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Monetary policy, fragility, and fund flows

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This paper contains research conducted within the network "Challenges for Monetary Policy Transmission in a Changing World Network" (ChaMP). It consists of economists from the European Central Bank (ECB) and the national central banks (NCBs) of the European System of Central Banks (ESCB).

ChaMP is coordinated by a team chaired by Philipp Hartmann (ECB), and consisting of Diana Bonfim (Banco de Portugal), Margherita Bottero (Banca d'Italia), Emmanuel Dhyne (Nationale Bank van België/Banque Nationale de Belgique) and Maria T. Valderrama (Oesterreichische Nationalbank), who are supported by Melina Papoutsi and Gonzalo Paz-Pardo (both ECB), 7 central bank advisers and 8 academic consultants.

ChaMP seeks to revisit our knowledge of monetary transmission channels in the euro area in the context of unprecedented shocks, multiple ongoing structural changes and the extension of the monetary policy toolkit over the last decade and a half as well as the recent steep inflation wave and its reversal. More information is provided on its website.

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Monetary Policy, Fragility, and Fund Flows*

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Abstract

We study how monetary policy is transmitted through the open-end investment fund (OEIF) sector and how this transmission depends on fund fragility. Using high-frequency identified ECB monetary policy surprises and daily share-class data on German-domiciled OEIFs from 2010 to 2023, we show that an unexpected 10 basis point monetary tightening reduces cumulative fund net inflows by more than 0.2 percentage points within two weeks (about 0.7 standard deviations of monthly sector flows). This effect is highly uneven: fragile funds—identified by an excessive flow response to past underperformance—experience an additional outflow of about 0.2 percentage points compared to their peers, implying a total response roughly three times as large as for non-fragile funds. Intuitively, the pattern is present only for unexpected tightening, not easing. Fragile bond funds reduce corporate bond holdings more strongly, and fragile funds meet redemptions by running down bank deposits. While the average fund increases deposits after tightening, fragile funds reduce deposits and shrink liquidity buffers amplifying the deposit channel. At the bank level, investor reallocations into overnight deposits induce a reallocation of deposits across banks. Overall, fund fragility emerges as a key state variable for monetary policy transmission and financial stability.

Keywords: monetary policy, investment funds, financial fragility
JEL Classification: E52, G1, G23

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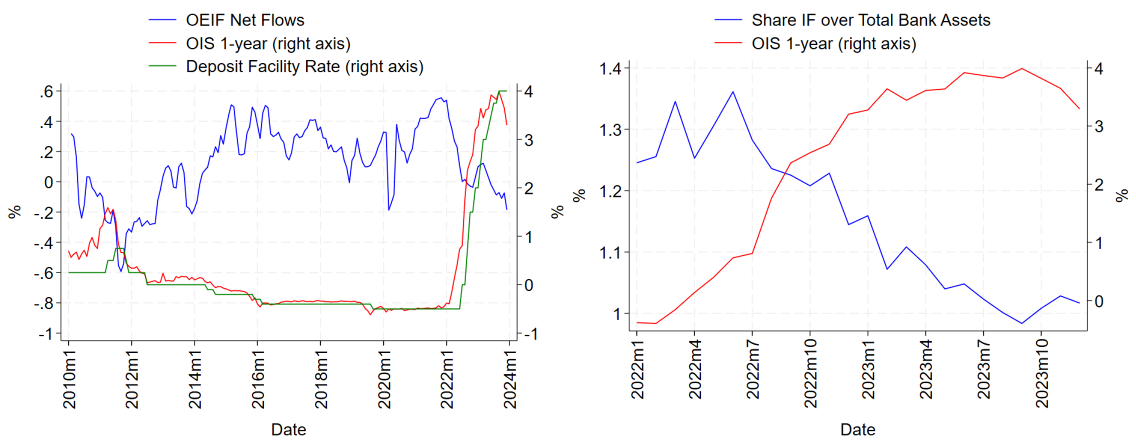
1 Introduction

Since the Global Financial Crisis (GFC), open-end investment funds (OEIFs) spurred the fast growth of non-bank financial institutions (NBFIs) as their total net assets almost quadrupled in this period to more than 40 trillion US dollars (IMF (2022)). In Germany, investment funds are the dominant NBFIs, making Germany the third largest domicile for those funds in the euro area behind Luxembourg and Ireland.[1] Despite the growing importance of OEIFs in the financial system, little is known about their role in the transmission of monetary policy,[2] even though they appear to be highly sensitive to rate changes: Net flows into the OEIF sector are responsive to changes in monetary policy (expectations) (see Figure 1, left panel). During the recent ECB tightening cylce, monthly net flows into German-domiciled OEIFs went down, from about 0.5% to -0.2%. At the same time, OEIFs' bank deposits, which largely constitute their liquidity buffers and account for 1% to 1.5% of German banks' balance sheet total, also substantially declined by roughly one quarter (see Figure 1, right panel).

Figure 1: Funds' Net Flows, Liquidity Buffers and Euro Area Interest Rates.



Notes: Monthly data. Blue line in left panel corresponds to three-month moving average of German OEIF net flows based on Morningstar. Blue line in right panel denotes the share of German banks' overnight deposits from euro area investment funds compared to total bank assets based on ECB Balance Sheet Items data. Investment funds exclude money market funds. Remaining lines are euro area interest rates.

[1]See Fricke and Wilke (2023).

[2]The few contribution looking into the interplay between monetary policy and investment funds include Feroli et al. (2014), Banegas et al. (2022), and Kuong et al. (2024) for U.S. bond funds, Giuzio et al. (2021) and Kaufmann (2022) for aggregate effects in euro area. Cetorelli et al. (2025) document a procyclical relationship between monetary policy and loan-fund flows. Fang (2025) provides evidence of a bond fund amplification of monetary policy to bond pricing, firm financing, and real activities.

In this paper, we study the role of OEIFs in the transmission of monetary policy. We document that unexpected monetary policy tightening leads, on average, to lower net flows into OEIFs. Our primary focus is on the interplay between financial stability and macroprudential policy in the fund sector and monetary policy transmission. The open-end structure makes investment funds inherently fragile, as poor performance can cause panic-induced fund share redemptions (Chen et al., 2010), while macroprudential measures such as swing pricing can mitigate this fragility (Jin et al., 2021).

We show that particularly fragile OEIFs, i.e. funds with an elevated sensitivity of flows to past underperformance, domiciled in Germany experience substantially stronger declines in their net inflows in response to a monetary tightening by the ECB. While we do not find evidence in our full sample of retail OEIFs that fragile funds reduce their corporate bond holdings more aggressively than other funds, our results indicate that fragile *bond* funds lower the share of corporate bonds in their portfolios, which is consistent with Fang (2025), who also documents that this sell-off depresses bond prices and restraints bond-funded firms' financing and real activity.

Beyond this, we uncover a novel effect: unlike other OEIFs, fragile funds draw down their bank deposits to meet the heightened fund share redemptions triggered by an unexpected monetary tightening. This newly documented mechanism implies that monetary-policy-induced outflows from fragile funds spill over to banks, generating outflows of unsecured wholesale deposits from banks that serve especially fragile funds. Such spillovers may amplify the deposit channel of monetary policy (Drechsler et al., 2017, 2025).

At the same time, though, we find that custodian banks whose retail clients predominantly hold shares in fragile funds experience a rise in overnight deposits during an unexpected monetary tightening, as these clients temporarily park their redemption proceeds in short-term deposits, thereby dampening the deposit channel at these (other) banks. Taken together, this suggests that redemption of fund shares in response to monetary policy shocks especially at fragile funds leads to a reallocation of deposits within the banking sector, from banks with a large share of fragile funds' wholesale deposits to custodian banks whose customers hold predominantly fragile fund shares.

Our findings have important implications for both financial stability and monetary policy transmission. Depending on funds' liquidity mismatch and resulting (perceived) fragility, an extreme unexpected monetary policy tightening can lead to panic-driven investor redemptions and expose OEIFs to liquidity stress. Given the growing importance of NBFIs in the euro area, this raises concerns that severe monetary policy actions may entail financial stability risks and increases the likelihood of financial dominance (Brunnermeier, 2016).

From a transmission perspective, monetary tightening affects both the funding obtained and provided by OEIFs, with a particularly important role of fragile funds. Fragile OEIFs amplify the transmission of monetary policy to bond markets and banks' wholesale deposits. A declining share of fragile funds, macroprudential regulation of OEIFs—such as liquidity management tools including swing pricing (FSB, 2023)—and direct central bank access or lender-of-last-resort facilities (Bank of England, 2024) can mute this channel. At the same time, such developments would reshape the deposit channel for banks: they dampen transmission for banks relying on OEIF wholesale funding, while potentially strengthening it for banks that receive inflows from investors reallocating out of fragile funds into deposits.

For our main analysis, we match Morningstar data with the Deutsche Bundesbank's Investment Fund Statistics to construct a daily, share-class-level dataset for all retail OEIFs domiciled in Germany, covering net flows, total net assets (TNA), and returns,[3] complemented by monthly fund-level bank deposit holdings. The sample spans all main fund types such as fixed-income, equity, and mixed funds.

To measure OEIF fragility, we estimate the overreaction of fund flows to negative past excess returns. We interpret this excess sensitivity to underperformance as a *sufficient statistic* for a fund's susceptibility to panic-induced withdrawals, as it captures the extent to which investors redeem not only in response to fundamentals but also in anticipation of others' redemptions. A range of fund characteristics shapes this excess reaction—including cash buffers (Morris et al., 2017), asset liquidity (Chen et al., 2010), investor composition, bank affiliation (Bagattini et al., 2023), and the availability of liquidity management tools such as swing pricing (Jin et al., 2021). While these characteristics may mitigate or amplify run risk in isolation, their joint effect is theoretically and empirically ambiguous. Our measure therefore captures the *net effect* of these interacting characteristics on panic-driven redemption risk. We also document how this excess sensitivity to underperformance

[3]We use the share-class as the unit of observation since fee structures and minimum investment requirements affect investor behavior (Goldstein et al., 2017).

varies systematically with observable fund characteristics.

In order to identify the effect of unexpected changes in monetary policy on the net flows of funds, we use plausibly exogenous monetary policy shocks following Jarociński and Karadi (2020), who define euro area monetary policy shocks as instances of negative co-movement between interest rates and stock markets within a narrow time window around ECB monetary policy press events. The value of the respective shock on such a day is equal to the percentage change of the interest rate in the 30-minute window around the press event.

We first estimate the average response of daily fund flows to monetary policy shocks using a panel local projections approach à la Jordà (2005), controlling for high-frequency covariates (past performance, lagged net flows, lagged TNA, and fund age) as well as share-class fixed effects. Following a unexpected monetary tightening of 10 basis points (bp), we find a significant decline in cumulative net inflows of more than 0.2 percentage points (pp) within two weeks, corresponding to roughly 0.7 standard deviations of aggregate monthly sector flows.

In our main specification, we allow for heterogeneous responses by interacting the monetary policy shock with a dummy identifying particularly fragile funds. We control for time-varying heterogeneity across fund types through daily fund-type fixed effects and isolate performance-driven redemptions by additionally interacting the fragility dummy with past performance. We find that, in response to a 10 bp surprise increase in interest rates, fragile funds experience a 0.2 pp stronger drop in net flows than non-fragile funds—their total effect is about three times the response of their peers.

Several results support our fragility narrative. First, fragile funds respond more strongly only to unexpected monetary tightening, not to surprise rate cuts. Second, their flows are also more sensitive to central bank shocks that convey negative information about macroeconomic conditions (Jarociński and Karadi, 2020). Third, when restricting the sample to fixed-income funds—which are generally more fragile (Goldstein et al., 2017)—and defining fragility based on elevated flow–performance sensitivity within this group, the estimated relative response of fragile funds to monetary tightening becomes even stronger. Our key results are robust across a range of specifications, including alternative sample splits, additional controls for aggregate market stress, and more stringent definitions of fund fragility.

Next, we examine whether the disproportionately large outflows from fragile funds following unexpected monetary policy tightening propagate monetary shocks further through the financial system. We first analyze whether funds reduce their corporate bond holdings in response to monetary policy shocks and the associated outflows, following Fang (2025), who shows that such sell-offs raise issuers' funding costs and affect real activity.[4] Regressing the change in the share of corporate bonds in OEIFs' fixed-income portfolios on unexpected monetary policy tightening, while controlling for time-varying fund-style and share-class fixed effects as well as additional time-varying fund characteristics, we find that funds on average reduce their corporate bond share by 0.3 pp in response to a 10 bp shock. However, an interaction term between the monetary policy shock and the fragility dummy is insignificant, indicating that, in the full sample, fragile funds do not sell corporate bonds more aggressively than their peers. Though, when restricting the sample to fixed-income funds—the primary investors in corporate bonds in our sample—, fragile funds display a significantly stronger response. Following a 10 bp tightening shock, fragile bond funds reduce their corporate bond portfolio share by about 0.5 pp compared to other bond funds, implying that fund fragility amplifies the transmission of monetary policy to bond markets.

Second, and more importantly, we examine whether funds draw down their bank deposits to meet redemptions following unexpected monetary policy tightening, thereby potentially amplifying the deposit channel of monetary policy within the banking sector (Drechsler et al., 2017, 2025). While existing evidence shows that OEIFs can deplete liquidity buffers held with banks during episodes of acute stress,[5] we study whether particularly fragile funds do so in response to monetary policy–induced outflows. Using funds' monthly bank deposit flows in a panel model and controlling for time-varying fund-type fixed effects as well as a rich set of fund characteristics, we find that, on average, funds *increase* their bank deposit flows by 9 bp of initial TNA following an unexpected 10 bp rate hike. In sharp contrast, fragile OEIFs *reduce* their bank deposit flows by about 2 bp of initial TNA, indicating that they draw on bank funding to meet elevated redemptions.

[4]Relatedly, Ma et al. (2022) show that more illiquid funds sold corporate bonds more aggressively during the COVID-19 crisis, which was also characterized by large outflows.

[5]For instance, Müller et al. (2025) show that distressed open-end mutual funds in Colombia stopped rolling over certificates of deposit with domestic banks, triggering significant liquidity shortages in the banking sector.

While this result shows that fragile funds run down bank deposits after an unexpected tightening, it is a priori unclear how this affects their overall liquidity buffers. Conceptually, fragile funds could (i) maintain a stable cash ratio, (ii) follow a pecking order in asset liquidation (Ma et al., 2022) and disproportionately deplete cash, or (iii) hoard cash in anticipation of further redemptions (Morris et al., 2017), thereby increasing cash ratios. We find that while non-fragile funds raise their liquidity buffers relative to fixed-income assets, particularly fragile fixed-income funds *reduce* their liquidity buffers by about 20 bp following a 10 bp unexpected tightening. This over-proportional depletion of liquid assets not only strengthens spillovers to the banking sector, but also renders fragile funds even more vulnerable to subsequent liquidity and monetary policy shocks.

Finally, we examine where investors reinvest the proceeds from redeeming fragile fund shares. We hypothesize that these proceeds are, at least temporarily, parked in overnight bank deposits. To test this hypothesis, we use the Bundesbank's Securities Holdings Statistics, which report security-by-security portfolio holdings of banks for retail customers. Based on these data, we construct for each custodian bank the value-weighted share of fragile funds held by its retail clients relative to their total fund holdings. This measure proxies the intensity with which a bank's customers redeem fragile fund shares in response to unexpected monetary policy tightening.

We interact this proxy with monetary policy shocks in a panel model with fixed effects to explain changes in overnight deposits at the bank level. While banks with below-average fragility exposure experience increased deposit *outflows* following a tightening shock, we find that custodian banks whose customers' exposure to fragile funds is two standard deviations above the mean receive increased deposit *inflows* of about 6 bp of initial bank assets in response to an unexpected 10 bp rate hike. This pattern indicates that when investors exit fragile funds during monetary tightening, they reallocate funds into bank deposits at their custodian banks, thereby muting ceteris paribus the deposit channel of monetary policy at those banks (Drechsler et al., 2017).

While these deposit inflows partially offset the wholesale deposit withdrawals of fragile funds at the aggregate level, their distribution across banks is uneven. Banks that rely more heavily on wholesale funding are disproportionately exposed to the outflows, whereas banks with a large custodian business and substantial retail exposure to fragile funds tend to benefit from deposit inflows. As a result, unexpected monetary tightening induces a reallocation of deposits within the banking sector, rather than a uniform contraction of bank funding.

Our paper contributes to three closely related strands of the literature. First, we build on the large literature on the fragility of OEIFs and the financial and real repercussions of fund runs. Because investors can redeem shares at short notice at net asset value while trading costs are borne by remaining investors, OEIFs are subject to strategic complementarities in redemptions (Chen et al., 2010). A growing body of work documents how this structural fragility is shaped by portfolio illiquidity, market conditions, liquidity buffers, investor composition, bank affiliation, and liquidity management tools such as swing pricing (Goldstein et al., 2017; Jiang et al., 2022; Falato et al., 2021a,b; Dekker et al., 2024; Jin et al., 2021; Dunne et al., 2023; Bagattini et al., 2023; Fecht et al., 2025). This literature primarily focuses on acute fragility during episodes of severe market stress, such as the GFC or the COVID-19 crisis, and on the amplification of exogenous liquidity shocks through fund runs. In contrast, we show that even during regular, unanticipated monetary policy shocks, outside crisis periods, inherent fragility is relevant. We provide novel evidence that more fragile OEIFs experience disproportionately larger outflows, liquidate more corporate bonds, and run down liquidity buffers following monetary tightening, thereby accounting for a main share of the transmission and amplification of routine monetary policy shocks.

Second, our paper contributes to the still relatively small literature on monetary policy transmission through OEIFs. Existing studies document how fund flows and portfolio choices respond to monetary policy using either aggregate data or specific fund segments, in particular bond funds (Feroli et al., 2014; Banegas et al., 2022; Giuzio et al., 2021; Kaufmann, 2022; Cetorelli et al., 2025; Fang, 2025). Most closely related is Kuong et al. (2024), who link expected monetary policy changes to fragility in U.S. corporate bond funds through net-asset-value staleness. We complement and extend this literature in several important dimensions. First, we focus on unexpected monetary policy shocks, which are relevant in the context of fragility. Second, we provide a broad cross-sectional measure of individual fund fragility based on asymmetric flow responses to underperformance that can be applied to multiple fund types rather than restricting attention to a single subsector. Third, we go beyond documenting flow responses and show that fragility is a key determinant of the downstream propagation of monetary policy, shaping both portfolio liquidation and spillovers to other parts of the financial system.

Third, we contribute to the literature on the deposit channel of monetary policy and the interaction between monetary tightening and funding fragility. A large body of work shows that banks' funding reacts to monetary policy through deposit supply and the deposit franchise value (Drechsler et al., 2017), while uninsured deposits are inherently run-prone (Drechsler et al., 2025). We extend this framework to the non-bank sector by showing that OEIFs—despite being valued at market prices and lacking deposit-like contracts—also experience a quantitative contraction in funding after monetary tightening, driven by fragility. Importantly, we establish that fragile funds meet these outflows by running down wholesale bank deposits, thereby linking fund fragility directly to the bank deposit channel of monetary policy. At the same time, retail reallocations from fragile funds into overnight deposits at custodian banks partially offset these effects, implying that monetary tightening induces a reallocation of deposits within the banking system rather than a uniform contraction.

Taken together, our results establish fund fragility as a key state variable for monetary policy transmission, linking the literature on OEIF fragility, non-bank transmission of monetary policy, and the deposit channel.

The remainder of the paper is organized as follows. Section 2 describes our data set and the definition of our key variables. In Section 3, we derive our measure for proneness to panics of funds to identify *fragile* funds. While Section 4 documents the baseline response of fund flows to monetary policy shocks, Section 5 contrasts the flow response of fragile and other funds to unexpected monetary policy changes. Section 6 studies the changes in fund portfolios in response to the monetary policy-induced flows, Section 7 focuses on investor reallocation, and Section 8 concludes.

2 Data and definitions

Our key data set encompasses daily net flow, return, TNA and age data from Morningstar from the beginning of 2010 to the end of 2023 at the share-class level for all OEIFs domiciled in Germany. Having such a long high-frequency data set helps to overcome potential bias in local projection settings with a shorter time dimension especially at longer forecast horizons (Herbst and Johannsen (2024)). We combine this data set, which includes further monthly fund characteristics, with monthly administrative data from the Deutsche Bundesbank. In particular, the Investment Funds Statistics (IFS) enables us to obtain a detailed picture of each fund's bank deposit holdings, which we use for our later analysis of the bank-fund nexus in Section 6. Finally, we also employ the Bundesbank's Securities Holdings Statistics (SHS) and Monthly Balance Sheet Statistics (BISTA) for our investigation, if retail investors hold the proceeds of redeemed fragile fund shares as additional deposits at their custodian banks, discussed in detail in Section 7.

The IFS data also allows us to purge our Morningstar data from index funds, such as ETFs. Furthermore, as strategic complementarities and thus runs are arguably less severe for institutional funds ("Spezialfonds") with fewer investors than for retail funds, where coordination is less straightforward (Goldstein et al. (2017)), we also exclude those funds from our data set and focus on German-domiciled open-end retail investment funds. Moreover, we drop all share-classes with TNA below €5 mln and age below one year to account for reporting errors in smaller funds and potential incubation bias, respectively (Fecht et al. (2025)). Furthermore, our data are free of survivorship bias. Finally, we winsorize all main financial variables at the 1st and 99th percentile to mitigate potential effects of outliers by every observed day or month, as applicable. Table 1 summarizes the share-class level observations by fund category for the 3,441 share-classes.[6] Of the 583 fixed-income share-classes, roughly 14% are corporate bond funds.[7]

Our main dependent variable measures net flows. We define the net flow for share-class i on day t in line with the literature (e.g. Chevalier and Ellison (1997)):

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}} \times 100 \tag{1}$$

As regards monetary policy surprises, we use high frequency-identified monetary policy

[6] We acknowledge that some fund types such as, e.g., money market funds are somewhat special as their underlying regulation or investment objectives are very different from more common OEIF types. However, we include all types as we focus on retail-oriented funds in general and as we control for fund type times time fixed effects in the main analysis. We also check the robustness of our results and document that our main results hold if we exclude money market funds from our analysis or if we restrict our sample to specific fund types such as fixed-income funds, which have been of particular interest in the fragility literature (e.g. Goldstein et al. (2017); Falato et al. (2021a)).

[7] The allocation to a corporate bond fund is based on the latest Morningstar Category, which is a more narrow measure than the Morningstar Global Broad Category Group and which identifies funds based on underlying portfolio holdings. These funds have on average more than 80% of corporate bond holdings in their fixed-income portfolio compared to 24% for the overall sample.

Table 1: Share-Class Level Observations by Type of Retail Fund.

Fund Type	Frequency	Percent
Allocation	2,573,996	48.27
Alternative	97,039	1.82
Convertibles	28,570	0.54
Equity	1,602,637	30.05
Fixed-Income	976,759	18.32
Money Market	53,814	1.01
Total	5,332,815	100.00

Notes: Fund types are based on Morningstar Global Broad Category Group. Allocation funds are mixed funds.

shocks from Jarociński and Karadi (2020), who in turn rely on data from Altavilla et al. (2019). For the euro area, the authors take the 1st principal component of changes in OIS rates of one- to twelve month maturities between shortly before and after ECB press events on Governing Council monetary meeting days. They then decompose this interest rate surprise into a sum of two orthogonal components and implement rotations that satisfy sign restrictions. A pure monetary policy surprise requires a negative co-movement of interest rates and stock market growth. Contrarily, a positive co-movement is required for a central bank information surprise, which is interpreted as the central bank disclosing private information to the market (e.g., an increase in the policy rate may be interpreted as an action to counter an otherwise overheating economic environment, i.e., as good news). The decomposition allows both shocks to be present in a given monetary policy event. In this paper, we focus mainly on genuine monetary policy surprises and use central bank information shocks in an extension. The value of the respective surprise variable on a given day is equal to the percentage change of the interest rate in the 30-minute window around the press event that is ascribed to the respective shock type. Hence, a positive monetary policy surprise indicates a tightening. In our sample, the largest tightening has a value of 0.19% while the largest easing amounts to -0.07%. By construction, the mean of the monetary policy surprise series is zero.

The high frequency-identification around ECB announcements supports an exogenous interpretation of the shocks - as it is highly unlikely that other fundamental factors change and affect interest rates within the short time window. Moreover, as our flow analysis is on the daily level, we are able to exploit a key advantage of the high frequency monetary surprise data. The value of the shock variable is only nonzero on press event days. Other studies that rest on monthly frequency need to sum up all daily data points over one month. However, the shocks are expected to have more imminent effects on fund flows given the possibility of daily redemptions. Hence, much information is lost in lower frequency analyses.[8] In contrast, combining our daily Morningstar data with the high frequency monetary policy shocks allows us to investigate immediate dynamic responses to monetary policy surprises.

3 Fund fragility

In an initial step, we sort funds into stable and fragile share-classes. Rather than directly modeling various fund characteristics that have been shown to affect the strategic complementarities among investors in a particular fund type, we use a fund's flow-performance sensitivity as a sufficient statistic to measure its susceptibility to panic-induced withdrawals. Importantly, our comprehensive proxy for the individual fragility of a mutual fund is applicable to any fund style. In the spirit of the literature using flow-performance regressions to demonstrate the fragility implications brought about by specific fund characteristics (e.g. Goldstein et al. (2017); Cetorelli et al. (2025); Dekker et al. (2024); Falato et al. (2021a), we impose nonlinearities in the form of a positive and concave relationship between fund flows and relative performance: To be identified as fragile, outflows from a fund should be more sensitive to underperformance than inflows to overperformance (Chen et al. (2010)). Hence, for our proxy to capture elevated proneness to panic-induced withdrawals, we do not only require a high, procyclical flow-performance sensitivity, but also an asymmetric relationship that is captured by the concavity requirement. We interpret high, procyclical, and concave flow-performance sensitivity as a key sufficient characteristic for general fragility of an individual fund because it indicates that investors not only withdraw because they are performance chasing, but that investors respond more sensitive to bad relative performance as they expect many other investors to withdraw, too, in case of underperformance.

For each share-class i, we estimate a weekly time-series model where net flows are

[8] For instance, in a monthly setting, one would expect the effects of monetary policy surprises on monthly variables to differ substantially if the monetary meeting is in the beginning of a month versus at the end of a month.

regressed on lagged relative performance and controls:

$$Flow_{i,t} = \alpha_i + \gamma_{1,i} ExR_{-,i,t-1} + \gamma_{2,i} ExR_{+,i,t-1} + \theta \mathbf{X}_{i,t} + \epsilon_{i,t}. \tag{2}$$

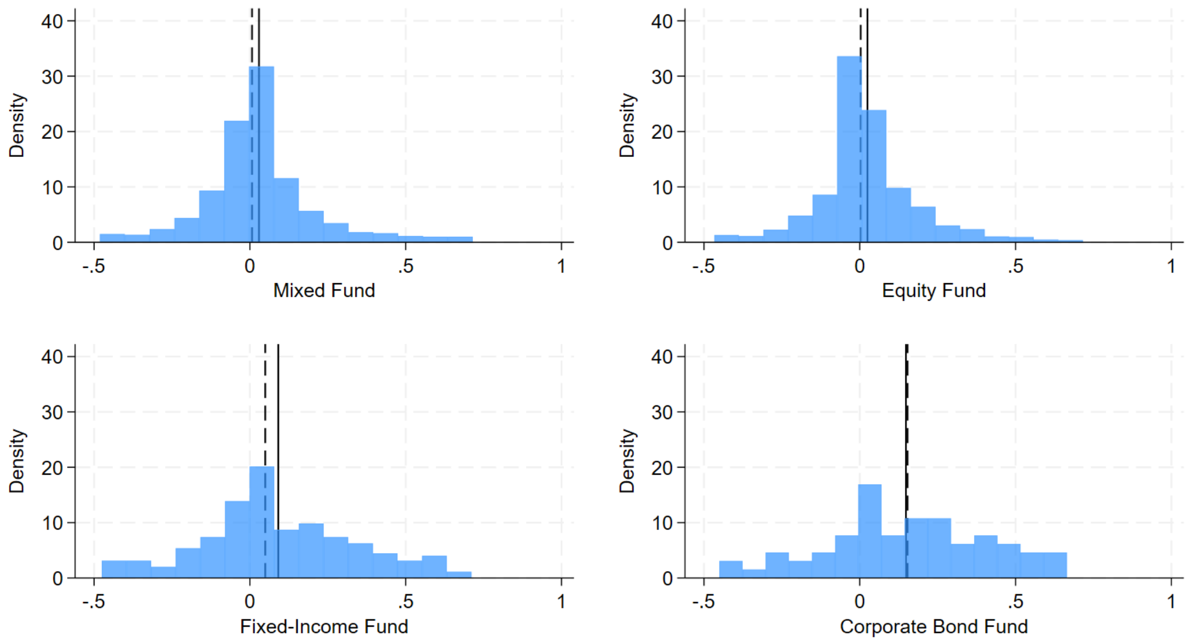
$ExR_{-,i,t-1}$ represents a share-class i's one-week lagged negative excess returns and otherwise takes on the value 0 whereas $ExR_{+,i,t-1}$ represents one-week lagged positive excess returns of that share-class and otherwise takes on the value 0. Excess returns are calculated by comparing total returns of a fund's respective share-class, which take into account share-class specific expenses such as management and administrative fees, against the appropriate benchmark (of the more than 150 benchmarks) for the respective Morningstar Category. $X_{i,t}$ is a vector of weekly controls, including logs of lagged TNA and age in days as well as lagged net flows to account for flow persistence.

As noted by Dekker et al. (2024), there is no theoretical prior on the appropriate horizon of lagged returns. We assume that retail investors are potentially more inert than institutional investors and do not necessarily react to (relative) poor performance in very short time horizons such as a single day. Thus, we resort to weekly frequency in our estimation. Nevertheless, our main results are robust to using plain returns, daily frequency, and additional lags of performance in Equation 2. Moreover, in our robustness analysis further below, we will impose stricter conditions on the identification of fragile funds, such as allowing for time-varying fragility.

By distinguishing between positive and negative lagged performance, we are able to identify funds with a procyclical and concave flow-performance pattern. We identify a fund as fragile if the estimated coefficients simultaneously meet the following three conditions: First, with respect to procyclicality, a positive coefficient $\hat{\gamma}_{1,i}$ indicates that outflows and negative excess returns are positively related. Second, by requiring $\hat{\gamma}_{1,i} > \hat{\gamma}_{2,i}$, concavity, i.e., a stronger reaction to negative relative performance, is ensured. Finally, to ensure a substantial procyclical performance-sensitivity, the individual coefficient estimate $\hat{\gamma}_{1,i}$ is required to be larger than the median of the whole distribution of this estimate across all funds (i.e., $\hat{\gamma}_{1,i} > med(\hat{\gamma}_1)$).[9] Combining all three restrictions ensures that we capture those funds that are especially prone to panic-induced withdrawals: funds where investors

[9] Note that, given that in our main analysis $med(\hat{\gamma}_1)$ equals roughly 0.013, the first restriction is automatically satisfied by the third restriction in our baseline.

Figure 2: Density of Estimated Negative Excess Return Coefficients for Main Fund Types.



Notes: Individual coefficient estimates for each share-class are based on Equation 2. Type is based on Morningstar Global Broad Category except for corporate bond funds, which are part of the fixed-income fund sample and identified using the narrower Morningstar Category. Means and medians are denoted by the solid and dashed lines, respectively. Coefficient estimates are trimmed at the 5th and 95th percentile to enhance readability.

respond much more strongly with outflows to their relative underperformance than with inflows to overperformance. We create a indicator variable for fragility, $Fragile_i$, that equals one if the restrictions are fulfilled and zero otherwise.

The distributions of the estimated negative excess return coefficients along with the corresponding means and medians for main fund types are shown in Figure 2. In line with previous literature (Chen et al. (2010); Goldstein et al. (2017)), funds that hold illiquid assets such as fixed-income funds and especially corporate bond funds, which are particularly prone to strategic complementarities in investor redemption decisions, exhibit a strongly positive flow-performance relationship in the presence of underperformance.

Summary statistics of the key variables in Table 2 indicate that some fund characteristics are similar between both groups. However, the group of fragile investment funds is comprised of a high-fraction of fixed-income funds and in particular the subgroup of corporate bond funds. Holdings of corporate bonds within the fixed-income portfolio are elevated in the fragile group. This is in line with expectations (Goldstein et al. (2017)).

Table 2: Summary Statistics by Fragility.

	Non-Fragile					Fragile				
Variables	N	mean	sd	min	max	N	mean	sd	min	max
$\hat{\gamma}_1$	2,905,232	-0.18	1.39	-58.76	38.24	2,427,583	0.37	3.22	0.01	126.76
$\hat{\gamma}_2$	2,905,232	0.06	1.97	-224.37	200.61	2,427,583	-0.22	1.18	-48.17	2.51
Log(Age in Days)	2,905,232	7.98	0.91	5.90	10.20	2,427,583	7.96	0.87	5.90	10.12
Return (%)	2,889,487	0.02	0.69	-16.82	10.92	2,415,038	0.02	0.64	-16.82	10.92
Net flow (%)	2,763,158	-0.00	0.28	-19.77	39.48	2,307,431	0.00	0.31	-24.02	39.48
Log(TNA)	2,819,321	17.66	1.37	15.44	22.56	2,351,103	17.76	1.44	15.44	22.56
Excess Return (%)	570,961	-0.04	0.95	-12.05	11.29	477,214	-0.03	0.89	-12.05	11.29
Corp Bond Holdings (%)	2,015,417	21.80	26.42	0.00	98.08	1,665,832	26.47	27.98	0.00	98.08
Excess Return Neg (%)	570,961	-0.33	0.62	-12.05	0.00	477,214	-0.30	0.58	-12.05	0.00
Excess Return Pos (%)	570,961	0.29	0.57	0.00	11.29	477,214	0.27	0.54	0.00	11.29
Corp Bond Fund	2,905,232	0.02	0.15	0.00	1.00	2,427,583	0.03	0.18	0.00	1.00
Mixed Fund	2,905,232	0.48	0.50	0.00	1.00	2,427,583	0.48	0.50	0.00	1.00
Equity Fund	2,905,232	0.33	0.47	0.00	1.00	2,427,583	0.27	0.44	0.00	1.00
Fixed-Income Fund	2,905,232	0.15	0.35	0.00	1.00	2,427,583	0.23	0.42	0.00	1.00
Money Market Fund	2,905,232	0.01	0.12	0.00	1.00	2,427,583	0.01	0.08	0.00	1.00
Other Fund	2,905,232	0.03	0.17	0.00	1.00	2,427,583	0.02	0.13	0.00	1.00

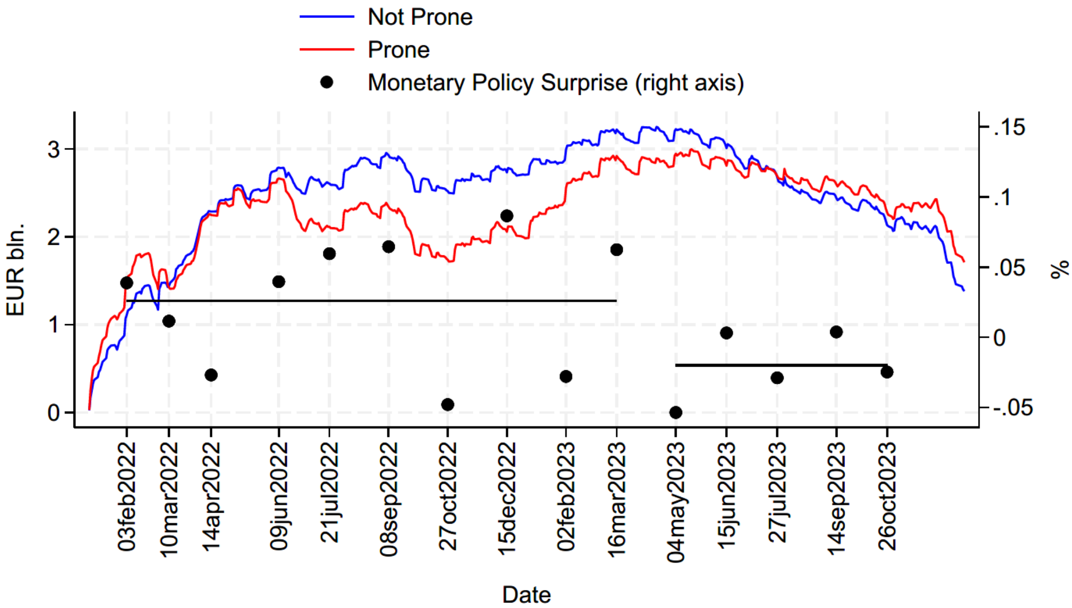
However, funds with other investment strategies are also commonly identified as fragile.

We run a battery of linear probability and logit models in which we regress the fragility dummy on various, partly low-frequency, characteristics.[10] We do this to get a deeper understanding about the specific share-class or fund characteristics that are related to a higher probability of fragility and check whether our measure can indeed be considered a sufficient statistic for a fund's fragility. We find that funds with a longer maturity of asset holdings, a larger share of high yield assets, and a larger TNA are more likely to be fragile while a higher share of cash holdings and higher costs of holding the fund are negatively related to the probability of being identified as fragile. While these factors and their signs can be rationalized to be in line with theory, the results highlight the fact that fragility depends on various characteristics and their interrelation. This is in line with the sufficient statistic-interpretation of our measure.

Looking at cumulative net fund flows during the recent ECB tightening cycle separately for fragile and relatively stable funds provides already some interesting insights. In Figure 3, cumulative net flows from 2022 until the end of our sample in 2023 are plotted separately for funds that are fragile and those that are not along with euro area monetary policy surprises. Between mid-2022 and until roughly the end of the first quarter of 2023, there was high-paced monetary tightening in the euro area. During this time, the ECB raised the policy rate from -0.5% to 3% in steps of at least 50 bp each, and the average

[10] The exact results are not reported here for brevity.

Figure 3: Cumulative Net Flows by Fragility and Monetary Policy Surprises.



Notes: Daily flow data spans the period 1-Jan-2022 to 31-Dec-2023. Black lines denote the average of monetary policy shocks for the two subsamples.

monetary policy shock is substantially positive. While being initially closely aligned and following a common trend, fragile funds' flows appear to have been relatively more hampered during the tightening cycle compared to their non-fragile counterparts. Particularly from mid-2022 to end of 2022, their cumulative net flows were notably decreasing, while the cumulative net flows of non-fragile funds remained largely unchanged.

Since about mid-2023, following a period of steady convergence, the cumulative flows of both groups have recoupled. In this time, the tightening cycle has slowed, with monetary policy surprises based on interest rate swaps indicating even an easing on average. This illustrative evidence indicates a potentially special role of monetary policy for fragile funds. However, it should be acknowledged that while substantial outflows were observed during the tightening cycle, they, of course, did not outweigh the massive growth that OEIFs have experienced over the whole sample period.

4 Do fund flows react to monetary policy shocks?

In this section, we first analyze how the net flows of OEIFs in general react to unexpected monetary policy changes - on impact and thereafter. If unexpected tightening leads to depressed net flows of funds, this would support our general interpretation of the policy shock as relevant and adverse for fund flows. This finding has been established in the literature before, especially for (corporate) bond funds (e.g. Fang (2025); Banegas et al. (2022); Feroli et al. (2014)). However, in contrast to the literature, we document the effect using daily data to investigate the immediate response to a policy shock as well as the subsequent dynamics over the following days.[11] We use the following panel local projection equation in the spirit of Jordà (2005):

$$Flow_{i,t+h} = \beta_h MPS_t + \theta_h \mathbf{X}_{i,t} + \alpha_i^h + \epsilon_{i,t+h}, \tag{3}$$

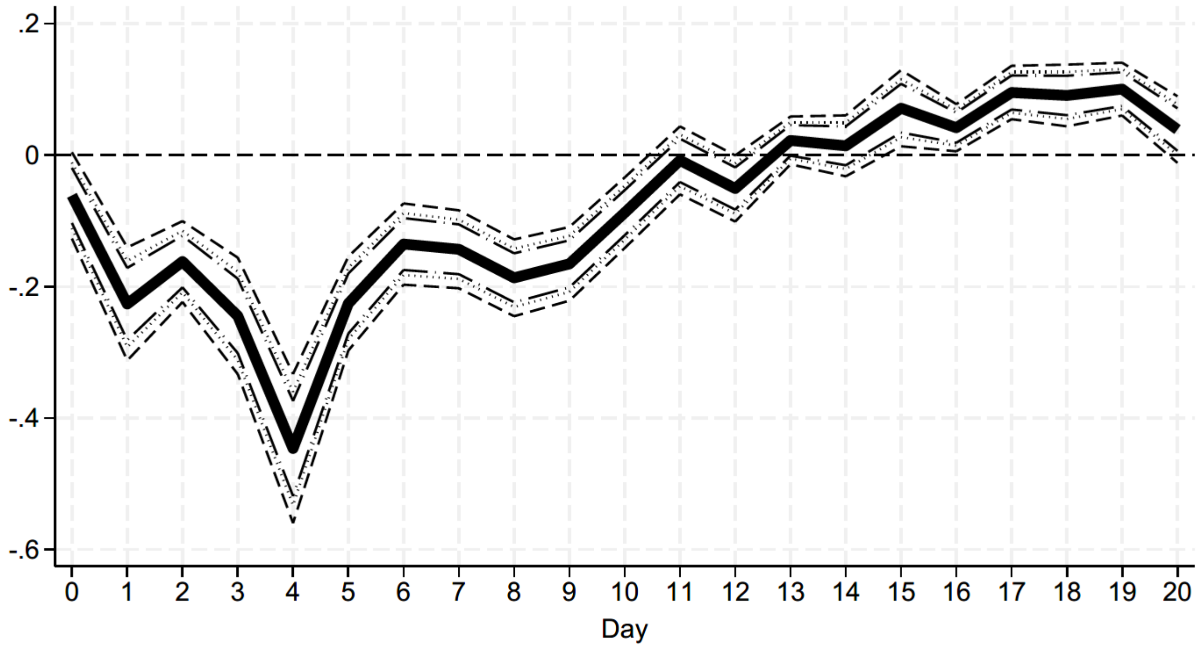
where $Flow_{i,t+h}$ corresponds to the net flows of share-class i, iterated forward over 20 business days, and MPS_t denotes the high frequency-identified monetary policy surprise on day t (and takes on the value zero otherwise). Share-class-specific time-varying controls $\mathbf{X}_{i,t}$ include lagged daily returns and lagged net flows to control for performance-chasing and persistence in flows. They also comprise logs of lagged TNA and age in days. Moreover, $\mathbf{X}_{i,t}$ includes five lags of all these variables.[12] Montiel Olea and Plagborg-Møller (2021) show that lag-augmented local projection inference is robust to highly persistent, potentially non-stationary data. We include share-class fixed effects to control for time-invariant effects of share-class characteristics that may also be related to fund type, fund family or funds with several share-classes. Standard errors are clustered at the share-class level. The local projections are based on roughly 5 mln. observations.

Figure 4 reports the local-projection based impulse response function of net flows to monetary policy shocks from Equation 3 for a horizon of 20 business days. Formally, we plot $\hat{\beta}_h$ and the corresponding confidence intervals (90%, 95% and 99%) for $h = 0$ to $h = 20$. Figure 4 shows a negative effect of monetary policy shocks on net flows, supporting the view that unexpected tightening leads to withdrawals. Investors might withdraw as alternative investments, e.g. in money markets, become more attractive. At the same time, higher policy rates might also lead to an (expected) devaluation of fund assets inducing investors to withdraw. Moreover, as investors expect others to withdraw, they might withdraw purely because they want to avoid bearing the costs of these withdrawals

[11] While Kuong et al. (2024) also use daily data to investigate the role of monetary policy for flows, they focus on average effects for the corporate bond fund sector and do not make use of high frequency-identified monetary policy surprise measures but instead focus on expected changes in interest rates. They also do not investigate the dynamic behavior of flows in the days after the monetary meeting.

[12] Results are robust to various alternative lag specifications including up to 30 lags.

Figure 4: Flow Reaction to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 3. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

and the subsequent trading costs incurred by the fund to rebalance the portfolio. Figure 4 also indicates that the negative effect on net flows persists for about ten business days, i.e., two weeks. The largest impact of unexpected tightening on fund net flows occurs only four business days after the monetary policy surprise. This can be seen as supporting the view that investors indeed respond to the withdrawals of others. The estimated effects are economically meaningful: a 10 bp unexpected interest rate increase leads to a decrease in cumulative net flows into a fund by more than 0.2 pp over two weeks, corresponding to roughly 0.7 standard deviations of aggregate monthly sector flows.

5 Flows of fragile funds and monetary policy

5.1 How do fragile funds fare compared to other funds?

Next, we turn to our first key question: Do fragile funds respond more sensitively to a given monetary policy shock just because investors at those funds are more worried that others' withdrawals will have (larger) negative externalities for their investment return?

In order to test this, we use the following local projection estimation:

$$Flow_{i,t+h} = \beta_h MPS_t \times Fragile_i + \theta_h \mathbf{X}_{i,t} + \alpha_i^h + \mu_{t,c}^h + \epsilon_{i,t+h}, \tag{4}$$

where the monetary policy surprises are interacted with the fragility indicator, $Fragile_i$. This allows to identify the *additional* sensitivity of fragile funds to monetary policy shocks compared to other funds.

To account for performance-induced withdrawals and in particular for heterogeneous effects of monetary policy on funds' asset values, we take several measures. First, the high-frequency share-class specific controls $\mathbf{X}_{i,t}$ are enriched with interactions of lagged returns with the fragility dummy to allow for differential effects of past performance for sensitive vs. less sensitive funds. This helps to differentiate our exogenous monetary tightening surprise interpretation from general return shocks. By including the interactions, we can control for direct performance effects that may have materialized just before the monetary policy shock, e.g. in anticipation of a monetary policy decision, and that have specific flow effects at fragile funds.

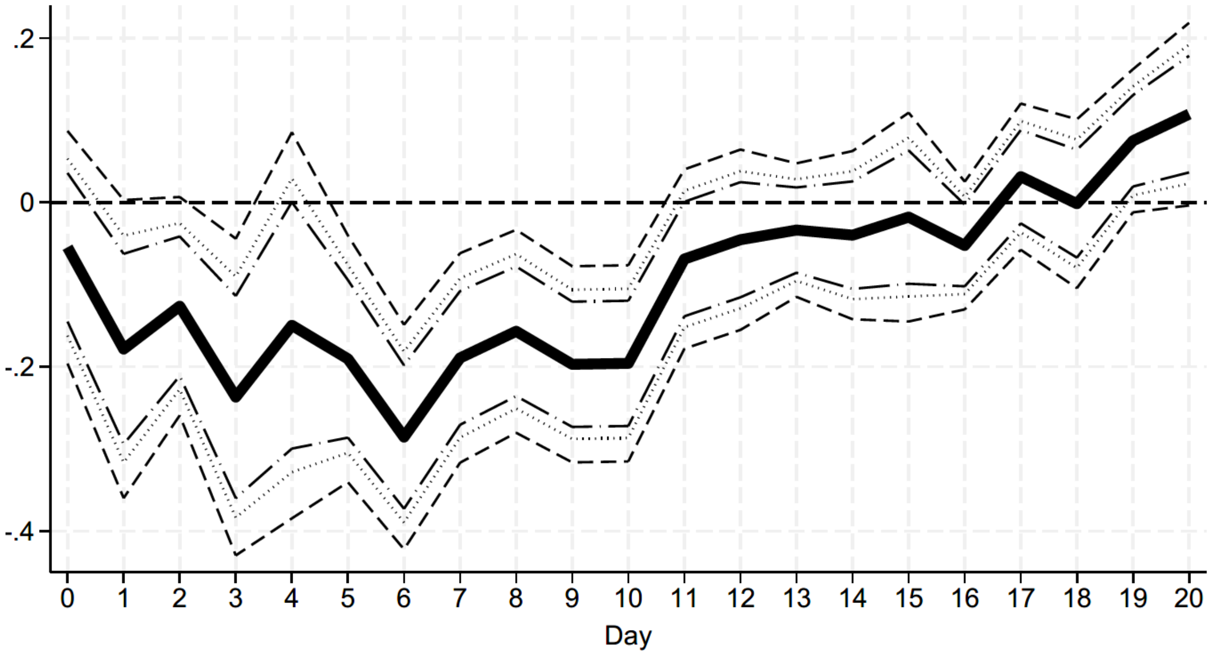
Second, we further account for potential valuation effects due to monetary policy affecting fund performance. On top of share-class fixed effects, which take care of time-invariant characteristics at the share-class and fund levels, we introduce date-by-fund-type fixed effects $\mu_{t,c}^h$ to account for time-varying unobserved heterogeneity at the fund type level.[13] These fixed effects account for confounding factors relating to macroeconomic dynamics and market developments that might affect fund investors such as, e.g., stock market volatility following the COVID-19 outbreak.[14] The date-by-fund-type fixed effects also control for heterogeneous effects of shocks, including monetary policy surprises, on funds that have a different investment focus. Hence, remaining heterogeneity in monetary policy shock reactions should mainly stem from the susceptibility of specific funds to panic-induced withdrawals, holding the fund-type-specific response of flows to a monetary policy shock constant.[15]

[13]The fund types are mainly based on Morningstar Global Broad Categories: allocation, alternative, convertibles, equity, fixed-income (now excluding corporate bond as indicated by the Morningstar Category), corporate bond, and money market.

[14]In our sensitivity analysis, we confirm robustness of our results when further accounting for these factors by, e.g., controlling for an interaction of fragility with stock market volatility as well as corresponding lags, which takes into account differential effects for fragile vs non-fragile funds.

[15]In order to check if our results might still be driven by contemporaneous performance effects, which

Figure 5: Flow Reaction of Fragile Funds to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

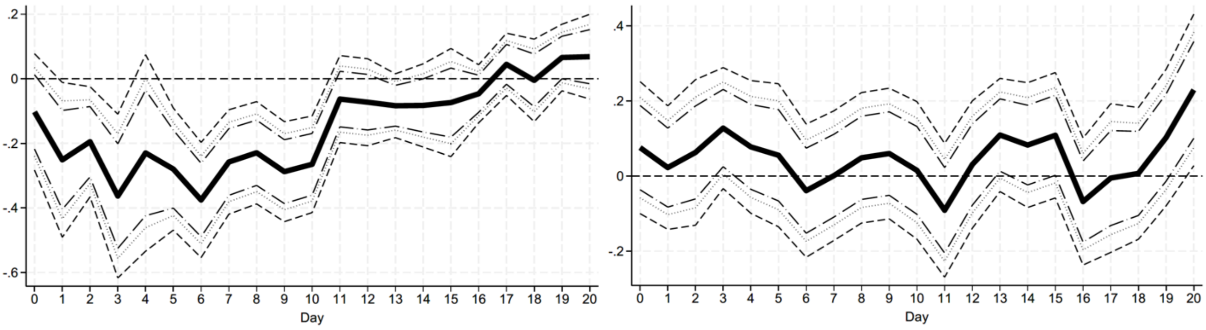
The coefficient of interest is β_h, measuring the impact of a monetary policy shock for fragile funds relative to their peers. Figure 5 reports $\hat{\beta}_h$ from iteratively estimating Equation 4.[16] The figure shows that there is a more negative effect of monetary policy tightening shocks on flows of fragile funds: Funds with strongly procyclical and concave flow-performance patterns are especially impaired by monetary policy shocks. Also, this differential effect lasts for about ten business days, i.e. two weeks, and is most pronounced by the beginning of the second week. Moreover, the differential effect is of similar size as the aggregate effect reported in the previous section and hence also economically meaningful: a reasonably large 10 bp tightening surprise decreases net flows of fragile funds by almost 0.2 pp (0.7 standard deviations of overall monthly flows) compared to less fragile funds.

To be able to assess the total effect of monetary policy surprises for fragile funds, we estimate a version of Equation 4, where we do not control for fund type times date

the shock might induce for fragile relative to other funds, we estimate Equation 4, but using returns as the dependent variable. On the day of the shock, the coefficient estimate $\hat{\beta}$ is negative but insignificant. This supports our notion of the monetary policy shock impact for fragile funds not being driven by contemporaneous performance developments that are specific for fragile funds but rather expectation-driven withdrawals.

[16]There are about 4.5 mln. observations in our estimations.

Figure 6: Flow Reaction of Fragile Funds to Surprise Monetary Tightening (Left Panel) and Easing (Right Panel).



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4 using two monetary policy surprise measures jointly, $(max(MPS_t, 0))$ and $(min(MPS_t, 0))$. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

fixed effects $\mu^h_{t,c}$. In this setting, the level effect of the monetary policy surprise is not absorbed. Table A.1 reports the estimated coefficients on MPS_t and $MPS_t \times Fragile_i$, i.e. $\hat{\beta}_h$, as well as their cumulative sums over the projection horizon. The coefficient estimates on the monetary policy surprise measure and on its interaction with fragility are both statistically significant over roughly two weeks, with the cumulative size of the coefficients over ten business days being -1.12 and -2.08, respectively. Hence, a 10 bp surprise monetary policy tightening decreases net flows of fragile funds by more than 0.3 pp in total $(0.1 \times (-1.12) + 0.1 \times (-2.08) = -0.32)$. This number amounts to more than one standard deviation of the aggregate monthly sector flows. The drop for fragile funds is roughly three times higher than the decrease for funds that are not identified as fragile.

In order to allow for a more precise attribution of the results provided so far to monetary tightening and to support our notion of adverse shocks, it is important to confirm that the results for fragile funds are driven by depressed net flows following a surprise monetary tightening instead of inflows following an easing. Hence, we repeat the analysis in Equation 4 but use two monetary policy measures jointly in the estimation, namely one that represents only tightening shocks $(max(MPS_t, 0))$ and another that captures only easing shocks $(min(MPS_t, 0))$. The results, illustrated in Figure 6, are in line with our expectations: unexpected monetary tightening is the predominant driver of the relative flow response, while the coefficients on the interaction of easing shocks with the fragility dummy are insignificant throughout the response horizon.

We perform several robustness tests, which are presented in detail in Appendix A.2

and include sample splits, controlling for an interaction of fragility with stock market volatility, using more granular fixed effects, and imposing stricter conditions for the identification of fragile funds. Three checks are particularly noteworthy. First, when we test the role of a substantially stricter definition of fragility by classifying as fragile only those share-classes in the top decile of negative excess return coefficients, the cumulative flow response of these highly fragile funds more than doubles relative to the baseline differential. This indicates that the severity of outflows following unexpected tightening increases with the degree of fragility. Second, we address a potential concern related to our fragility identification: since fragility is determined based on the full sample, funds that reacted strongly to performance shocks during the recent ECB tightening cycle might be disproportionately labeled as fragile, raising the possibility that the negative relationship between net flows and tightening could be an artifact of our time-invariant identification of fragile funds. To mitigate this concern, we allow fragility to vary over time by estimating rolling-window flow-performance regressions and reclassifying funds dynamically based only on predetermined information. The resulting impulse response closely resembles our baseline findings, alleviating concerns that the time-invariant nature of our fragility measure may give rise to reverse-causality issues. Third, we further tackle a related concern: performance-sensitive funds might be those whose performance is also particularly sensitive to monetary policy shocks. In our baseline local projection framework with fund type times date fixed effects, we already address this concern, but we further probe two aspects. To further work against the concern that our results are driven by the fragility measure itself being driven by monetary policy surprises, we incorporate even more granular fund-style information already into the identification stage. In a complementary check, we drop all observations falling within two weeks after an ECB Governing Council announcement from the fragility identification stage. Across both tests, the estimated impulse responses remain highly similar to the baseline, mitigating concerns that our findings are driven by the fragility measure being contaminated by monetary policy shocks.

5.2 Further supporting evidence

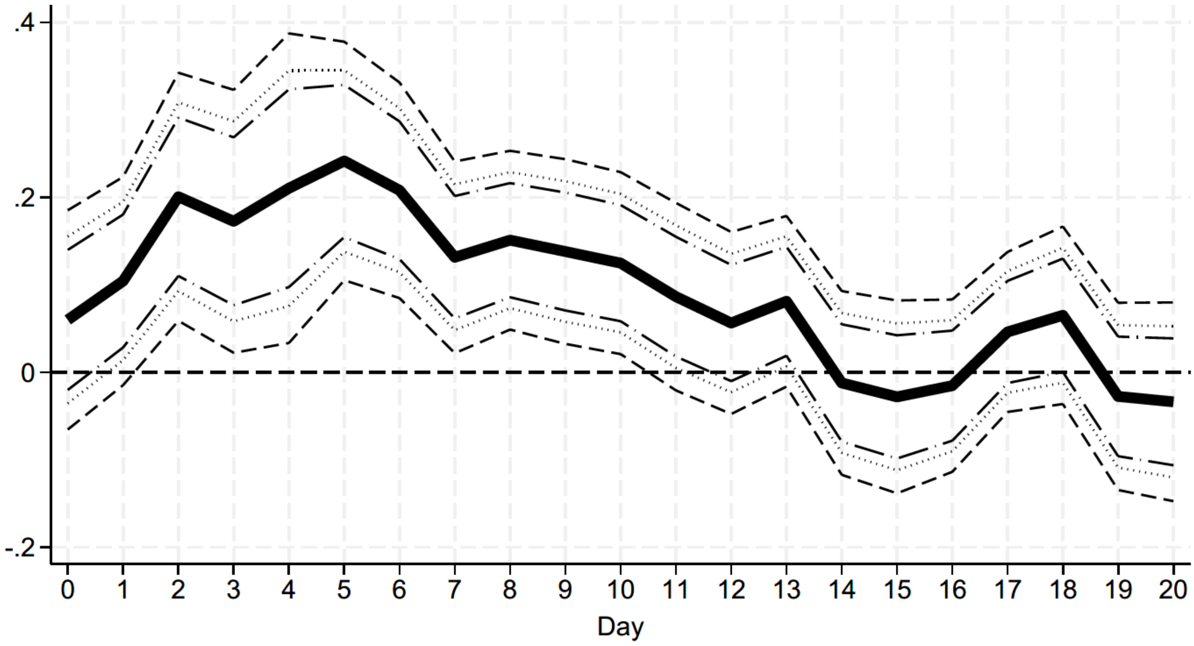
In this section, we provide further evidence that supports our narrative that fund fragility is a crucial determinant of investor redemption behavior in an adverse monetary policy environment. First, we document net outflows following adverse central bank information shocks. Second, we conduct our main two-step analysis for fixed-income funds, which are generally more fragile (Goldstein et al., 2017) and report even stronger responses. Finally, we contrast our fragility measure with singular fund characteristics that have been emphasized in the literature.

As discussed in Section 2, the methodology of Jarociński and Karadi (2020) allows to differentiate between pure monetary policy shocks, characterized by a negative co-movement of interest rates and stock markets, and central bank information shocks, characterized by a positive co-movement of the two. A negative central bank information shock indicates an unexpected decrease in interest rates accompanied by a drop in the stock market. This could e.g. be rationalized by the central bank conveying negative information about the state of the economy through its interest rate decision and monetary policy communication. Hence, adhering to our reasoning regarding effects of adverse central bank shocks, we would expect that a negative information shock leads to a negative flow reaction. This is confirmed by Figure 7, which shows a positive relationship when estimating Equation 4 with central bank information instead of pure monetary policy shocks. An interest rate drop along with a decrease in stock markets is associated with additional net outflows from fragile share-classes. The effect is similar in size compared to the case of a pure monetary policy shock.[17]

Negative implications of strategic complementarities and run-behavior in the fund sector have been particularly stressed in the fixed-income environment (e.g. Goldstein et al. (2017)). A limited liquidity of fund assets exacerbates the liquidity mismatch externality, amplifying withdrawals resulting from strategic complementarities. This is especially relevant as the maturity of fixed-income funds' assets is usually comparatively high, making these funds prone to valuation decreases following monetary tightening. To assess whether the fragility mechanism is particularly relevant in this sector, we repeat our main two-step analysis for the subsample of fixed-income funds as identified using the Morningstar Global Broad Category, where we include and differentiate between corporate bond (identified using Morningstar Category) and other bond funds. More precisely, we estimate the specifications in Equations 2 and 4 for the subsample. In this setting, we

[17]By construction, pure monetary policy and central bank information shocks are uncorrelated. Hence, including both shock types jointly in Equation 4 yields virtually identical responses as in Figures 5 and 7.

Figure 7: Flow Reaction of Fragile Funds to Central Bank Information Shocks.

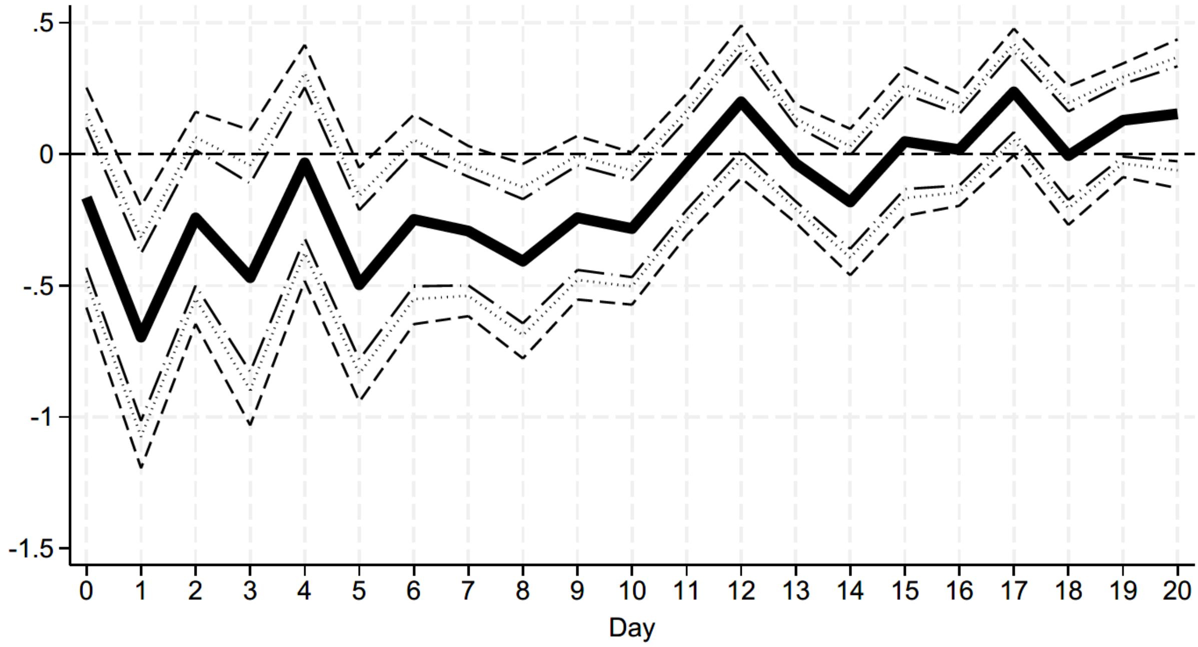


Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4 using central bank information shocks instead of pure monetary policy surprises. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

also get a negative response of net flows of fragile funds to monetary policy tightening relative to other funds, with the response for the fixed-income sample being substantially larger than for the whole sample, see Figure 8. Furthermore, performing a corresponding analysis specifically targeting corporate bond funds demonstrates a comparable significant response, see Appendix A.3. Here, corporate bond funds are characterized as those with more than 50% corporate bond holdings within their fixed-income portfolios to accommodate any potential misclassification of fund types, while still maintaining an ample sample size. Notably, we also observe negative responses for corresponding subsample analyses on equity and allocation funds, respectively, which are also provided in Appendix A.3. These results indicate that the mechanism we propose in this paper is highly relevant for fund types typically emphasized in the fund fragility literature, yet not limited to them.

In a related setting, we assess whether our measure derived from the elevated sensitivity to negative relative performance is indeed a sufficient statistic to proxy individual fragility of a mutual fund of any style. To do this, we implement specifications where we replace the fragility dummy with less broad and overarching fund characteristics than our key statistic measure which, however, have been shown to be relevant for strategic

Figure 8: Flow Reaction of Fragile Fixed-Income Funds to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specifications in Equations 2 and, to create this chart, 4 for a subsample of fixed-income funds. Fixed-income funds are identified using the Morningstar Global Broad Category, where we include and differentiate between corporate bond (identified using Morningstar Category) and other bond funds. Long dashed, dotted and short dashed lines denote 90%. 95% and 99% confidence intervals, respectively.

complementarities and fragility of funds: corporate bond as well as cash holdings. Reminiscent of Goldstein et al. (2017), we interact the monetary policy surprise with a dummy variable that equals one if a fund's corporate bond holdings as a share of the fixed-income portfolio in a preceding month were larger than the sample median (instead of interacting the monetary policy surprise with the fragility dummy). In our full sample of various fund types, we do not find evidence that the corporate bond holdings dummy matters for the transmission of monetary policy shocks. Similarly, in a model in which we replace the fragility variable with a dummy for predetermined low cash holdings of a fund, which Goldstein et al. (2017) demonstrate to be a suitable proxy for illiquidity in their sample of corporate bond funds, we do not find a significant coefficient on the interaction term. These findings, which are reported in Appendix A.4, namely that individual fund characteristics, which are very useful for analyses of strategic complementarities in certain fund segments, do not condition the outflows following monetary surprise tightening in our full sample, is in line with the sufficient statistic-interpretation of our fragility measure. Against the background of investigating the entire range of OEIF types in our main analysis above, the fragility measure captures fragility better than singular fund specifics.

6 Portfolio reallocation

Our previous analysis has shown that particularly fragile OEIFs' flows respond more sensitively to monetary policy shocks. In this section we investigate whether these larger scale outflows transmit monetary policy impulses further into the financial system. In particular, we analyze whether there is also a differential adjustment of funds' portfolios regarding 1) their corporate bond holdings, which have been shown by Fang (2025) to affect bond-funded firms financing conditions and real activity, and 2) their liquidity buffers, which mainly comprise bank deposits and interact with the bank deposit channel Drechsler et al. (2017).

Corporate bonds

We investigate whether funds that are particularly fragile adjust their relative portfolio allocations in corporate bonds—measured as the share of corporate bond holdings within their fixed-income portfolios—differently from other funds following monetary policy tightening. We estimate different variations of monthly regressions

$$Y_{i,t} = \beta MPS_t \times Fragile_i + \theta \mathbf{X}_{i,t} + Fixed\ Effects + \epsilon_{i,t}. \tag{5}$$

The dependent variable is the change in the portfolio weight of corporate bond holdings relative to the total fixed-income portfolio of share-class i between month t and $t-1$, i.e. $Y_{i,t} = (\frac{Corporate\ Bond\ Portfolio_{i,t}}{FI\ Portfolio_{i,t}} - \frac{Corporate\ Bond\ Portfolio_{i,t-1}}{FI\ Portfolio_{i,t-1}}) \times 100$ (based on Morningstar data). The vector of control variables, $\mathbf{X}_{i,t}$, also includes MPS_t if applicable, while $Fixed\ Effects$ refers to a combination of share-class and monthly date-by-type fixed effects. The exact specifications are indicated in Table 3, which provides the results. In Columns 1 to 3, we use the full sample of all funds. To first generate a baseline, we drop the fragility dummy from the regression in Column 1. Column 2 introduces the interaction between monetary policy shocks and the fragility dummy, but includes only share-class fixed effects to be able to compare the baseline effect with the differential effect, while Column 3 features the higher-dimensional fixed effects. Since corporate bond holdings

Table 3: Monetary Policy Surprises and Corporate Bond Portfolio Adjustment of Fragile Funds.

Dependent Variable (Δ)	(1) Corporate Bonds	(2) Corporate Bonds	(3) Corporate Bonds	(4) Corporate Bonds
MPS	-2.746***	-2.854***		
	(0.559)	(0.821)		
MPS × Fragile		0.429	0.093	-4.730*
		(1.108)	(1.113)	(2.867)
Lagged Return	-0.017***	-0.015*	-0.040***	-0.031
	(0.006)	(0.008)	(0.014)	(0.030)
Lagged Return × Fragile		-0.006	-0.008	0.037
		(0.012)	(0.012)	(0.032)
Lagged log(TNA)	0.098	0.032	0.123*	0.263**
	(0.062)	(0.064)	(0.069)	(0.111)
Log(Age in Days)	-0.315***	-0.230***	-0.164	0.029
	(0.076)	(0.082)	(0.134)	(0.196)
Lagged Corporate Bonds	-0.153***	-0.158***	-0.162***	-0.094***
	(0.006)	(0.006)	(0.007)	(0.010)
Lagged Cash & Equivalents	0.011***	0.010***	0.011***	0.051***
	(0.002)	(0.003)	(0.003)	(0.008)
Lagged Δ Cash & Equivalents	0.062***	0.064***	0.064***	0.073***
	(0.005)	(0.005)	(0.005)	(0.013)
Lagged Flow	0.024**	0.021**	0.035***	0.045***
	(0.010)	(0.011)	(0.011)	(0.016)
Observations	154,964	142,016	141,984	27,949
Adj. R-squared	0.084	0.087	0.123	0.091
Sample	All	All	All	Fixed-Income
ISIN Fixed Effects	Yes	Yes	Yes	Yes
Month × Type Fixed Effects			Yes	Yes

Notes: Coefficient estimates based on different versions of monthly regressions of the model in Equation 5, using variables, samples, and fixed effects as indicated. Corporate Bonds are holdings that are measured as a share of the total fixed-income portfolio of a fund. Thus, $Y_{i,t} = (\frac{Corporate\ Bond\ Portfolio_{i,t}}{FI\ Portfolio_{i,t}} - \frac{Corporate\ Bond\ Portfolio_{i,t-1}}{FI\ Portfolio_{i,t-1}}) \times 100$. Cash & Equivalents is defined as cash and cash-like short-term fixed-income assets with a maturity of up to three months and also measured as a share of the total fixed-income portfolio. Control variables include lags and first differences as indicated. Robust standard errors clustered at the share-class, i.e. ISIN, level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

are largely concentrated on fixed-income funds, in Column 4 we restrict the sample to fixed-income funds. In this subsample, corporate bonds comprise approximately 44% of the fixed-income portfolio.

We observe that funds typically decrease their corporate bond holdings relative to their fixed-income investments when faced with an unexpected tightening (refer to Columns 1 and 2 of Table 3). However, fragile funds do not appear to reduce their corporate bond portfolio share more significantly (see Columns 2 and 3 of Table 3). In our sample, corporate bond holdings play a minor role at most funds, resulting in little variation. When we restrict our sample to fixed-income funds, we observe that the more fragile fixed-income funds indeed decrease the share of corporate bonds in their portfolios more considerably in response to an unexpected monetary tightening compared to other fixed-income funds (see Column 4 of Table 3). The estimated coefficient of the interaction term of -4.73 suggests that in response to a 10 bp tightening shock, fragile bond funds allocate 0.5 pp less of their portfolio to corporate bonds as compared to other bond funds. Thus particularly fragile bond funds sell off their corporate bond holdings more aggressively in response to outflows induced by an unexpected monetary tightening.

These findings are consistent with Fang (2025) who assesses the scale of the monetary policy transmission mechanism through US bond funds and shows that, overall, these funds lower their corporate bond holdings following monetary policy tightening, which comes with a reduction in the price of these bonds and bond issuance of firms. While Fang (2025) does not disentangle the effect of fund fragility, Ma et al. (2022) show more illiquid fixed-income funds had to sell off corporate bonds more aggressively than other funds in the COVID-19 period.

Bank deposits

Next, we investigate whether elevated fund share redemptions in response to an unexpected monetary tightening induce funds to withdraw their bank deposits causing a spillover to the banking sector. Specifically, we examine whether fragile funds, which require more liquidity to accommodate higher shareholder withdrawals, actually decrease their cash at banks in response to unexpected monetary policy tightening by estimating funds' bank-deposit flows using Equation 5. The left-hand side of Equation 5 now depicts the month-on-month change in the amount of a fund's bank deposits, derived from Bundesbank's IFS database and normalized by the fund's lagged TNA, i.e. $Y_{i,t} = (\frac{Bank\ Deposits_{i,t} - Bank\ Deposits_{i,t-1}}{TNA_{i,t-1}}) \times 100$.

Table 4: Monetary Policy Surprises and Bank Deposit Flows of Fragile Funds.

Dependent Variable (Scaled by Lagged TNA)	(1) Δ Bank Deposits	(2) Δ Bank Deposits	(3) Δ Bank Deposits
MPS	0.864***	1.317***	
	(0.293)	(0.429)	
MPS × Fragile		-1.521**	-1.544***
		(0.601)	(0.595)
Lagged Return	0.018***	0.014***	0.041***
	(0.003)	(0.003)	(0.006)
Lagged Return × Fragile		0.007	0.007
		(0.006)	(0.006)
Lagged log(TNA)	-0.009	-0.018	-0.049**
	(0.022)	(0.024)	(0.024)
Log(Age in Days)	-0.035*	-0.020	-0.087**
	(0.019)	(0.020)	(0.035)
Lagged Corporate Bonds	0.010***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)
Lagged Bank Deposits	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Lagged Scaled Δ Bank Deposits	-0.243***	-0.250***	-0.253***
	(0.005)	(0.006)	(0.006)
Lagged Flow	0.035***	0.034***	0.028***
	(0.006)	(0.006)	(0.006)
Observations	180,877	164,014	163,992
Adj. R-squared	0.071	0.074	0.094
ISIN Fixed Effects	Yes	Yes	Yes
Month × Type Fixed Effects			Yes

Notes: Coefficient estimates based on different versions of monthly regressions of the model in Equation 5, using variables and fixed effects as indicated. Bank Deposits represents the amount of bank deposits of a fund share-class in thousands of euro. Thus, $Y_{i,t} = (\frac{Bank\ Deposits_{i,t} - Bank\ Deposits_{i,t-1}}{TNA_{i,t-1}}) \times 100$. Control variables include lags and first differences as indicated. Robust standard errors clustered at the share-class, i.e. ISIN, level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 reports the regression results for three variations of Equation 5. In Column 1 we do not allow for a differential effect of monetary policy shocks on fragile funds and only consider fund fixed effects. The positive and highly significant coefficient on the monetary policy surprise indicates that funds on average increase their wholesale deposits in the banking sector in response to an unexpected increase in short-term interest rates: a 10 bp unexpected tightening is related to an increase in an average fund's deposit inflow of about 9 bp of its TNA. This presumably reflects that deposit remuneration becomes more attractive for wholesale depositors.

However, the effect is very heterogeneous across different funds: Column 2 shows a distinct reaction of fragile fund deposit flows to unexpected monetary policy changes: whereas other funds significantly boost their bank deposits following an unanticipated tightening, fragile funds typically reduce them. Other funds increase their deposit holdings by 13 bp of their TNA in response to a 10 bp tightening surprise, while fragile funds reduce their deposit holdings by 2 bp normalized by the lagged TNA. Thus, banks with predominantly deposits from fragile funds suffer from a modest negative spillover of the liquidity pressures of fragile funds. This finding is corroborated by the respective, highly significant $\hat{\beta}$-coefficient in the setting with higher-dimensional fixed effects displayed in Column 3.

While these results suggest that fragile funds use a greater portion of their bank deposits in response to increased redemptions after an unexpected tightening, it remains unclear whether these funds withdraw more deposits simply because they face larger fund share redemptions or whether they are adjusting their portfolio composition. In theory, a fragile fund could 1) preserve a specific cash ratio, 2) adhere to a pecking order (Ma et al. (2022)) following monetary surprises and subsequent outflows, thus disproportionately depleting relative cash reserves, or 3) accumulate cash in anticipation of outflows, which means increasing cash reserves in anticipation of further redemptions (Morris et al., 2017), leading to a smaller decrease or even an increase in cash ratios. While 2) would amplify the spillover of the liquidity pressure to the banking sector, 3) would mute it.

Thus, in the next step we investigate whether fragile funds also respond by adapting the portfolio weight of their overall cash buffers differently than other funds. In examining the rebalancing of funds' overall cash reserves, we employ again Equation 5, where the dependent variable is now expressed as $Y_{i,t} = (\frac{Cash\ \&\ Equivalent\ Portfolio_{i,t}}{FI\ Portfolio_{i,t}} - \frac{Cash\ \&\ Equivalent\ Portfolio_{i,t-1}}{FI\ Portfolio_{i,t-1}}) \times 100$. This reflects changes in the monthly holdings of cash and highly liquid short-term maturity assets, represented as a percentage of the entire fixed-income portfolio.[18]

Table 5: Monetary Policy Surprises and Cash-Like-Assets Portfolio Adjustment of Fragile Funds.

Dependent Variable (Δ)	(1) Cash & Equiv.	(2) Cash & Equiv.	(3) Cash & Equiv.	(4) Cash & Equiv.	(5) Cash & Equiv.	(6) Cash & Equiv.
MPS	1.577*	3.233***		0.442	2.720*	
	(0.811)	(1.192)		(1.090)	(1.553)	
MPS × Fragile		-3.958**	-4.030**		-4.670**	-4.539**
		(1.725)	(1.726)		(2.230)	(2.077)
Lagged Return	0.030***	0.017	0.023	-0.032*	-0.019	-0.019
	(0.010)	(0.013)	(0.022)	(0.018)	(0.029)	(0.035)
Lagged Return × Fragile		0.039*	0.042**		-0.018	-0.032
		(0.021)	(0.021)		(0.037)	(0.034)
Lagged log(TNA)	-0.255***	-0.280***	-0.480***	-0.021	-0.054	-0.285*
	(0.090)	(0.100)	(0.103)	(0.113)	(0.134)	(0.146)
Log(Age in Days)	-0.245**	-0.265**	0.396**	-0.687***	-0.805***	-0.057
	(0.108)	(0.115)	(0.182)	(0.124)	(0.133)	(0.214)
Lagged Corp. Bonds	0.005	0.004	0.006	0.006	0.005	0.003
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)
Lagged Cash & Equiv.	-0.179***	-0.182***	-0.188***	-0.196***	-0.196***	-0.222***
	(0.006)	(0.006)	(0.007)	(0.013)	(0.013)	(0.013)
Lagged Δ Cash & Equiv.	-0.169***	-0.166***	-0.166***	-0.138***	-0.142***	-0.135***
	(0.008)	(0.008)	(0.008)	(0.015)	(0.016)	(0.016)
Lagged Flow	0.013	0.013	-0.008	-0.074***	-0.070***	-0.056**
	(0.017)	(0.018)	(0.019)	(0.021)	(0.023)	(0.022)
Observations	154,964	142,016	141,984	31,112	27,949	27,949
Adj. R-squared	0.122	0.123	0.148	0.123	0.125	0.176
Sample	All	All	All	Fixed-Income	Fixed-Income	Fixed-Income
ISIN Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Month × Type Fixed Effects			Yes			Yes

Notes: Coefficient estimates based on different versions of monthly regressions of the model in Equation 5, using variables, samples, and fixed effects as indicated. Cash & Equiv. is defined as cash and cash-like short-term fixed-income assets with a maturity of up to three months and measured as a share of the total fixed-income portfolio of a fund. Thus, $Y_{i,t} = (\frac{Cash\ \&\ Equivalent\ Portfolio_{i,t}}{FI\ Portfolio_{i,t}} - \frac{Cash\ \&\ Equivalent\ Portfolio_{i,t-1}}{FI\ Portfolio_{i,t-1}}) \times 100$. Control variables include lags and first differences as indicated. Robust standard errors clustered at the share-class, i.e. ISIN, level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Table 5, we provide results using the three familiar specifications: (i) baseline without the interaction term, (ii) baseline including the interaction between fragility and the monetary policy shock, and (iii) higher-dimensional fixed effects. Columns 1 to 3 use the full sample. As liquidity buffers in the dependent variable are scaled by the fixed-income portfolio, which is particularly representative of bond-fund assets, Columns 4 to 6 restrict the sample to fixed-income funds for comparability.

[18]The data for this variable are from Morningstar.

The coefficients on the monetary policy surprise measure in both Columns 1 and 4 offer tentative evidence supporting the earlier finding of increasing liquidity buffers on average in response to an unexpected increase in short-term rates. However, when allowing for some fund heterogeneity, the picture becomes more nuanced. In Columns 2 and 5, the estimated coefficients of MPS are 3.23 and 2.72, respectively. They indicate that more stable funds scale up their cash ratio by about 0.3 pp following a 10 bp monetary policy tightening potentially in order to benefit from higher interest rates offered on short-term interest-bearing deposits. However, the effect on cash shares of fragile funds is negative. The coefficient estimates on $MPS \times Fragile$ are significantly negative, with the coefficients based on the fixed-income subsample larger in absolute size. Fragile fixed-income funds, whose cash buffers comprise approximately 9.7% of their fixed-income portfolio and which experience much stronger investor redemptions than their more stable counterparts, lower their cash-to-fixed-income asset ratio by roughly 0.5 pp compared to other funds and 0.2 pp overall in response to an unexpected 10 bp monetary policy tightening, see Column 5, which corresponds to a reduction in their cash ratio by 2.1%. When further improving the identification of the tightening effect on fragile funds by saturating the model with high dimensional fixed effects, the estimated coefficients of about -4 and -5 are confirmed in Columns 3 and 6.

These results suggest that fragile funds not only withdraw deposits from the banking sector proportional to their elevated investor redemptions but also significantly run down their cash ratios as opposed to their more resilient counterparts. As a result, during periods of unexpected monetary tightening, fragile funds contribute to an outflow of wholesale deposits from the respective banks. These findings suggest that fragile funds' deposit withdrawals might amplify the deposit channel of monetary policy and aggravate the liquidity pressures in the financial system. At the same time, the decline in cash ratios particularly at fragile funds also suggests that these funds become more vulnerable during a monetary tightening to liquidity shocks including those induced by further tightening.

7 Household deposit flows

Our prior analysis shows that net flows to funds tend to decrease following an unexpected tightening of monetary policy, especially for fragile funds. Consequently, these fragile funds disproportionately withdraw their bank deposits to redeem fund shares, thereby intensifying the deposit channel of monetary policy through wholesale deposit outflows at exposed banks. A pertinent question, however, is what investors do with the proceeds from redeeming their fund shares. It could be speculated that they at least temporarily retain these proceeds in their bank deposit accounts (given also that the remuneration might rise), generating a compensatory deposit inflow that partially counteracts the wholesale deposit outflow caused by the withdrawals of fragile funds. As a result, the banking sector as a whole might not see a reduction in deposits due to the outflow of funds from fragile OEIFs. Some banks could be more affected by wholesale deposit outflows from fragile funds, while others might benefit from the increased deposit holdings of investors in these fragile funds.

In this section, we want to test whether indeed investors hold the proceeds of redeemed (fragile) fund shares as additional deposits. The Bundesbank's SHS data set reports on a security-by-security basis for each bank the aggregate portfolio holdings of its retail customers at a monthly frequency.[19] We match the SHS at the bank level with the Bundesbank's BISTA data set that reports for each bank the aggregate overnight, time, as well as savings deposits from retail customers. Assuming that retail investors' custodian banks are typically also the banks at which they have their deposit accounts, we can then test whether the larger redemption of fragile fund shares is associated with larger retail deposit inflows at the custodian bank.

We aggregate the granular holdings data on the bank-month level and calculate the relative weight of fragile fund shares in the total fund share holdings of households at each bank b in month t:

$$Fragile\ Share_{b,t} = \frac{\sum_{i \in Fragile} Household\ Holdings_{i,b,t}}{\sum_{i} Household\ Holdings_{i,b,t}}. \tag{6}$$

This measure reports the time-varying bank-specific fragility share in households' fund holdings, which takes on values between 0 and 1 and has an average of 0.34. As endogenous variable we derive from BISTA two household deposit measures on the bank-month level: (i) households' overnight money and (ii) households' longer-term deposits including time

[19]The SHS also reports holdings of other key investor classes such as firms, banks, and NBFIs. Households are by far the most important shareholder sector in retail OEIFs.

and savings deposits, i.e. total household deposits minus overnight money. For both deposit types, we construct the month-on-month change in the amount of bank deposits of all households scaled by lagged total bank assets. We then estimate the following regression equation:

$$\left(\frac{Deposits_{b,t} - Deposits_{b,t-1}}{Bank\ Assets_{b,t-1}}\right) \times 100 = \beta MPS_t \times Fragile\ Share_{b,t-1} + \theta \mathbf{X}_{b,t} + Fixed\ Effects + \epsilon_{b,t}, \tag{7}$$

where the deposit measure in the numerator of the dependent flow variable refers to either overnight or longer-term deposits. $\mathbf{X}_{b,t}$ includes MPS_t, if not absorbed by the fixed effects, and $Fragile\ Share_{b,t-1}$ in levels as well as lagged bank characteristics such as the bank's equity ratio in percent. $Fixed\ Effects$ refers to either only bank or bank and time fixed effects.[20] We aim to inform on how the effect of surprise tightening, which - as we have shown - leads to outflows especially from fragile OEIFs, ultimately affects households' deposit holdings when households have a heavy ex ante loading on fragile funds at the custodian bank, i.e. when there is high flow-potential at the bank. In the latter fixed effects specification, our preferred setting, we directly control for the aggregate interest rate environment and isolate the effect of the monetary shock for different levels of fragility- and hence fund-outflow-intensity. Thus, we can reasonably well identify households' deposit inflows due to monetary policy shock-induced fund withdrawals.

Table 6 reports the results, with Columns 1 and 2 referring to households' overnight deposit flows while Columns 3 and 4 show the results for longer-term deposit flows. Columns 2 and 4 introduce monthly date fixed effects on top of bank fixed effects. The highly significant and positive coefficient of interest on the interaction between the monetary policy surprise and the predetermined fragility share in Column 1 shows that larger-than-average ex ante share of households' fragile fund holdings at a bank is associated with an increase in household overnight deposit inflows at that bank.[21] For instance, an ex ante fragility share of about 0.68, which is twice the mean or about two standard deviations larger than the mean fragility share, in combination with a 10 bp tightening shock translates into increases in overnight deposit flows by roughly 0.06 pp ($0.1 \times (-0.629) + 0.1 \times 0.68 \times 1.869 = 0.064$)

[20] Note that, as usual, we model the unexpected part of monetary policy changes, not the overall interest rate environment or already anticipated changes thereof. Hence, our results should not be interpreted as informing on general responses of household deposit flows to higher deposit remuneration.

[21] A 10 bp monetary policy tightening shock is associated with no change in overnight deposit net flows ($0.1 \times (-0.63) + 0.1 \times a \times 1.87 = 0$) for a share of fragile fund share holdings of $a = 0.34 = \overline{Fragile\ Share}$.

Table 6: Monetary Policy Surprises, Fragility-Intensity and Bank-Deposit Flows of Households.

Dep. Var. (Scaled by Lagged Bank Assets)	(1) Δ Overnight Money	(2) Δ Overnight Money	(3) Δ Longer-term Deposits	(4) Δ Longer-term Deposits
MPS	-0.629*** (0.188)		-0.030 (0.060)	
MPS × Lagged Fragile Share	1.869*** (0.550)	1.278** (0.582)	-0.541*** (0.161)	0.109 (0.154)
Lagged Fragile Share	0.172*** (0.031)	-0.033 (0.026)	0.043* (0.024)	-0.028 (0.023)
Lagged log(Bank Assets)	-0.278*** (0.022)	-0.141*** (0.020)	0.158*** (0.011)	-0.063*** (0.016)
Lagged Equity Share	0.010 (0.010)	0.003 (0.009)	0.009** (0.004)	-0.000 (0.004)
Lagged Overnight Money	-0.000*** (0.000)	-0.000* (0.000)		
Lagged Scaled Δ Overnight Money	0.009 (0.007)	-0.041*** (0.007)		
Lagged Longer-term Deposits			-0.000* (0.000)	-0.000** (0.000)
Lagged Scaled Δ Longer-term Deposits			0.309*** (0.020)	0.224*** (0.017)
Observations	161,720	161,720	118,608	118,608
Adj. R-squared	0.023	0.204	0.144	0.230
Bank Fixed Effects	Yes	Yes	Yes	Yes
Month Fixed Effects		Yes		Yes

Notes: Coefficient estimates based on different versions of monthly regressions of the model in Equation 7, using variables and fixed effects as indicated. $Y_{b,t} = (\frac{Deposits_{b,t} - Deposits_{b,t-1}}{Bank\ Assets_{b,t-1}}) \times 100$, where Deposits refers to Overnight Money (Columns 1 and 2) or Longer-term Deposits (Columns 3 and 4), respectively. Overnight Money represents the amount of households' overnight deposits held at a bank in thousands of euro. Longer-term Deposits represents the amount of households' time and savings deposits, i.e. total deposits minus Overnight Deposits, held at a bank in thousands of euro. Fragile Share represents the relative weight, between 0 and 1, of Fragile share-classes in the total fund holdings of households at each bank in a certain month. Control variables include lags and first differences as indicated. Robust standard errors clustered at the bank level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

of the bank's total assets. A fragility share of 1 would translate into a deposit flow increase of 0.12 pp of total bank assets. This corresponds to 0.2 standard deviations of monthly household deposit flows - a substantial number given the vast availability of outside options for households. In Column 2, the results are confirmed and comparative in size when additionally taking into account time-fixed effects. This finding is consistent with the idea that households keep a significant share of the proceeds from their fund share redemptions in overnight money at their custodian bank before potentially further investing them into other assets.

Given that the remuneration of time and savings deposits is typically more responsive to changes in monetary policy rates, households could also reallocate the proceeds of their fund share redemptions in those longer-term deposits. However, we do not find evidence for corresponding household inflows into these longer-term deposits at ex ante highly fragile-intensive banks following surprise tightening. In Column 3, without month fixed effects, the coefficient on the interaction term is negatively significant, indicating more depressed net flows for more fragile-intensive banks. The corresponding coefficient in Column 4 is insignificant. Hence, we conclude that while households do not take up longer-term savings and time deposits at the same bank, the findings on overnight money implies that households' deposit inflow after particularly fragile fund share redemptions attenuates the deposit channel of monetary policy at those custodian banks and (partially) off-sets the overall withdrawals of wholesale deposits from OEIF in the banking sector as a whole. In particular, banks more heavily relying on wholesale funding from fragile funds experience deposit outflows while banks with substantial custodian business whose customers hold predominantly fragile fund shares benefit.

8 Conclusion

Using granular high-frequency data and a comprehensive measure of a fund's individual fragility potential that is based on the degree of investors' overreaction to temporary underperformance, as opposed to overperformance, we demonstrate that monetary policy transmission through the OEIF sector is highly heterogeneous. In particular, fragile funds experience significantly larger net outflows in response to an unexpected monetary policy tightening than their less fragile peers, implying an overall effect approximately three times as large. In contrast, no differential effect is observed after monetary policy easing, consistent with our proposed mechanism. These flow dynamics translate into distinct fund portfolio and liquidity adjustments. Elevated net outflows after monetary tightening are associated with a larger reduction in corporate bond portfolios for fragile bond funds, suggesting that the fragility of funds amplifies the transmission of monetary policy into bond markets. Moreover, while the average fund increases bank deposit flows after tightening, fragile funds do the opposite: they draw down deposits and shrink liquidity buffers to meet heightened redemptions. As a result, during periods of unexpected monetary tightening, fragile funds contribute to an outflow of wholesale deposits from the respective banks, suggesting that fragile funds' deposit withdrawals might amplify the deposit channel of monetary policy and aggravate the liquidity pressures in the financial system. At the same time, banks whose customers are heavily invested in fragile funds receive significant overnight deposit inflows after monetary tightening as these clients temporarily park their redemption proceeds. This dampens the deposit channel at these (other) banks and suggests a reallocation of deposits within the banking sector. Banks with a large share of wholesale deposits coming from fragile funds experience deposit outflows while banks with substantial custodian business whose customers hold predominantly fragile fund shares benefit. Together, our results imply that monetary policy tightening through the OEIF sector is mainly transmitted and amplified by fragile funds. Moreover, regulatory changes affecting the fragility of OEIFs can shape the effectiveness of monetary policy. The introduction of mandatory liquidity management tools or alender-of-last-resort facility for NBFIs can dampen the transmission of monetary policy tightening outlined in this paper.

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Appendix

A.1 Total flow reaction of fragile and other funds

Table A.1: Flow Reaction of Fragile and Other Funds to Monetary Policy Surprises.

Horizon in Business Days	Coefficient		Cumulative Sum of Coefficient		Observations
	MPS	MPS × Fragile	MPS	MPS × Fragile	
0	-0.02 (0.03)	-0.07 (0.06)	-0.02	-0.07	4,607,039
1	-0.13*** (0.04)	-0.19** (0.07)	-0.15	-0.26	4,547,551
2	-0.11*** (0.03)	-0.15*** (0.05)	-0.26	-0.41	4,559,960
3	-0.12*** (0.04)	-0.26*** (0.08)	-0.38	-0.67	4,563,288
4	-0.35*** (0.06)	-0.16* (0.09)	-0.73	-0.83	4,560,898
5	-0.14*** (0.03)	-0.20*** (0.06)	-0.87	-1.04	4,558,175
6	-0.00 (0.03)	-0.31*** (0.05)	-0.87	-1.34	4,554,557
7	-0.06** (0.03)	-0.18*** (0.05)	-0.93	-1.52	4,542,300
8	-0.11*** (0.03)	-0.18*** (0.05)	-1.04	-1.70	4,529,619
9	-0.07** (0.03)	-0.19*** (0.05)	-1.11	-1.89	4,533,457
10	-0.01 (0.03)	-0.18*** (0.05)	-1.12	-2.08	4,536,810
11	0.03 (0.03)	-0.07 (0.04)	-1.09	-2.15	4,533,328
12	-0.03 (0.03)	-0.04 (0.04)	-1.12	-2.19	4,527,966
13	0.04** (0.02)	-0.03 (0.03)	-1.08	-2.22	4,522,834
14	0.03 (0.03)	-0.03 (0.04)	-1.05	-2.26	4,510,609
15	0.09*** (0.03)	-0.02 (0.05)	-0.96	-2.28	4,491,849
16	0.06*** (0.02)	-0.05 (0.03)	-0.90	-2.33	4,481,724
17	0.07*** (0.02)	0.03 (0.03)	-0.83	-2.30	4,478,051
18	0.09*** (0.03)	-0.00 (0.04)	-0.74	-2.30	4,476,149
19	0.06*** (0.02)	0.08** (0.03)	-0.68	-2.22	4,475,403
20	-0.01 (0.03)	0.11** (0.04)	-0.69	-2.11	4,471,929

Notes: Local projection coefficient estimates and their cumulative sums based on estimating the specification in Equation 4 but omitting fund type times date fixed effects $\mu^h_{t,c}$. Robust standard errors clustered at the share-class, i.e. ISIN, level are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

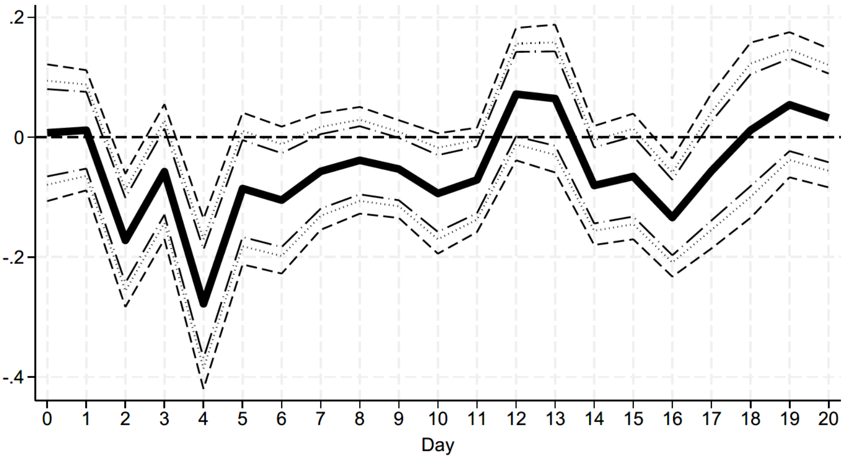
A.2 Robustness tests

We perform several analyses that confirm the relevance of fund fragility in explaining net flows following unexpected monetary policy tightening. These include sample splits, controlling for stock market volatility, and imposing stricter conditions on the identification of fragile funds, such as allowing for time-varying fragility.

Sample splits

First, we evaluate the robustness of our results by adopting another, similar specification commonly used in the literature and, in addition, examining whether our findings hold specifically during the recent euro area monetary policy tightening cycle. In particular, we, firstly, retain only fragile share-classes in our local projection sample instead of using an interaction term - similar to e.g. Dunne et al. (2023) - and, secondly, restrict the sample period to the monetary policy tightening episode in the two years 2022 and 2023. Figure A.1 plots the impulse response of this specification (which is based on the local projection specification in Equation 3). The result confirms an important role of the recent monetary policy tightening cycle for the flows of fragile funds albeit more volatility is observed, potentially due to the comparatively small number of 15 monetary policy meetings.

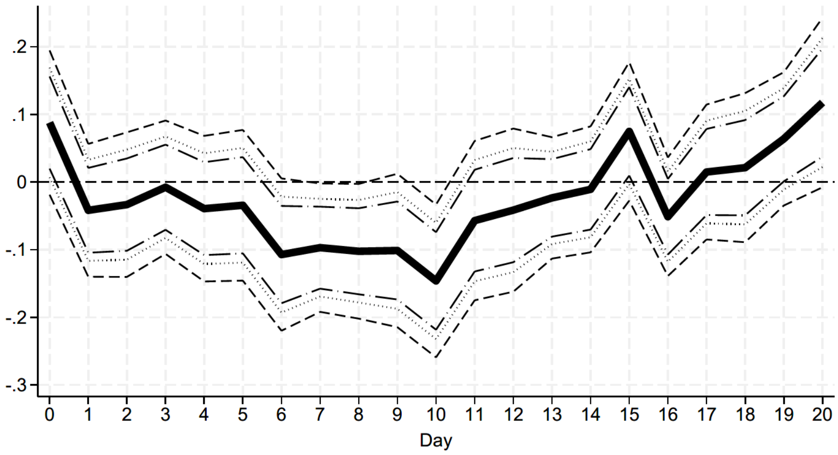
Figure A.1: Flow Reaction to Monetary Policy Surprises based on Subsample of Fragile Funds for the Years 2022 and 2023.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 3 for the subsample of fragile funds in the years 2022 and 2023. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

Our main results also remain qualitatively robust when excluding the period of heightened volatility during the COVID-19 crisis in March 2020 from our full sample, although the absolute

Figure A.2: Flow Reaction of Fragile Funds to Monetary Policy Surprises excluding March 2020.



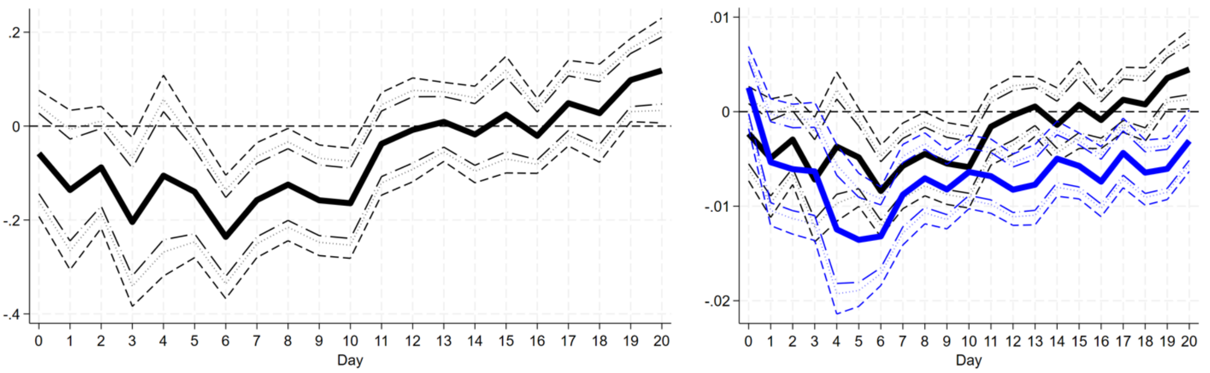
Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4 but excluding the period of heightened volatility during the COVID-19 crisis in March 2020 from our sample. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

magnitude of the response decreases, see Figure A.2. This suggests that the COVID-19 episode accounts for part of our results, which we interpret as further validation of our proposed mechanism: while particularly relevant during a brief period of heightened stress in the mutual fund market, it was not limited to this period.

Stock market volatility

Moreover, we ensure that our results are robust when accounting for broader shifts in overall investor risk-taking, uncertainty, or market illiquidity that extend beyond monetary policy events. To control for the impact of these factors on investor net flows in sensitive funds relative to non-sensitive funds—without being restricted to monetary policy event days—we incorporate a stock market volatility index. In the spirit of Goldstein et al. (2017), we extend Equation 4 by introducing an interaction term between the daily change in the German equity volatility index (VDAX) and the fragility dummy, along with the corresponding lags as control variables. The estimated coefficient of interest, $\hat{\beta}_h$, which captures the impact of a monetary policy shock on fragile funds relative to other funds, slightly decreases in absolute magnitude—potentially due to multicollinearity on monetary policy event days—but remains negative and statistically significant, see the left panel of Figure A.3. The right panel of Figure A.3 shows the estimated coefficients on fragility interacted with standardized monetary policy shocks (black) and standardized VDAX changes (blue). As expected, also the coefficients on the interaction of fragility

Figure A.3: Flow Reaction of Fragile Funds to Monetary Policy Surprises in the VDAX analysis.



Notes: Local projection coefficient estimates (solid lines) based on estimating the specifications in Equation 4 when adding an interaction of the daily change in the German equity volatility index, the VDAX, with the fragility dummy as a control measure (as well as the corresponding lags). The left panel shows the response of net flows to fragility interacted with the monetary policy shock. The right panel shows the responses to fragility interacted with standardized monetary policy shocks (black) and VDAX changes (blue). Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

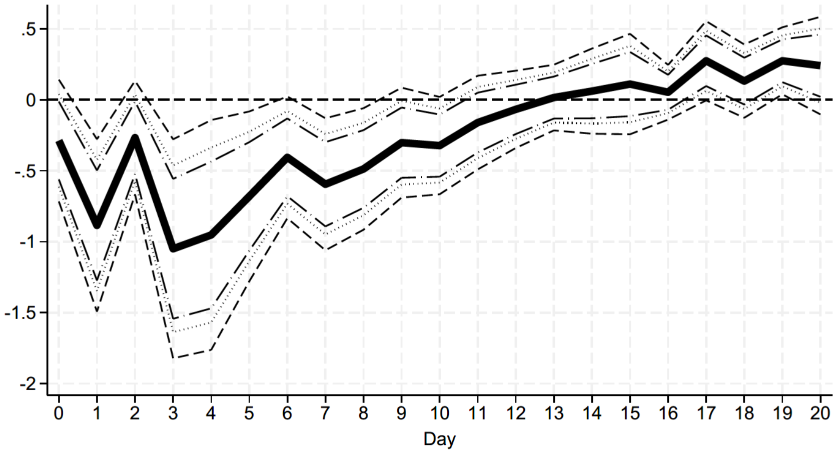
and the VDAX are negative and significant over time. Higher volatility is related to outflows of fragile share-classes compared to less fragile share-classes. While the coefficients on the interaction with the stock market volatility index are comparatively larger, they naturally do not allow a causal interpretation as exogeneity cannot be established - in contrast to the monetary policy surprise, which represents solely the *unexpected part* of a policy decision.

Fragility-identification and granular fixed effects

Next, we test the role of a more stringent identification of fragility to panic-induced withdrawals. In a first check, we use a higher cutoff in the initial step of our analysis, namely $\hat{\gamma}_{1,i} > p90(\hat{\gamma}_1)$. That is, we only identify a share-class as fragile if its individual negative excess return coefficient estimated in Equation 2 is in the highest decile of coefficients (while still satisfying the remaining two conditions). The resulting cumulative response of the net flows of these highly fragile funds to surprise monetary tightening relative to other funds becomes more than twice as large, see Figure A.4. This finding points to the conclusion that the more flighty fund investors are following underperformance in general, the stronger they react to unexpected monetary policy tightening as they are increasingly concerned that other investors' withdrawals will have larger negative externalities for themselves.

A major concern related to our identification of fragile funds is that it is based on the full sample and, as a consequence, funds whose net flows were particularly flighty following negative

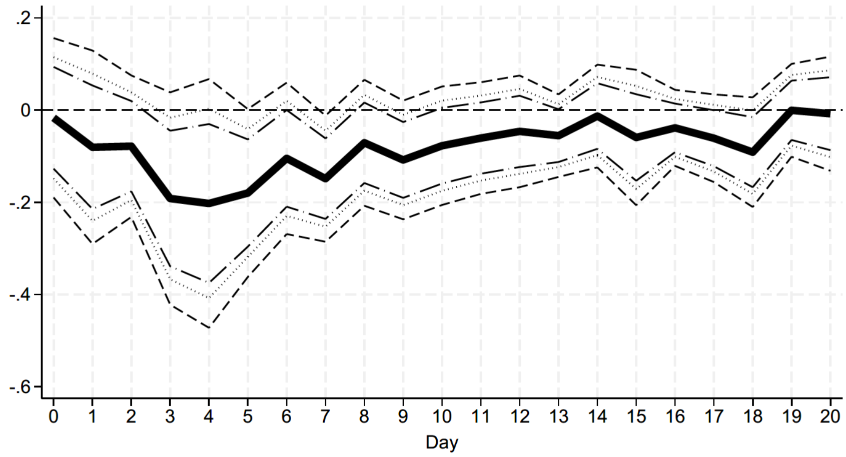
Figure A.4: Flow Reaction of Very Fragile Funds (Top Decile) to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4 but previously using $\hat{\gamma}_{1,i} > p90(\hat{\gamma}_1)$ as a stricter condition for the identification of fragile funds. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

performance shocks during the recent tightening cycle, which dominates at the end of our sample period, could therefore be disproportionally identified as fragile. Thus, our finding that fragile funds' net flows are more responsive to tightening shocks could be an artifact of our time-invariant identification of the measure. In order to mitigate this concern, we investigate if our results are robust to allowing for time-varying fragility by employing rolling-window regressions for the identification of fund fragility. Specifically, we use rolling-window regressions in Equation 2 to get time-varying coefficient estimates for each share-class as well as distributions across all funds, both of which we employ to dynamically sort funds into fragile and non-fragile buckets. The rolling window spans five years, with a minimum length of two years, thereby limiting the role of only recent developments for the identification of fragility and preventing excessive transitions between fragile and non-fragile states for a given share-class while preserving sufficient variation. Over the full sample period, the median number of share-class-specific transitions between these states is three. While we do lose almost a third of the observations in our sample, the procedure ensures that at each monetary policy event, fragility is predetermined, i.e. only preceding observations are relevant for the classification into fragile and non-fragile funds. Figure A.5 presents estimates of the coefficients of interest, β_h, when correspondingly estimating the specification in Equation 4, replacing $Fragile_i$ with a time-varying fragility measure, $Fragile_{i,t}$. The impulse response function confirms the results from our baseline specification. This finding alleviates concerns that the time-invariant nature of our fragility measure may give rise to reverse causality issues.

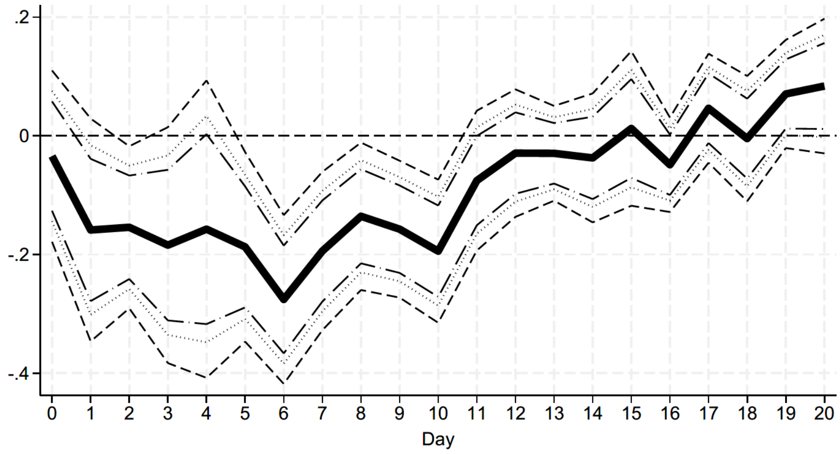
Figure A.5: Flow Reaction of Time-Varying Fragile Funds to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4, replacing $Fragile_i$ with a time-varying fragility measure, $Fragile_{i,t}$. Specifically, we use rolling-window regressions to identify fragility in Equation 2, allowing fragility to vary over time. The rolling window spans five years. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

Finally, a related concern is that performance-sensitive funds might be those funds whose performance is also particularly sensitive to monetary policy shocks. In our baseline local projection framework, we already address this concern by the incorporation of time-varying fund-type fixed effects for the seven broad fund categories, which help to account for time-varying characteristics of e.g. corporate bond funds. As an initial robustness check, we further refine this approach by using more granular fund-type classifications—specifically, approximately 150 Morningstar Categories instead of the seven broad types employed in the main analysis—for the time-by-type fixed effects in the local projection framework to further ensure that we appropriately control for heterogeneous effects of monetary policy on funds' asset values across different fund styles. The results, reported in Figure A.6, are very similar to our baseline impulse response functions. To further work against the concern that our results are driven by the fragility measure itself being affected by monetary policy surprises, we next also adapt our identification of fragility to this setting. Specifically, we demean the share-class specific coefficient estimates from Equation 2, $\hat{\gamma}_{1,i}$ and $\hat{\gamma}_{2,i}$, with the respective average coefficient estimate over all share-classes belonging to the underlying Morningstar Category from these initial regressions before applying our three conditions for identifying fragile share-classes. Thus, we take into account various investment style-specific characteristics already at this stage. Thereafter, we run the local projection specification in Equation 4 and use again the higher-dimensional day-by-Morningstar Category fixed effects. The results in Figure A.7 are again very similar to our baseline estimates. As an ultimate test, we run a specification where in our fragility identification stage, we drop all observations

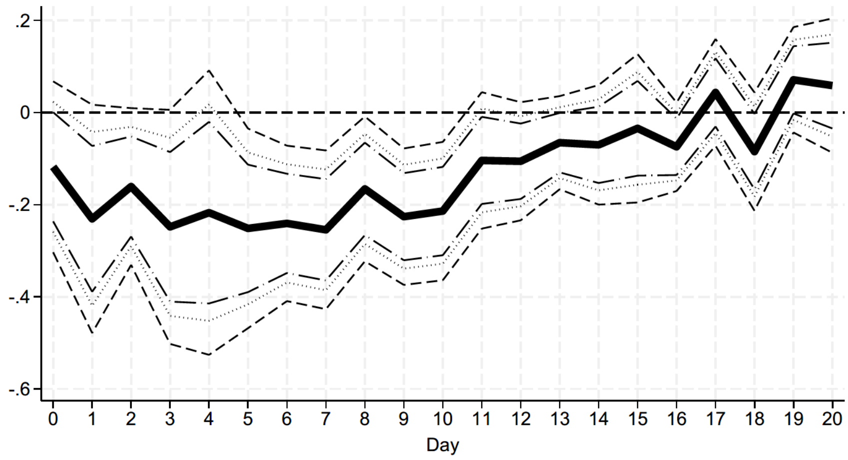
Figure A.6: Flow Reaction of Fragile Funds to Monetary Policy Surprises using Higher-Dimensional Fixed Effects.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4, where $\mu^h_{t,c}$ denotes time times type fixed effects based on more granular fund types, namely roughly 150 Morningstar Categories instead of the seven types used in the main analysis. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

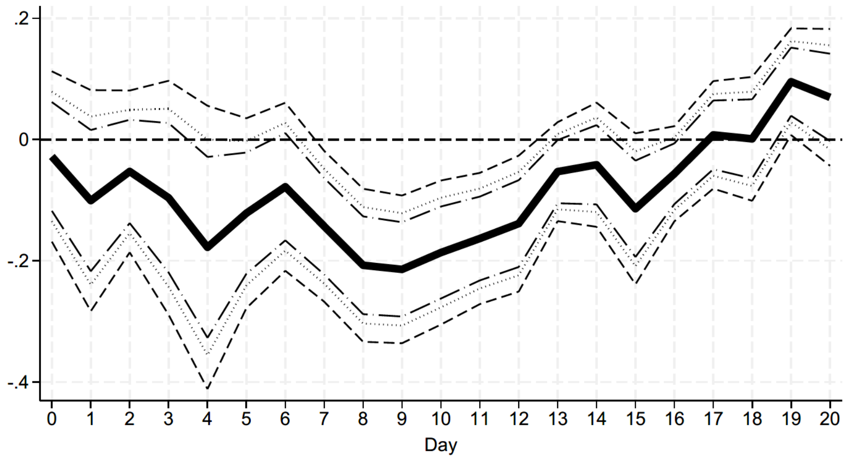
that are within two weeks following an ECB Governing Council monetary policy announcement. The corresponding estimates based on Equation 4 also confirm our baseline results, see Figure A.8. Hence, we mitigate concerns that our findings are driven by the fragility measure being affected by monetary policy surprises.

Figure A.7: Flow Reaction of Fragile Funds, Identified with Demeaned Excess Return Coefficient Estimates, to Monetary Policy Surprises using Higher-Dimensional Fixed Effects.



Notes: Local projection coefficient estimates (solid line) based on (1) demeaning the share-class specific coefficient estimates from Equation 2, $\hat{\gamma}_{1,i}$ and $\hat{\gamma}_{2,i}$, with the respective average coefficient estimate over all share-classes belonging to the underlying Morningstar Category from these initial regressions before applying the three conditions for identifying fragile share-classes and (2) estimating the specification in Equation 4, where $\mu^h_{t,c}$ denotes time times type fixed effects based on the roughly 150 Morningstar Categories instead of the seven types used in the main analysis. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

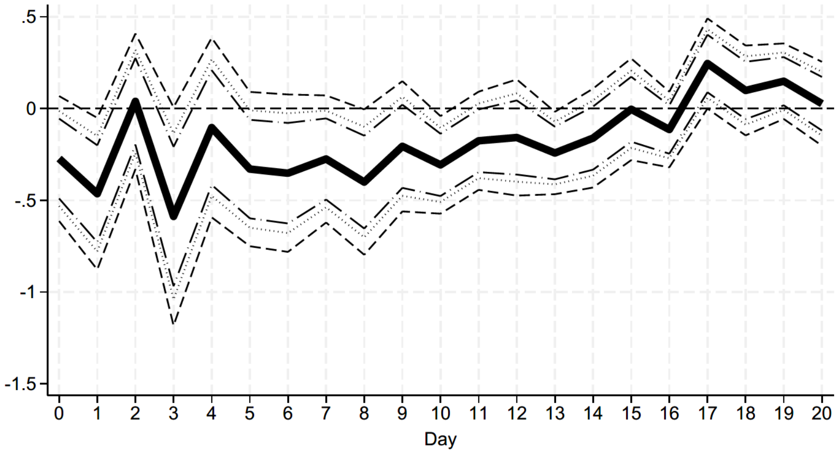
Figure A.8: Flow Reaction of Fragile Funds, Identified Without Observations Shortly After ECB Announcements, to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4 but dropping all observations that are within two weeks following an ECB Governing Council monetary policy announcement in the previous fragility identification stage (Equation 2). Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

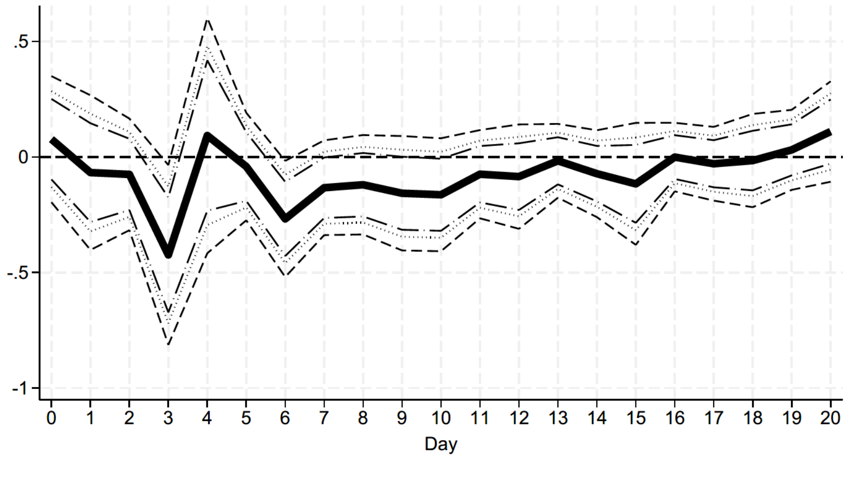
A.3 Subsample analysis of fund types - additional figures

Figure A.9: Flow Reaction of Fragile Corporate Bond Funds to Monetary Policy Surprises.



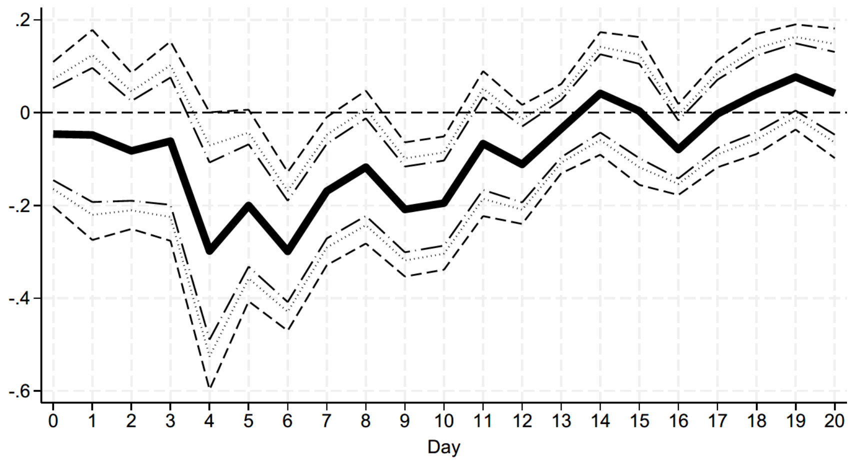
Notes: Local projection coefficient estimates (solid line) based on estimating the specifications in Equations 2 and, to create this chart, 4 for a subsample of corporate bond funds. Corporate bond funds are defined as funds that have more than 50% of corporate bond holdings in their fixed-income portfolio in a respective month. Long dashed, dotted and short dashed lines denote 90%. 95% and 99% confidence intervals, respectively.

Figure A.10: Flow Reaction of Fragile Equity Funds to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specifications in Equations 2 and, to create this chart, 4 for a subsample of equity funds. Equity funds are identified using the Morningstar Global Broad Category. Long dashed, dotted and short dashed lines denote 90%. 95% and 99% confidence intervals, respectively.

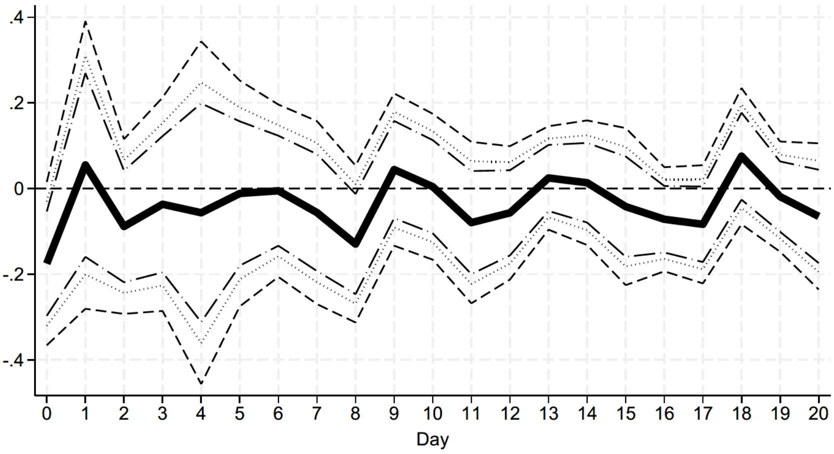
Figure A.11: Flow Reaction of Fragile Allocation Funds to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specifications in Equations 2 and, to create this chart, 4 for a subsample of allocation funds. Allocation funds are identified using the Morningstar Global Broad Category. Long dashed, dotted and short dashed lines denote 90%. 95% and 99% confidence intervals, respectively.

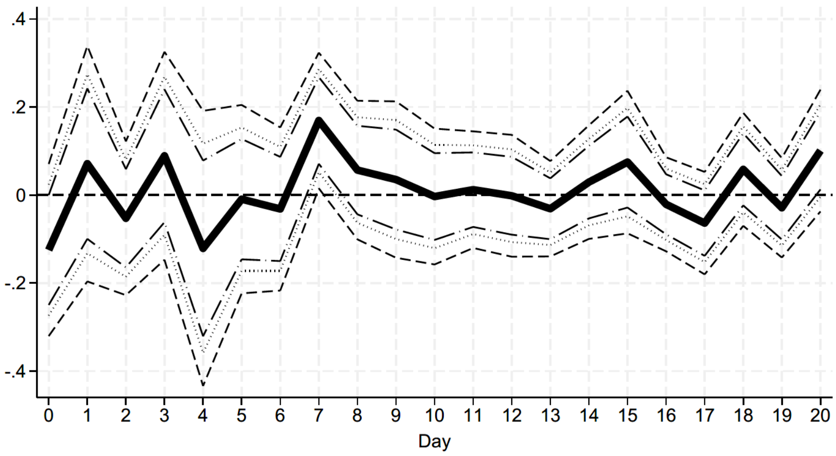
A.4 Analysis of singular fund characteristics - figures

Figure A.12: Flow Reaction of Funds with Elevated Corporate Bond Holdings to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4 for the full sample but replacing the fragility dummy with an indicator variable for elevated corporate bond holdings. The variable equals one if a fund's corporate bond holdings as a share of the fixed-income portfolio in a preceding month are larger than the sample median and zero otherwise. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.

Figure A.13: Flow Reaction of Funds with Low Cash Holdings to Monetary Policy Surprises.



Notes: Local projection coefficient estimates (solid line) based on estimating the specification in Equation 4 for the full sample but replacing the fragility dummy with an indicator variable for low cash holdings. The variable equals one if a fund's cash holdings as a share of the fund's total assets in a preceding month are lower than the sample median and zero otherwise. Long dashed, dotted and short dashed lines denote 90%, 95% and 99% confidence intervals, respectively.