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Common Asset Holdings as an Amplifier of Open-ended Funds Liquidity Risk: Evidence from Global Fixed-Income Funds

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Abstract

Liquidity mismatch risk ("liquidity risk") of open-ended funds (OEFs) has been shown to affect financial stability during past episodes of financial market turbulence and is a key concern of regulators. While policy discussion usually focuses on OEFs managing their own liquidity risk, this study examines the risks arising from OEFs' interconnections through common asset holdings in their investment portfolios. There are three major findings. First, we find a significant and positive relationship between the fund flows of OEF peers with highly similar portfolios, which we can attribute to peers' portfolio actions rather than occurring randomly. Second, the relationship is stronger in times of financial market stress, and stronger on OEFs with larger inherent liquidity risk, which suggests that common asset holdings can amplify OEFs' liquidity risk in stressful times. Third, the estimated relationship is also found to be significant between OEFs domiciled in different jurisdictions, implying that common asset holdings can contribute to cross-border spillovers of OEF liquidity risk. Further scenario analysis demonstrates the economic significance of the effect of common asset holdings on OEF liquidity risk under a shock event, highlighting the relevance of incorporating OEF interconnections in systemic assessment of OEFs' resilience against liquidity risk.

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1. Introduction

Liquidity mismatch risk (“liquidity risk” hereafter) of open-ended funds (OEFs), arising from a mismatch of OEFs’ assets (liquidity of asset holdings, “market liquidity”) and liabilities (liquidity to meet redemption requests, “funding liquidity”), has been shown to affect financial stability during episodes of financial market stress (Baranova et al., 2017; Falato et al., 2021a; Lewrick and Claessens, 2021; Ma et al., 2022), and has been subject to continued scrutiny by regulators, central banks and international organisations. A case in point is the ongoing reviews of the recommendations to OEFs’ liquidity risk management by the Financial Stability Board (FSB). These seek to reduce OEFs’ structural liquidity mismatch and improve the use of liquidity risk management tools to manage liquidity risk in the aftermath of the March 2020 global financial market turmoil.

Policy discussions so far have focused on OEFs managing their own liquidity risk, with less attention given to the risks arising from the interconnections between OEFs. One major source of interconnections is the assets invested in common by OEFs (referred to as “common asset holdings” hereafter). In the event of large fund outflows, OEFs may be forced to sell their asset holdings at a discount, which in turn affects the returns of peers holding the same assets and exerts pressure on their flows. In a seminal study on asset fire sale spillovers, Coval and Stafford (2007) show that equity mutual funds in the US experiencing large outflows tend to create price pressures in the securities held in common by other funds. Drawing on the flow, return and portfolio holdings of fixed income funds domiciled in the US, Falato et al. (2021b) find that fire sales induced by investor redemptions can adversely affect peer funds' performance and flows.

Given the global nature of OEFs which can invest in assets across borders, common asset holdings could act as a channel through which liquidity risk of OEFs in one jurisdiction causes spillovers to those in other jurisdictions. More specifically, in the event of large redemptions, OEFs may react by selling securities in another market possibly because of better liquidity, thus spreading shocks across markets and borders. The impact of common asset holdings on OEF liquidity risk thus merits study from the perspective of cross-border spillover effects.

This study attempts to shed light on the extent on OEFs interconnectedness with respect to common asset holdings and the associated impacts on their liquidity risk. In particular, we want to answer the following questions:

1. Do OEF peer flow relationships exist with common asset holdings?
2. Can we attribute the OEF peer flow relationship to the portfolio action of peer funds (“peer flow effects”)?
3. Are peer flow effects stronger on OEFs with relatively larger liquidity risk, particularly in times of stress?
4. Is there any evidence of peer flow effects among OEFs domiciled in different jurisdictions?

The first two questions attempt to establish a relationship between OEFs’ common asset holdings and fund flows (a “peer flow relationship”), and to verify if such a relationship can be attributed to the effect of the portfolio actions of peers with highly similar portfolios (i.e. a “peer flow effect”). After verifying the existence of the “peer flow effect”, the third question examines periods of financial market stress and evaluates if common asset holdings add to the liquidity risks of OEFs. The fourth question sheds light on whether common asset holdings constitute a significant channel for the cross-border spillovers of OEF liquidity risk.

We focus on fixed-income funds in this study. Compared with equities, fixed-income securities are less liquid instruments such that the expected price impact due to sales of fixed-income funds' holdings could be more pronounced and therefore, the spillover effects due to common asset holdings. More specifically, we consider the largest fixed income funds around the world whose portfolio actions are more likely to exert a price influence on underlying fixed income holdings, while the consideration of fixed-income funds domiciled in different jurisdictions allows us to study cross-border spillover effects. In addition to evaluating the statistical significance of OEF common asset holdings using econometric models, understanding its economic significance is important from the perspective of financial stability assessment. To this end, a simple scenario analysis is conducted to assess the extent to which common asset holdings add to OEF liquidity risk in a shock scenario.

There are three major findings in this study. First, we find a significant and positive relationship between fund flows of OEF peers with highly similar portfolios, which we further show can be attributed to peers' portfolio actions rather than occurring randomly. Second, the relationship is stronger in times of financial market stress, and stronger on OEFs with larger inherent liquidity risk, which suggests that common asset holdings can amplify OEFs' liquidity risk in stressful times. Third, the peer flow relationship is estimated to be statistically significant between OEFs domiciled in different jurisdictions, suggesting that the peer flow effect due to common asset holdings can contribute to cross-border spillovers of OEF liquidity risk. Results from our scenario analysis highlight the economic significance of the effect of common asset holdings on OEF liquidity risks.

Our study contributes to the literature in two aspects. First, our findings add to the growing literature on the financial stability implications of OEF interconnections, by providing fresh empirical evidence of the impact of common asset holdings on OEF liquidity risk using a sample that covers the most recent financial stress episodes. Second, in contrast to previous studies that mainly use fund-level data from one country or region to study the interconnectedness among funds and the associated risks, we employ a cross jurisdictions dataset to conduct our analysis. This helps shed light on common asset holdings as a channel through which OEF liquidity risk could spillover across borders.

The paper is organised as follows. Section 2 reviews related literature. Section 3 discusses our OEF sample and how we measure common asset holdings. Section 4 presents our empirical models and findings. Section 5 presents results of the scenario analysis and the last section concludes.

2. Literature review

This study relates to two strands of literature. The first one focuses on the financial stability implications of the liquidity risks of mutual funds. Studies have shown that mutual funds, especially those with illiquid assets, are vulnerable to asset fire sales during periods of financial market stress, which increase returns volatility and price pressures on the underlying assets and adds to financial stability risks. For instance, Coval and Stafford (2007) find that funds facing substantial outflows tend to reduce existing portfolio positions, exerting downward pressure on the prices of securities held in common by distressed funds in equity markets. Similarly, Baranova et al. (2017) develop a stress simulation framework showing that investor redemptions can lead to a significant increase in spreads in the corporate bond market, potentially causing market dislocation and threatening financial stability. Falato et al. (2021b) suggest that fire sales induced by investor redemptions can have spillover effects, adversely affecting peer funds' performance, flows, and with a negative impact on bond prices.

More recent studies have uncovered further evidence from observations during the COVID-19 pandemic. Falato et al. (2021a) document major outflows in corporate bond funds during the pandemic using daily microdata, highlighting that fund illiquidity and vulnerability to fire-sale spillovers are important sources of financial fragility. Lewrick and Claessens (2021) observe elevated redemptions of open-ended bond funds during the March 2020 market turmoil, leading to procyclical asset sales that add to pressures on bond prices despite the widespread use of liquidity management tools. Assets, particularly bonds, held by more illiquid mutual funds were found to be more fragile with higher returns volatility during the pandemic (IMF, 2022; Jiang et al., 2022; Ma et al., 2022). Last but not least, Fricke and Wilke (2023) find that cross-fund investments significantly affected individual security returns, especially for corporate bonds, during the financial stress episode in March 2020.

Apart from asset fire sales, the literature covers strategic complementarities among investors in the mutual fund sector that could trigger “fund runs”. Using data on net outflows from US equity mutual funds, Chen et al. (2010) finds that mutual funds with illiquid assets, where complementarities are stronger, exhibit a stronger sensitivity of outflows in response to poor past performance than funds with liquid assets. Their findings provide empirical evidence of financial market fragility due to vulnerability to investor runs. Similarly, IMF (2022) highlights a “liquidity mismatch” among OEFs that offer daily redemptions and hold illiquid assets, which could increase the likelihood of investor runs.

Other studies focus on how mutual fund managers adjust their portfolios in response to redemption pressures. Morris et al. (2017) find that instead of using cash buffers to meet redemption pressures, fund managers may hoard cash and meet redemption requests by selling other asset holdings. Such cash hoarding is found to be the rule rather than the exception in the case of bond mutual funds, with less liquid bond funds displaying stronger cash hoarding. Jiang et al. (2021) further show that corporate bond mutual funds tend to reduce liquid asset holdings during tranquil market conditions. However, when aggregate uncertainty rises, these funds tend to scale down their liquid and illiquid assets proportionally to preserve the liquidity of their portfolios. Andreas Schrimpf et al. (2021) also provide evidence of cash hoarding by bond funds during March 2020 market turmoil.

The second strand of literature investigates the interconnectedness between financial institutions and its implications for systemic risk and market contagion. Interconnectedness through common asset holdings has attracted much attention. Looking at the interconnections between European OEFs and UK regulated banks and insurance companies, Barucca et al. (2021) find that different types of financial institutions have common asset holdings despite having relatively unconcentrated portfolios. Poledna et al. (2021) find that neglecting the risk of interbank exposures arising from overlapping portfolios results in an underestimation of systemic risk levels by up to 50% in Mexico. Girardi et al. (2021) study financial interconnections in the US insurance sector and find that similar portfolios relate to larger subsequent common sales. Koide and Hogen (2022) find that common asset holdings between bond funds and regional banks has risen, making regional financial institutions more vulnerable to global market shocks. In addition to common asset holdings, Fricke and Wilke (2023) provide another perspective of interconnectedness focusing on cross-fund investments, specifically mutual funds investing in other funds. They find that diversification and liquidity management considerations play a role in such cross investments.

3. OEF sample and common asset holdings

3.1 OEF sample

We obtain a sample of fixed income OEFs for this study in three steps. We start with the 20,000 largest fund share classes (belonging to about 7,000 funds) with net fixed income holdings larger than 30% of the net asset values (NAV) of fund share classes from Morningstar.[3,4] About 6,000 funds having detailed portfolio information at least back to 2019. We screen the portfolio holdings of these funds and exclude those with majority holdings in other mutual funds (primarily fund of funds or feeder funds), as we do not have sufficient information to trace the portfolio of these funds at the securities level. We further remove funds with actual corporate and government bond holdings that are less than 70% of their total portfolio holdings. As we will cover in the next part, we consider OEFs' common asset holdings at a securities' issuer level, focusing on funds with actual corporate and government bond holdings in majority part of their portfolios helps to ensure that we are able to classify the majority of portfolio holdings at a securities' issuer level in our fund sample.

Our final OEF sample consists of 3,413 funds, covering monthly fund metrics (e.g., fund flows and returns) and quarterly portfolio information from 2019 to 2023.[5] While the number of the sampled funds is less than 20% of the number of fixed income OEFs based on our definition, their total size is equivalent to about 60% of the total size of the latter. This ensures the representativeness of our data sample.[6] Despite a relatively short time period for our sample, it includes major financial market stress events in recent years, in particular the March 2020

[3] Morningstar Direct covers over 300,000 OEF share classes from over 70 jurisdictions around the world. Morningstar Direct's data providers do not guarantee the accuracy, completeness or timeliness of any information provided by them and shall have no liability for their use.

[4] We restrict our fixed income OEF sample to large funds given the significant time and effort required to retrieve fund level portfolio information from Morningstar. Fund characteristics such as return and size are reported at a share class level while portfolio holdings are only available at a fund level. We aggregate the share class level figures to a fund level for our analysis.

[5] While Morningstar reports monthly portfolio information for some OEFs, we opt for quarterly portfolio information in the construction of funds' common asset holdings for a wider fund coverage, as it is more common for OEFs to report their quarterly position to Morningstar. Such reporting frequency aligns with the usual reporting requirement by securities regulators (e.g., US SEC).

[6] The geographical distribution of our sample of OEFs is consistent with the geographical distribution of all fixed income OEFs based on our definition and covered by Morningstar.

financial market turmoil, the Russia-Ukraine conflict in 2022 and the banking sector turmoil in March 2023. Our sample therefore enables us to examine the effects of OEF common asset holdings in times of financial market stress.

3.2 OEF common asset holdings

We follow Girardi et al. (2021) and adopt cosine similarity to measure the extent of common asset holdings at an issuer level of portfolio securities between fund pairs. Cosine similarity between portfolios of a given fund pair *i* and *j* at the end of quarter *t* is given by Equation (1) below:

$$similarity_{i,j,t} = \frac{\boldsymbol{w_{i,t}} \cdot \boldsymbol{w_{j,t}}}{\|\boldsymbol{w_{i,t}}\| \cdot \|\boldsymbol{w_{j,t}}\|} \quad (1)$$

where $w_{i,t}$ and $w_{j,t}$ represent the portfolio weight vectors of funds i and j at the end of quarter t, respectively.[7] Then, cosine similarity is calculated as the dot product of the fund pair's portfolio weight vectors normalized by the product of the vectors' lengths. By construction, cosine similarity is bounded between -1 and 1, so that we can have a standardized measurement of fund portfolio similarity across different fund pairs.[8] Intuitively, cosine similarity of a fund pair is closer to one when they have more portfolio holdings in common (i.e. larger common asset holdings), and closer to zero if their portfolios are very different (i.e. minimal common asset holdings). As funds can hold short positions in certain assets, it is possible for cosine similarity to be negative although this is rare.[9]

To create the portfolio weight vector for a given fund's portfolio, we first identify the issuer of each portfolio holding where available. Portfolio holdings where the issuers can be identified are mainly bond and equity securities.[10] As shown in Chart 1, the portfolio holdings whose issuers can be identified account for more than 95% of the total portfolio of our sampled funds, suggesting that cosine similarity can capture a large extent of OEF common asset holdings at a securities' issuer level. After mapping all portfolio holdings with respective issuers, we construct the portfolio weight vector using the portfolio share of securities by each issuer.

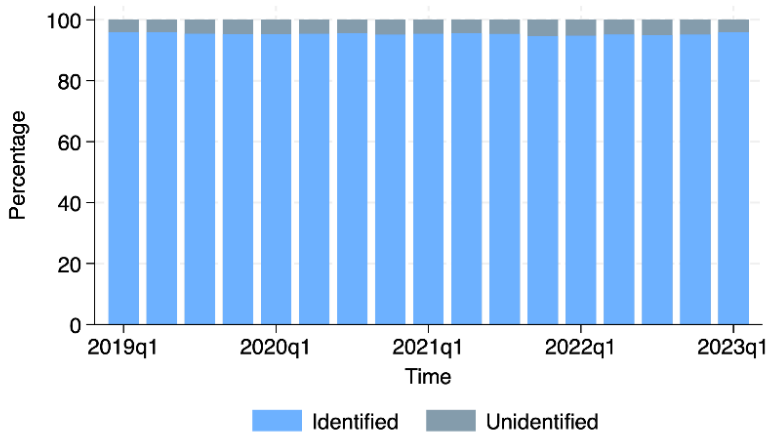
[7] $\|\boldsymbol{w_{i,t}}\| = \sqrt{\sum_{k=1}^{N} (w_{i,t}^{k})^2}$ where $w_{i,t}^{k}$ is the k[th] element of vector $\boldsymbol{w_{i,t}}$.

[8] Another commonly used metric for common asset holdings is the proportion of common holdings (see Zhu and Woltering, 2021; Fricke and Wilke, 2023). We prefer cosine similarity over this measure due to the ease of interpretation and better comparability with other measure of fund similarity (specifically, correlation of fund returns, see later part of Section 3.2).

[9] Negative cosine similarity exists when two funds hold similar assets but in exact opposite positions (one fund holding long and the other fund holding short positions).

[10] Appendix A provides details on identification of issuers for funds' portfolio holdings.

Chart 1: Percentage of OEFs' identified portfolio weight



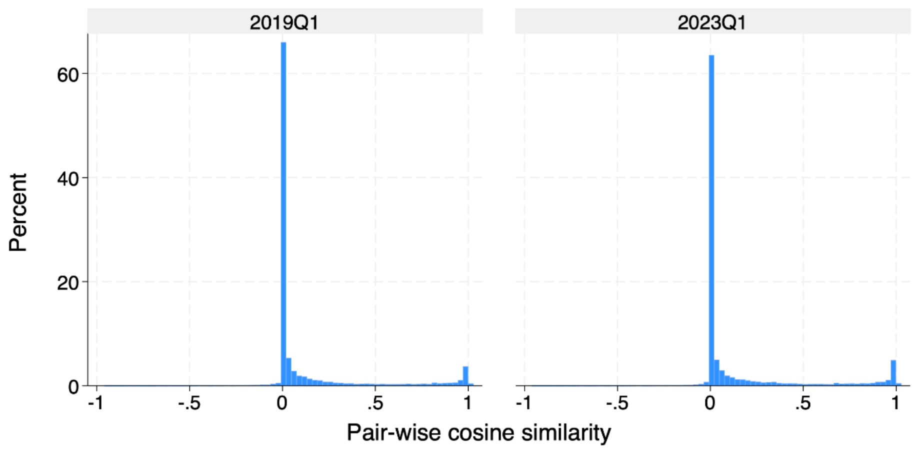
Note: This chart breaks down the security holdings of our sample funds by whether or not their issuers can be identified, as of the percentage of total NAV of our sample funds at each quarter end. Source: Morningstar and authors' estimates

Chart 2 compares the distribution of cosine similarity of sampled fund pairs at the end of Q1 2019 (the start of the portfolio holding sample) and Q1 2023 (the end of the portfolio holding sample) respectively. In both case, the distribution exhibits a flipped J shape with most observations concentrated around zero yet with a considerable mass at the right-hand tail, and very few observations in negative territory. More specifically, for Q1 2023 (i.e., the right chart), 13% of the fund pairs have a portfolio similarity larger than or equal to 0.5, which we regard as highly similar portfolios, 4% larger than or equal to 0.3 and smaller than 0.5 (moderately similar portfolios) and 80% larger than or equal to 0 and smaller than 0.3 (little similar portfolios).[11,12] Furthermore, as depicted in Chart 3, the proportion of highly similar and moderately similar portfolios fund pairs is relatively stable from 2019 to 2021 while the share of highly similar portfolios shows an upward trend since Q1 2022. The non-negligible share of funds with highly similar portfolios provides the foundation for our analysis on the relationship between OEF common asset holdings and flows.

[11] As there is no commonly agreed thresholds to our best knowledge, the chosen thresholds reference the commonly accepted thresholds for Pearson correlation coefficient, notwithstanding the different statistical meaning of two measures (Pearson coefficient measure the relationship of two data series while cosine similarity captures the relationship of two vectors), so that a value of 0.5 for cosine similarity is not strictly equivalent to a value of 0.5 for the Pearson correlation coefficient. However, as our results show, the peer OEFs classified in this way do indeed result in statistically different peer flow relationships (and is not due to randomness), which in turn helps to justify the selected thresholds. Table A2 and A3 in Appendix A visualises these thresholds with examples.

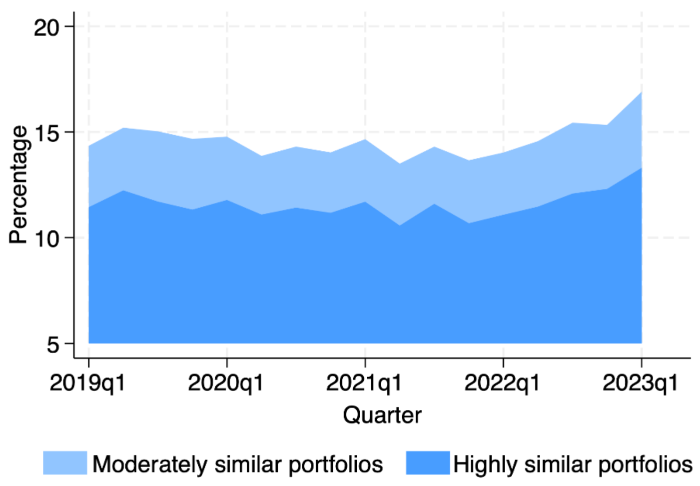
[12] The large concentration of cosine similarity around zero (implying portfolios of most sampled OEF pairs are totally different) align with the large diversity of benchmark attached to these funds as reported by Morningstar. Funds with the same benchmark are more likely to share more common asset holdings.

Chart 2: Distribution of OEFs' portfolio similarity at the end of 2019Q1 and 2023Q1



Note: This chart presents the distribution of the pair-wise cosine similarity of sampled fund pairs at the end of Q1 2019 and Q1 2023. Source: Morningstar and authors' estimates

Chart 3: Trend of OEFs' portfolio similarity



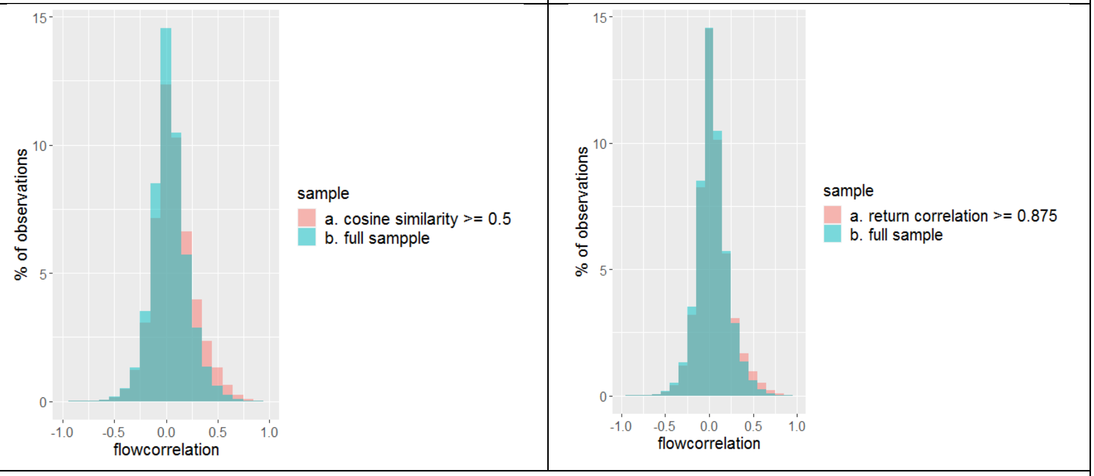
Note: This chart presents the proportion of highly similar and moderately similar portfolio fund pairs over the sample period. Fund pairs are defined as having highly similar portfolios when their portfolio similarity is larger than or equal to 0.5, and moderately similar portfolios when their portfolio similarity is larger than or equal to 0.3 and smaller than 0.5. Source: Morningstar and authors' estimates

To get a sense on the relationship between OEF common asset holdings and flows, the left panel of Chart 4 compares the distribution of the pair-wise correlation of monthly fund flows for i) for fund pairs with highly similar portfolios (i.e. cosine similarity is larger than or equals to 0.5, which is about 89th percentile of data sample, shaded pink in the Chart) and ii) all sampled fund pairs (shaded green in the chart). As can be seen, the distribution of fund pairs with moderately or highly similar portfolios (pink shading) is skewed more to the right side when compared to all sampled fund pairs (green shading), implying that fund pairs have a larger chance of displaying more correlated flows when they share a more similar portfolio.

Panel b makes a similar comparison but instead of common asset holdings, it divides the fund pairs based on the pair-wise correlation of monthly returns, a commonly used and more readily available indicator for fund similarity (e.g. Lewrick and Claessens, 2021). To make a fair comparison with Panel a, the pink shaded area in Panel b covers fund pairs with a returns correlation larger than 0.875, which is about 89th percentile of the pair-wise returns correlations in the data sample. As can be seen, the pink shaded area in Panel b is notably less skewed to the right when compared with the green shaded area (all sampled fund pairs) than that observed in Panel a. Overall, Chart 4 shows that fund portfolio similarities based on detailed portfolio holdings can provide additional information regarding the relationship between OEFs' interconnections and their flows.

Chart 4: Fund flow correlation, common asset holdings and return correlation

a. by common asset holdings | b. by return correlation



Note: This chart compares the distribution of the pair-wise correlation of the monthly flows of all sampled fund pairs (green shading), and the sub-sample of sampled fund pairs (pink shading) with cosine similarity larger than or equal to 0.5 (Panel a) and the sub-sample of sampled fund pairs with the correlation of monthly fund return larger than or equal to 0.875 (Panel b) respectively. Source: Morningstar and authors' estimates

4. Empirical model and results

In this Section, we discuss the empirical models we use to address our four research questions and findings (Section 4.1). Section 4.2 reports the results from robustness tests.

4.1 The relationship between common asset holdings and fund flows

4.1.1. Do peer flow relationships exist with common asset holdings?

To answer this question, we examine whether the fund flows of individual OEFs have a stronger association with the fund flows of its peers with similar portfolios than those of peers with less similar portfolios. In particular, we estimate Equation (2) below:

$$flow_{i,t} = \beta_1 peerflow_{high,t} + \beta_2 peerflow_{moderate,t} + \beta_3 peerflow_{little,t} + \gamma control_{i,t-1} + u_i + \lambda_{d,t} + \varepsilon_{i,t} \qquad (2)$$

The dependent variable $flow_{i,t}$ is the fund flow of OEF i in month t, based on net assets and returns in USD terms[13] following the established practice in the literature (Chen et al., 2010;

[13] $flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1+Ret_{i,t})}{TNA_{i,t-1}}$, where $TNA_{i,t}$ is the total net asset of fund i at time t, and $Ret_{i,t}$ is the return of fund i at time t.

Zhu and Woltering, 2021). To examine the role of common asset holdings, the model includes $peerflow_{high,t}$, $peerflow_{moderate,t}$ and $peerflow_{little,t}$ which capture the average size-weighted contemporaneous fund flows of peer funds with a high, moderate and low degree of similarity in asset holdings with OEF *i*. The degree of similarity is based on pair-wise cosine similarity between fund *i* and other sampled funds in the previous quarter-end.[14] Equation (2) also includes $control_{i,t-1}$, which is a battery of control variables including the lagged fund return, liquidity, size and age. u_i is the fund fixed effect to control for the time-invariant unobservable features of each fund, while $\lambda_{d,t}$ is the fund domicile-month fixed effect to control for the time-varying unobservable factors in the domicile of each fund, such as the domicile-specific macroeconomic trends and market fluctuations. Appendix B gives the definition of each variable and summary statistics.

Our core interest is the sign and magnitude of the model coefficients β_1, β_2 and β_3. Specifically, if the fund flows of an individual OEF are related to those of its peers with more similar portfolios, we should observe β_1 to be significantly positive, and larger than β_2 and β_3.

Table 1 reports the results from estimating Equation (2). Among the coefficients of the three main explanatory variables, $peerflow_{high,\,t}$ and $peerflow_{moderate,\,t}$ are positive and significant while $peerflow_{little,t}$ is not statistically significant. This supports the hypothesis of a positive and significant relationship between fund flows of OEFs that have a high degree of similarity in their portfolios.[15] In terms of the magnitude, the estimate of β_1 is 0.13, indicating that a one percentage point increase (decrease) in peer fund flows with a high degree of similarity in their portfolios is associated with a 0.13 percentage point increase (reduction) in the monthly fund flows of fund *i*. The estimated relationship weakens by almost half for peers with moderate portfolio similarity, with the estimated β_2 being 0.07 only.[16] Importantly, as reported in the penultimate row of Table 1, the difference of the estimated β_1 ($peerflow_{high,\,t}$) and β_2 ($peerflow_{moderate,\,t}$) is statistically significant, indicating that flow relationship between sampled OEFs and their peers does differ with the degree of commonality in asset holdings.

We further find that the fund flow relationship between OEFs and their peers with highly similar portfolios is asymmetric with respect to general financial market conditions, and the relationship is stronger in times of market stress. This is tested by introducing an interaction term to $peerflow_{high,t}$ to separate estimates of β_1 in times of market stress and other periods, using a dummy variable that equals one when the VIX index is larger than the 75th percentile of the sample, and zero otherwise, as laid out in Equation (3) below:

$$\begin{aligned} flow_{i,t} = {} & \beta_1 peerflow_{high,t} + \beta_2 peerflow_{moderate,t} + \beta_3 peerflow_{little,t} \\ & + \beta_4 peerflow_{high,t} * Stress_t + \gamma control_{i,t-1} + u_i + \lambda_{d,t} + \varepsilon_{i,t} \qquad (3) \end{aligned}$$

Under this set-up, a positive and significant β_4 indicates a peer flow relationship that is stronger in times of financial market stress. Column 2 of Table 1 shows that this is indeed the

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[14] Accordingly, for each fund *i* the lists of fund peers used to calculate the three *peerflow* measures are not fixed across time. This better captures the dynamics in the interconnections between OEFs due to common asset holdings.
[15] The three constructed $peerflow$ variables do not display high correlation (less than 0.4 for any given pair), suggesting a low risk of collinearity if all three variables are included in the regression model.
[16] We have further examined the economic significance of the estimated peer flow relationship on the liquidity risk of sampled OEFs using a scenario analysis. See Section 5 for more details.

case, as the estimate of β_4 is 0.15 and statistically significant. Considering together with the estimate of β_1, the results suggest that the relationship between fund flows of individual OEFs and their peers with highly similar portfolio is almost two times larger (0.23 = 0.08 + 0.15) during periods of financial market stress compared with other periods (0.08)[17]. This finding suggests that the positive correlation that we find is mostly driven by a high correlation during periods of financial stress. As we will examine further below, we can attribute the peer flow relationship to common asset holdings, which is more likely to generate a larger impact in times of market stress when OEFs might be forced to sell assets at a discounted price.

4.1.2. Can we attribute the peer flow relationship to the portfolio actions of peer funds (a "peer flow effect")?

As discussed in the *Introduction*, one major channel through which the fund flows of an OEF may be affected by peers with highly similar portfolios is price pressures caused by asset sales. While a stronger flow relationship between funds with highly similar portfolios in times of stress reported earlier may lend some support to this transmission channel, it is also possible that such association could be driven by common factors (say, collective redemptions by investors due to unstable market conditions), other than similarity of portfolios and the investment decisions of peer funds.

To verify that we can attribute the estimated flow relationship to the portfolio actions of peer funds, we modify Equation (4) by splitting the $peerflow_{high,\,t}$ into two components, more specifically $peerflow_{high,t}^{larger\ sell\ pres}$ and $peerflow_{high,t}^{smaller\ sell\ pres}$ that capture the weighted average fund flows of two groups of peers with highly similar portfolios, with one being more prone to asset fire-sales ($peerflow_{high,t}^{larger\ sell\ pres}$) and the other being less prone to asset fire-sales ($peerflow_{high,t}^{smaller\ sell\ pres}$), as shown in Equation (4) below:

$$\begin{aligned} flow_{i,t} = {} & \beta_1^{larger} peerflow_{high,t}^{larger\ sell\ pres} + \beta_1^{smaller} peerflow_{high,t}^{smaller\ sell\ pres} \\ & + \beta_2 peerflow_{moderate,t} + \beta_3 peerflow_{little,t} + \gamma control_{i,t-1} + u_i + \lambda_{d,t} \\ & + \varepsilon_{i,t} \qquad (4) \end{aligned}$$

The most direct way to demonstrate the effect of peers' portfolio actions is to link up the assets sold by peer funds and the flows of fund *i* holding similar assets. One problem is that information on asset-level transactions by sampled OEFs is not available, so we consider three different proxy indicators that capture an OEF's proneness to asset fire sales in different dimensions.[18]

The first indicator is the "flow-driven asset sales" ($flow\_driven\_sale_{i,t}$) based on actual fund flows and changes in cash holdings following Shek, Shim and Shin (2018) as shown in Equation (5). With a negative value of $flow_{i,t}$ denoting a net flow-driven asset sales, there are two cases which would result in a net flow-driven asset sales by OEFs as per Equation (5). First, for funds facing outflows, if the decrease in its cash holdings is less than the amount of outflows (i.e., the condition "$flow_{i,t} < \Delta C_{i,t} < 0$" in the first row), this indicates that fund managers

[17] The results are similar if we use highly similar portfolio fund peers experience outflow as an indicator of stress.
[18] Even though we are focusing on peers with relatively more similar portfolio, it is possible that funds sell assets that are not held by their peers, and thus there is not direct impact on their portfolio values resulting in outflows from peer funds. Nevertheless, peer funds that are judged to have a proneness to asset fire sales may still be considered as more likely to affect the flows of fund *i* on average.

accommodate part of investors' redemption demand through asset sales, and such "flow-driven asset sales" can be measured by the difference between outflows and the decrease in cash holdings; Second, if cash holding increase when a fund has outflows, it indicates that the fund manager is selling more assets than necessary to meet redemptions, so that "flow-driven asset sales" in this case is just the amount of outflow as per Shek, Shim and Shin (2018). In both cases, the resulting $flow\_driven\_sale_{i,t}$ is negative, with a more negative value corresponding to a larger flow-driven asset sales. Holding other things equal, we would expect OEFs with larger flow-driven asset sales to introduce stronger price pressures on the assets they held, and thus a larger peer flow effect on funds holding the same assets.

$$flow\_driven\_sale_{i,t} = \begin{cases} flow_{i,t} - \Delta C_{i,t}, & flow_{i,t} < \Delta C_{i,t} < 0 \text{ } or \text{ } 0 < \Delta C_{i,t} < flow_{i,t} \\ flow_{i,t}, & flow_{i,t} < 0 < \Delta C_{i,t} \text{ } or \text{ } \Delta C_{i,t} < 0 < flow_{i,t} \\ 0, & \Delta C_{i,t} < flow_{i,t} < 0 \text{ } or \text{ } 0 < flow_{i,t} < \Delta C_{i,t} \end{cases} \quad (5)$$

The second indicator is based on a peer's tendency to hoard cash. Some studies have shown that cash holding levels sometimes may not truly reflect actual liquidity demand from redemptions, because some funds tend to hold more cash or high-liquid assets for precautionary reasons, referred to as "cash hoarding" behaviour (e.g. Morris et al., 2017; Lewrick and Claessens, 2021). OEFs with a higher cash hoarding tendency will sell more assets compared to their counterparts with a lower cash hoarding tendency. We measure a fund's cash hoarding tendency by the historical occurrence of each OEF's cash hoarding behaviour as in Morris et al. (2017).[19]

The third indicator measures the concentration of the portfolio of each OEF using the Herfindahl-Hirschman Index (HHI). Intuitively, OEFs with a more concentrated portfolio could transmit higher price pressures to underlying assets during liquidation. Among two peers of highly similar portfolios with fund *i*, the peer with a more concentrated portfolio is expected to display a stronger peer flow relationship with fund *i*.

We construct the variables $peerflow_{high,t}^{larger\ sell\ pres}$ and $peerflow_{high,t}^{smaller\ sell\ pres}$ by splitting highly similar fund peers into two equal halves using the median value of the four above-mentioned indicators respectively. As both groups share similar portfolios with fund *i*, if the positive peer flow relationship obtained earlier is attributable to portfolio actions of the peers, we would expect β_1^{larger}, which corresponds to the group of peers with highly similar portfolios to fund *i* and who are more prone to asset fire sales, to be significantly more positive than $\beta_1^{smaller}$, which represents highly similar peers who are less prone to asset fire sales.

Table 2 presents the regression results. Specifically, the estimated β_1^{larger} are significantly more positive than $\beta_1^{smaller}$ for all three different proxies of peers' proneness to asset fire sale, with the magnitude of the estimated β_1^{larger} close to twice that of the estimated $\beta_1^{smaller}$. These results provide indirect evidence that the peer flow relationship reported earlier can be attributed to the portfolio actions of peers with highly similar portfolios, that is 'peer flow effects'. This suggests there may be spillover effects of OEF liquidity risk through a common asset holdings channel.[20]

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[19] If an OEF has an outflow and an increase in cash holdings in the same month, it is defined as cash hoarding.

[20] To further control for idiosyncratic demand for cash across different funds' investors, we have repeated the analysis using the expected peer flows (see also Section 4.2), and the results are consistent with those reported in Table 2. The estimates are not reported for brevity.

4.1.3. Is the peer flow effect stronger on OEFs with larger liquidity risk, particularly in times of financial market stress?

One major financial stability concern related to peer flow effects arising from funds' portfolio actions is whether this exacerbates funds' liquidity risk, particularly in times of financial market stress. To shed light on this, we test whether the peer flow effect is stronger on funds that potentially face a larger liquidity risk. Specifically, we introduce interaction terms of $peerflow_{high,t}$ with an indicator variable $D_{i,t}$ as denoted in Equation (6):

$$flow_{i,t} = \beta_1 peerflow_{high,t} + \beta_2 peerflow_{moderate,t} + \beta_3 peerflow_{little,t} + \beta_4 peerflow_{high,t} * D_{i,t} + \beta_5 D_{i,t} + \gamma control_{i,t-1} + u_i + \lambda_{d,t} + \varepsilon_{i,t} \quad (6)$$

where $D_{i,t}$ denotes three different fund-specific features that capture the liquidity risk of OEF *i*. The first feature is fund *i* with very low cash holdings, specifically, funds with cash holdings smaller than the 10th percentile of the sample. Holding other things equal, funds *i* with smaller liquidity buffers could be more prone to redemption pressures, as investors anticipate they would need to liquidate more heavily during periods of financial market stress to meet redemption demands, which may further worsen their performance and lead to more redemption demands, and thus a higher liquidity risk (IMF, 2022). The second feature is the performance of fund *i* in month *t-1*. This builds on the classic flow-performance relationship where a negative fund performance in the past would likely lead to more negative flows from a fund (Coval and Stafford, 2007; Chen et al., 2010). The third feature indicates if fund *i* is a high-yield bond fund. High yield bonds are perceived to have lower market liquidity, particularly in times of stress.[21] If peer flow effects amplify the liquidity risk facing fund *i*, we should observe a more positive β_1 (which measures the peer flow effect on funds with larger liquidity risk) than β_4 (which measures the peer flow effect on funds with lower liquidity risk). As our focus is the impact of peer flow effect on OEF liquidity in times of market stress, we estimate Equation (6) on a sub-sample of observation during the market stress periods, specifically, monthly periods where the VIX index is larger than 75th percentile of the full sample period.

Table 3 reports the results. The model estimates suggest that, in times of stress, the peer flow effect from peers with highly similar portfolios is significantly stronger on funds that have 1) lower cash holdings or 2) prior negative performance, or are 3) high-yield bond funds, as evidenced by the positive and statistically significant coefficient on the interaction term (see row $peerflow_{high,t} * D_{i,t}$). Together, these results indicate that the peer flow effect is stronger on funds that are already subject to larger liquidity risk, demonstrating the role of common asset holdings in increasing OEFs liquidity risk in times of stress.

[21] We define a fund as a high-yield bond fund if more than 50% of its fixed income holdings have a credit rating of BB or below, or are not rated, on average over the sample period.

4.1.4. Does the peer flow effect exist among OEFs domiciled in different jurisdictions?

Our dataset of OEFs in different jurisdictions allow us to further investigate the cross-border impact of the peer flow effect. To shed light on this, we reconstruct the three peer flow measures ($peerflow_{high,t}$, $peerflow_{moderate,t}$ and $peerflow_{little,t}$) for each fund *i* by only considering the peers that are domiciled in different jurisdictions to fund *i*, before re-estimating Equation (2) and (3).

Table 4 reports the estimation results. Similar to the baseline results reported in Table 1, the fund flows of peers with a higher portfolio similarity exhibit a more positive and statistically significant relationship with the flows of fund *i* compared to peers with less portfolio similarity (see row $\boldsymbol{\beta}_1 - \boldsymbol{\beta}_2$ in Column 1). We again find that the positive correlation is mostly driven by the high correlations during stress period (see row $\boldsymbol{\beta_1} + \boldsymbol{\beta}_4 - \boldsymbol{\beta}_2$ in Column 2). Overall, our results suggest a significant peer flow effect on OEFs across different jurisdictions, providing support for the existence of the cross-border spillover effects of OEF liquidity through common asset holdings.

4.2 Robustness tests

This section discusses the results of three robustness tests to our baseline results in Table 1. Given our baseline model setting in Equation (2), one potential concern with Equation (2) is that the main explanatory variables $peerflow_{high,t}$, $peerflow_{moderate,t}$ and $peerflow_{little,t}$ in the current month could be correlated with the error term due to common factors that impact all OEFs, even though the inclusion of fund domicile-time fixed effects partially control for possible unobservable common factors for funds in the same domicile. Accordingly, three different tests are conducted that address this concern.

In the first test we replace the actual $peerflow$ with the "expected" $peerflow$ that depends purely on past flows and returns information of respective peers. More specifically, for each month *t* we follow Coval and Stafford (2007) and estimate a cross-sectional regression as in Equation (7).

$$flow_{i,t} = \alpha_i + \sum_{k=1}^{12} \beta_j flow_{i,t-k} + \sum_{k=1}^{12} \gamma_j return_{i,t-k} + \varepsilon_{i,t} \qquad (7)$$

We then calculate the expected $flow_{i,t}$ as the fitted value using the time series average of the regression coefficients of Equation (7) above. Finally, we re-construct the $peerflow_{high,t}$, $peerflow_{moderate,t}$ and $peerflow_{little,t}$ variables based on the expected $flow_{i,t}$ variable before estimating Equation (2) again. In this case, the expected $peerflow$ variables basically capture the information from period $t-1$ or earlier, and are therefore less likely to be correlated with the error term in the period t. The estimated coefficients of the $peerflow$ variables capture the impact of fund flows from the highly interconnected fund peers that can be directly explained by their past flows and performances and isolated from the impact of common factors at time *t*.

Column 1 in Table 5 reports the results of the first test, which, similar to the baseline results in Table 1, shows the estimated β_1 to be significant and positive, and larger than β_2 and β_3. In addition , Column 2 shows that the estimated β_1 is significantly more positive in times of stress when the "expected" $peerflow$ measures are used.

The second test addresses the endogeneity concerns using an instrumental variable approach. We re-estimate Equation (2) and Equation (3) using the one period lagged terms of $peerflow_{high,t}$, $peerflow_{moderate,t}$ and $peerflow_{little,t}$ as instruments. The results are reported in Columns 3 and 4, which are consistent with our baseline findings.

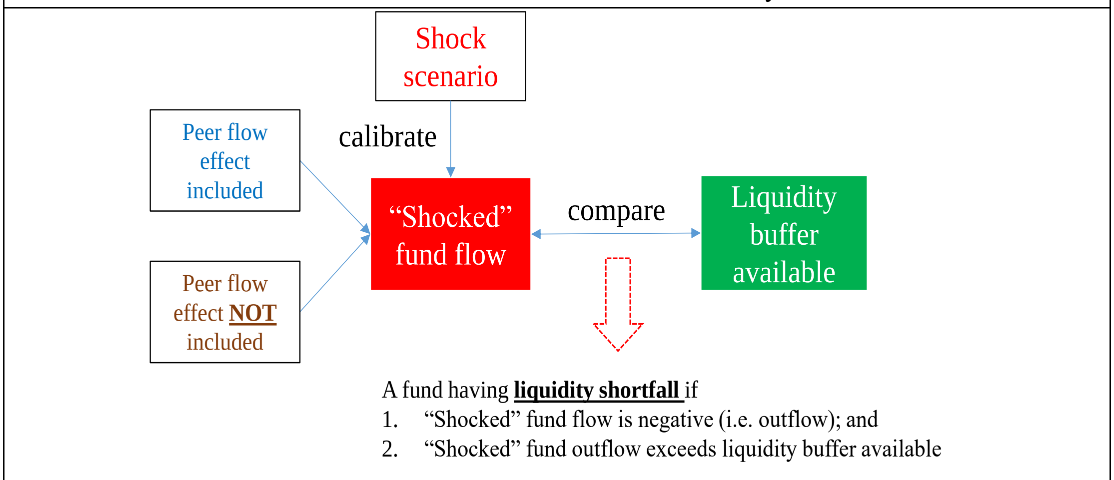
The third test conducts a placebo test where for each fund *i* in month *t* we randomly assign the peers into three groups, instead of by the extent of common asset holdings with fund *i*, and construct the three $peerflow$ variables. If the positive peer flow relationship is driven by common factors that are not specifically related to common asset holdings, we would still observe a positive and significant coefficient for a randomly constructed $peerflow$.

Table 6 reports the results. It is worth noting that the three $peerflow$ measures constructed by random assignment are highly correlated with each other, as they basically capture the average level of fund flows in the market. As such, we only include one measure at a time in the estimation.[22] As shown in Table 6, the estimated coefficient for $peerflow$ is not significantly positive whichever $peerflow$ is used, regardless of whether it is a period of stress or not. Results of the placebo test therefore provide further support that the positive peer flow relationship obtained in the baseline model is not driven by overall fund flow fluctuations in the market, and is instead attributable to the common asset holdings among OEFs.

5. Scenario analysis

We wrap up the study by conducting a scenario analysis on the economic significance of common asset holdings under a stress scenario. More specifically, we apply the framework of liquidity stress testing in Bouveret (2017) and ESMA (2019) to estimate the share of sampled funds that would experience a liquidity shortfall following a shock. By comparing the share of funds with a liquidity shortfall, with and without the peer flow effect, we are able to deduce the economic impact of common asset holdings among funds.

Chart 5: Framework of scenario analysis



[22] The pair-wise correlations are all over 0.8 for any pair of three peer flow measures.

Chart 5 above outlines the two inputs required for conducting the scenario analysis. First, the fund flows under the shock scenario ("shocked" fund flow) needs to be assumed. ESMA (2019) suggests that the "shocked" fund flow can be calibrated using either a "pure" or "scenario-based" redemption approach.[23] Given the objective of assessing the impact of common asset holdings, we opt for the scenario based approach in our analysis. More specifically, given a shock scenario, we first calibrate the impact of the shock on a fund's returns ("shocked" fund return), before estimating the "shocked' fund flow. Compared to the "pure" redemption approach where a certain magnitude of outflows is imposed directly, the scenario based approach allows us the option of incorporating the peer effect of common asset holdings in calibrating the "shocked" flow.[24] As regarding the shock scenario, we consider a sharp increase in interest rate, whose impact on fund returns (and thereby fund flows) is highly relevant to our sampled fixed income OEFs.

The second component is the liquidity buffer available to individual OEFs. Among the two commonly-used approaches for calibrating OEFs' liquidity buffer, specifically i) liquidity buckets and ii) time to liquidation,[25] we use the former in this analysis given the ease of computation and interpretation. In particular, we follow ESMA (2019) and apply a high-quality liquid assets (HQLA) approach based on the Basel III liquidity regulatory requirements on banks. To apply the HQLA approach on OEFs, the funds' portfolio holdings are split into groups according to their asset classes (sovereign bonds, corporate bonds, equities etc.) and ratings, with each group given a liquidity weight. The liquidity buffer available to a fund is then calculated as the sum of the share of each group in the fund's portfolio (as a percentage of the fund's NAV) weighted by its liquidity weight.[26]

Taking the two inputs together, an OEF is considered as having liquidity shortfall if the fund experiences an outflow under the assumed interest rate shock and if the magnitude of outflow exceeds its liquidity buffer. By repeating the calibration of "shocked" flows, with and without the peer effect of common asset holdings included, we can compare the portion of funds that would be subject to a liquidity shortfall.[27]

Chart 6 reports the estimated impact of an one percentage point (ppt) interest rate increase shock, represented by the change in the share of sampled OEFs with a liquidity shortfall from

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[23] In the "pure" redemption approach, a certain magnitude of "shocked" outflows based on historical distribution or expert judgment is directly imposed. While easy and flexible to use, the pure approach lacks a theoretical foundation, as the sources of the shock are not explained. The aggregation of fund-specific results at the sector level may also be a problem under the pure approach as it may not be realistic to observe all funds experiencing the same amount of outflows at the same time. Meanwhile, in the scenario-based approach, all funds under the test would be subject to the same assumed macro-financial shock, where one needs to assess first the impact of the shock on the returns of the fund (or flows directly), and then the net flows from investors. The scenario-based approach facilitates the aggregation of fund-specific results since the fund under tests are subject to the same macro-financial settings.

[24] Appendix C describes the procedure of calibrating "shocked" flow given an interest rate in more details.

[25] For the liquidity buckets approach, assets in the portfolio of funds are classified in different buckets representing different degrees of market liquidity where the liquidity of the fund is measured by the sum of weight of asset allocation weighted by respective liquidity level. In the time to liquidation approach, liquidity is measured by the time required to sell securities without causing a large price impact.

[26] We follow ESMA (2019) on the liquidity weights assigned to different asset classes and ratings. See Appendix C for details.

[27] An interest rate shock could also result in liquidity demand (and therefore liquidity risk) for OEFs through channels other than investor redemptions, for example margin calls on derivative positions. We have not considered such channels in our analysis due to data limitation.

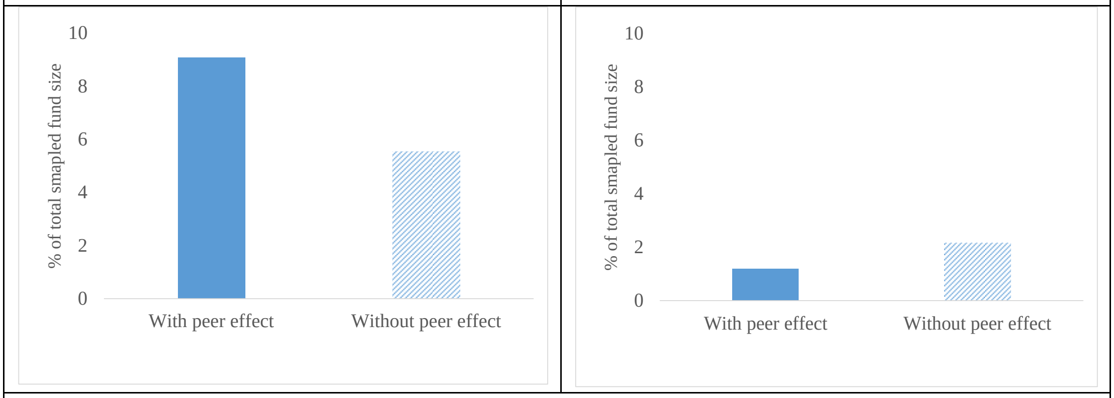
the baseline case when the interest rate shock is not applied.[28] We separate the analysis for high yield bond funds and non-high yield bond funds in our sample (Panels a and b respectively), as ESMA (2019) reports a much larger share of high-yield bond funds with a liquidity shortfall than for other fund types under shock.[29] Estimates for the case with and without the peer flow effect included are represented by solid and shaded bars respectively.

There are two key observations. First, consistent with ESMA (2019), there is a much larger increase in the share of funds with a liquidity shortfall for high yield bond funds than for other sampled fixed income funds, when the interest rate shock is introduced. More specifically, the solid bars in Chart 6 shows that the share of high-yield bond funds with a liquidity shortfall increases by 9 ppts (Panel a),[30] compared to just one ppt increase for non-high yield bond funds (Panel b) .

Second, and perhaps more importantly, the impact of the interest rate shock is estimated to be larger when the peer flow effect is taken into account, again for high yield bond funds. To see this, the shaded bars in Panel a show that when peer flow effects are not considered, the increase in the share of funds with a liquidity shortfall from the baseline case would be just 6 ppts,[31] which is 50% smaller with than the case when peer flow effects are included (9 ppts, solid bars). The noticeable difference between the two cases quantifies the economic significance of the peer flow effect. Finally, the minimal difference observed for non-high yield bond funds reconciles with our earlier finding that the peer flow effect tends to be more pronounced on funds with larger inherent liquidity risks.

Chart 6: Share of sampled funds with liquidity shortfall under 1% interest rate shock

a. High-yield bond funds | b. Non-high yield bond funds



Notes: 1) This chart depicts the estimated change in the share of sampled OEFs with liquidity shortfall under one ppt interest rate increase shock from the baseline case where the interest rate shock is not imposed, with (solid bars) and without peer flow effect (shaded bars) included, for sampled high-yield bond funds (Panel a) and non-high yield bond funds (Panel b) respectively. 2) A fund is defined as having liquidity shortfall when the expected flow given a scenario is negative (i.e., outflows) and when the outflows exceeds its liquidity buffer. 3) For results with peer effect included, the estimated peer flow relationship as reported in Section 4.1 is included when we calibrate the expected flow of funds given the scenario (see Appendix C). Source: Authors' estimates.

[28]In the baseline scenario, the historical average return of individual funds is used instead of the "shocked" fund return to calibrate the expected fund flows.
[29] Up to 40% of sampled high-yield bond funds are found to experience a liquidity shortfall under the severe but plausible outflow shock assumptions considered by ESMA (2019), compared with just a few percentage points in other fund types such as equity funds and mixed funds.
[30] More specifically, the share would increase from 3% under the baseline case to 12% under the interest rate shock (i.e., a 9 ppts increase).
[31] The share would increase from 3% under the baseline case to 9% under the interest rate shock (i.e., a 6 ppts increase).

6. Conclusions

The financial stability implications of the interconnections among financial entities are subject to continuous discussion and analysis by central banks and international organisations. This study examines the issue from the perspective of common asset holdings among OEFs, whose fire sales of assets due to investors redemption could exert downward pressures on the returns of funds holding the same assets, in turn triggering investors' outflows from these funds. This study provides fresh evidence of the impact of common asset holdings on OEF liquidity risk using a data sample that covers major market stress episodes in recent years.

By constructing a measure of common asset holdings using detailed portfolio holdings for over 3,400 of the largest fixed-income funds globally, we derive three major findings in this study. First, we find a significant and positive relationship between fund flows of OEF peers with highly similar portfolios, which we further show can be attributed to peers' portfolio actions (rather than appearing randomly). Second, the relationship is stronger in times of financial market stress, and stronger on OEFs with a larger liquidity risk, which suggests that common asset holdings can amplify OEFs' liquidity risk during periods of financial market turbulence. Third, the estimated relationship is found to be significant between OEFs domiciled in different jurisdictions, implying that common asset holdings can contribute to cross-border spillovers of OEF liquidity risk. Scenario analysis using a hypothetical shock scenario setting demonstrates the economic significance of the effect of common asset holdings on OEF liquidity risks.

Overall, our results support the case that common asset holdings are a significant channel through which OEF liquidity risk can spillover to other OEFs and across borders, with robustness tests being carried out to alleviate the possible endogeneity concerns on our empirical results. That said, our results are subject to two limitations. First, our sample only includes the largest OEFs that invest mainly in corporate and government bonds due to the time and effort required to gather data on detailed portfolio holdings from our source. Even though our sampled OEFs already account for a representative share of fixed-income funds globally, a larger sample that covers more funds as well as other investment strategies will definitely enhance the generalizability of the results. This will also allow us to compare the effect of common asset holdings across different investment strategies by OEFs.

Second, though our empirical approach enables us to associate the effect of common asset holdings to the portfolio actions of peers, we have not examined related issues such as price impacts and second-round effects, as Falato et al. (2021b) did for the US market, due to the lack of detailed security-level transaction data across markets. A better understanding of these issues would provide a more comprehensive assessment of the systematic impact of OEF common asset holdings on the global financial system.

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Appendix

A. Classification of fund portfolio holdings at the issuer level

To identify the issuers of the fund portfolio holdings, we begin by classifying the asset holdings into primary asset classes and then identifying the issuers of each security based on its asset class. Table A1 presents the classification of the primary asset classes and their issuer-level identification criteria. Among all the types of security holdings defined in the Morningstar database, we can identify the issuers of each security of asset classes including corporate bonds, government bonds, supranational bonds, equity shares and equity index derivatives. For other asset types such as cash, mutual fund shares, commodities, alternative investments where particular issuer cannot be identified, we do not include weights attached to these assets in the portfolio weight vector for calculating the cosine similarity measure. As these assets only account for a small part of the sampled funds' portfolios (see also Chart 1), such exclusion does not greatly affect the portfolio information captured by the weight vectors.

Table A1: Asset class and issuer classification of OEFs' portfolios

Primary asset class	Issuer identification
Corporate bonds	Identify the corresponding corporate entity
Government bonds	Identify the corresponding country/economy
Supranational bonds	Group as one supranational issuer
Equity shares	Identify the corresponding corporate entity
Equity Index derivatives	Identify the corresponding equity index
Other asset and liabilities	/

For the asset classes listed in Table A1, we apply different identification strategies of security issuers. For corporate bonds and equity shares, we identify the corporate entities that issued the securities by matching the security names to corporate names using the S&P Capital IQ database. Considering the difference between bonds and equity, the corporate bonds and equity shares issued by the same company are classified as having different issuers[32]. For government bonds, we identify the country or economy of the securities as their issuers. For equity index derivatives such as equity index futures, we identify the underlying equity index as the "issuer". For supranational bonds such as bonds issued by multilateral development banks, since the share of securities in this asset class accounts for a small share,[33] we just group them together as one issuer.

Table A2 gives several examples of OEF's portfolios to illustrate different levels of cosine similarity and Table A3 reports the matrix of cosine similarity of all fund pairs in the example. In this example, there are assets issued by three issuers A, B and C, and each row presents the portfolio weight vector of one fund. For fund pair (Fund 1, Fund 2), they invest in totally different assets, and the cosine similarity calculated according to Equation (1) is 0. For fund pair (Fund 3, Fund 4) and (Fund 5, Fund 6), portfolio overlapping exists, with their cosine similarity scores equalling 0.33 and 0.5 respectively. The latter pair has a higher extent of

[32] For example, if fund *i* holds 100% of the corporate bonds issued by company A and fund *j* holds 100% of equity shares issued by company A, fund *i* and *j* will be considered to have completely different asset allocation at issuer level instead of having identical issuer-level allocation.
[33] The average portfolio weight of supranational bonds holdings in the sample is around 5%.

overlapping. For fund pair (Fund 6, Fund 7), the two funds have exactly the same portfolio vectors and thus a cosine similarity of 1.

Table A2: Example of OEFs' portfolios

	Asset A	**Asset B**	**Asset C**
Fund 1	0	0	100
Fund 2	100	0	0
Fund 3	10	20	70
Fund 4	70	20	10
Fund 5	0	50	50
Fund 6	50	50	0
Fund 7	50	50	0

Table A3: Cosine similarity matrix

	Fund 1	**Fund 2**	**Fund 3**	**Fund 4**	**Fund 5**	**Fund 6**	**Fund 7**
Fund 1	/	0	0.95	0.14	0.71	0	0
Fund 2	0	/	0.14	0.95	0	0.71	0.71
Fund 3	0.95	0.14	/	0.33	0.87	0.29	0.29
Fund 4	0.14	0.95	0.33	/	0.29	0.87	0.87
Fund 5	0.71	0	0.87	0.29	/	0.5	0.5
Fund 6	0	0.71	0.29	0.87	0.5	/	1
Fund 7	0	0.71	0.29	0.87	0.5	1	/

B. Data definition and summary statistics

Table B1: Definitions of main variables

Variable	definition
$\boldsymbol{flow}$	OEF *i*'s monthly flow
$\boldsymbol{peerflow_{high}}$	Weighted average (by size) of fund flows of funds whose portfolio similarity with OEF *i* are larger than or equal to 0.5
$\boldsymbol{peerflow_{moderate}}$	Weighted average (by size) of fund flows of funds whose portfolio similarity with OEF *i* are larger than or equal to 0.3 and smaller than 0.5
$\boldsymbol{peerflow_{little}}$	Weighted average (by size) of fund flows of funds whose portfolio similarity with OEF *i* are larger than or equal to 0 and smaller than 0.3
$\boldsymbol{return}$	Monthly alpha of OEF *i* from a one-factor market model[34]
$\boldsymbol{age}$	Number of years since the OEF *i*'s inception
$\boldsymbol{size}$	Total asset value of OEF *i*
$\boldsymbol{cash}$	Asset value of the cash equivalents OEF *i* holds
$\boldsymbol{crisis}$	Dummy, equals 1 if the VIX of current month exceeds 75th percentile of the sample
$\boldsymbol{high\_yield}$	Dummy, equals 1 if the asset holdings with rating of BB or below (or not rated) account for over 50% on average during the sample period of OEF *i*'s portfolio
$\boldsymbol{corp\_bond}$	Dummy, equals 1 if corporate bond holdings are larger than government bond holdings and account for over 50% on average during the sample period of OEF *i*'s portfolio
$\boldsymbol{low\_cash}$	Dummy, equals 1 if the cash equivalent holdings in the previous month of OEF *i* is within the lowest decile
$\boldsymbol{neg\_return}$	Dummy, equals 1 if the alpha in the previous month of OEF *i* is negative

Table B2: Summary statistics of main variables

Variable	N	Mean	SD	P25	Median	P75
$\boldsymbol{flow}$	150310	0.380	4.530	-1.330	0	1.520
$\boldsymbol{peerflow_{high}}$	150310	0.550	1.400	-0.240	0.640	1.310
$\boldsymbol{peerflow_{moderate}}$	150310	0.380	1.500	-0.540	0.400	1.220
$\boldsymbol{peerflow_{little}}$	150310	0.580	0.680	0.130	0.640	1.040
$\boldsymbol{return}$	150310	-0.610	0.850	-1.270	-0.610	-0.0300
$\boldsymbol{age}$	150310	14.69	10.97	6	12	21
$\boldsymbol{size}$	150310	20.06	1.380	19.19	19.99	20.86
$\boldsymbol{cash}$	150310	1.520	4.560	0	0	2.180

[34] The monthly alpha is the estimated constant term of the rolling regression of fund *i*'s return (in excess of risk-free rate captured by the one-month Treasury bill rate) on the return of Bloomberg Global Aggregate Index (in excess of risk-free rate captured by the one-month Treasury bill rate) over the past 24 months, as given by $\alpha_{i,t}$ in the following equation: $Ret_{i,t} - R_{f,t} = \alpha_{i,t} + \beta_{i,t} * (Ret_{benchmark,t} - R_{f,t}) + \varepsilon_{i,t}$

C. Calibration of inputs to the scenario analysis

This appendix details the procedure of calibrating the two major inputs the scenario analysis, specifically i) "shocked" flows and ii) liquidity buffer.

"Shocked" flows

1. For each fund *i* in the sample, calibrate the "shocked" return (excess return "alpha" over benchmark bond return) using Equation (C1):

$$return_i^{alpha} = i^{shock} * Duration_i - \beta_i * i^{shock} * Duration_{benchmark} \quad \text{(C1)}$$

where i^{shock} is the assumed interest rate shock, and $Duration_i$ and $Duration_{benchmark}$ are the average duration of fund i's fixed income portfolio and benchmark bond index respectively. β_i is the historical estimated relationship between fund i's total fund return and the return of the benchmark bond index.

2. For each fund *i*, calculate the expected "shocked" flow without peer effect based on the panel regression model in Equation (C2):

$$flow_{i,t} = \gamma control_{i,t-1} + u_i + \lambda_{d,t} + \varepsilon_{i,t} \quad \text{(C2)}$$

where $\mathrm{control}_{i,t}$ includes key characteristics of fund *i* including return, age, size and cash holdings, as defined in Appendix Table B1. u_i denotes the fund fixed effect while $\lambda_{d,t}$ represents the domicile-time fixed effects. The model is similar to those in Section 4.1 but without the effect of peer fund flows included. The expected "shocked' flow without peer effect is then just the fitted value of the above model using the calibrated "shocked" return obtained from step 1, and the sample average value for other explanatory variables.

3. For each fund *i*, calculate the expected "shocked" $peerflow_{high,t}$, $peerflow_{moderate,t}$ and $peerflow_{little,t}$ using the expected "shocked" flows without peer effects as obtained in step 2 for funds other than i.

4. For each fund *i*, calculate the expected "shocked" flow with peer effect as the fitted value of the estimated panel model regression in Equation (5), using the calibrated "shocked" return obtained in step 1, expected shocked *peerflows* obtained in step 3 and the sample average value for other explanatory variables. More specifically, we adopt the estimated coefficients reported in Column 3 of Table 3 to capture the flow-return and the peer flow relationship in times of market stress, and the differences in the peer flow relationship between high-yield bond funds and other sample fixed-income funds.

Liquidity buffer

1. For each fund i, the available liquidity buffer is calculated using Equation (C3) below:

$$Liquidity\ buffer_i = \sum_{k=1}^{n} w_k * group_{k,i} \text{ (C3)}$$

where $group_k$ is the total share of portfolio holdings (% of fund NAV) assigned to group k and w_k is the liquidity weighted assigned to group k. The groupings and the respective liquidity weight reference ESMA (2016) and are given in Table C1 below:

Table C1: Liquidity weighting for different asset classes

Asset classes	AAA - AA	A	BBB	Below BBB or not rated
Government bonds	100	85	50	0
Corporate bonds	85	50	50	0
Securitised securities	65	0	0	0
Equities	50	50	50	50
Cash	100	100	100	100

Table 1: Estimated peer flow relationship by level of common asset holdings

This table reports the results of the fixed effects panel regression models in Equation (2) and (3) using monthly data sample that covers the period of April 2019 to June 2023. The dependent variable is the monthly fund flow in percentage point. Explanatory variables include the three $peerflow$ variables, which are the size-weighted average of fund flows of the fund peers with high, moderate, or little portfolio similarity. The set of control variables includes the lagged fund return, liquidity, size and age, with detailed definition presented in Table B1. Column (2) additionally include an interaction term $peerflow_{high,\,t} * Stress_t$, where $Stress_t$ is a dummy variable that equals to one when the VIX index in the month is greater than 75th percentile of the sample, and vice versa. The last two rows report the differences of corresponding coefficients, with the asterisk denoting their statistical significance. All regressions include fund and fund domicile-month fixed effects. Robust standard errors are in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, 10% level, respectively.

	$flow$ (1)	$flow$ (2)
$peerflow_{high,\,t}$ (β_1)	0.126***	0.079***
	(0.011)	(0.013)
$peerflow_{high,\,t} * Stress_t$ (β_4)		0.150***
		(0.024)
$peerflow_{moderate,\,t}$ (β_2)	0.070***	0.065***
	(0.011)	(0.011)
$peerflow_{little,t}$ (β_3)	-0.077	-0.067
	(0.061)	(0.061)
$return_{t-1}$	0.434***	0.434***
	(0.044)	(0.044)
age_{t-1}	-0.041	-0.041
	(0.039)	(0.039)
$size_{t-1}$	-0.949***	-0.949***
	(0.041)	(0.041)
$cash_{t-1}$	0.013***	0.013***
	(0.005)	(0.005)
Fund FE	YES	YES
Fund domicile#month FE	YES	YES
Observations	150,310	150,310
Number of funds	3413	3413
R-squared	0.146	0.146
$\beta_1 - \beta_2$	0.056***	0.014
$\beta_1 + \beta_4 - \beta_2$		0.164***

Table 2: Verifications of peer flow effects

This table reports the results of the fixed effects panel regression model in Equation (4) using monthly panel data sample covering the sample period of April 2019 to June 2023. The dependent variable is the monthly fund flow. Explanatory variables include $peerflow_{high,t}^{larger\ sell\ pres}$ that captures the weighted average fund flows of the group peers with highly similar portfolio and more prone to asset fire-sale, and $peerflow_{high,t}^{smaller\ sell\ pres}$ for the group of peers with highly similar portfolio but less prone to asset fire-sale. A peer with highly similar portfolio is defined as more prone to asset fire-sale if 1) if its monthly flow-driven sale falls into the lower 50% (corresponding to larger negative values) among all highly interconnected fund peers (Column 1); 2) if the occurrence of its past cash hoarding behaviours falls into the upper 50% (Column 2) or 3) if the HHI of its portfolio falls into the upper 50% (Column 3). The last row reports the differences of corresponding coefficients, with the asterisk denoting their statistical significance. All regressions include fund and fund domicile-month fixed effects. Robust standard errors are in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, 10% level, respectively.

	$flow$ (1)	$flow$ (2)	$flow$ (3)
$peerflow_{high,t}^{larger\ sell\ pres}$ (β_1^{larger})	0.072***	0.092***	0.071***
	(0.013)	(0.011)	(0.011)
$peerflow_{high,t}^{smaller\ sell\ pres}$ ($\beta_1^{smaller}$)	0.041***	0.051***	0.042***
	(0.011)	(0.010)	(0.011)
$peerflow_{\text{moderate},\,t}$	0.034**	0.049***	0.047***
	(0.014)	(0.011)	(0.012)
$peerflow_{\text{little},\,t}$	-0.103	-0.058	-0.101
	(0.070)	(0.052)	(0.070)
$return_{t-1}$	0.410***	0.313***	0.469***
	(0.049)	(0.036)	(0.051)
age_{t-1}	-0.022	-0.039	-0.022
	(0.024)	(0.031)	(0.046)
$size_{t-1}$	-0.692***	-0.595***	-1.056***
	(0.047)	(0.031)	(0.052)
$cash_{t-1}$	0.000***	0.023***	0.007*
	(0.000)	(0.005)	(0.004)
Fund FE	YES	YES	YES
Fund domicile#month FE	YES	YES	YES
Observations	147,074	148,096	147,635
Number of funds	3350	3350	3350
R-squared	0.141	0.174	0.138
$peerflow_{high,t}^{larger\ sell\ pres}$ for	Larger flow-driven sales	Larger cash hoarding tendency	More concentrated portfolio
$\beta_1^{larger} - \beta_1^{smaller}$	0.031*	0.041***	0.29*

Table 3: Stronger peer flow relationship for funds with higher inherent liquidity risks in times of market stress

This table reports the results of fixed effects panel regression model in Equation (6) using the monthly data sample that cover the periods where the VIX index is larger than 75th percentile between April 2019 and June 2023. The dependent variable is the monthly fund flow. Explanatory variables include interaction term $peerflow_{high,t} * D_{i,t}$, where $D_{i,t}$ is a dummy variables that equals one when fund i is with larger inherent liquidity risk, and vice versa. A fund i is defined as having larger inherent liquidity risk if 1) its cash holding is less than 10th percentile of the sample (Column 1); 2) its return in previous period is negative (Column 2); 3) it is a high-yield bond fund (Column 3). Other explanatory variables are the same as in Table 1. The last two row report the differences of corresponding coefficients, with the asterisk denoting their statistical significance. All regressions include fund and fund domicile-month fixed effects. Robust standard errors are in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, 10% level, respectively.

	$flow$	$flow$	$flow$
	(1)	(2)	(3)
$peerflow_{high,\,t}$ (β_1)	0.182***	0.153***	0.119***
	(0.022)	(0.025)	(0.026)
$peerflow_{high,\,t} * D_{i,t}$ (β_4)	0.086*	0.087**	0.176***
	(0.048)	(0.036)	(0.036)
$D_{i,t}$	0.151	0.004	
	(0.112)	(0.087)	
$peerflow_{moderate,\,t}$ (β_2)	0.135***	0.135***	0.132***
	(0.022)	(0.022)	(0.023)
$peerflow_{little,t}$	0.010	0.012	-0.040
	(0.106)	(0.106)	(0.110)
$return_{t-1}$	0.515***	0.538***	0.567***
	(0.084)	(0.095)	(0.087)
age_{t-1}	-0.062	-0.060	-0.027
	(0.080)	(0.081)	(0.083)
$size_{t-1}$	-1.222***	-1.222***	-1.207***
	(0.091)	(0.091)	(0.092)
$cash_{t-1}$	0.015	0.011	0.007
	(0.013)	(0.013)	(0.013)
$D_{i,t}$ refers to	low_cash	neg_return	$high\_yield$
Fund FE	YES	YES	YES
Fund domicile#month FE	YES	YES	YES
Observations	39,197	39,197	39,197
Number of funds	3319	3319	3319
R-squared	0.249	0.249	0.250
$\beta_1 - \beta_2$	0.047	0.018	-0.048
$\beta_1 + \beta_4 - \beta_2$	0.133**	0.105***	0.121***

Table 4: Estimated cross-border peer flow relationship by level of common asset holdings

This table reports the results of the fixed effects panel regression models in Equation (2) and (3) using monthly data sample that covers the period of April 2019 to June 2023. The dependent variable is the monthly fund flow in percentage point. Explanatory variables include the three $peerflow$ variables, which are the size-weighted average of fund flows of the fund peers that are domiciled in different jurisdictions to fund *i* and with high, moderate, or little portfolio similarity. The set of control variables includes the lagged fund return, liquidity, size and age, with detailed definition presented in Table B1. Column (2) additionally include an interaction term $peerflow_{high,\,t} * Stress_t$, where $Stress_t$ is a dummy variable that equals to one when the VIX index in the month is greater than 75th percentile of the sample, and vice versa. The last two rows report the differences of corresponding coefficients, with the asterisk denoting their statistical significance. All regressions include fund and fund domicile-month fixed effects. Robust standard errors are in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, 10% level, respectively.

	$flow$ (1)	$flow$ (2)
$peerflow_{high,\,t}$ (β_1)	0.081***	0.050***
	(0.012)	(0.014)
$peerflow_{high,\,t} * Stress_t$ (β_4)		0.099***
		(0.026)
$peerflow_{moderate,\,t}$ (β_2)	0.051***	0.048***
	(0.012)	(0.012)
$peerflow_{little,t}$ (β_3)	-0.001	-0.008
	(0.081)	(0.081)
$return_{t-1}$	0.386***	0.385***
	(0.049)	(0.049)
age_{t-1}	-0.027	-0.028
	(0.044)	(0.044)
$size_{t-1}$	-1.696***	-1.695***
	(0.056)	(0.056)
$cash_{t-1}$	0.001	0.001
	(0.005)	(0.005)
Fund FE	YES	YES
Fund domicile#month FE	YES	YES
Observations	135,077	135,077
Number of funds	3220	3220
R-squared	0.141	0.141
$\beta_1 - \beta_2$	0.029*	0.002
$\beta_1 + \beta_4 - \beta_2$		0.101***

Table 5: Robustness check of baseline results (expected peerflow and IV)

This table reports the robustness check of the baseline results in Table 1. In column (1)-(2), we use size-weighted average of expected fund flows of the fund peers instead of the raw fund flows when constructing the three $peerflow$ variables. The expected fund flow is estimated using the fund returns and flows over the previous 12 months as the explanatory variables. In column (3)-(4), we use one-period-lagged terms of the three $peerflow$ variables in equation (2) as their instruments and perform two-stage least square estimation. The last two rows report the differences of corresponding coefficients, with the asterisk denoting their statistical significance. All regressions include fund and fund domicile-month fixed effects. Robust standard errors are in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, 10% level, respectively.

	expected *peerflow* estimation		IV estimation	
	(1)	(2)	(3)	(4)
$peerflow_{high,\,t}$ (β_1)	0.170***	0.135***	0.409***	0.320***
	(0.026)	(0.029)	(0.055)	(0.060)
$peerflow_{high,\,t} * Stress_t$ (β_4)		0.122**		0.282***
		(0.055)		(0.081)
$peerflow_{\text{moderate},\,t}$ (β_2)	0.104***	0.104***	0.116**	0.099**
	(0.027)	(0.027)	(0.045)	(0.046)
$peerflow_{\text{little},t}$ (β_3)	0.078	0.064	0.001	0.037
	(0.099)	(0.100)	(0.172)	(0.172)
$return_{t-1}$	0.480***	0.479***	0.348***	0.349***
	(0.044)	(0.044)	(0.036)	(0.036)
age_{t-1}	-0.049	-0.049	-0.042	-0.042
	(0.039)	(0.039)	(0.030)	(0.030)
$size_{t-1}$	-0.953***	-0.953***	-0.642***	-0.641***
	(0.041)	(0.041)	(0.030)	(0.030)
$cash_{t-1}$	0.014***	0.014***	0.027***	0.027***
	(0.005)	(0.005)	(0.005)	(0.005)
Fund FE	YES	YES	YES	YES
Fund domicile#month FE	YES	YES	YES	YES
Observations	147,277	147,277	149,400	149,400
Number of funds	3412	3412	3407	3407
R-squared	0.154	0.154	0.003	0.001
$\beta_1 - \beta_2$	0.066*	0.008	0.294***	0.077
$\beta_1 + \beta_4 - \beta_2$		0.247***		0.694***

Table 6: Robustness check of baseline results (Placebo test)

This table reports the results of the Placebo test on baseline results in Table 1. The dependent variable remains the monthly fund flow in percentage point, while three $peerflow$ variables are constructed based on three groups of randomly assigned fund peers. Column (1) to (3) reports the results of Equation (2) for three different $peerflow$ variables respectively while columns (4) to (6) reports the results of Equation (3). Only one of three randomly constructed $peerflow$ variable is included at a time due to high correlation between the three $peerflow$ variables. All regressions include fund and fund domicile-month fixed effects. Robust standard errors are in parentheses. Statistical significance is denoted by ***, ** and * at the 1%, 5%, 10% level, respectively.

	$flow$	$flow$	$flow$	$flow$	$flow$	$flow$
	(1)	(2)	(3)	(4)	(5)	(6)
$peerflow$	-0.035	-0.003	-0.056**	-0.008	-0.003	-0.079**
	(0.027)	(0.027)	(0.027)	(0.032)	(0.032)	(0.032)
$peerflow * Stress_t$				-0.085	0.002	0.076
				(0.058)	(0.058)	(0.058)
$return_{t-1}$	0.345***	0.344***	0.344***	0.345***	0.344***	0.344***
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)
age_{t-1}	-0.040	-0.040	-0.040	-0.040	-0.040	-0.040
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
$size_{t-1}$	-0.629***	-0.629***	-0.629***	-0.629***	-0.629***	-0.629***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)	(0.030)
$cash_{t-1}$	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Random peer group	1	2	3	1	2	3
Fund FE	YES	YES	YES	YES	YES	YES
Fund domicile#month FE	YES	YES	YES	YES	YES	YES
Observations	150,310	150,310	150,310	150,310	150,310	150,310
Number of funds	3413	3413	3413	3413	3413	3413
R-squared	0.166	0.166	0.166	0.166	0.166	0.166