



**Universitat
Pompeu Fabra**
Barcelona

Department
of Economics and Business

Economics Working Paper Series

Working Paper No. 1886

**Geographic shareholder dispersion and
mutual fund flow risk**

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April 2024

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April 19, 2024

Abstract

Exploiting the Securities Holdings Statistics from the Eurosystem, we study the relation between shareholder country concentration and flow risk for euro area mutual funds. We find that funds with a more geographically dispersed investor base experience more volatile flows. The link between shareholder country concentration and flow risk is a widespread phenomenon: It holds for funds investing in different asset classes and in different regions. However, we find no difference in net performance between funds with more and less concentrated shareholders, which suggests that any potential costs of investors' geographic dispersion are offset by either enhanced liquidity management or superior performance. Additional tests reveal that investors in funds with higher geographic shareholder dispersion are more sensitive to fund performance, consistently with a clientele effect driving our findings. Finally, we show that the positive association between geographic investor dispersion and flow risk holds for different measures of flow risk and is not driven by institutional investors, non-euro area investors, or the COVID-19 episode.

Keywords: Geographic shareholder dispersion; Mutual-fund flow risk; Mutual fund fragility; cross-border funds.

JEL classification: G23; G11; G17.

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1 Introduction

How does the geographic dispersion of a mutual fund's investor base affect its flow risk? While the literature has investigated different aspects of mutual fund flow risk, it provides no answer to this question. The reason is that mutual funds must disclose their portfolio holdings with precision, but they must provide only limited information about their shareholders. Therefore, we only know the identity of a mutual fund's shareholders that are themselves institutional investors and subject to mandatory portfolio disclosure. Commercial mutual fund databases provide information on the countries in which a fund is available for sale, but the fact that a fund is registered for sale in a given country does not imply that it is actually sold in that country. And even in that case, this information is not enough to quantify the degree of internationalization of a fund's investors. In this paper, we fill this gap in the literature by exploiting data from the Securities Holdings Statistics by Sector (SHSS), collected by the Eurosystem. This data set contains information on the holders of securities in the euro area (EA) or with a EA custodian, including mutual fund shares. The data allow us to quantify exactly the fraction of a mutual fund's shares owned by investors in each country in the EA as well as total ownership by non-EA residents. It therefore provides us with a unique opportunity to measure the geographic dispersion of EA mutual funds' shareholders and relate it to fund flow risk and other fund characteristics. Our findings reveal a robust link between shareholder country concentration and mutual fund flow risk, with potentially important implications for fund fragility and systemic risk.

While mutual funds registered for sale in the US are also domiciled in the US, cross-border funds, i.e., funds domiciled in one country and sold in a different country, are very common outside the US ([Khorana, Servaes, and Tufano, 2009](#)). This is particularly true in Europe, where mutual funds complying with the UCITS (Undertakings for Collective Investment in Transferable Securities) Directive can be sold in any country of the EU. In our data set, although a majority of funds domiciled in a given country are held by residents in that country, cross-border holdings are substantial. As of September 2020, one-third of funds domiciled in the EA in our sample were held by investors from more than one country, with holdings in each country larger than or equal to 1% of all shares. Although Luxembourg is the country of domicile with the largest number of cross-border funds, many cross-border funds are domiciled in other countries, such as France, Germany, Austria, and Belgium. In relative terms, Austria, Portugal and Luxembourg, have the highest fraction of funds owned by non-residents. The data also reveal substantial heterogeneity across countries of residence. For instance, while Spanish residents invest almost exclusively in funds

domiciled in Spain, Belgian residents invest more in foreign funds than in domestic funds in terms of number of funds.

In this paper, we focus on the flow risk of cross-border funds. It is well known that investor redemptions from open-end mutual funds impose a cost on the investors remaining in the fund, particularly if the fund holds less liquid assets and in periods of low market liquidity (Coval and Stafford, 2007). Moreover, the risk of redemptions is fueled by strategic complementarities among investors, i.e., by investors' actions being influenced by their beliefs about the intentions of other investors, which makes funds fragile institutions (Chen, Goldstein, and Jiang, 2010; Goldstein, Jiang, and Ng, 2017).

We hypothesize that funds with a more geographically dispersed investor base are more exposed to flow risk. Our hypothesis is grounded on the observation that mutual fund investors, like investors in other asset classes, exhibit familiarity bias (Bailey, Kumar, and Ng, 2011). This suggests that investors are generally less likely to purchase shares of funds domiciled outside their country of residence. However, sophisticated investors are less prone to biases and, therefore, more likely to evaluate funds solely on the basis of risk-adjusted performance and self-select into foreign funds. As a consequence of this clientele effect, we would expect funds with a more geographically dispersed investor base to have a higher fraction of performance-sensitive investor base and, therefore, be more exposed to redemption risk. Moreover, strategic complementarities may exacerbate the clientele effect, as sophisticated investors understand that other similarly performance-sensitive investors respond quickly to shocks.

To test our hypothesis, we combine data from two primary sources: the SHSS database and Morningstar. The SHSS database contains detailed information on securities holdings, institutional sectors, and country of origin, at the quarterly frequency. Using this data, we identify mutual fund shares held by both euro-area households and institutional investors, calculating fund ownership based on market value. The Morningstar database contains fund characteristics for open-end mutual funds, including returns, assets under management, flows, expense ratios, investment category, country of domicile, and the identity of the asset management company. We focus our analysis on funds where a substantial majority, specifically at least 80%, of their assets are held by residents within the EA. Our data covers the period from 2009Q1 to 2020Q3.

We construct four measures of Shareholder Country Concentration (SCC): concentration ratios (CR) for 1, 2, and 3 countries, i.e., the fraction of assets held by shareholders in the top countries, and the Herfindahl–Hirschman index (HHI). To measure flow risk we compute the standard deviation of daily flows

in a given month. We then regress flow volatility on geographic concentration measures and controls, including past risk-adjusted performance—estimated using the [Fama and French \(2015\)](#) 5-factor model augmented with momentum (plus the default and term factors in the case of allocation and fixed-income funds), fund size, fund family size, past flows, return volatility, expense ratio, fund age and family age. Importantly, we control for the fraction of the fund’s assets owned by institutional investors. In our baseline regressions, in addition to time fixed effects, we include fund fixed to account for potential time-invariant determinants of flow risk.

Our results reveal a strong negative association between all our measures of SCC and flow volatility. This association is also economically significant. Such negative relation between SCC and flow risk is not due to differences between funds sold in just one country and multi-country funds: If we include in the analysis only funds owned by investors from more than one country, the relation between SCC and flow risk remains very similar.

The negative association between flow risk and SCC is a widespread phenomenon. It holds for funds investing in all three asset classes (equity, fixed income, and allocation) and in all regions, with the notable exception of North America.

To verify whether the negative association between SCC and flow risk is the consequence of a clientele effect as hypothesized, we test whether investors in funds with a geographically dispersed investor base are more sensitive to fund performance. More specifically, we regress monthly fund flows on well-known flow determinants, including fund recent performance, as well our SCC and interactions of SCC with performance. The test results confirm that flows into less concentrated funds are more sensitive to fund performance, consistently with our hypothesized economic mechanism. The increased sensitivity to performance is particularly large for funds both in the bottom and top performance quintiles.

We then ask whether the higher flow risk of funds with a geographically dispersed investor base hampers their performance. To answer this question, we regress realized monthly risk-adjusted performance (alpha) on fund and fund family characteristics as well as SCC measures. The estimated coefficients of SCC are small and insignificant. One possible explanation for this finding is that asset managers anticipate the heightened flow risk associated with a more geographically dispersed investor base and respond to it by managing liquidity dynamically, consistently with the findings of [Jiang et al. \(2021\)](#). Another possible explanation is that the presence of more sophisticated investors provides asset managers with stronger incentives to invest in generating alpha, as shown by [Guercio and Reuter \(2014\)](#),

which offsets the increase in transaction costs.

Finally, we perform four robustness tests. First, we show that our results are robust to replacing the standard deviation of daily flows with two measures of *downside* flow risk: the semideviation of daily flows and the maximum outflow in the month. Second, we show that our results are not driven by different types of investors (such as mutual funds, insurance companies, households) exhibiting different preferences for funds with more or less geographically dispersed investors. In particular, if we repeat the analysis for the subsample of funds held predominantly by households, the estimated coefficients on all SCC measures and their significance remain almost unaltered. Third, we find similar results if we control for the share of non-EA investors in the fund’s ownership. Fourth, we show that our results are not driven by the COVID-19 crisis.

Our paper contributes to the literature on the risk of mutual fund flows and mutual fund fragility. This literature has investigated the circumstances that mitigate or exacerbate flow risk, the possibility of runs on mutual funds, and the consequences of flow risk for fund investment strategies and fund performance (Chordia, 1996; Nanda, Wang, and Zheng, 2009; Chen, Goldstein, and Jiang, 2010; Schmidt, Timmermann, and Wermers, 2016; Goldstein, Jiang, and Ng, 2017; Anand, Jotikasthira, and Venkataraman, 2021; Jin, Kacperczyk, Kahraman, and Suntheim, 2022; Gómez, Prado, and Zambrana, 2022). We contribute to this literature by unveiling the geographic dispersion of a mutual fund’s investor base as a determinant of flow risk.

Our paper is related to the work of Ferreira, Massa, and Matos (2018), who study equity funds whose shareholders and stock holdings are located in different countries (decoupled funds). Using information on where the country is legally authorized to sell to identify decoupled funds, the authors find that such funds exhibit a flatter flow-performance relation and outperform otherwise similar funds.¹ The authors argue that such funds enjoy a competitive advantage, as their investors do not experience wealth shocks (and liquidity needs) precisely when the fund’s portfolio value declines. Our findings complement theirs by showing that when a fund’s investors are decoupled from each other, they tend to be more sensitive to performance, which may explain the higher flow risk experienced by those funds.

Our paper is most closely related to a recent study by Allaire, Breckenfelder, and Hoerova (2023). These authors use the SHSS database to investigate outflows from EA bond funds in the COVID-19

¹Ferreira, Massa, and Matos (2018) also measure investor-fund decoupling by the negative of the correlation between the aggregate fund flows of funds in the countries where the fund is registered for sale and the stock market returns of the countries in which the fund invests.

crisis of 2020. The authors find that mutual funds with a higher fraction of assets under management owned by other mutual funds experienced larger outflows, whereas mutual funds held by retail investors experienced less outflows. They also find that mutual funds held by residents outside the EA experienced larger outflows than funds held by EA residents. While that study investigates the role of different investor types, our focus is on the geographic dispersion of funds' investor base. Indeed, our robustness tests show that our findings are not driven by investor type but hold also for funds owned by retail investors. Moreover, while [Allaire, Breckenfelder, and Hoerova \(2023\)](#) investigate the COVID-19 crisis, we study a long period and show that our results remain unchanged if we exclude 2020 from our sample.

Our findings have important potential implications for investors and asset managers of cross-border funds, as they unveil a strong link between the country concentration of the fund's shareholders and flow risk. They are also of interest to regulators, who are concerned with the threat on financial stability posed by mutual fragility, especially in less liquid asset classes ([International Monetary Fund, 2022](#)).

2 Data

This section provides a comprehensive description of our dataset and the construction of some of the variables used in the analysis. The definitions of the complete set of variables used in the paper can be found in [Table A1](#) in the Appendix.

We build a novel dataset combining two main data sources: (1) the Securities Holdings Statistics by Sector (SHSS) collected by the Eurosystem, which contains quarterly information on holdings of all securities held in the euro area or with a euro area custodian; and (2) the Morningstar Direct database (Morningstar for short), which covers detailed fund-share level data including flows, performance, expense ratio, and additional information on the funds and fund families. In what follows, we describe the two data sources. We then present summary statistics for the sample resulting from the merge between the SHSS and Morningstar databases.

2.1 The SHSS database

The first source is the Securities Holdings Statistics – Sector of the Eurosystem (SHS-S). The confidential version of this database contains granular information on holdings of all securities held by euro-area

residents with a break-down by institutional sector² and country of origin³ of the holder, at a quarterly frequency, from 2009 to 2020.⁴ From this database we obtain the identifiers (ISIN code) of all mutual funds shares held both by euro-area households and by euro-area institutional investors, such as insurance companies and pension funds, banks and other financial intermediaries. We then retrieve for such funds the corresponding shareholding amounts at market value to calculate our measures of fund ownership.

2.2 The Morningstar database

Our second data source is Morningstar Direct – a survivorship bias-free database, including both active and dead funds – which provides us with the main characteristics, such as flows, performance, total expense ratios and ongoing charges, total net assets (TNA) of the universe of mutual funds traded worldwide. We restrict our sample to actively managed open-ended mutual funds classified according to the Morningstar global broad category, as Allocation, Equity or Fixed-Income funds.

We construct both daily and monthly net fund flows as is standard in the mutual fund literature:

$$Flows_{i,t} = \frac{TNA_{i,t} - (1 + r_{t,t}) * TNA_{i,t-1}}{TNA_{i,t-1}} \quad (1)$$

where $TNA_{i,t}$ is total net assets of fund i at time t and $r_{i,t}$ is the fund's return.

Based on daily fund flows, we derive several flow risk metrics at the fund-month level: the standard deviation of flows (flow volatility), flow semideviation, and the size of the largest daily outflow.

2.3 The merged dataset

Both our sources are at the fund share class level, as identified by the ISIN code. A single mutual fund may offer several share classes to investors, which differ in their fees structures but have the same portfolio holdings, managers, and returns before fees. As is common in the mutual fund literature, we conduct

²The institutional sector dimension of the dataset is defined according to the 2010 European System of Accounts and distinguishes between more than a dozen different investor types. For our purposes, we group investors into two categories: 1) Households, 2) Institutional investors, by aggregating deposit-taking corporations general government, Insurance corporations, pension funds, money market funds, non-money market funds, non-financial corporations, other financial intermediaries.

³The country dimension of the dataset includes investor country of origin as long as (i) investors reside in the euro area, (ii) investors reside in non-euro area EU countries that also collect SHS investor data (e.g., Bulgaria, the Czech Republic, Denmark, Hungary, Poland and Romania), and iii) country of origin can be recorded for non-resident investors' holdings that are deposited with a euro area custodian (e.g., US investors' holdings of securities deposited in Luxembourg).

⁴The data for the period from 2009 to the third quarter of 2013 are considered 'experimental' as they are compiled based on voluntary data provided by the euro-area national central banks, but from our checks these data are of comparable quality than those for the following sub-period.

our analysis at the fund level by aggregating multiple share classes of the same fund – as identified by the FundId. This avoids duplicated observations and, importantly, allows us to compute the ownership share by EA investors at the fund level. For each fund, we compute this measure as the ratio between the market value of the fund shares held by euro-area investors – i.e., households and institutional investors – and the Total Net Assets (TNA) of the fund. For other quantitative attributes related to the main fund characteristics (e.g., net returns, and expenses), we follow the standard practice in the literature and calculate TNA-weighted averages; for the year of origination, we consider the oldest share class.

Our analysis is primarily focused on actively managed open-end funds that invest a majority of their assets in equities and bonds, both for comparability with previous studies and given that these funds account for a large share of the euro-area market. Therefore, as is standard in the literature, we exclude funds that are not open-end (e.g., Exchange-Traded funds) or funds investing in other assets classes (i.e., real estate funds, commodity funds, money market funds), sector funds, and passively managed funds.

Because we have sectoral data of good quality only on the amount held by euro-area investors, we need to exclude investment funds that also serve a foreign clientele, i.e. investors with residence outside EA countries. Due to limited sectoral breakdown in the SHS-S and custodial bias, we are unable to distinguish between the two types of clientele (households and institutional investors) for these funds. To address this issue, we exclude funds with a legal domicile within or outside the euro-area⁵, which typically have foreign residents as their main clientele. Therefore, we exclude from our sample those funds for which the median ratio between the market value of the shares held by euro-area investors and the fund size is less than 80 percent.

After applying these filters, the merged SHSS-Morningstar sample represents, on average, more than 11,000 unique funds over the period 2009Q1–2020Q3 (Figure 2, left panel). Over the same period, the sample represents a significant amount of the total net assets of the industry, which grew from about USD 620 billion to approximately USD 2,600 billion (Figure 2, right panel). We note that more than 95 per cent of the investor base is tracked in the SHS-S dataset.

⁵Although most investment funds domiciled in the euro-area are primarily sold to investors within the euro-area – so that the total amount owned by both types of investors is generally close to the fund size – there are also cases of mutual funds where this is not entirely accurate. This is particularly true for funds domiciled in European financial centres, such as Luxembourg and Ireland.

2.4 Measuring fund performance

For each fund-quarter we compute risk-adjusted net returns (alphas) adopting the Fama-French five factor model (Fama and French, 2015; Fama and French, 2017) augmented with the momentum factor (Carhart, 1997), as in Pástor and Vorsatz (2020) and many other prior works. The factors we use are conditional on the fund’s investment geographical focus, which is revealed by the Morningstar category assigned. We use global factors in the case of funds investing worldwide, and regional factors in the case of funds focusing on a specific geographical area, considering the following regions: North-America, Europe, Japan, Asia-Pacific excluding Japan, and emerging markets. All global and regional factors are retrieved from Kenneth French’s website.⁶ In particular, we adopt the following specification for funds whose investment strategy is mainly represented by stocks:

$$R_{i,t,s} = \alpha_{i,s} + \beta_{1,i,s}MKT_{t,s} + \beta_{2,i,s}SMB_{t,s} + \beta_{3,i,s}HML_{t,s} + \beta_{4,i,s}RMW_{t,s} + \beta_{5,i,s}CMA_{t,s} + \beta_{6,i,s}MOM_{t,s} + v_{i,t,s} \quad (2)$$

where $R_{i,t,s}$ is the return of fund i which invests in region s in month t in excess of the risk-free rate; $MKT_{t,s}$ is the market excess return in the fund’s investment region; $SMB_{t,s}$ for the average return of the portfolio of small minus that of big capitalization stocks in the fund’s relevant region; $HML_{t,s}$, is the average return of the portfolio of high minus that of low book-to-market stocks in the fund’s relevant region; $RMW_{t,s}$ is the average return of the portfolio of robust minus that of weak operating profitability stocks in the fund’s relevant region; $CMA_{t,s}$ is the average return of the portfolio with conservative minus that of aggressive investment policies stocks; while, finally, $MOM_{i,s}$ is the difference in returns between the portfolio with past 12-month stock winners and that with the past 12-months losers in the fund i investment region.

In addition to equity funds, as mentioned above, we also estimate the performance of funds that invest in bonds since they account for a substantial share of the euro-area market. Following Fama and French (1993), we calculate risk-adjusted return for these type of funds by augmenting the model (2) with two

⁶We are thankful to Kenneth French for making factors data available in his [webpage](#).

additional factors by adopting the following specification:

$$R_{i,t,s} = \alpha_{i,s} + \beta_{1,i,s}MKT_{t,s} + \beta_{2,i,s}SMB_{t,s} + \beta_{3,i,s}HML_{t,s} + \beta_{4,i,s}RMW_{t,s} + \beta_{5,i,s}CMA_{t,s} + \beta_{6,i,s}MOM_{t,s} + \beta_{7,i,s}TERM_{t,s} + \beta_{8,i,s}DEF_{t,s} + v_{i,t,s} \quad (3)$$

where $TERM_{t,s}$ is the difference between the returns on long-term government bonds and the one-month government bond, and $DEF_{t,s}$ is the difference in returns between long-term corporate bonds and long-term government bonds. Both these factors are also defined according to the relevant investment region. Data on bond indices are retrieved from Morningstar Direct.

For both equations (2) and (3), we estimate factor exposure by regressing the previous 36 months of fund excess net returns on the factors. In practice, we require at least 30 months of past returns for a fund to be included in our analysis. We then compute monthly realized alpha in the next month as the difference between the fund’s excess return in that month and the dot product of the vector of estimated betas and the vector of factor realizations in that month.

3 Cross-border mutual fund ownership in the euro area and summary statistics

In this section, we first provide stylized facts about the prevalence of cross-border holdings of mutual funds in the EA, and then provide summary statistics for selected variables.

To explore cross-border holdings, We focus on the last period of our sample, September 2020, and compute for each country (or region) of domicile d and each country (region) of ownership o , the total number of funds domiciled in country d that have shareholders in country o . To avoid counting funds with only a small fraction of their shares held by residents in country o , we impose a minimum ownership threshold of 1% of the fund’s assets by residents in country o for that fund to be considered as being owned in that country. The results are displayed in Table 1. In the same table, we also report the number of funds available for sale, as reported by Morningstar, for each country of domicile and country registered for sale. This allows us to measure discrepancies between actual cross-border holdings and a proxy for this variable based on availability for sale.

Some interesting stylized facts emerge from Table 1. First, although funds tend to be owned by residents in the country where the fund is domiciled, cross-country ownership is very common. Residents from every country and region considered hold shares in funds domiciled in Luxembourg. Ireland is

home to fewer funds, but its funds are held by residents in all countries considered, too. Perhaps, more surprising is the fact that funds domiciled in Austria, Belgium, France, and Germany, are often held by residents in other countries. Part of cross-country ownership seems to be the consequence of cultural affinity and/or economic integration. For instance, 404 funds domiciled in Austria are owned by German investors accounting for more than 1% of the ownership of those funds' assets. This is 60% the number of Austria-domiciled funds owned by Austrian shareholders. Also, 182 funds domiciled in France are held by residents in Belgium, which is 44% the number of Belgium-domiciled funds held by Belgian residents. Part of cross-border ownership also seems to be driven by institutional investors: Residents in Luxembourg hold shares of 745 and 200 funds domiciled in France and Germany, respectively.

These numbers for cross-country ownership can differ substantially from the number of funds available for sale for each pair of countries. In Table 1, we have marked in dark (light) red discrepancies between number of funds owned and number of funds available for sale that are equal to or larger than 100 (50) funds. The largest discrepancies are found for funds domiciled in Luxembourg. Many of these funds are available for sale in countries where they have no owners or owners collectively hold less than 1% of the fund. For instance, while 1,079 Luxembourg funds were legally authorized to be sold in Austria in September 2020, only 348 of those funds met the 1% minimum ownership threshold in Austria. Outside Luxembourg, we find that 163 France-domiciled funds were registered for sale in Spain, but Spanish investors only owned 58 French funds by an amount higher than 1% of the funds' shares.

Finally, we also find some cases where the number of funds owned by residents in that country exceeds the number of funds available for sale. We mark these cases in dark and light blue if the discrepancy is at least 100 or 50, respectively. One possible explanation for this discrepancy is that the Morningstar's available-for-sale variable is time-invariant, as it refers to the last reference date whereas SHSS data is time-varying and captures the effective holders. These discrepancies highlight the risks of using the variable country available for sale as a proxy fund ownership in that country.

Figure 2 shows graphically the number of funds held by residents in each country/region of funds domiciled in each country/region as of September 2020. The graph clearly shows that cross-border investments are very common in the EA, and not the exception. Only Denmark and Spain stand out as countries whose residents own mainly only domestic funds.

In Table 2 we report selected summary statistics for fund-quarter observations in our sample covering the period from 2009 to 2020, disaggregated by the number of different countries in which residents hold

shares of the fund. In order to include all funds used in the analysis, we do not impose a minimum investment threshold. More specifically, we classify a fund as being held by residents in 1 country if all of the fund’s shares are held by residents in one country of the EA. In doing so, we ignore holdings of the fund’s shares by foreign (i.e., non-EA residents).⁷

Funds held by residents in multiple countries tend to be larger than funds with shareholders in just one country. More specifically, the median fund sold in one EA country manages assets worth USD 37.7 million. The median fund with owners in 2-9 countries or in 10 or more countries manages USD 61.5 million and USD 290 million, respectively. Cross-border are also older and tend to belong to larger and older fund families. Differences in risk-adjusted performance or returns are not evident across the different subsamples. Finally, we notice that SCC measures are high for the whole sample, 87.72% (95.22%) of the average (median) fund’s shares are held by residents of a single country. Even for the group of funds with owners in 10 or more countries, the fraction of shares in the top country is relatively large: 79.41% (88.22%) for the average (median) fund, respectively.

Importantly, our three measures of flow risk are lowest for the group of funds with shareholders concentrated in a single country of residence, both in terms of mean and median values. However, there do not appear to be differences between the subsample of funds sold in 2-9 countries and the subsample of funds sold in more than one country. Moreover, it is unclear whether these differences hold once we account for differences in other characteristics. We perform this analysis in the next section.

4 Shareholder country concentration and flow risk

In this section, we test our main hypothesis that mutual funds with a more geographically dispersed investor base exhibit higher flow risk. To test this hypothesis, we regress flow risk at the fund-month level on different measures of SCC and controls. In particular, we start by estimating the regression equation:

$$Flow\ volatility_{it} = \mu_{1,t} + \mu_{2,cat} + \mu_{3,comp} + \mu_{2,dom} + \gamma_1 SCC_{it-1} + X_{it-1}\Delta + \epsilon_{it}, \quad (4)$$

where the dependent variable, $Flow\ volatility_{it}$, is the standard deviation of daily net flows to fund i in month t in basis points, $\mu_{1,t}$, $\mu_{2,cat}$, $\mu_{3,comp}$ and $\mu_{2,dom}$ denote fixed effects for month, Morningstar Global Category, management company, and country of domicile, respectively. SCC_{it-1} denotes the shareholder

⁷We do, however, consider non-EA as a different country when computing concentration ratios. In our final sample, such holdings are limited to 20% of the fund’s shares.

country concentration for fund i based on SHSS ownership data reported in the previous quarter. We consider four different measures of SCC: concentration ratio in the top 1, 2, and 3 countries, and the Herfindhal-Hirschman index. X_{it-1} is a vector of control variables that includes: past alpha (the intercept of the time series regression of fund excess returns on the factors for the three-year period ending in month $t - 1$, in percentage points); fund and family size (in logs of USD millions); net inflows to the fund in the prior 12 months (in percentage points); return volatility over the prior 12 months (standard deviation, in percentage points); Total Expense Ratio (TER) in the previous month (in percentage points); and the age of the fund and the fund’s family (in logs of years). We cluster standard errors by both time and fund.

The estimation results are shown in Panel A of Table 3. In column 1, we do not include any measure of SCC. Past performance is positively and significantly associated with flow risk, consistently with the abundant empirical evidence that investors chase recent performance. Flow risk is also higher for smaller funds, funds with higher recent flows, higher return volatility, and younger funds. Funds charging lower expense ratios experience greater flow risk.

In columns 2-5, we include our four measures of SCC, one in each column. The coefficients on all measures are negative and statistically significant at the 1%. In terms of the economic magnitude of the association, a one standard deviation increase in CR1 (16.6%) is associated with a 0.2 ($= \frac{0.406 \times 16.6}{33.55}$) standard deviation decrease in flow volatility. To put this economic magnitude in perspective, a one standard deviation increase in fund size (1.53), is associated with a 0.053 standard deviation decrease in flow volatility, and a one standard deviation increase in fund size (0.59), is associated with a 0.058 standard deviation decrease in flow volatility. The economic magnitude of the association between flow risk and SCC is very similar for the other three measures.

In columns 6 and 7, we control for institutional ownership, i.e., the share of the fund’s assets in the hands of institutional investors. As argued by Goldstein et al. (2017), strategic complementarities are less of a concern to institutional investors, since they hold larger shares of a mutual fund. On the other hand, Allaire et al. (2023) show that mutual funds, the most important type of institutional investors in EA funds, were largely responsible for the outflows experienced by European bond funds during the COVID-19 crisis of 2020. Consistently with the findings of Allaire et al. (2023), funds with higher institutional ownership experience higher flow risk. However, SCC (which we measure with CR3 and HHI), remains statistically significant, and similar in magnitude.

While the results of Table 3 indicate that in our data flow risk and SCC are negatively related, it could be that mutual funds with a more geographically dispersed investor base are fundamentally different in some unobservable dimension that is also related to flow risk. To account for time-invariant fund characteristics, we include fund fixed effects (and eliminate fixed effects that do not vary for a given fund). That way, we are comparing flow risk for each fund across periods with different degrees of shareholder country concentration. That is, we estimate:

$$Flow\ volatility_{it} = \mu_{1,t} + \mu_{2,i} + \gamma_1 SCC_{it-1} + X_{it-1}\Delta + \epsilon_{it}, \quad (5)$$

The estimation results are shown in Panel B of Table 3. Across all specifications, the estimated coefficients on SCC measures remain negative and statistically significant at the 1% level. The economic magnitude is lower than in Panel A, where we have no fund fixed effects. This suggests that the estimated coefficients in Panel A are only partially, not fully, explained by cross-sectional differences in flow risk between funds with lower and higher SCC. By including fund fixed effects, we know that as SCC increases *for a given fund*, flow risk decreases. More specifically, a one standard deviation increase in CR1 (16.6%) is associated with a 0.098 standard deviation decrease in flow risk ($= \frac{0.199 \times 16.6}{33.55}$). The economic significance for the other measures of SCC is similar.

A natural question is whether the positive association between flow risk and the geographic dispersion of funds' shareholders that we document in this paper is entirely driven by differences between funds sold in just one country and cross-border funds. To answer this question, we reestimate equation 5 for a restricted sample that includes only funds with shareholders from more than one country. This restriction leads to a 22% reduction of the regression sample size. The results are displayed in Panel C of Table 3. The coefficients on all four measures of SCC remain negative and statistically significant. In fact, the coefficients are slightly larger than in Panel B. Therefore, our results are not due only to differences between single-country and multi-country funds.

We now ask whether the relation between SCC and flow risk concentrates in a particular group of funds or is a more general phenomenon in our data. More specifically, we augment the regression equation 5 by adding interactions between the SCC measures and indicator variables for the three asset classes: Allocation, Equity, and Fixed Income. Note that funds do not switch across asset classes, so any first-order effects of asset classes on flow risk are already absorbed by fund fixed effects. The results are shown on Table 4. The estimated coefficients for all the interaction terms are negative and statistically significant

for all measures of SCC. The strongest association between flow risk and SCC is for equity funds.

In Table 5, we investigate whether our results are driven by funds investing in specific regions. To do this, we include interactions of indicator variables for the fund’s investment region with SCC. In almost all cases, the coefficients on the interactions are negative and significant. A notable exception is funds investing in North American markets. In this case, the sign of the coefficient changes across measures of concentration and is never statistically significant. Also, the coefficient for the interaction between CR3 and the indicator for Japan is negative but not statistically significant. Once again, these results suggest that the association between shareholder geographic concentration is not specific to a particular investment objective.

5 Shareholder country concentration and flow-performance sensitivity

The results of section 4 provide robust evidence that funds that experience a decrease in SCC must deal with greater flow volatility. The evidence is consistent with our hypothesis, but our hypothesis entails a specific economic mechanism, i.e., Shareholders willing to invest in cross-border funds are more sophisticated and therefore, less prone to familiarity bias, but also more willing to compare funds in terms of their after-fee performance. This would make flows to funds with more geographically dispersed shareholders more sensitive to performance and consequently, more volatile. In this section, we provide direct evidence consistent with this clientele effect.

In particular, we estimate the regression equation:

$$\begin{aligned} Flow_{it} = & \mu_{1,cat \times t} + \mu_{2,i} \\ & + \gamma_1 Performance_{i,t-1} + \gamma_2 Performance_{i,t-1} \times SCC_{it-1} + \gamma_3 SCC_{it-1} \\ & + X_{it-1} \Delta + \epsilon_{it}, \end{aligned}$$

where the dependent variable, $Flow_{it}$, is the net inflow of money to fund i in month t (in %). We regress the fund’s flow on $Performance_{i,t-1}$, which is either Past alpha, defined as in the previous regressions, i.e., the intercept of the time series regression used to estimate fund alphas in the prior 36 months, or Return rank of the fund, i.e., its position relative to all other funds in its investment category in terms of their return over the previous year, normalized to range from 0 (worst fund) to 1 (best fund). We also include two measures of SCC as regressors, CR3 and HHI, as well as the interaction of SCC with performance.

We are interested in the coefficient on the interaction. A negative and statistically significant coefficient would support our hypothesis that shareholders of funds with less country-concentrated shareholders are more sensitive to performance. The vector of control variables, X , includes: fund size, family size, total expense ratio, fund age, and family age. We also include an indicator variable, *No load*, that equals 1 if none of the fund’s share classes charges loads. In addition to fund fixed effects, we include investment category by month fixed effects. This allows us to account for the possibility of investors flocking to or fleeing from certain categories at the same time.

The results are shown in Table 6 for Past alpha (columns 1 and 2) and Return rank (columns 3 and 4), as measures of performance. Consistently with our clientele hypothesis, the estimated coefficient on the interaction between past performance and the concentration ratio is negative and statistically significant for both measures of performance and for both measures of SCC, at either the 5% or the 1% significance level. Therefore, investors in funds with *less* geographically concentrated shareholders are more sensitive to recent performance, consistently with our hypothesis.

The increase in sensitivity associated with more geographically dispersed investors is economically significant. Consider, for instance, a fund that increases its Return rank within its investment category by 25% (roughly one standard deviation). Other things equal, the estimated coefficients from column 3 imply that if the fund’s CR3 is in the median of the distribution (97.68%), it benefits from an extra monthly net flow of 0.139% ($= 5.247 \times 0.25 - 0.048 \times 0.25 \times 97.68$) or 1.67% per year. However, if the fund’s CR3 is one standard deviation *lower*, 88.22% ($=97.68\% - 9.46\%$), then the extra flow to the fund is 0.253% per month or 3.037% per year. Using HHI to measure concentration (column 4), the corresponding increase in flows is 0.116% per month for funds with median HHI and 0.263% per month for funds with one standard deviation lower HHI.

The mutual fund literature has provided evidence that the flow-performance relation is often not linear both in the US and in other countries (see [Ferreira, Keswani, Miguel, and Ramos \(2012\)](#) for an international comparison). It is therefore natural to ask whether shareholders in funds with less concentrated investors are more sensitive to performance when performance is poor, when it is good, or for any level of performance. To answer this question, we follow [Sirri and Tufano \(1998\)](#) and estimate a regression equation where flows are a piecewise linear function of the fund’s Return rank with breakpoints at the 20th and 80th percentiles. In particular, we define the following three variables: Low performance = $\text{Min}(\text{Return rank}, 0.2)$; Middle performance = $\text{Min}(0.6, \text{Return rank} - \text{Low performance})$; and High

performance = $\text{Min}(0.8, \text{Return rank} - \text{Middle performance} - \text{Low performance})$, and regress monthly flows on these variables and their interactions with CR3 and HHI. The results are reported in Table 7. For a fund with median CR3, the flow-performance relation is non-linear with flows being more sensitive to return rank in bottom and top quintile regions. More specifically, given the estimated coefficients from column 1, the slopes of the flow-performance relation for a fund with a median value of CR3 (97.68%) are 1.027 in the bottom quintile of the return distribution, 0.471 in the center, and 1.155 in the top quintile. As CR3 decreases, the slope of the flow-performance relation increases in every region, but more so for funds in both tails of the distribution. Therefore, the flow-performance relation becomes steeper, particularly for the worst and best mutual funds. In particular, for a fund with CR2 one standard deviation lower than the median, the slopes in the bottom quintile, 2-9 quintiles, and top quintile are 2.058, 0.745, and 2.46, respectively. The same conclusion is true if we use HHI to measure SCC (column 2).

In sum, the results of this section provide support for the economic mechanism proposed in the paper. Investors that self-select into funds with dispersed shareholders are more sensitive to differences in performance. They are particularly sensitive to performance in the two tails of the performance distribution. This increased sensitivity of flows to funds with more extreme performance can explain why funds with more dispersed investors exhibit higher flow risk.

6 Shareholder country concentration and performance

In this section, we investigate whether the increased flow risk of mutual funds with geographically dispersed investors hurts the performance of this funds. To answer this question, we estimate the regression equation:

$$Alpha_{it} = \mu_{1,t} + \mu_{2,i} + \gamma_1 SCC_{it-1} + X_{it-1} \Delta + \epsilon_{it}, \quad (6)$$

where the dependent variable, $Alpha_{it}$ is fund i 's realized risk-adjusted return in month t , calculated as the excess return of fund i in month t minus the dot product of the vector of factor realizations in month t and the vector of fund i 's betas, estimated over the previous 36 months, in basis points. We use the same controls as in equation 5, including past performance, i.e., the intercept of the time-series regression used to estimate betas, to account for possible performance persistence. The results are reported in Table 8.

In Panel A, we show the results for all funds. Consistently with the results of [Chen et al. \(2004\)](#) for US mutual funds, fund size is negatively and significantly associated with performance in all specifications. In

contrast with their findings, the size of the fund’s family is negatively associated with fund performance, but only when we control for SCC. Older funds exhibit higher performance. As for our measures of SCC, we find that CR2, CR3, and HHI, are *positively* and significantly associated with fund performance. However, when we control for institutional ownership, the estimated coefficients become much smaller and significance vanishes. In Panel B, we repeat the analysis only for funds sold in multiple countries and our conclusions are identical. Therefore, we find no evidence that the geographic dispersion of a fund’s investor base hurts its performance despite the associated increase in flow risk.

One possible explanation for this finding is that asset managers anticipate the heightened flow risk associated with a more geographically dispersed investor base and the increase in flow risk. To mitigate potential costs, managers manage liquidity dynamically, as shown by [Jiang et al. \(2021\)](#). For instance, they may increase the liquidity of their holdings. Another explanation is that the presence of more sophisticated investors provides asset managers with stronger incentives to invest in generating alpha, and this improved performance offsets the increase in transaction costs. This explanation is consistent with [Guercio and Reuter \(2014\)](#) that funds catering to more sophisticated investors, exert more effort to generate alpha, and less effort to provide investors with costly services, such as advice. The two explanations are not mutually exclusive. Asset managers will optimally trade off the benefits of internationalizing their investor base against the potential costs of dealing with more volatile flows.

7 Robustness tests

Finally, we perform four robustness tests. First, we test whether our results are robust to using measures of *downside* flow risk instead of the standard deviation of flows. To do this, we re-estimate equation 2, replacing the dependent variable with the Flow semideviation or the Maximum outflow experienced in the month by the fund.⁸ In Tables 9 and 10 report the estimation results. Coefficients on SCC for flow semideviation are negative and significant, while the coefficients on SCC for maximum outflow, which is defined to be positive when the fund experiences net outflows, are positive and highly significant. Therefore, our conclusions are robust to measuring downside flow risk instead of flow risk.

Second, in Table 11 we test whether our results are driven by different types of investors (e.g., mutual funds, insurance companies, households), which have different degrees of elasticity, also have different

⁸Different measures capture various aspects of downside risk. For example, while the semi-standard deviation focuses on negative deviations from the mean, maximum outflow captures the worst-case scenario within a specific period. Using several metrics allows to provide a comprehensive assessment of the potential risks.

preferences in terms of geographically dispersed funds. While this may indeed be the case, it is not the goal of our paper. To eliminate the influence of different investor types, we focus on retail funds and reestimate equation 5 on this subsample, i.e., funds held predominantly by households. More specifically, we allow a maximum institutional share of 10 per cent of total assets under management for the fund to be included in our sample, which leads to a large reduction of our sample size. Estimation results are qualitatively similar to those shown in Table 3. Although the estimated coefficients on SCC and their significance are slightly smaller than in the mains sample, they remain negative in all specifications and significant in all specifications by one.

Third, in Table 12 we test whether our results are robust to controlling for the share of foreign investors in the fund’s ownership, defined as shareholders outside the EA, as in [Allaire et al. \(2023\)](#). Our conclusions remain unchanged. Estimated coefficients on SCC measures remain negative and statistically significant. Interestingly, the coefficient on foreign ownership is negative in all specifications and statistically significant in columns (3) and (4), where we control for institutional ownership. Therefore, contrary to the findings of [Allaire et al. \(2023\)](#) for the COVID-19 crisis, we find that a larger share of foreign investors is associated with lower volatility of fund flows.

Finally, in light of the findings of [Allaire et al. \(2023\)](#) we redo the main analysis by removing the COVID-19 period from the sample entirely. This analysis allows us to verify whether the strong link between SCC and flow risk that we document in the paper is driven by that particular period of turmoil characterized by historically large outflows. The results of this robustness test, reported in Table 13, are virtually the same as in the main analysis, confirming that the pattern we unveil in this paper is general and not period-specific.

8 Conclusions

We investigate the relationship between the geographic dispersion of a mutual fund’s investor base and its flow risk, focusing on cross-border funds within the euro area. Exploiting a unique data set from the Securities Holdings Statistics by Sector (SHSS), we are able to measure for the first time the degree of geographic dispersion of EA mutual funds and study its relation to flow risk.

Our findings reveal that funds with a more geographically dispersed investor base exhibit higher flow risk. This association holds across different asset classes and investment regions. The results are consistent with a clientele effect. Funds that attract investors from multiple countries also attract more elastic

investors. Further tests reveal that investors in cross-border funds are more sensitive to performance, consistently with a clientele effect driving our main results.

Interestingly, while flow risk is higher for funds with a geographically dispersed investor base, we find no evidence that funds with more geographically dispersed investors underperform otherwise similar funds. This suggests that asset managers of cross-border funds may actively manage liquidity in response to increased transaction costs or face stronger incentives to generate alpha.

Finally, the link between the geographic dispersion of fund investors and flow risk is robust to using different measures of flow risk, restricting the sample to retail funds, controlling for non-EA fund ownership, and removing the COVID-19 crisis from the sample.

Our findings hold important implications for investors, asset managers, and regulators. For investors and asset managers of cross-border funds, understanding the link between shareholder concentration and flow risk is crucial for risk management and investment decision-making. Regulators, particularly those concerned with financial stability, should take into account the higher risk posed by cross-border funds, especially in less liquid asset classes. Overall, this study contributes to the broader literature on mutual fund outflows and sheds light on the importance of investor geography in understanding fund fragility.

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Figure 1: **Distribution of Fund Holdings: Country of Ownership vs Country of Domicile**

This figure shows graphically the number of funds held by residents in each country/region of funds and domiciled in each country/region in 2020.

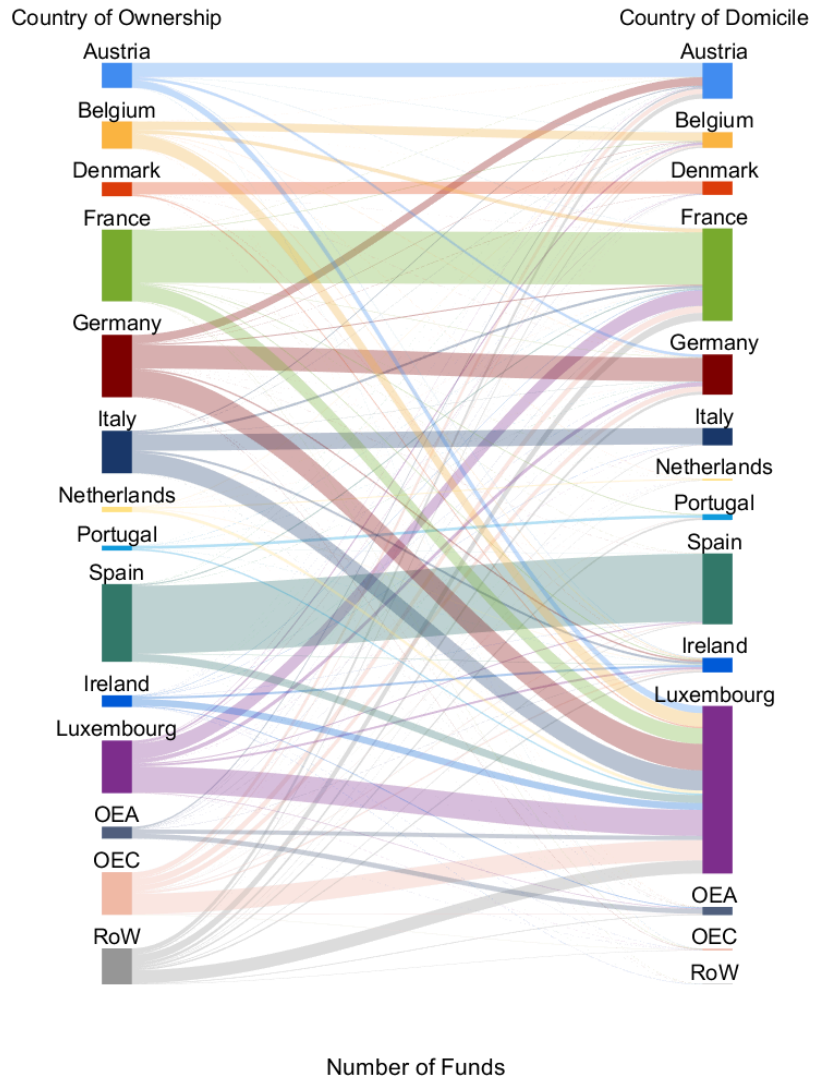


Figure 2: **Sample composition: Number of unique funds and total net assets by asset class**

This figure shows graphically the sample composition both in terms of number of funds (left panel) and total net assets in billions of USD (right panel) by asset class over the period 2009Q1–2020Q3.

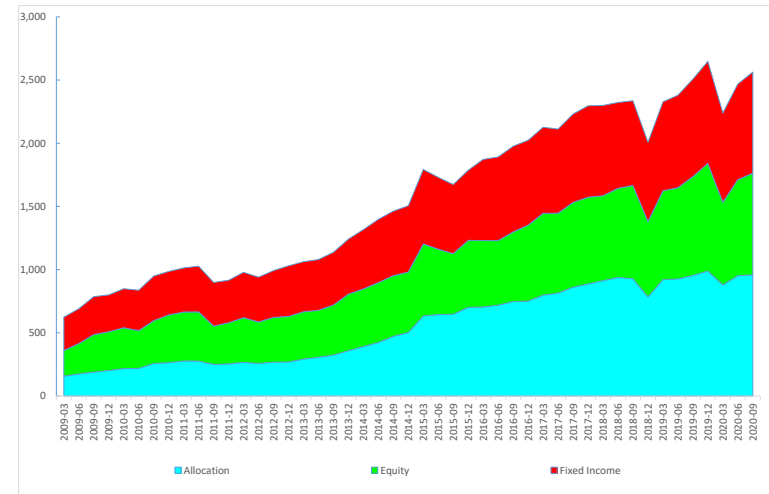
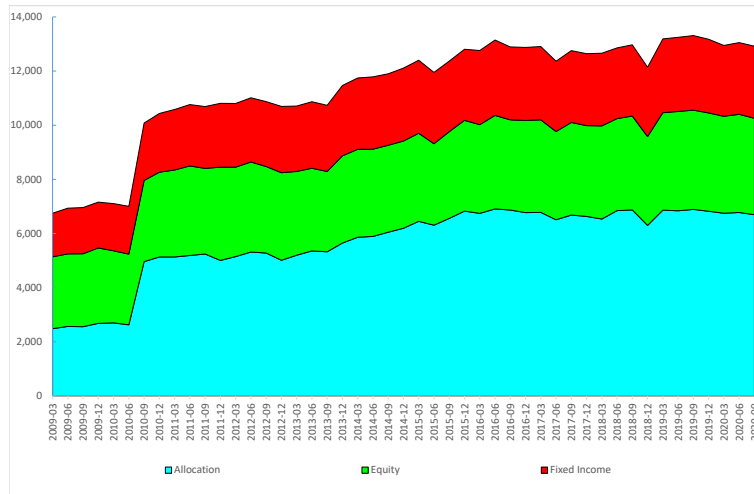


Table 2: **Summary Statistics**

This table reports descriptive statistics for fund-quarter observations in our sample, disaggregated by the number of different countries in which residents hold shares of the fund. In order to include all funds used in the analysis, we do not impose a minimum investment threshold. All variables are defined in the Appendix (see Table A1).

Number of countries of ownership	Variable	Mean	S.D.	25th ptile.	Median	75th pctl.	Obs.
1	Fund size	3.71	1.46	2.64	3.63	4.69	89,323
	Family size	8.28	1.94	7.02	8.42	9.70	89,308
	Fund age	2.23	0.53	1.78	2.28	2.62	89,324
	Family fund age	3.50	0.57	3.17	3.59	3.86	89,324
	Alpha	-24.13	206.53	143.99	-31.08	79.29	88,499
	Return volatility	4.51	2.18	2.83	4.18	5.72	89,324
	Flow volatility	23.08	32.15	2.40	10.98	29.04	89,324
	Flow semideviation	30.38	59.81	1.69	9.34	29.18	81,130
	Maximum outflow	-51.71	89.71	-57.57	-14.52	-0.83	89,324
	CR1	96.92	6.60	97.35	99.61	100.00	86,450
	CR2	96.92	6.60	97.35	99.61	100.00	86,450
	CR3	96.92	6.60	97.35	99.61	100.00	86,450
	HHI	0.94	0.11	0.95	0.99	1.00	86,450
2-9	Fund size	4.17	1.34	3.23	4.12	5.09	211,481
	Family size	8.61	1.96	7.41	8.71	10.22	211,467
	Fund age	2.36	0.57	1.92	2.39	2.76	211,481
	Family age	3.61	0.54	3.29	3.69	3.96	211,481
	Alpha	-22.55	214.77	-143.01	-30.96	82.46	208,787
	Return volatility	4.57	2.41	2.75	4.02	5.82	211,481
	Flow volatility	27.36	33.19	6.52	14.39	34.29	211,481
	Flow semideviation	37.81	64.23	6.14	14.50	37.73	201,284
	Maximum outflow	-64.76	94.86	-74.52	-27.21	-9.46	211,481
	CR1	87.92	14.64	82.69	94.16	98.37	206,142
	CR2	92.79	9.61	89.88	96.96	99.22	206,142
	CR3	93.71	8.69	91.16	97.52	99.45	206,142
	HHI	0.81	0.20	0.69	0.89	0.97	206,142
10+	Fund size	5.64	1.29	4.81	5.67	6.49	101,100
	Family size	9.72	1.62	8.61	10.21	10.93	101,094
	Fund age	2.61	0.63	2.18	2.68	3.05	101,100
	Family age	3.87	0.50	3.49	3.96	4.22	101,100
	alpha	-21.21	212.02	-135.74	-25.84	82.31	99,995
	Return volatility	4.15	2.40	2.43	3.47	5.19	101,100
	Flow volatility	29.06	35.22	6.22	14.49	37.80	101,100
	Flow semideviation	37.04	61.76	6.03	14.02	37.78	99,299
	Maximum outflow	-64.92	94.56	-74.41	-26.14	-10.59	101,100
	CR1	79.41	21.43	67.68	88.22	96.46	100,523
	CR2	87.00	14.81	81.79	93.02	97.92	100,523
	CR3	89.98	11.63	85.73	94.62	98.43	100,523
	HHI	0.70	0.27	0.50	0.78	0.93	100,523
All	Fund size	4.44	1.53	3.33	4.41	5.53	401,904
	Family size	8.82	1.95	7.58	9.03	10.42	401,869
	Fund age	2.40	0.59	1.93	2.43	2.82	401,905
	Family age	3.65	0.55	3.30	3.73	4.08	401,905
	Alpha	-22.57	212.27	-141.46	-29.67	81.66	397,281
	Return volatility	4.45	2.36	2.66	3.93	5.66	401,905
	Flow volatility	26.84	33.55	5.73	13.68	34.00	401,905
	Flow semideviation	36.03	62.74	5.30	13.31	35.89	381,713
	Maximum outflow	-61.90	93.82	-70.74	-24.48	-7.53	401,905
	CR1	87.72	16.60	83.25	95.22	98.91	393,115
	CR2	92.22	11.23	89.57	97.17	99.37	393,115
	CR3	93.46	9.46	91.04	97.68	99.54	393,115
	HHI	0.81	0.22	0.70	0.91	0.98	393,115

Table 4: **Shareholder Concentration and Flow Volatility - By Asset Class**

This table reports regression results for Flow Volatility at the fund level. The dependent variable is Flow Volatility computed as the standard deviation of daily flows in a given month. The sample includes all funds with at least 80 per cent of their assets held in the euro area or with a euro area custodian. The sample period is from January 2009 to September 2020. All variables are defined in the Appendix (see Table A1). Standard errors are White-corrected for heteroskedasticity and clustered at the fund and time level. Fixed effects are reported in the table. * indicates significance at 1% (***), 5% (**), 10% (*).

	(1)	(2)	(3)	(4)	(5)	(6)
CR1 x Allocation	-0.102*** (0.039)					
CR1 x Equity	-0.272*** (0.034)					
CR1 x Fixed income	-0.172*** (0.034)					
CR2 x Allocation		-0.113** (0.047)				
CR2 x Equity		-0.176*** (0.043)				
CR2 x Fixed income		-0.090** (0.042)				
CR3 x Allocation			-0.100** (0.048)		-0.232*** (0.048)	
CR3 x Equity			-0.123*** (0.041)		-0.284*** (0.042)	
CR3 x Fixed income			-0.046 (0.041)		-0.200*** (0.043)	
HHI x Allocation				-8.022*** (2.728)		-10.758*** (2.740)
HHI x Equity				-21.050*** (2.503)		-23.597*** (2.469)
HHI x Fixed income				-13.881*** (2.625)		-18.663*** (2.555)
Instit. ownership					0.221*** (0.019)	0.195*** (0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306,334	306,334	306,334	306,334	306,334	306,334
R-squared	0.333	0.332	0.332	0.333	0.335	0.336
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE x Global Broad Category FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Fund	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Time	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Shareholder Concentration and Flow Volatility - By Investment Region

This table reports regression results for Flow Volatility at the fund level. The dependent variable is Flow Volatility computed as the standard deviation of daily flows in a given month. The sample includes all funds with at least 80 per cent of their assets held in the euro area or with a euro area custodian. The sample period is from January 2009 to September 2020. All variables are defined in the Appendix (see Table A1). Standard errors are White-corrected for heteroskedasticity and clustered at the fund and time level. Fixed effects are reported in the table. * indicates significance at 1% (**), 5% (**), 10% (*).

	(1)	(2)	(3)	(4)	(5)	(6)
CR1 x Asia pacific (ex Japan)	-0.185* (0.097)					
CR1 x Developed	-0.305*** (0.041)					
CR1 x Europe	-0.159*** (0.027)					
CR1 x Japan	-0.566*** (0.142)					
CR1 x North America	-0.148 (0.112)					
CR2 x Asia pacific (ex Japan)		-0.256** (0.119)				
CR2 x Developed		-0.211*** (0.048)				
CR2 x Europe		-0.105*** (0.032)				
CR2 x Japan		-0.319* (0.183)				
CR2 x North America		0.090 (0.164)				
CR3 x Asia pacific (ex Japan)			-0.249** (0.119)		-0.417*** (0.120)	
CR3 x Developed			-0.155*** (0.047)		-0.315*** (0.047)	
CR3 x Europe			-0.077** (0.031)		-0.224*** (0.032)	
CR3 x Japan			-0.046 (0.210)		-0.229 (0.200)	
CR3 x North America			0.158 (0.156)		-0.012 (0.160)	
HHI x Asia pacific (ex Japan)				-20.280*** (7.215)		-24.318*** (7.332)
HHI x Developed				-22.578*** (3.123)		-25.612*** (3.038)
HHI x Europe				-12.523*** (1.817)		-16.026*** (1.790)
HHI x Japan				-45.559*** (12.195)		-44.414*** (12.084)
HHI x North America				-9.255 (10.119)		-12.907 (9.763)
Instit. ownership					0.221*** (0.018)	0.195*** (0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	306,334	306,334	306,334	306,334	306,334	306,334
R-squared	0.334	0.333	0.333	0.334	0.336	0.337
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE x Investment Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Fund	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by Time	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: **Shareholder Concentration and Flow-Performance Sensitivity (Linear)**

This table reports regression results for Flow at the fund level. The dependent variable is the net inflows to the fund in the month. The sample includes all funds with at least 80 per cent of their assets held in the euro area or with a euro area custodian. The sample period is from January 2009 to September 2020. All variables are defined in the Appendix (see Table A1). Standard errors are White-corrected for heteroskedasticity and clustered at the fund and time level. Fixed effects are reported in the table. * indicates significance at 1% (***), 5% (**), 10% (*).

	Performance =			
	Past alpha		Return Rank	
	(1)	(2)	(3)	(4)
Performance	2.044*** (0.463)	1.571*** (0.200)	5.247*** (0.555)	2.890*** (0.223)
Performance x CR3	-0.010** (0.005)		-0.048*** (0.006)	
Performance x HHI		-0.558** (0.220)		-2.664*** (0.243)
CR3	0.002 (0.004)		0.027*** (0.004)	
HHI		0.743*** (0.225)		2.071*** (0.249)
Fund size	-1.017*** (0.068)	-1.010*** (0.068)	-0.951*** (0.067)	-0.943*** (0.066)
Family size	0.233*** (0.081)	0.231*** (0.080)	0.215*** (0.081)	0.214*** (0.081)
TER	0.166*** (0.046)	0.165*** (0.046)	0.195*** (0.047)	0.195*** (0.047)
Fund age	-1.649*** (0.186)	-1.602*** (0.187)	-1.748*** (0.192)	-1.703*** (0.192)
Family age	-0.374 (0.378)	-0.390 (0.377)	-0.418 (0.388)	-0.434 (0.387)
No load	-0.136 (0.229)	-0.146 (0.229)	-0.163 (0.230)	-0.172 (0.230)
Observations	409,766	409,766	404,574	404,574
R-squared	0.122	0.124	0.121	0.124
Fund FE	Yes	Yes	Yes	Yes
MS Category x Month FE	Yes	Yes	Yes	Yes
Cluster Fund	Yes	Yes	Yes	Yes
Cluster Time	Yes	Yes	Yes	Yes

Table 7: **Shareholder Concentration and Flow-Performance Sensitivity (Piecewise Linear)**

This table reports regression results for Flow at the fund level. The dependent variable is the net inflows to the fund in the month. The sample includes all funds with at least 80 per cent of their assets held in the euro area or with a euro area custodian. The sample period is from January 2009 to September 2020. All variables are defined in the Appendix (see Table A1). Standard errors are White-corrected for heteroskedasticity and clustered at the fund and time level. Fixed effects are reported in the table. * indicates significance at 1% (***), 5% (**), 10% (*).

	(1)	(2)
Low performance	11.674*** (3.350)	5.384*** (1.373)
Middle performance	3.304*** (0.680)	2.017*** (0.281)
High performance	14.635*** (5.094)	7.582*** (1.749)
Low performance \times CR3	-0.109*** (0.036)	
Middle performance \times CR3	-0.029*** (0.007)	
High performance \times CR3	-0.138** (0.053)	
Low performance \times HHI		-4.895*** (1.632)
Middle performance \times HHI		-1.814*** (0.322)
High performance \times HHI		-7.371*** (2.006)
CR3	0.034*** (0.007)	
HHI		2.302*** (0.369)
Fund size	-0.950*** (0.067)	-0.942*** (0.066)
Family size	0.214*** (0.081)	0.214*** (0.081)
TER	0.195*** (0.047)	0.196*** (0.047)
Fund age = L,	-1.748*** (0.192)	-1.702*** (0.192)
Family age	-0.414 (0.388)	-0.432 (0.387)
True no load = 1b,	0.000 (0.000)	0.000 (0.000)
No load	-0.165 (0.230)	-0.175 (0.230)
Constant	3.745** (1.615)	4.992*** (1.529)
Observations	404,574	404,574
R-squared	0.123	0.124
Fund FE	Yes	Yes
Month \times Category FE	Yes	Yes
Cluster Time	Yes	Yes

Table 12: **Shareholder Concentration and Flow Volatility - Foreign Investors**

This table reports regression results for Flow Volatility at the fund level. The dependent variable is Flow Volatility computed as the standard deviation of daily flows in a given month. The sample includes all funds with at least 80 per cent of their assets held in the euro area or with a euro area custodian. The sample period is from January 2009 to December 2020. All variables are defined in the Appendix (see Table A1). Standard errors are White-corrected for heteroskedasticity and clustered at the fund and time level. Fixed effects are reported in the table. * indicates significance at 1% (***), 5% (**), 10% (*).

	(1)	(2)	(3)	(4)
Past alpha	1.439*** (0.370)	1.373*** (0.369)	1.421*** (0.366)	1.372*** (0.366)
Fund size	-2.478*** (0.379)	-2.631*** (0.374)	-3.210*** (0.360)	-3.351*** (0.356)
Family size	0.052 (0.570)	0.077 (0.566)	0.076 (0.573)	0.109 (0.569)
Annual flows	0.032*** (0.003)	0.032*** (0.003)	0.031*** (0.003)	0.030*** (0.003)
Return volatility	0.160 (0.126)	0.168 (0.125)	0.181 (0.124)	0.190 (0.124)
TER	0.379 (0.281)	0.380 (0.284)	0.505* (0.275)	0.500* (0.279)
Fund age	-0.753 (1.245)	-1.575 (1.225)	-0.350 (1.221)	-1.081 (1.205)
Family age	4.329 (3.518)	4.571 (3.494)	3.707 (3.515)	3.969 (3.493)
CR3	-0.079*** (0.025)		-0.188*** (0.026)	
HHI		-14.495*** (1.461)		-17.546*** (1.463)
Foreign ownership	-0.045 (0.030)	-0.036 (0.029)	-0.091*** (0.032)	-0.111*** (0.031)
Inst. ownership			0.170*** (0.017)	0.164*** (0.016)
Observation	392,391	392,391	392,391	392,391
R-Squared	0.318	0.319	0.320	0.321
Fund FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Cluster by Fund	Yes	Yes	Yes	Yes
Cluster by Time	Yes	Yes	Yes	Yes

Appendix

Table A1: Variable definitions.

(Realized) Alpha	The difference between the fund's excess return in month t and the dot product of the vector of estimated betas using data from $t - 36$ to $t - 1$ and the vector of factor realizations in month t , in basis points. (Source: Morningstar)
Annual flows	Growth rate of TNA over the previous year, net of internal growth (assuming reinvestment of dividends and distributions), in %. (Source: Morningstar)
CR1, CR2 and CR3	Concentration ratios: Fraction of assets held by shareholders in the top 1, 2, and 3 countries, in %. (Source: Securities Holdings Statistics)
Domicile	The country in which the fund is legally organized. (Source: Morningstar)
Family age	Number of years since inception of the oldest fund of the asset management company, in logs. (Source: Morningstar)
Family size	TNA in USD millions of the fund family (asset management company) to which the fund belongs, in logs. (Source: Morningstar)
Flow	Growth rate of TNA in the month, net of internal growth (assuming reinvestment of dividends and distributions), in %. (Source: Morningstar)
Flow semideviation	Semideviation of the net daily flows of the fund in a month, in basis points. (Source: Morningstar)
Flow volatility	Standard deviation of the net daily flows of the fund in a month, in basis points. (Source: Morningstar)
Foreign ownership	Share of TNA held by non euro-area investors, in %. (Source: SHS-S)
Fund age	Number of years from inception of the oldest share class of the fund, in logs. (Source: Morningstar)
Fund size	Total net asset value in USD millions of the fund, in logs. (Source: Morningstar)
Global Morningstar Category	The Global Morningstar Category identifies funds based on their actual investment styles as measured by their underlying portfolio holdings (portfolio and other statistics over the past three years). (Source: Morningstar)
HHI	Herfindahl-Hirschman index of ownership share (Source: Securities Holdings Statistics)
Household ownership share	Share of TNA held by euro-area households investors. (Source: SHS-S)
Institutional ownership	Share of TNA held by institutional investors, in %. (Source: SHS-S)
Low performance	Min(Return rank, 0.2) (see definition of Return rank below). (Source: Morningstar)

(continued)

Middle performance	Min(0.6, Return rank – Low performance) (see definition of Return rank below). (Source: Morningstar)
High performance	Min(0.8, Return rank – Middle performance – Low performance) (see definition of Return rank below). (Source: Morningstar)
Maximum outflow	The absolute value of the largest daily outflow of the fund in a month, in basis points. (Source: Morningstar)
Past alpha	Intercept of the time-series regression of the fund's excess return on the Fama-French Regional 5/7 factors plus momentum, estimated over the previous 3 years, in %. (Source: Morningstar and Kenneth French' website)
Return rank	The position of the fund relative to all other funds in the same investment category and the same month in terms of their return over the previous 12 months, normalized to range from 0 (worst fund) to 1 (best fund). (Source: Morningstar)
Return volatility	Standard Deviation of monthly fund returns over the last year, with at least a minimum of 10 observations. (Source: Morningstar)
Total expense ratio (TER)	Total annual expenses as a percentage of TNA (Source: Morningstar)