**	-0.66**	-0.96*	-2.07*	-1.74	-1.51
	(-1.61)	(-1.81)	(-2.10)	(-2.26)	(-2.31)	(-1.71)	(-1.76)	(-1.08)	(-0.85)
Constant	0.03**	0.04	0.00	-0.05	-0.07	-0.01	-0.34	0.07	0.24
	(2.00)	(1.29)	(0.07)	(-0.97)	(-1.25)	(-0.11)	(-1.29)	(0.27)	(0.81)
R^2	0.07	0.16	0.22	0.19	0.21	0.28	0.42	0.54	0.58
Within R^2	0.00	0.01	0.02	0.02	0.02	0.03	0.04	0.04	0.05
# share classes	971	969	968	965	963	956	940	910	895
# Funds	354	354	354	354	353	351	347	337	332
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel A: Holdings by investor sector (share in percent) and aggregate TNA, over time



Panel B: Flows by investor sector (percent of lagged TNA), over time

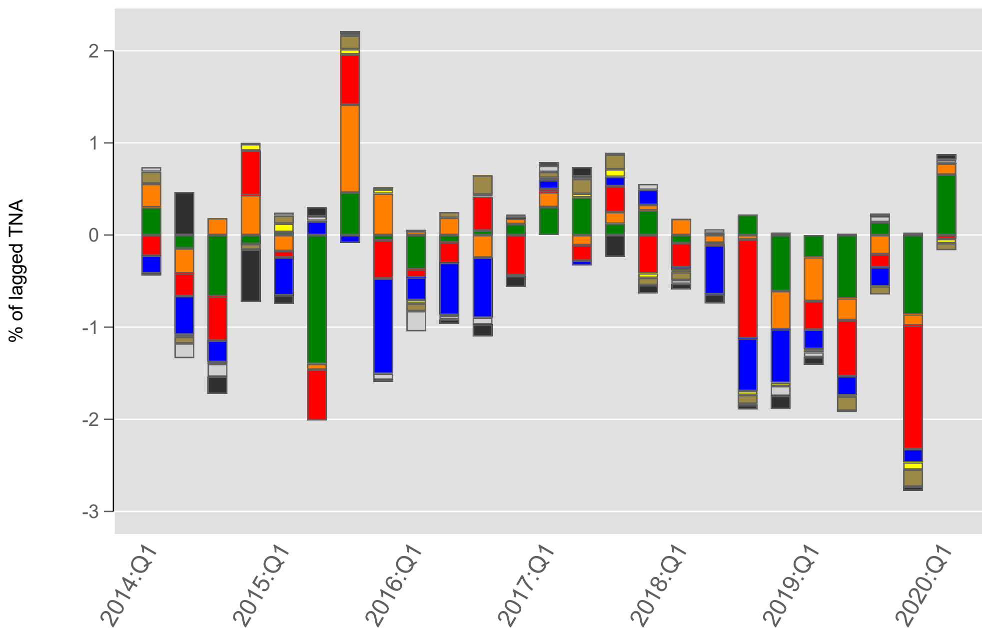
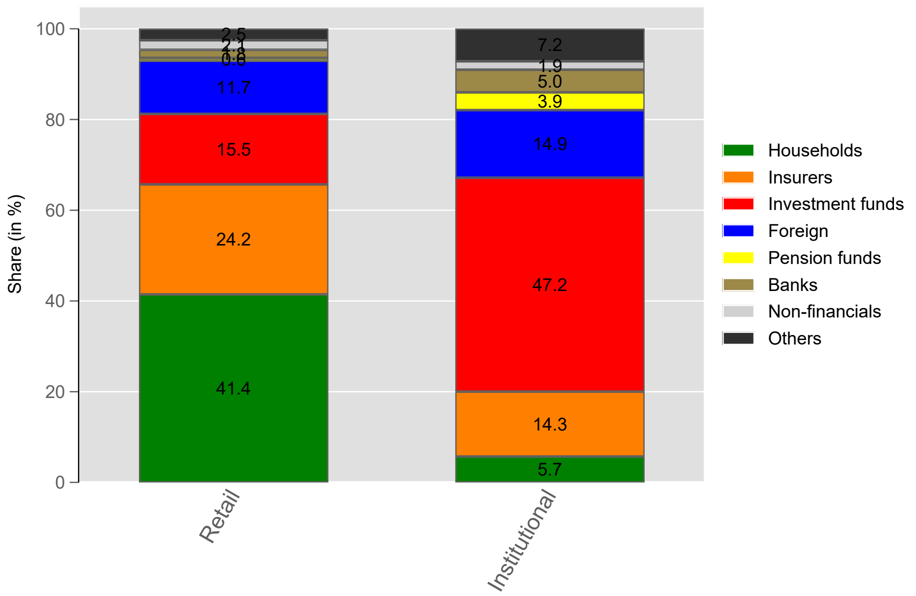
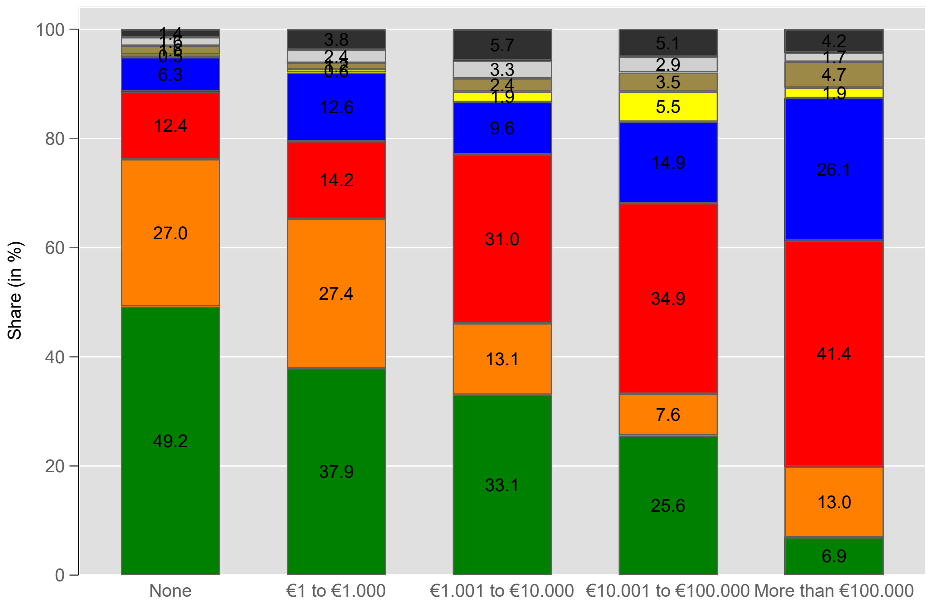


Figure 1:
Mutual fund holdings and net flows by investor sector, over time
Panel A of Figure 1 shows the ownership composition of our sample mutual funds by investor sector, over time. The dashed line (corresponding to the right-hand y-axis) shows that aggregate TNA of funds in our sample. Panel B shows the funds' corresponding percentage flows by investor sector and over time. Percentage flows are computed as EUR-flows divided by funds' net assets at the end of the previous quarter. The sample period is 2013:Q4 until 2020:Q2.

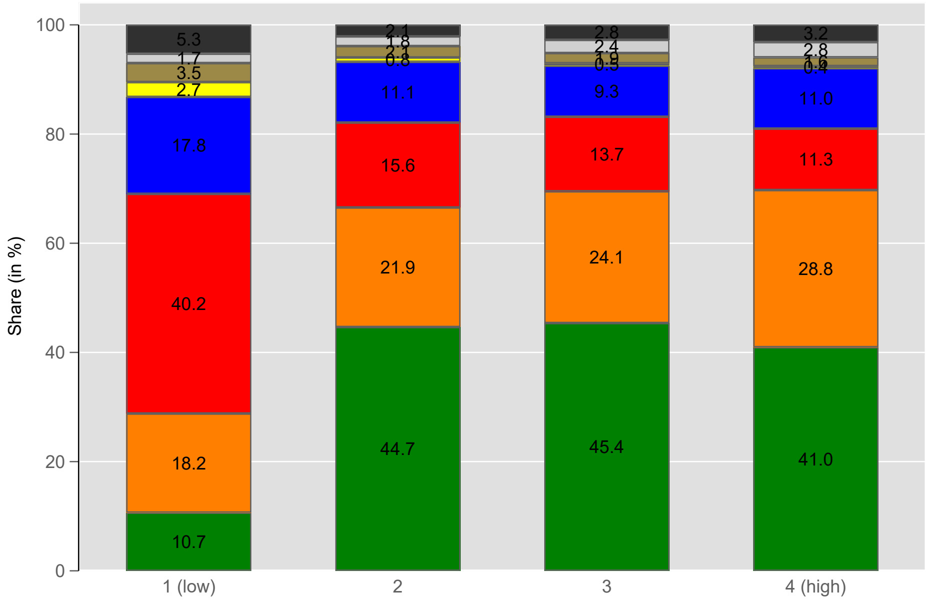
Panel A: Breakdown by share class type



Panel B: Breakdown by minimum investment required



Panel C: Breakdown by expense ratio



Panel D: Breakdown by ratio of small-to-mid-cap holdings

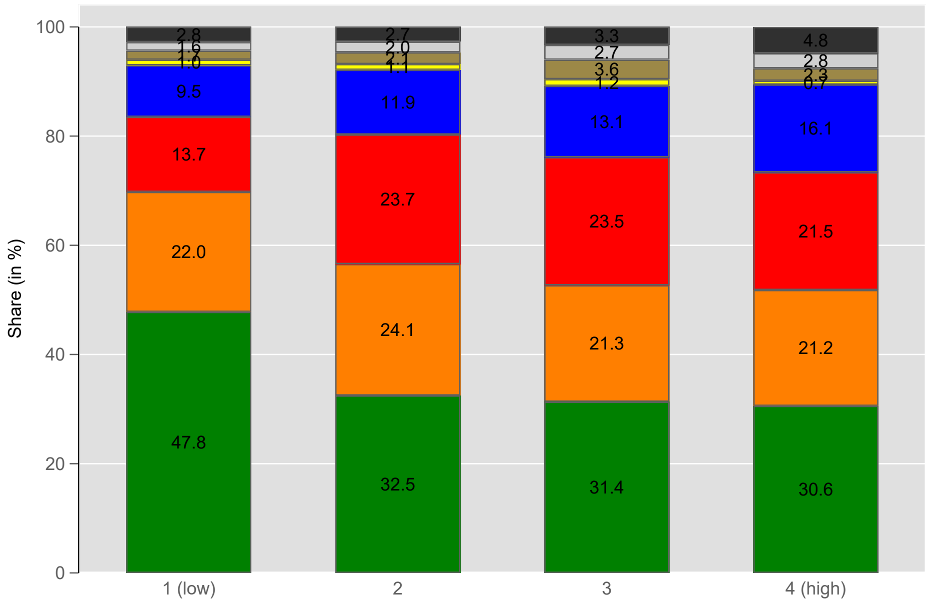
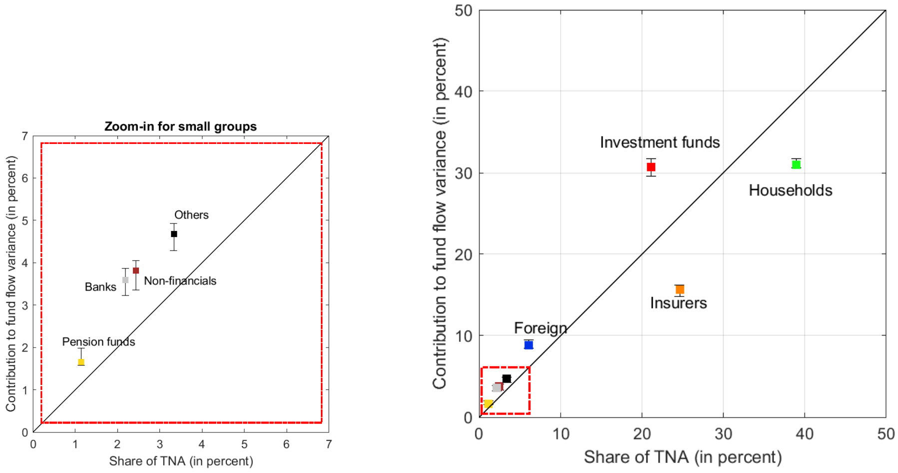


Figure 2:
Ownership structure: breakdowns by fund characteristics
Figure 2 shows the ownership composition of our sample mutual funds by various share class level characteristics (averaged over time). Breakdowns are provided by share class type (Panel A), minimum investment required (Panel B), expense ratio (Panel C), and share of small-to-mid-cap oriented holdings (Panel D). Investor sectors' ownership shares are averaged over the full sample (2013:Q4–2020:Q2).

Panel A: All flows



Panel B: Inflows and Outflows

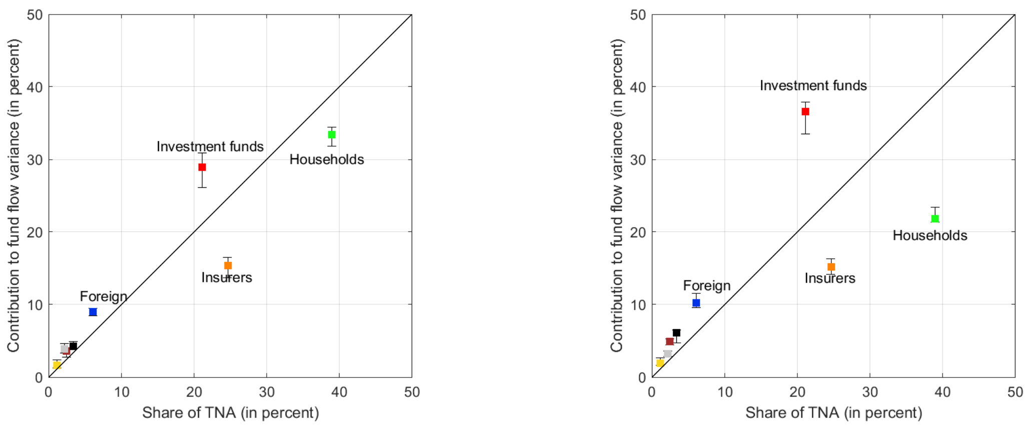


Figure 3:
Flow contribution of investor sectors (fund-level)
Figure 3 shows results for all fund-level flows (Panel A) and separately for inflows and outflows (Panel B). Investor sectors' flow contributions are measured by their Shapley value (see e.g. (Shapley, 1954; Joseph, 2019)). Investor sectors' Shapley values (y-axis) are plotted against the relative size of their equity mutual fund holdings (x-axis). Shapley values are computed based on bootstrapping (with re-sampling) over 1,000 repetitions. The sample period is 2013:Q4–2020:Q2.

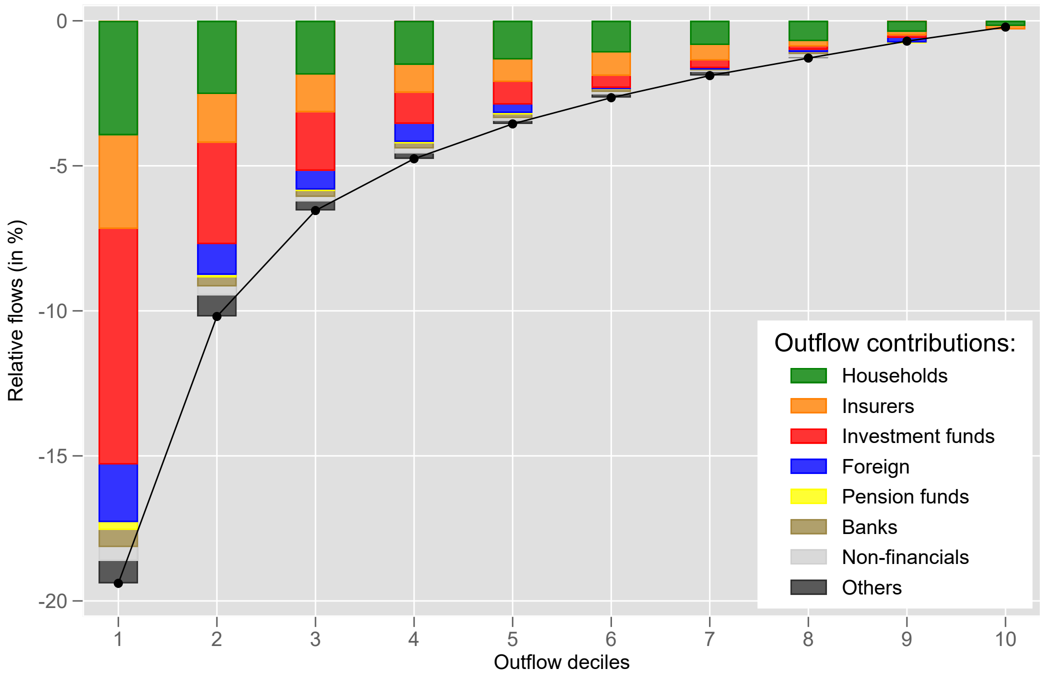
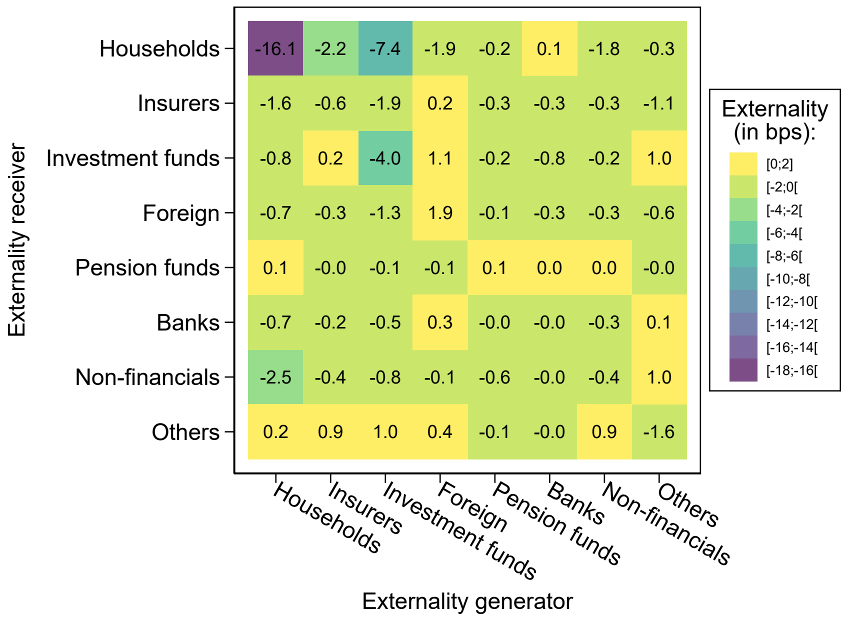


Figure 4:
Outflow contributions by investor sector
Figure 4 shows the contribution of each investor sector to our sample funds' TNA-weighted outflows. Provided are deciles of the (relative) outflow distribution. The sample period is 2013:Q4 until 2020:Q2.

Panel A: Flow externality decomposition



Panel B: Excess flow externality decomposition

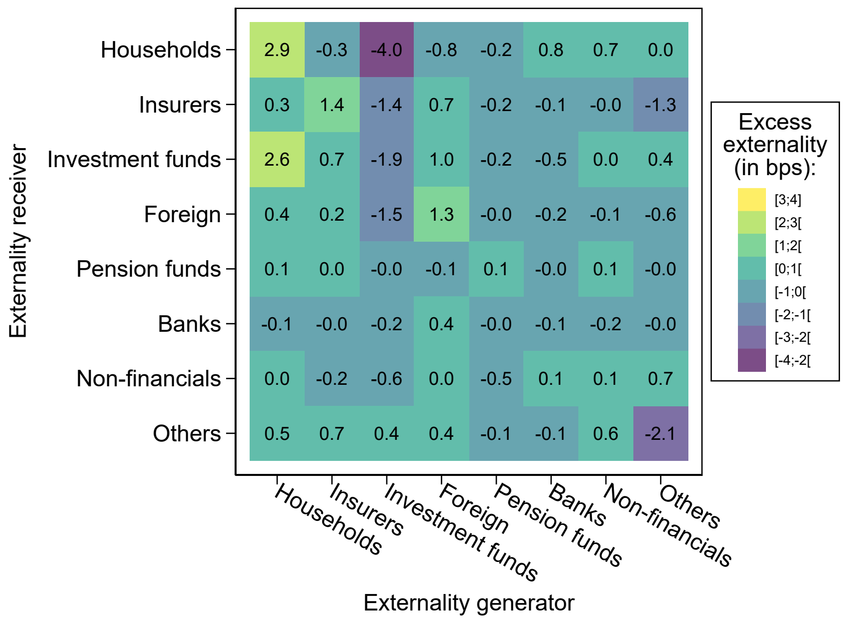


Figure 5:
Network perspective on the flow externality
Figure 5 decomposes the flow externality in mutual funds simultaneously by originator and receiver. The heat maps show the contribution of different investor sectors (columns) on the externalities received by different investor sectors (rows). Panel A shows the decomposition of the overall flow externality, Panel B shows the decomposition of the excess externality, which measures whether the flow externality originating from sector i to sector j is stronger than what would be expected under the null of uniform outflow behavior for the given holding structure. The decomposition is based on the estimation results shown in Table 4, Column (1), which yields a reduction in quarterly fund performance of -45 bps following outflows of more than 10% in the previous quarter for illiquid funds. Externality and excess externality are measured in bps.

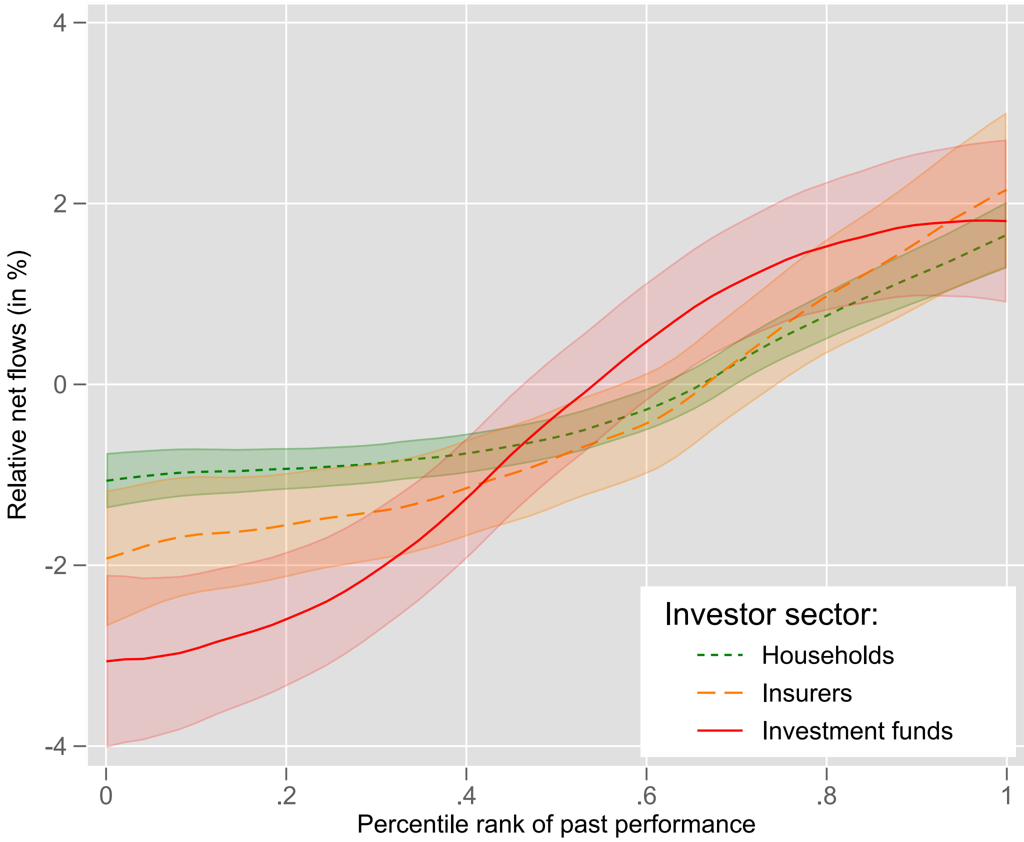


Figure 6:
Flow-performance relationship by investor sector.
Figure 6 shows the relationship between net flows of different investor sectors and the fund's lagged performance rank (ranging from 0 to 1). We employ the semi-parametric estimation approach by Robinson (1988), where we control for standard fund characteristics, including fund size, fund age, expense ratio, a dummy for back-end loads, lagged fund flows, and contemporaneous aggregate flows to the fund family and fund category. Shaded areas represent 90% confidence intervals.

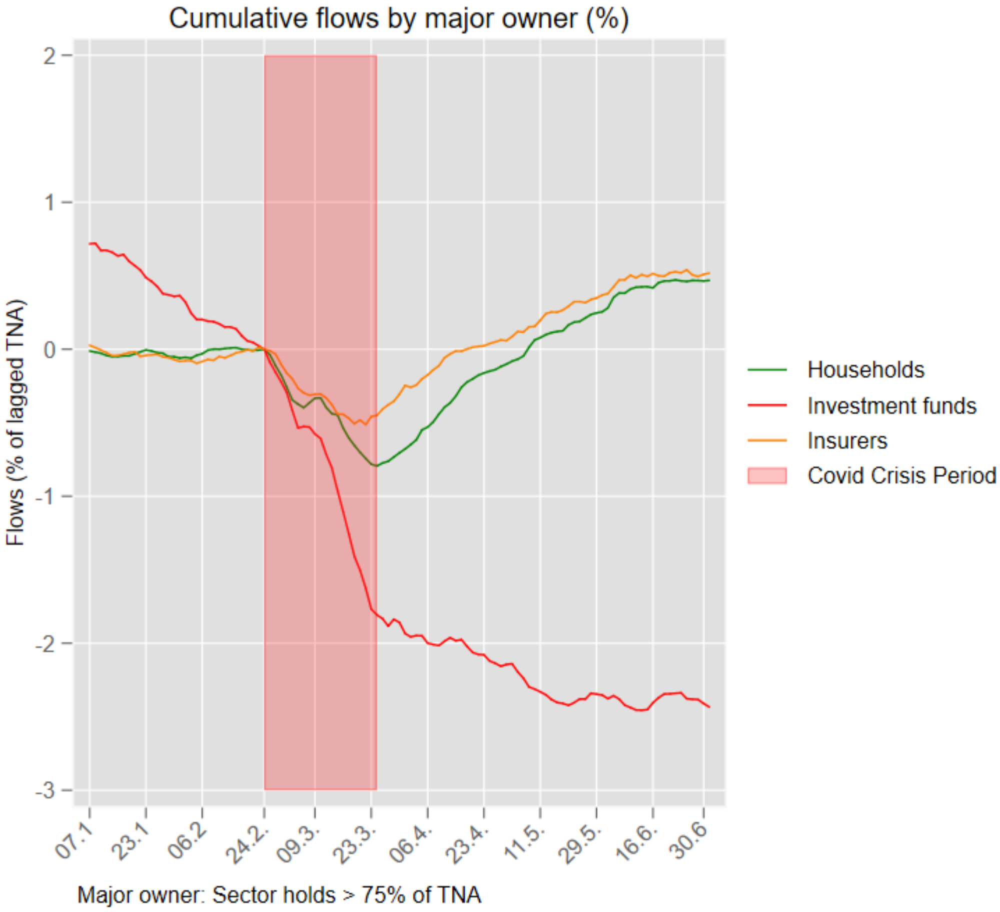


Figure 7:
Redemption behavior of major sectors during the COVID-19 market turmoil
Figure 7 shows cumulative daily flows into our sample funds in which private households (green line), insurers (orange line) or investment funds (red line) are major holders. Flows are reported as a percentage of the share classes' lagged TNA. Flows are weighted by share class TNA and cumulated over the period from 1st January 2020 to 30th June 2020 and cover the COVID-19 related market turmoil between 24th February 2020 and 23rd March 2020 (shaded red area). An investor sector is classified as major owner if its holdings exceed 75% of the share class TNA.

Data Appendix

Table A.1:
Overview over variable definitions
Table A.1 gives an overview over major variables used throughout the paper. Columns contain variable name, variable unit, variable definition and data source.

Name	Unit	Definition	Data source
Fund age	years	Time since inception of the oldest share class.	Morningstar
Alpha	percent	We compute benchmark adjusted performance the following way: $Alpha = (Return - \beta \times Benchmark) \times 100$, where $Return$ is a fund's quarterly realized (net) return, $Benchmark$ is the quarterly return of the index portfolio selected for each fund category by Morningstar, and β is a fund's benchmark beta estimated over 36 months.	Morningstar
AlphaRank	[0,1]	Percentile rank (ranging from 0 - 1) of fund $Alpha$ measured over the past 24 months.	Morningstar
Load fees	(0/1)	Dummy variable that equals one if either the front load or deferred load fee is non-zero.	Morningstar
Institutional fund	(0/1)	Dummy variable that equals one if the fund has at least one institutional share class	Morningstar
RelFlows^a	percent	fund level relative net flow of investor sector i relative to the fund's lagged TNA, computed as: $(TNA_{t,f,i} - TNA_{t-1,f,i} \times (1 + Return_{t,f}))/TNA_{t-1,f} \times 100$.	Morningstar, SHS-S
RelFlows^b	percent	fund level relative net flow of investor sector i relative to the lagged TNA of the sector in the same fund, computed as: $(TNA_{t,f,i} - TNA_{t-1,f,i} \times (1+Return_{t,f}))/TNA_{t-1,f,i} \times 100$.	Morningstar, SHS-S
RelFlows	percent	share class or fund level relative net flow, computed as: $(TNA_{t,f} - TNA_{t-1,f} \times (1 + Return_{t,f}))/TNA_{t-1,f} \times 100$, where TNA is the total net asset of a fund/share class at quarter t and $Return_t$ is the corresponding quarterly return over quarter t.	Morningstar
Large Outflows	(0/1)	Dummy variable that equals one if a funds' relative quarterly flows (RelFlows) are smaller or equal -10%.	Morningstar
Fund family flow	percent	Quarterly relative flows of a fund's asset manegement company.	Morningstar
Fund category flow	percent	Quarterly relative flows to the fund's Morningstar category.	Morningstar
Illiquid fund	(0/1)	Dummy variable that equals one if the share of micro, small, and mid-cap stocks is in the top 25 percent, and zero otherwise.	Morningstar
Family size	EUR	Aggregate TNA of fund family	Morningstar
Fund size	EUR	TNA of fund	Morningstar
Return	percent	Quarterly return at the share class or fund level as the compounded monthly return.	Morningstar
Market return	percent	Quarterly return on Morningstar's Global Markets Index.	Morningstar
Fund TNA	EUR	fund level total net assets	Morningstar
Investor sector TNA	EUR	total net assets of investor sector i in fund f	SHS-S

Turnover	percent	We define sector turnover as the minimum of investor groups' aggregate purchases or sales in a quarter, divided by average investor groups' holdings during that period: $Turnover_{i,t} = min(Sales_{i,t}, Purchases_{i,t})/(1/2(TNA_{t-1} + TNA_t))$	Morningstar, SHS-S

Internet Appendix

Who creates and who bears flow externalities in mutual funds?

Table IA.1:
Fund flow externality regression

Table IA.1 shows the results for a regression as in Chen et al. (2010). The dependent variable is $\text{Alpha}_{f,t}$, which is the category-beta adjusted return of fund f in quarter t (in %). The key explanatory variables are Outflows_{t-1}, which is a dummy variable that equals 1 for outflows larger than 10% of the fund's TNA, and Illiquid fund_{t-1}, which is a dummy variable that equals one for if a fund's portfolio share of small and mid cap stocks falls into the top quartile of all funds. Control variables are lagged fund performance of the previous four quarters, lagged size of the fund and its expense ratio. The sample period is 2013:Q4–2020:Q2. We report t-statistics based on standard errors clustered at the fund level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
	Dependent variable $\text{Alpha}_{f,t}$ (in %)	
Outflows_{t-1}	-0.07	0.09
	(-1.09)	(1.43)
Outflows_{t-1} × Illiquid fund_{t-1}		-0.64***
		(-3.69)
Illiquid fund_{t-1}		0.29***
		(5.72)
Alpha_{t-1}	0.09***	0.08***
	(8.99)	(8.84)
Alpha_{t-2}	0.04***	0.04***
	(4.50)	(4.02)
Alpha_{t-3}	0.13***	0.13***
	(17.22)	(16.71)
Alpha_{t-4}	0.01	0.01
	(1.64)	(1.18)
$\log(\text{TNA}_{t-1})$	0.06***	0.07***
	(5.25)	(5.54)
Expense ratio $_{t-1}$	-0.10***	-0.12***
	(-3.32)	(-4.07)
Constant	-2.24***	-2.31***
	(-8.85)	(-9.21)
Time fixed effects	Yes	Yes
R^2	13.06	13.23
Obs.	29,789	29,789

Table IA.2:
Expense ratios by different investor sectors: Within-fund analysis

Table IA.2 shows the result for the fixed effects panel regression studying expenses paid by different investor sectors. The dependent variable is $Expense\ ratio_{t,f,i}$, which is the value-weighted expense ratio in fund f payed by investor group i in quarter t. Explanatory variables are dummy variables for the respective investor groups, where households serve as reference group represented in the regression constant. Columns (1) and (2) show OLS estimates, columns (3) and (4) WLS estimates, where observations are weighted by the relative net asset share of each investor group in a given quarter. The sample period is 2013:Q4–2020:Q2. We report t-statistics based on standard errors clustered at the fund level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Dependent variable: *Expense ratio*			
	(1)	(2)	(3)	(4)
	OLS	OLS	WLS	WLS
Insurers	-0.089***	-0.040***	-0.099**	-0.043***
	(-9.26)	(-7.90)	(-2.30)	(-3.41)
Investment funds	-0.319***	-0.214***	-0.512***	-0.271***
	(-22.56)	(-22.10)	(-11.85)	(-11.96)
Foreign	-0.163***	-0.129***	-0.306***	-0.275***
	(-17.56)	(-15.73)	(-5.58)	(-9.94)
Pension funds	-0.509***	-0.227***	-0.630***	-0.302***
	(-18.42)	(-12.70)	(-10.51)	(-7.15)
Banks	-0.088***	-0.043***	-0.314***	-0.170***
	(-8.03)	(-8.01)	(-4.06)	(-5.19)
Non-financials	-0.012*	-0.018***	-0.046	-0.046***
	(-1.95)	(-5.89)	(-1.22)	(-3.12)
Others	-0.047***	-0.040***	-0.346***	-0.137***
	(-5.64)	(-9.37)	(-4.03)	(-6.74)
Households (Constant)	1.864***	1.827***	1.696***	1.620***
	(140.28)	(562.52)	(59.33)	(183.41)
R^2	0.03	0.89	0.10	0.90
Within R^2		0.08		0.17
Obs.	253,338	252,889	253,338	252,889
Fund-quarter FE	No	Yes	No	Yes

Table IA.3:

Fund flow externality decomposition: Excluding the COVID-19 stock market crash

Table IA.3 repeats the analysis of Table 4 but excludes the 2020 stock market crash following the outbreak of the COVID-19 pandemic. Specifically, the sample period is 2013:Q4–2019:Q4. The table decomposes the flow externality in mutual funds across holder sectors. Column (1) shows the total externality (quarterly return, in basis points) arising from large redemptions at the end of the previous quarter (RelFlows $\leq$ -10%) in illiquid funds (share of micro, small, and mid-cap stocks is in the top 25 percent of funds), Columns (2)-(9) report the decomposition across different sectors. Externality^{generated} shows how much each sector contributes to the externality, Externality^{received} shows how much of the externality each sector absorbs, Externality^{H0} shows how much each sector would contribute/absorb under the null hypothesis of uniform outflow behavior (i.e. all sectors withdraw money proportional to their TNA shares). (Externality^{received} - Externality^{generated}) reports the net externality of each sector, (Externality^{generated} - Externality^{H0}) reports the excess externality originated by each sector, and (Externality^{received} - Externality^{H0}) reports the excess externality received by each sector. We report t-statistics based on standard errors clustered at the fund level in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Total	Households	Insurers	Investment funds	Foreign	Pension funds	Banks	Non-financials	Others
Externality^{generated}	-25.93	-6.97	-4.64	-12.18**	0.67	1.01	-0.55	0.97	-4.24*
		(-1.15)	(-1.03)	(-2.08)	(0.17)	(1.20)	(-0.27)	(0.43)	(-1.66)
Externality^{received}	-25.93	-14.34**	-5.33	-4.39	-0.33	-0.23	-1.07	-2.21**	1.96
		(-2.12)	(-1.40)	(-1.11)	(-0.19)	(-0.78)	(-0.91)	(-2.55)	(1.13)
Externality^{H0}	-25.93	-13.55**	-5.08	-5.43	-0.04	0.00	-0.86	-1.39	0.41
		(-2.07)	(-1.37)	(-1.32)	(-0.02)	(0.01)	(-0.75)	(-1.31)	(0.30)
Externality^{received} - Externality^{generated}	0.00	-7.37**	-0.68	7.78*	-1.00	-1.24	-0.52	-3.17*	6.20*
		(-2.21)	(-0.21)	(1.92)	(-0.29)	(-1.51)	(-0.27)	(-1.74)	(1.90)
Externality^{generated} - Externality^{H0}	0.00	6.58**	0.43	-6.75**	0.72	1.00	0.31	2.36*	-4.66*
		(2.36)	(0.16)	(-2.00)	(0.24)	(1.47)	(0.19)	(1.68)	(-1.80)
Externality^{received} - Externality^{H0}	0.00	-0.79	-0.25	1.04	-0.28	-0.23*	-0.21	-0.82*	1.54**
		(-1.33)	(-0.46)	(1.41)	(-0.55)	(-1.67)	(-0.73)	(-1.75)	(2.00)
Obs.	624								

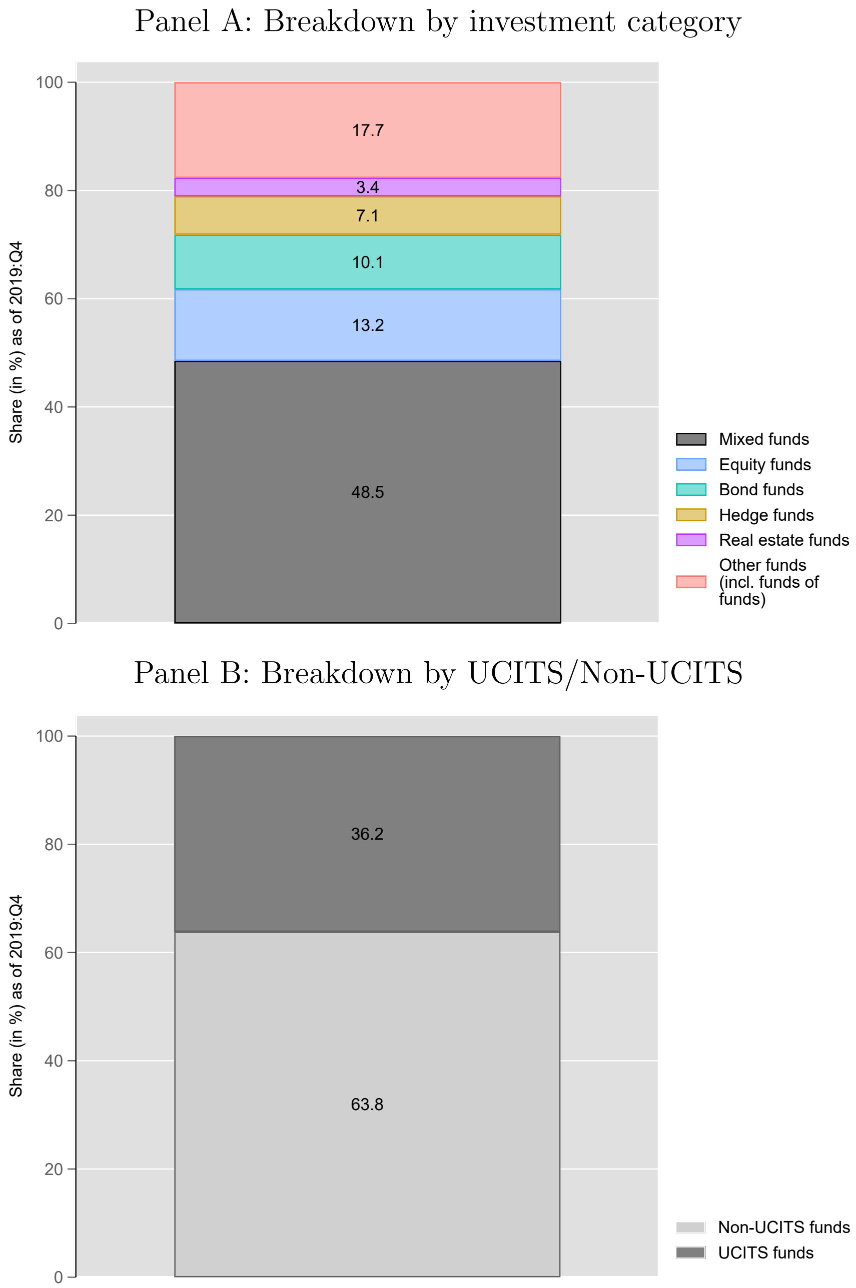


Figure IA.1:
Distribution of the investment fund sector's fund share holdings in the euro area.
Figure IA.1 breaks down the reported aggregate fund share holdings of all euro area investment funds as reported by the Investment Funds Balance Sheet Statistics publicly provided in the European Central Bank's Statistical Data Warehouse. As of 2019:Q4 these holdings amounted to 2.33 trillion Euros across all euro area investment funds. Panel A shows the breakdown by the reporting funds' investment category, where the category *Other* is a residual group that is not further subdivided but includes, among others, funds of funds. Panel B shows the breakdown by UCITS funds versus non-UCITS funds (comprising mainly so-called Alternative Investment Funds). Note that non-UCITS funds are predominantly institutional-oriented, whereas UCITS funds are generally open to both retail and institutional investors. Based on SHS data, we estimate that the subset of UCITS funds displays an aggregate household ownership share of 20% across all investment categories, whereas non-UCITS funds display an aggregate household ownership share of 11%.* Therefore, our best estimate of the institutional share of the euro area investment fund sector's aggregate fund holdings is $(64\% \times 0.89 + 36\% \times 0.8) = 86\%$.

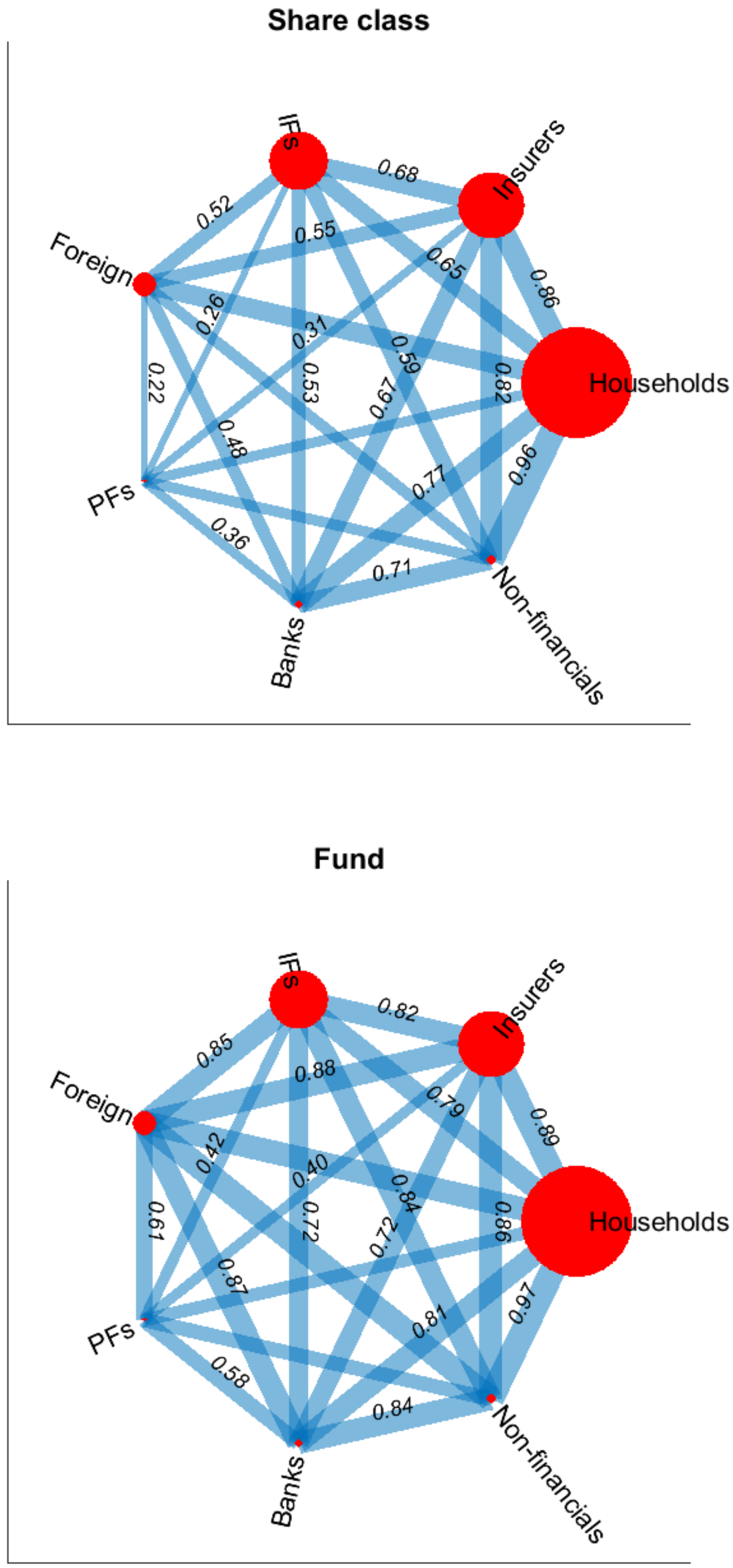


Figure IA.2:
Portfolio overlap of investor types
Figure IA.2 shows the average portfolio overlap across the full sample for each pair of investor groups. Following Antón and Polk (2014), the overlap between investor groups i and j is defined as $\text{Overlap}_{i,j} = \frac{\sum_{\mathcal{H}} \text{TNA}_{i,\mathcal{H}} + \text{TNA}_{j,\mathcal{H}}}{\text{TNA}_i + \text{TNA}_j}$, where $\mathcal{H}$ is the set of share classes (funds) that i and j are both invested in.

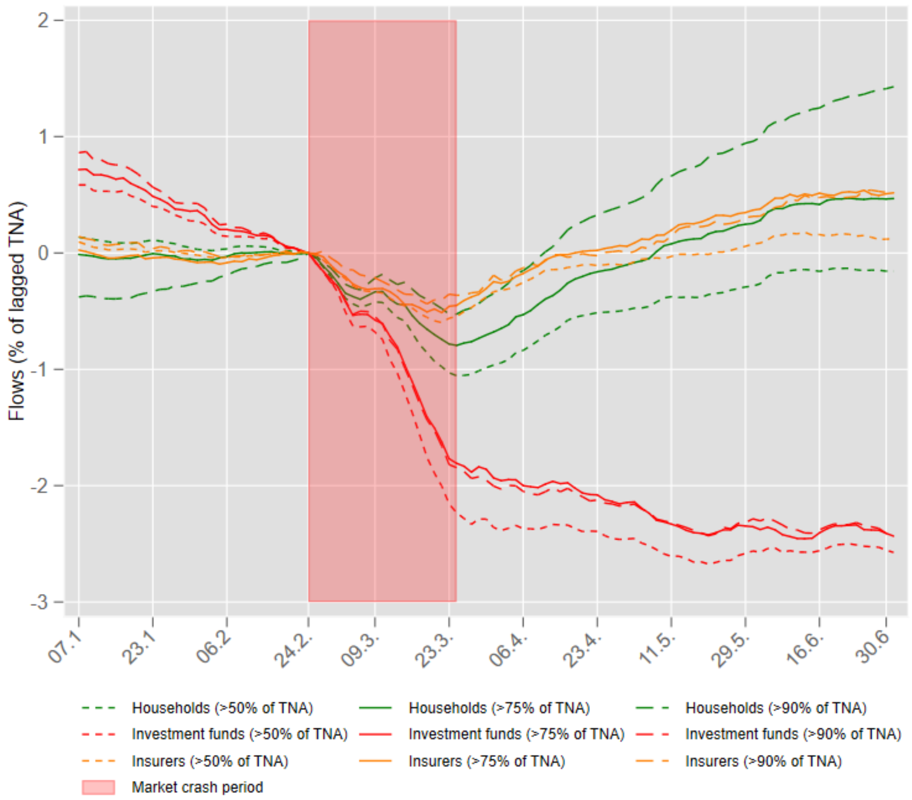


Figure IA.3:
Redemption behavior of major sectors during the COVID-19 market turmoil (different thresholds)
Figure IA.3 shows cumulative daily flows of our sample funds in which private households (green line), insurers (orange line) or investment funds (red line) are major holders. Flows are reported as a percentage of the share class' lagged TNA. Flows are weighted by share class TNA and cumulated over the period from 1st January 2020 to 30th June 2020 and cover the COVID-19 related market turmoil between 24th February 2020 and 23rd March 2020 (shaded red area). An investor group is classified as major owner if it holds more than 75% of share class TNA outstanding.

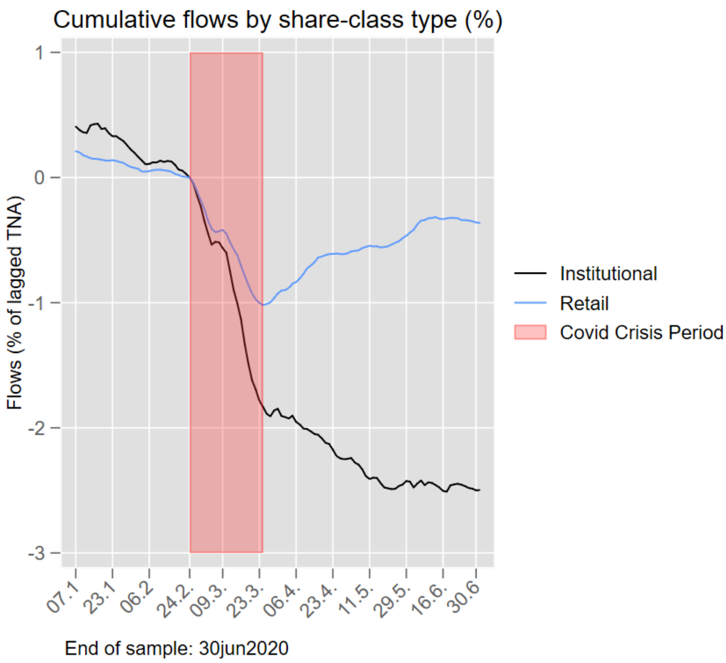


Figure IA.4:
Investor behaviour during the COVID-19 market turmoil, illustrated by common proxies
Figure IA.4 shows cumulative daily flows of our sample funds by share class type (retail versus institutional). Flows are reported as a percentage of the share classes' lagged TNA. Flows are weighted by share class TNA and cumulated over the period from 1st January 2020 to 30th June 2020 and cover the COVID-19 related market turmoil between 24th February 2020 and 23rd March 2020 (shaded red area).