# Liquidity support and distress resilience in bank-affiliated mutual funds

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#### Abstract

Using a unique data set that comprises the security holdings of each systemically relevant bank in the euro area, we show that parent banks purchase fund shares of their affiliated funds when the latter suffer large-scale withdrawals from other investors. This support seems to contain liquidity crises: bank-affiliated funds experience less volatile flows even though they maintain lower cash buffers, and have a lower flowsperformance sensitivity. However, the provided liquidity support strongly depends on the parent banks' stability: we find that poorly capitalized banks purchase significantly fewer fund shares of their affiliated distressed funds. Using the COVID-19 crisis as an exogenous shock, we also show that funds whose shares were in the portfolio of riskier and more affected parent banks not only did not receive liquidity support, but bore the brunt of the banks' deleveraging effort. Moreover, funds more exposed to the UK after the Brexit referendum as well as funds more exposed to Italy during the Italian political turmoil in May 2018 experienced larger outflows if they were 1) unaffiliated, 2) affiliated to a riskier bank, or 3) affiliated to an Italian or UK parent bank. Our results identify novel channels of contagion between banks and shadow banks. They not only show that stable banks are better suited to stabilize their funds in crisis times through direct liquidity support – they also highlight that shocks to parent banks spill over and impair the stability of their affiliated funds.

 ${\rm JEL~codes:~G2;~G23;~G3}$ 

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## 1 Introduction

The interconnectedness between banks and non-bank financial intermediaries is a key challenge for financial stability and a major concern for the effectiveness of macro-prudential policies (European Central Bank, 2020). Due also to secular trends, like population ageing, and the low interest rate environment, asset management companies, in particular investment funds, gained substantially in importance in the last decade (Financial Stability Board, 2020). Investment funds usually have an open-end structure, i.e. investors can redeem their shares at the net asset value, which brings about a first-mover-advantage for withdrawing investors and complementarities in investors' redemption decisions, particularly for funds invested in illiquid assets (Chen et al., 2010). These complementarities can lead to panic-induced fund outflows exacerbating the performance sensitivity of fund flows. In most countries – especially in continental Europe – asset management companies and thus their investment funds are often part of a bank holding company. While the liquidity support of parent banks can mitigate excess volatility in affiliated fund flows and thereby contain funds' fragility (Franzoni and Giannetti, 2019; Fecht et al., 2020), the liquidity support might also affect parent banks' resilience and lead to financial contagion. Moreover, sudden changes in parent banks' ability to provide liquidity support, or suddenly emerging doubts of investors with respect to the banks' willingness to provide support, can lead to excessive fund outflows undermining the stability of investment funds.

In this paper, we empirically study the liquidity support of parent banks to their affiliated investment funds. We study whether this support is able to contain excessive fund flow volatility and performance sensitivity, and whether it leads to detrimental spillovers between banks and their affiliated mutual funds. Using a comprehensive data set on the portfolio composition, performance and flows of 30 thousand European investment funds matched with the proprietary investment fund share holdings of the largest 26 European banking groups on a security by security level for the period 2013Q4-2020Q1, we show that parent banks buy fund shares of their distressed affiliated funds on their own account. Specifically, when an affiliated fund experiences large net withdrawals from other investors, the parent bank purchases fund shares to (partially) offset the liquidity outflow and contain the need to liquidate parts of the funds' portfolio. Since we do not find that banks purchase shares of other distressed funds with which they are not affiliated, the observed investment behavior of banks cannot be explained by a general contrarian trading strategy. This is a novel channel of support not previously identified in the literature. Our results further show that affiliated funds' flows display a lower volatility and a lower sensitivity to negative performance, while at the same time these funds hold lower precautionary cash buffers, which supports the view that indeed the liquidity support from parent banks suppresses negative complementarities in investors' redemptions.

Next, we show that the liquidity support depends' on the parent banks' financial strength. When regressing affiliated funds' cash ratios on parent banks' health proxies, such as their capital ratios and CDS spreads, we find that funds affiliated with less risky

<sup>&</sup>lt;sup>1</sup>Franzoni and Giannetti (2019) provide evidence suggesting that affiliated hedge funds obtain liquidity support, but they do not identify the channels. Fecht et al. (2020) show that German banks direct their clients' portfolio towards shares of distressed affiliated funds, but do not invest in these assets on their own account.

banks maintain a lower cash ratio even when controlling for the fund's investment style, which can be seen as a first evidence of (positive) spillovers of parent banks' health to their affiliated mutual funds. In line with this, we find that in particular well capitalized banks purchase shares of their distressed affiliated funds. At the same time, liquidity provision is absent when many of the bank's affiliated funds experience outflows, suggesting that banks' ability or willingness to assume the risks associated with liquidity support are limited.

Naturally, there are good reasons to expect a lot of unobserved heterogeneity between bank-affiliated and unaffiliated investment funds that might also explain the observed differences in the volatility of flows and in the flows-performance sensitivity. In order to better identify the effect of bank affiliation, we exploit two exogenous shocks to specific segments of the financial markets: the outcome of the Brexit referendum in June 2016 and unexpected distress in the market for Italian sovereign bonds in May 2018 caused by political uncertainty following national elections in Italy. Looking at both events, we find confirmation that, among funds highly exposed respectively to UK financial securities and to Italian government bonds, bank-affiliated funds are insulated from investor withdrawals provided that the parent bank is not exposed to the shock and that it is financially solid. Conversely, we also gather evidence that an increase in bank risk as a result of the exposure to Brexit and to the Italian sovereign is linked to outflows from funds affiliated to the distressed institution even when they do not hold a direct portfolio exposure to the affected assets. This highlights a novel channel of financial contagion and suggests that distress in the banking system spills over to the mutual fund sector via investor expectations on the basis of ownership links.

We also analyse distress in the mutual fund industry in March 2020 as a consequence of the COVID-19 pandemic and show that funds whose shares were in the portfolio of riskier and more affected parent banks did not receive liquidity support, but were part of the deleveraging investment efforts. This highlights the limit of the support provided by parents' banks when a broad-based financial shock occurs.

Our findings make an important contribution to the literature that explores the interrelationships between the different business units of a financial conglomerate and how they affect financial stability. On one hand, we uncover dynamics through which a particular ownership structure of asset management companies can improve the resilience of investment funds and the overall stability of the financial system. On the other hand, we also highlight substantial dependencies between the banking sector and the asset management industry, identifying an important channel of financial contagion via which distress can spread between different segments of the financial system.

The rest of the paper is organised as follows. Section 2 contains a review of the literature. Section 3 describes the data and the two main samples used for the empirical analysis. Section 4 further details the institutional setting and develops the main hypotheses. In section 5 we lay out the methodology and discuss the results. Section 6 concludes.

# 2 Related literature

Our paper is related to various strands of the literature. First, it speaks to the research studying the relationship between flows and performance in mutual funds and strategic

complementarities in fund investors' redemptions. Chen et al. (2010) show that investors in equity funds with illiquid assets (where complementarities are stronger) overreact to bad performance compared to investors in liquid equity funds. This suggests that the illiquidity of fund assets may generate a first-mover advantage among investors, amplifying their response to bad performance. However, this pattern disappears in funds where the shareholder base is composed mostly of large investors, which are more likely to internalize the externalities of large redemptions. Goldstein et al. (2017) present similar findings for bond funds. Our results suggest that the presence of an external "investor of last resort" – such as the parent bank – which would internalize the cost of fund failure (e.g. reputational) similarly mitigates fund investors' first-mover advantage.

Second, our paper contributes to an emerging literature that investigates how financial institutions direct investment from healthy business units to business units in financial distress. Our assessment of the stability of fund flows shares some similarities with the findings in Franzoni and Giannetti (2019). They show that, while financial-conglomerateaffiliated hedge funds perform worse than other hedge funds on average, they also have a lower flow-performance sensitivity, and this difference is particularly pronounced during financial turmoil. Our paper builds on similar findings, but adds novel evidence under two main dimensions. First, we identify a channel via which bank affiliation makes funds more stable, namely banks' direct intervention to purchase shares of distressed funds. Second, we establish a clear link between the support provided by the parents' banks and their financial stability. In this respect, Fecht et al. (2020) also find direct evidence of liquidity support from banks to mutual funds. They show that banks use their distribution network to generate liquidity inflows from their clients into affiliated funds that otherwise experience excessive outflows. However, we go further and analyse how the reliance of funds on a safety net within the conglomerate may lead to financial contagion from the parent bank as bank distress spills over to the conglomerate's asset management arm. Our results also complement the findings in Sialm and Tham (2016), who show that the prior stock price performance of US parent companies is positively correlated with the flows of the affiliated mutual funds.

Other studies find evidence supporting the view that funds derive benefits from their affiliation to a financial conglomerate. Fecht and Wedow (2014) give evidence that banks also provide liquidity support for their troubled open-end real estate funds that are under outflows pressure. Kacperczyk and Schnabl (2013) show that money market funds that were part of a financial conglomerate were more likely to receive direct support from their sponsors in the week after Lehman's bankruptcy.

Our paper is also closely related to other recent studies that investigate conflicts of interest in asset management firms that are part of a financial conglomerate and an opportunistic behavior of multi-unit bank holding companies which could damage affiliated investment funds. Funds could act as funding vehicles for their parent banks: Golez and Marin (2015) provide evidence that Spanish funds support the stock price of the parent bank, in particular after bad news and around seasoned equity offerings. Gil-Bazo et al. (2019) find that the same funds provide funding support to their parent company via purchases of bonds in the primary market, especially in times of financial stress and to riskier banks

with limited access to funding. Additionally, affiliated funds could be used to redistribute risk from the parent bank to unleveraged investors: Bagattini et al. (2018) document that German banks benefited from the support of their mutual funds by shifting risky euro-area sovereign bonds from their portfolio during the sovereign debt crisis. In light of our findings, we argue that these results do not necessarily imply that banks abuse their mutual funds. In fact, most of the findings in this literature are consistent with bank holding companies using the different entities to achieve a mutual liquidity insurance, which could have desirable effects from a financial stability point of view.

Fund managers have also been found to support the bank's lending business by steering their investment policy towards stocks of the bank's clients (Ferreira et al. (2018)) and by overpaying for bank-underwritten IPOs (Ber et al. (2001)), at the expense of the investors in the fund. In contrast, some authors show other examples of how close ties between asset managers and financial institutions can be beneficial to fund investors. Massa and Rehman (2008) offer evidence that bank-affiliated mutual funds benefit of private information obtained by the controlling bank in its lending business with the respective firm. Mola and Guidolin (2009) find that affiliated analysts are likely to assign favorable ratings to stocks that are included in the portfolios of affiliated mutual funds.

Finally, several papers study how liquidity insurance within asset management firms and the optimization of performance at the firm level can generate distortions in delegated asset management and lead to redistribution of wealth across mutual fund investors. Gaspar et al. (2006) and Eisele et al. (2020) show that mutual fund families strategically reallocate performance among sibling funds in order to increase overall family profits. Bhattacharya et al. (2013) find evidence for liquidity insurance within mutual fund families which appears to benefit both the investment firm and the investors of funds suffering liquidity withdrawals, at the expense of the shareholders of the liquidity-supplying funds.

# 3 Data and sample construction

For our empirical analysis, we obtain two key data sets: the first is from the European Central Bank's securities holdings statistics by banking group (SHSG) and reports the proprietary security holdings of the 26 biggest banking groups operating in the euro area. The second data set comprises balance sheet and securities holdings information for open-end mutual funds domiciled in the European Union from Refinitiv's Lipper for Investment Management.

The first sample we construct focuses on banks' holdings of mutual funds' shares. The data set for the securities holdings statistics lists the quarterly holdings of banks on a security-by-security basis for the time period 2013Q4 to 2020Q1. For our analysis, we filter for all instruments that are classified as investment fund shares (instrument ESA classification F511), which include mutual funds, ETFs and (in minor part) other fund types, such as private equity funds and hedge funds. As our analysis focuses on mutual funds, we use the ECB's investment fund statistics and Lipper to identify the fund type and keep only mutual funds, while dropping ETFs and other fund types. Then, we use a hand-collected matching list to match banks to their affiliated asset management companies, i.e. to asset management companies which are fully owned or majority-owned by the parent

bank, and ultimately to the asset management companies' mutual funds. In doing so, we take into account changes in the ownership structure of asset management companies that occurred during the sample period.

In total, the 26 banks hold 25,490 different investment fund share classes (identified by their ISIN) over the sample period. We match the bank holdings on a security-quarter basis with fund data from Lipper such as size, flows, performance and cash holdings. We find that 87% of the funds are covered in Lipper, although additional reporting gaps occasionally occur for single attributes, and keep a final 15,788 ISIN identified as mutual funds. While for 3 banks none of these funds are affiliated to them, affiliated funds represent a significant part of the other banks' mutual fund portfolios. Figure 1 shows that, in aggregate, the market value of shares of affiliated funds held by the parent banks is similar to the market value of all other mutual fund shares in the portfolio of the 26 banking groups.

We are interested in identifying fund flows (share redemptions and purchases) generated by banks in our sample, and distinguishing them from flows ascribable to all other investors. First of all, net flows at the fund share class level over a quarter are provided by Lipper on the basis of the following formula, which uses the evolution of a fund's total net assets (TNA) while netting out the assets' return:

Share-class flows<sub>kt</sub> = 
$$TNA_{kt} - TNA_{kt-1} \times R_{kt}$$
 (1)

where k denotes the fund share, t denotes the quarter, and  $R_{kt}$  is the gross return of the fund's portfolio in period t. Typically, share withdrawals and purchases across different share classes of the same fund are pooled together and netted, after which the necessary amount of securities is purchased or sold by the manager in order to meet investor flows. As a consequence, our variable of interest is percent flows at the fund level. We calculate this quantity via the following formula:

Fund flows<sub>jt</sub> = 
$$\left(\sum_{k=1}^{K_j} \text{Share-class flows}_{kt} \middle/ \sum_{k=1}^{K_j} \text{TNA}_{kt-1} \right) \times 100,$$
 (2)

where we sum the total net flows over all share classes  $k \in \{1, ..., K_j\}$  belonging to fund j, and we scale the total net flows by the fund's aggregate assets over all share classes.<sup>2</sup>

To construct fund flows generated by a single investor (in this case, a bank), we calculate the implied return  $R_{kt}$  of equation (1) from the flows and size provided by Lipper, and we use it to account for quarter-on-quarter changes in the market value of the fund shares held by the bank which are not due to share redemptions or investment:

Bank flows<sub>ijt</sub> = 
$$\sum_{k=1}^{K_j} \left( \frac{\text{Market Value Held}_{ikt} - \text{Market Value Held}_{ikt-1} \times R_{kt}}{\sum_{k=1}^{K_j} \text{TNA}_{kt-1}} \right) \times 100 \quad (3)$$

where each of the addends of the outer sum represents percent flows generated by bank i by buying or selling fund share k. In this way, we obtain a quantity with the same unit

 $<sup>^2</sup>$ After this step, we drop any observation where the resulting percent flow is greater than 200% or less than -60%. Flows of that size are rare and are typically related to structural changes in the fund, e.g. mergers (cf. Coval and Stafford (2007)).

of measure as the fund flows computed in (2), with the difference that the percent flows in formula (3) are those generated by a single investor (bank i) by trading in fund j.<sup>3</sup>

Finally, we aggregate all flows generated by the banks in our sample at the fund level to obtain our last key variable, i.e. fund flows generated by outside investors:

Non-bank flows<sub>jt</sub> = Fund flows<sub>jt</sub> - 
$$\sum_{i=1}^{26} \text{Bank flows}_{ijt}$$
. (4)

Computing the flows from outside investors by deducting the flows from each bank  $i \in \{1, ..., 26\}$  from the total flows allows us to obtain a variable at the fund j and quarter t level, independent of bank i. Exogeneity with respect to the sample of bank holdings is key to identifying the effect of Non-bank  $flows_{jt}$  on the investment decisions of different banks.

Panel A of Table 2 presents summary statistics for this sample. The contribution to fund flows stemming from banks' trades is null in approximately two thirds of the observations, reflecting periods when banks simply hold the fund shares. However, in around 5% of the overall observations, banks execute sizeable trades which generate flows amounting to over 1% of the fund's total assets under management. The mutual funds in banks' portfolios that are affiliated to the holding bank make up 17% of the observations. Given that according to Figure 1, conversely, affiliated funds outweigh other funds in market value terms, this implies that bank holdings of affiliated funds tend to be larger. On average across the sample, banks own shares amounting to 2% of a mutual fund's value.

The second sample focuses on mutual funds domiciled in the European Union and it is drawn from Lipper at a monthly frequency, subsequently aggregating different share classes into a single fund. We download time-invariant fund attributes – such as asset type, investment style, client type (institutional or retail), management company – as well as time-varying characteristics such as portfolio allocations, size, performance, and flows at a monthly frequency.

Lipper also lists the ultimate parent of a fund's management company. However, this attribute is static and isn't always accurate. Therefore, we manually validate the information given by Lipper and research possible changes in ownership during the sample period in holding companies' accounts, management companies' websites and financial news outlets. To be able to do this, we limit our search to those parent companies (as initially provided by Lipper) which, for at least one month, are either associated to at least 20 mutual funds or whose funds' TNA exceeds €5 billion.

The resulting sample covers 85% of the mutual funds registered in Lipper, and 95% of their TNA. We drop closed-end mutual funds, funds that track an index and private funds, as well as real estate and commodities funds, and we are left with 31,903 primary mutual funds. Of these, we exclude from our analysis 2,056 small funds with TNA under €5 million. Our final sample is composed of 33% equity funds, while 31% are classified as mixed-assets, and bond funds make up 26% of the observations. 6% are alternative assets funds and 4%

 $<sup>^3</sup>$ To temper the effect of outliers, of micro-funds and of possible inconsistencies between the market values provided by Lipper and those reported in the SHSG, we execute a number of data cleaning steps: we drop observations whenever the bank flows are greater than 90% or lower than -90%, when the implied return  $R_{jt}$  is greater than 1.3 or lower than 0.7, when the market value held by a bank exceeds the aggregate fund value, and when the aggregate fund value is lower than €5 million.

money market funds. The funds' assets under management increase from  $\leq$ 4.8 trillion at the beginning of the sample in January 2014 to  $\leq$ 7.6 trillion in the last month of March 2020.

Figure 2 shows that affiliated funds make up the better part of the open-end mutual funds industry in Europe. They represent between 57% and 65% of the total and hold over half of the aggregate TNA. Our sample contains funds domiciled in 25 countries (all the EU28 countries with the exception of Croatia, Bulgaria and Romania). Overall, more than one third of the funds are domiciled in Luxembourg, 12% are domiciled in France, followed by Great Britain, Spain, and Ireland. Figure 3 shows that, also in terms of assets under management, Luxembourg is home to the largest share of both affiliated and unaffiliated funds. As Luxembourg-domiciled funds are mostly owned by foreign asset management companies or by Luxembourgian subsidiaries created ad-hoc, the picture changes when we look at the nationality of the funds' ultimate parents. As it emerges from Figure 4, the United States are among the most important countries which host banks and other financial corporations owning European mutual funds. In terms of banking conglomerates, the relative majority of funds by TNA is ultimately ascribable to French holding companies. Among non-EU countries, also Switzerland plays an important role, being host of a number of universal banks as well as banks focusing on private wealth management which lead sizeable asset management businesses.

In this sample, we do not have securities holdings information for all the parent banks. Therefore, instead of looking for direct evidence of liquidity support to affiliated mutual funds, we study the effect of bank affiliation on the overall behavior of fund investors, which is reflected in fund flows and in funds' management of cash buffers. On top of focusing on the distinction between bank-affiliated funds and funds belonging to independent asset management companies or to non-bank financial conglomerates, for those funds that are affiliated to a bank, we also examine the influence of the parent bank's financial health and portfolio composition. To this end, we merge a subsample of the bank-affiliated funds with key items from their ultimate parent's balance sheet, drawn from the COREP and FINREP datasets of euro area significant institutions (SIs) and less significant institutions (LSIs). In particular, our analysis uses banks' capital and liquidity ratios and their on-balance-sheet exposure to specific countries in percentage of total assets. We are able to match between 40% (liquidity coverage ratio) and 59% (capital ratio) of the observations in our sample of affiliated funds. Finally, we also retrieve CDS spreads from Refinitiv's Eikon for all banks in our sample, whenever these are available, matching 51% of bank-affiliated funds.<sup>4</sup> As a result, over 70% of affiliated funds are matched to at least one of the three measures of parent bank solidity (capital, liquidity and CDS spread).

The raw data at the share class level also contain an indicator for whether the fund is open to retail investors or dedicated to institutional investors, with the latter being the case in approximately one fourth of the observations. In our data at the fund level, we collapse this variable into a value-weighted average, representing the fraction of fund assets that are owned by institutional investors.

Panel B of Table 2 presents summary statistics for this sample, broken down into

<sup>&</sup>lt;sup>4</sup>We use CDS with a 5-year tenor, as these are usually the most liquid contracts.

affiliated and non-affiliated funds in order to facilitate a comparison between the two groups. Affiliated funds are smaller (median TNA of €71 million versus €94 million) and cater to a lower proportion of institutional investors (on average 16% of TNA versus 24%). Affiliated funds tend to have slightly lower fees, but they also appear to underperform compared to unaffiliated funds both in terms of raw returns and in terms of risk-adjusted returns (Jensen's alpha). However, as both return measures also display a lower standard deviation in affiliated funds, their underperformance might be due to unaffiliated funds being more risky as well as differentiating their investment strategy to a higher extent from the provided benchmark.

Our two samples allow us to conduct two sets of distinct but complementary analyses. With the bank holdings sample we gather direct evidence of one of the mechanisms that banks use to provide a liquidity backstop to affiliated funds for a subset of the largest institutions (which nevertheless represent a large share of the banking and asset management businesses in Europe). The monthly sample, thanks to the larger fund cross-section, allows us to study how the mechanisms identified in the first sample translate into widespread peculiarities of fund flow dynamics and liquidity management in affiliated funds as opposed to their unaffiliated peers.

# 4 Institutional background and hypotheses

Easy redemption options in mutual funds can create run risks because investors have an incentive to exit faster than the others given that the liquidation value of fund shares declines the longer investors wait to exit. This decline in value happens because asset managers may deal with large redemptions by using cash buffers and by selling relatively more liquid assets first. Additionally, if the costs of selling assets is passed on to the remaining investors, such effects are intensified for funds investing in relatively less liquid assets.

First, we exploit our Lipper sample and analyze whether affiliated funds are more resilient to underperformance, as a result of fears of runs among investors failing to materialize thanks to the liquidity insurance function provided by the parent bank. If this is true, the sensitivity of flows to past bad performance should be attenuated, as investors' decisions will depend less on the expectations around their peers' actions. Furthermore, while funds' illiquidity has been shown to aggravate the first-mover advantage and hence increase the sensitivity of flows to underperformance (Chen et al. (2010) and Goldstein et al. (2017)), illiquidity should not play a role in funds whose investors are not worried about strategic complementarities as they will react only to performance per se. Our conjecture as to the role of bank affiliation is summarized in the following hypothesis.

**Hypothesis 1:** Outflows are less sensitive to bad past performance in affiliated funds than in comparable unaffiliated funds. Additionally, while flows-to-performance sensitivity is relatively higher if a non-affiliated fund is illiquid, illiquidity does not affect sensitivity in affiliated funds.

Another indicator that a fund is more stable and less prone to cyclicality and shocks than its peers is the volatility of its flows. If the parent institution provides liquidity support to the fund in case of distress, we expect its flows to be less volatile for two reasons. First, if the parent bank carries out fund share purchases, it behaves as a contrarian investor and helps smoothing fund flows. Second, if investor expect that the fund can rely on a "free" liquidity insurance from an investor of last resort, then their reaction to other investors' non-informative withdrawals and other temporary market stimulus should be muted as it will not be driven by strategic complementarities in withdrawals. We therefore formulate the following hypothesis.

**Hypothesis 2:** Flows of bank-affiliated funds are less volatile than flows of comparable funds that are not affiliated to a bank.

Finally, we study the funds' holdings of cash and cash equivalents. In general, asset managers appear to actively manage their liquidity risks with precautionary cash buffers in view of possible idiosyncratic or systematic outflow pressures. IMF (2015) finds that funds hold higher cash buffers when they face more volatile flows from investors (in line with a precautionary motive) and when these investors are primarily less stable retail investors. However, holding cash is costly as fund managers forgo profitable investment opportunities. On the other hand, if funds can count on stable sources of liquidity, such as repos with an institution at favourable prices, then presumably they can set their precautionary cash buffer at a lower level. Following the above line of reasoning, we formulate the following hypothesis.

**Hypothesis 3:** Other things equal, bank-affiliated funds hold a lower cash buffer than unaffiliated funds.

Parent banks can step in to provide liquidity to distressed funds, in the context of a mutual liquidity insurance scheme and because they would internalize part of the losses if they already hold a stake in the fund. An emergency intervention by the mother institution can prevent that the fund deplete its cash buffers, decrease the quality of its asset portfolio and incur liquidation costs, thereby contributing to attenuate strategic complementarities and defuse risks of an investor run on the fund.

Banks have substantially three ways to provide support to affiliated funds in periods of stress: they can do so by providing liquidity via lending, for example in the form of repurchase agreements; by buying illiquid securities that the fund manager intends to sell off; or by directly purchasing the fund's shares. In this paper we focus on the last contingency. In particular, we formulate the following hypothesis.

**Hypothesis 4:** Banks tend to purchase shares of distressed affiliated funds that are experiencing excessive outflows.

It is sensible to expect that not all banks can effectively put in place support mechanisms to prevent distress at their affiliated mutual funds. Firstly, not all banks might have the opportunity to enlarge their investment portfolio purchasing fund shares in response to unexpected liquidity shocks. Indeed, investing in mutual funds likely causes an increase in the bank's risk-weighted assets (unless it is matched by a correspondent divestment from similar assets), thereby driving down regulatory capital ratios and possibly forcing the bank

to set aside more equity to prevent a capital shortfall. The appetite for banks to intervene on the mutual funds' market might also rest on their available liquidity. As it is easier for banks to purchase additional fund shares by using their available liquidity than by liquidating part of their securities portfolio, banks with a higher liquidity ratio might be more prone to step in in case of affiliated funds' liquidity crisis. This reasoning leads us to the following hypothesis:

**Hypothesis 5:** The strength of banks' support to affiliated funds via share purchases in case of excessive outflows is positively correlated to their capital and liquidity ratios.

So far, our hypotheses reflect the view that funds that belong to banking conglomerates are perceived to be more stable by investors. This should be particularly true if the parent bank is financially solid. This is in line with the findings in Sialm and Tham (2016), which show that prior performance of the management company's stock spills over to the affiliated mutual fund flows even though it has no correlation with the subsequent performance of the funds. However, the effects of this perceived stability in the event that distress materializes are a priori not clear, not least because it might give rise to adverse incentives in the fund management. For instance, the existence of a potential safety net within the financial conglomerate of bank-affiliated funds may lead managers at these funds to lower the cash buffer, leaving the funds more fragile in the event of abnormal withdrawals in case the parent institution is not actually willing or able to intervene. For this reason, next we study the impact of unexpected shocks which exogenously affect a specific segment of affiliated and unaffiliated funds. We conjecture that bank-affiliated funds would be more shielded from shocks which do not affect their parent bank, or which their parent bank is expected to withstand because of its financial solidity. As a consequence, under these conditions, affiliated funds are expected to be in a better position to withstand the negative shock.

**Hypothesis 6:** In the aftermath of a common negative shock in financial markets to which they are exposed, funds affiliated to banks not exposed to the shock tend to experience less outflows than comparable unaffiliated funds. This is especially true if the parent bank is financially solid.

The motivation for all the previous hypotheses lies in the view that the existence of a banking conglomerate exerts a positive influence on affiliated funds, ultimately because the potential liquidity support provided to the funds by the parent company changes investors' optimal behavior in equilibrium. However, the existence of this potent channel that works via investor expectations suggests that the same channel might also operate in reverse. Specifically, if the financial health of a bank suddenly worsens following a crisis, investors might decide to flee its affiliated funds because the shock that hit the bank means that the protection that it had been providing to its funds ceases to exist. Further, fund investors might fear that deteriorating financial conditions at the bank could draw resources from the other parts of the conglomerate, and possibly lead to defaults. For these reasons, we conjecture that distress in the banking arm spills over to the asset management arm, affecting funds that would otherwise be insulated from the shock.

**Hypothesis 7:** In the aftermath of a financial shock affecting banks, a contagion effect from the banking side to the asset management side of financial conglomerates occurs, with the

result that mutual funds with no direct portfolio exposure to crisis assets which are affiliated to exposed banks experience abnormal outflows.

# 5 Results

## 5.1 Flows and cash management in affiliated funds

We start by studying the impact of bank affiliation on investor behavior. Our key dataset for the following analysis contains mutual funds domiciled in the European Union that are reported in Lipper.

One way in which investor behavior is reflected in observable characteristics is the sensitivity of fund flows to performance. Typically, investors evaluate mutual funds based on past performance and flock to those that outperformed their peers in relatively recent periods, while withdrawing their investment from those that performed poorly. Previous literature also highlights that there are important differences between the behavior of retail investors and that of institutional investors in this context (see e.g. Goldstein et al. (2017)). While institutional investors are more sensitive to underperformance (likely as a result of increased monitoring), they are less sensitive to the composition of the fund's portfolio.

If parent banks act as stabilizers of their funds in bad times, attenuating strategic complementarities in redemptions, we expect the effect of bad performance on flows to be more moderate in affiliated funds, and especially we expect the type and liquidity of the fund's assets to matter less. In order to disentangle the effect of bank affiliation from that of institutional investors, in the empirical analysis we disregard those funds which have a large share of institutional ownership.<sup>5</sup> We test this conjecture via the following regression:

Fund flows<sub>jt</sub> = 
$$\beta_1 \cdot \text{Alpha}_{j,t-1} \times \mathbb{1}_{\text{Alpha}_{j,t-1} > 0} + \beta_2 \cdot \text{Alpha}_{j,t-1} \times \mathbb{1}_{\text{Alpha}_{j,t-1} < 0}$$
  
+  $\beta_3 \cdot \text{Alpha}_{j,t-1} \times \mathbb{1}_{\text{Alpha}_{j,t-1} > 0} \times \text{Affiliated}_{jt} +$  (5)  
$$\beta_4 \cdot \text{Alpha}_{j,t-1} \times \mathbb{1}_{\text{Alpha}_{j,t-1} < 0} \times \text{Affiliated}_{jt} + Controls_{jt} + \gamma_{kt},$$

where  $Alpha_{j,t-1}$  is fund j's "alpha" over quarters t-2 and t-1 calculated via a one-factor model that uses as a benchmark the fund's Lipper Global classification group, and  $\gamma_{ft}$  represents sets of dummies for each combination of month t and fund style f. We define fund style as a set of three characteristics: asset type, geographical focus and classification group. Including these fixed effects allows us to benchmark the sensitivity of flows on a sample of funds that are similar in terms of asset composition and investment objective. Time-varying fund controls include a lag of fund flows, the logarithm of TNAs, the total expense ratio, the age of the fund and the proportion of institutional investors.

In the above regression, positive  $\beta_1$  and  $\beta_2$  identify the typical flows-performance relation found in the asset management industry, as investor demand for a fund respectively increases following good performance and decreases following bad performance. On the

 $<sup>^5 \</sup>rm We$  proxy institutional ownership of a fund via the presence of share classes dedicated to institutional investors, and drop funds where these share classes cover more than 40% of the fund's TNA (amounting to 21% of the original observations).

other hand,  $\beta_3$  and  $\beta_4$  measure whether the sensitivity of flows to performance is different in bank-affiliated funds in comparison to non-bank-affiliated ones.

Table 3 presents the results. Column (1) shows that, coherently with the literature on mutual fund flows, past performance, as measured by the fund's alpha over the previous six-month period, is a strong predictor of fund flows regardless of its sign (coefficients of 6-month alpha interacted with sign dummies). The reaction to negative performance is slightly larger than to positive: one standard deviation lower alpha translates into 0.44 percentage points higher monthly outflows. However, in the case of bank-affiliated funds, the sensitivity to negative performance decreases by 38%, and there is also a significant difference in flows sensitivity following outperformance (27% reduction).

Investors' behavior may differ a lot across the different asset classes in which funds invest. First of all, the asset class of the securities largely determines the liquidity of a fund's portfolio, which in turn influences strategic complementarities. Additionally, Goldstein et al. (2017) document that outflows are more sensitive to underperformance of corporate bond funds than are inflows to outperformance, while this relation has been found to be frequently convex in equity funds. For these reasons, to get a deeper insight into investors' behavior, we re-run the regression separately by fund type. In columns (2) to (4), we split the sample respectively in equity, bond and mixed-assets funds. First of all, the sample split reveals that the flows-to-performance sensitivity estimated for unaffiliated funds is considerably higher in bond funds than in equity and mixed assets funds (0.30 versus 0.14-0.17 for outperformance and 0.21 versus 0.16 for underperformance). As bond funds are on average more illiquid than their counterparts investing in equities, this finding is consistent with previous literature uncovering evidence that retail investors in illiquid funds tend to be more sensitive to past performance. Second, looking at affiliated funds, it is clear that the lower sensitivity to negative performance identified in the full sample mostly originates from investors in bond funds (opposing negative coefficient of -0.1), while there is only a small difference with respect to outflows following underperformance at affiliated compared to unaffiliated equity (-0.03) and mixed-assets (-0.04) funds.

In column (5), the same regression for alternative-assets funds – which may often be particularly illiquid – reveals a heightened sensitivity to bad performance in unaffiliated fund investors (0.35), but again this is not the case in affiliated funds (offsetting coefficient of -0.28). Finally, in the small sample of the more liquid money market funds we don't find statistically significant outflows following underperformance (column (6)).

In summary, the analysis of model (5) yields two main insights. First, investors at bank-affiliated funds seem less inclined to run away following underperformance. Second, while for unaffiliated funds we find confirmation for the result that outflows following underperformance are particularly marked when the fund holds generally more illiquid assets, investors of bank-affiliated funds seem not to care about the composition of the fund's assets (and thus about their market liquidity) when reacting to bad performance, as outflows at these funds follow underperformance to a similar extent in equity, mixed assets and bond funds (net sensitivities are 0.13, 0.13 and 0.11 respectively).

Another sign that mutual funds have a more stable and less pro-cyclical investor base is the volatility of their flows, which we would expect to be lower in affiliated than in other

comparable funds, as stated in Hypothesis 2. As flows react to performance, we also expect a more volatile return to correlate with more volatile flows. Thus, we estimate the effect of bank affiliation on fund volatility, controlling for the standard deviation of fund returns as well as other fund characteristics:

$$\sigma(\text{Flows})_{jt} = \beta_1 \cdot \text{Affiliated}_{j,t-12} + \beta_2 \cdot \sigma(\text{Return})_{jt} + Controls_{j,t-12} + \gamma_{ft},$$
 (6)

where we compute the standard deviation of monthly flows over the 12 months to month t and the standard deviation of monthly fund returns over months t-12 to t-1. Also in this estimation, we focus on funds which are predominantly retail, where the weight of institutional-oriented share classes does not exceed 40% of the fund's TNA.

Table 4 presents the results of the estimation of (6) testing Hypothesis 2. In column (1), we start by including only month fixed effects. As expected, we find evidence that funds with more volatile performance have more volatile flows ( $\beta_2 = 0.17$ , p < 0.01). In addition to this, flows of affiliated funds are markedly less volatile ( $\beta_1 = -0.27$ , p < 0.01). Time-varying fund style fixed effects only partly explain this difference ( $\beta_1 = -0.13$  in column (2), p < 0.05). In both specifications, a high share of institutional investors is also associated with more volatile flows. Flows of bigger, more expensive and older funds instead fluctuate less.

In columns (3) and (4), we add fund fixed effects to the estimation. This allows us to identify the effect of affiliation specifically for those funds whose affiliation status changed over the sample period. In other words, we look at the question of whether a change in ownership of a mutual fund has an impact on the variability of its flows. The effect of becoming bank-affiliated (resp. unaffiliated) is estimated to be stronger than before and statistically significant and decreases (resp. increases) the volatility of fund flows by 0.37, or 11% of the sample mean, in the estimation with month-fund style fixed effects. In this within-fund estimation, the volatility of performance does not have a significant impact on the volatility of flows. Finally, column (5) shows that when an interaction term between affiliation and return volatility is added, affiliation has a double effect. On the one hand, it is again associated with lower volatility overall (negative coefficient of Affiliated). On the other hand, it also reduces the sensitivity of the volatility to past performance. This is again positive for unaffiliated funds (coefficient of  $\sigma(Return)$ ), but drops when a fund becomes affiliated, stabilising the fund's investor base (negative coefficient of Affiliated  $\sigma(Return)$ ).

A low volatility of fund flows is a desirable characteristic for fund managers because it reduces the thickness of the precautionary cash buffer that they have to hold in order to meet unexpected outflows, thereby freeing up resources that can be invested in risky assets to increase the fund's expected return. An additional channel via which funds can benefit from the parent bank's role as investor of last resort is the following: if managers know they can rely on an emergency liquidity intervention, then they do not need to hold as much cash on a regular basis. We test this hypothesis by using the portfolio's cash percent allocation as a dependent variable, and estimate the following regression on the same sample

of predominantly retail funds as before:

$$\operatorname{Cash}_{jt} = \beta_1 \cdot \operatorname{Affiliated}_{jt} \times \operatorname{Alternatives fund}_j + \beta_2 \cdot \operatorname{Affiliated}_{jt} \times \operatorname{Bond fund}_j + \beta_3 \cdot \operatorname{Affiliated}_{jt} \times \operatorname{Equity fund}_i + \beta_4 \cdot \operatorname{Affiliated}_{jt} \times \operatorname{Mixed fund}_j + \operatorname{Controls}_{jt} + \gamma_{ft},$$
(7)

where  $Cash_{jt}$  is the level of cash the fund is holding in percent of total assets at the end of month t. Fund controls include the volatility of monthly fund flows  $\sigma(Fund\ flows)_{jt}$ , computed over months t-11 to t, the contemporaneous flows, as well as the log of fund TNA and age, the total expense ratio, institutional ownership and six-month alpha.<sup>6</sup>

Table 5 presents the results of the estimation. First, we run regression (7) with simply time fixed effects (column (1)). The control variables reveal that larger, cheaper, and older funds hold less cash (not shown). Also the volatility of flows is positively related to cash holdings. Taking equity funds as the base category, the estimation shows that the other three categories all hold higher level of cash on average, coherently with the fact that funds holding less liquid assets ought to insure themselves against extreme outflows. Unaffiliated alternatives funds allocate to cash a striking 13.59% more than equity funds, likely to balance their investment in particularly illiquid assets. The cash buffer of bond funds exceeds that of equity funds by 1.81 percentage points. The excess is 5.01 percentage points for mixedassets funds, suggesting that, behind the generic denomination, some funds in this category may also invest in illiquid assets to a greater extent than bond funds. Looking instead at affiliated funds, equity funds and funds investing in alternative assets are able to limit their cash holdings, with the latter having on average 4.95 percentage point lower buffers than their unaffiliated peers. Next, in order to compare funds with a more similar portfolio composition, we test a more restrictive specification including month-fund style fixed effects, which also absorb the average cash holdings of funds by asset type. Column (2) shows that this estimation confirms the result that affiliated equity and alternatives funds hold less cash, while this now holds also for mixed-asset funds. Only for bond funds is there no significant difference.

Another way of assessing the effect of bank affiliation on funds' capacity to slim down their cash holdings while assuaging the concern that this be due to differences in portfolio composition is to perform a within-fund estimation, exploiting those funds whose company's structure changed as a consequence of a merger or an acquisition. This allows us to study how becoming bank-affiliated changes the fund's liquidity management strategy. In column (3) we do this by testing regression (7) with fund fixed effects. Although for the other asset classes the coefficients turn non-significant, the estimation reveals that, after being acquired by a bank holding company or by a financial conglomerate including a bank, bond funds decrease their cash buffer by 1.37 percentage points on average (p<0.05).

Funds which can afford to hold lower cash buffers are purportedly those that can rely on direct liquidity support from the parent institution. Our hypotheses posit that the capacity of banks to provide liquidity support be positively related to their financial solidity. Therefore, it is natural to test whether funds' cash allocation is affected by balance-sheet and/or market-based measures of the parent bank's financial solidity. Restricting the sample

 $<sup>^6</sup>$ We exclude money market funds as these funds hold mostly liquid assets and cash-like assets customarily as part of their investment strategy.

to bank affiliated funds, we estimate the following regression:

$$\begin{aligned} \operatorname{Cash}_{jt} &= \beta_1 \cdot \operatorname{Capital\ ratio}_{j,t-1} \times \operatorname{Alternatives\ fund}_j + \beta_2 \cdot \operatorname{Capital\ ratio}_{j,t-1} \times \operatorname{Bond\ fund}_j + \\ \beta_3 \cdot \operatorname{Capital\ ratio}_{j,t-1} \times \operatorname{Equity\ fund}_j + \beta_4 \cdot \operatorname{Capital\ ratio}_{j,t-1} \times \operatorname{Mixed\ fund}_j + \operatorname{Controls}_{jt} + \gamma_{ft}, \end{aligned} \tag{8}$$

where we use the quarterly supervisory data on Tier 1 capital ratio for the subsample of banks for which they are available. Column (4) of Table 5 shows that each percentage point increase in the parent bank's capital ratio corresponds to 0.19% lower cash holdings in bank-affiliated bond funds and 0.18% in mixed funds. As before, more volatile flows lead to higher cash holdings, but the corresponding coefficient is larger than in the previous sample: now, a one-standard-deviation higher volatility leads to an additional 0.57 percentage points of cash buffer ( $\simeq 0.123 \times 4.65$ ). Thus, next we address the question whether volatile flows increase cash buffers in the same way irrespective of the parent bank's solidity. We do this by adding to the regression an interaction term between volatility and capital ratio. As a matter of fact, from column (5) it emerges that a higher bank capitalisation leads to a smaller influence of the volatility of outflows on the safety buffer (negative coefficient of Capital ratio  $\times \sigma(Flows)$ ). Column (6) shows that the standalone effect of the bank's capital ratio does not hold in the within-fund estimation, which might be due to its relative stability over time. Nevertheless, a high level of capital is still significant in determining a dampened sensitivity of cash buffers to flow volatility.

Finally, we run a sort of robustness test by replacing the bank capital ratio with the CDS spread. The motivation for this is twofold: first, since neither of the two variables is available for all banks, the two estimations are run on two different subsets of our sample of affiliated funds that are not completely overlapping. Second, the CDS spread is arguably a better measure of investors' perception of financial solidity of a bank, because it captures expectations of financial markets as to a possible default of the institution and it instantaneously incorporates innovations. Testing regression (8) with the CDS spread yields again evidence that bond funds of banks that are considered to be more solid (lower CDS spread) afford to keep lower cash holdings (columns (7) and (8)), while a lower CDS spread also induces a lower sensitivity of cash to the volatility of flows (column (8)). Only in the withinfund estimation is the CDS spread not significant in explaining cash holdings directly, but it still reduces the overall sensitivity of cash to flows volatility (column (9)).

In conclusion, these results suggest that the solidity of the parent bank, described by well-established measures of financial health such as the capital ratio and the CDS spread, is important in determining its ability to step in to support distressed affiliated funds, as well as in cementing the corresponding perception of stability among fund investors.

# 5.2 Banks' liquidity support to funds via share purchases

In this section, we exploit our sample of banks' securities holdings, and test whether banks provide liquidity support to affiliated funds by purchasing the funds' shares, as conjectured in Hypotheses 4. We construct the fund flows (in other words, trades in fund shares) originating from banks and from all other investors respectively as in expression (3) and (4).

In a robustness specification, the bank trade variable is computed at the fund share class (ISIN) level, in order to exploit the maximum degree of granularity provided by our dataset, and account for differences between share classes of the same fund that might affect bank behavior (for instance the fee structure and, ultimately, net performance). However, in our baseline analysis we construct overall fund flows by aggregating flows in all share classes, as shown in (3) and (4). The rationale for this is that, in mutual funds offering multiple share classes, the manager operates on a single portfolio of assets; share issuance and redemption from different share classes are pooled together, and the resulting outflows/inflows determine whether the fund manager has to liquidate or purchase assets. When a bank decides to increase its holdings in a mutual fund's shares in order to provide liquidity support, then, it is reasonable to hypothesize that it does so after observing the outflows at the aggregate fund level rather than at the single share class level. As a consequence, a measure of fund stress should be based on the aggregate flows across the fund's share classes.

#### 5.2.1 General analysis of bank support

First, we study whether banks put in place a backstop for affiliated funds when these have to meet large outflows as a result of idiosyncratic or systematic conditions. The first challenge is that the banks in our sample might tend to purchase distressed funds because they are contrarian investors, or because they act as market makers. We can account for these effects via a panel fixed-effects specification that allows us to control for observed and unobserved time-varying heterogeneity both across banks and across funds using bank-quarter and fund style-quarter (or fund-quarter) fixed effects. To identify whether outflow pressure in affiliated funds leads the parent bank to provide liquidity by purchasing shares, we estimate the following regression model:

Bank flows<sub>ijt</sub> = 
$$\beta_1 \cdot \text{Non-bank flows}_{jt} \times \text{Affiliated}_{ijt} +$$
  
+  $\beta_2 \cdot \text{Non-bank flows}_{jt} \times \text{Is Outflow}_{jt} \times \text{Affiliated}_{ijt} + \gamma_{ft} + \alpha_{it},$  (9)

with

Affiliated<sub>ijt</sub> = 
$$\begin{cases} 1 & \text{if fund } j \text{ is affiliated to bank } i \text{ at date } t, \\ 0 & \text{otherwise.} \end{cases}$$

Is  $Outflow_{jt}$  is a dummy that is equal to 1 if  $Non-bank\ flows_{jt}$  is negative, and 0 otherwise, while  $\gamma_{ft}$  and  $\alpha_{it}$  represent sets of dummies which account, respectively, for fund style-quarter fixed effects and bank-quarter fixed effects.

Table 6 shows the result of our analysis based on specification (9), which allows us to study the effect of fund inflows and outflows on banks' investment decisions. In columns (1) to (3), we run regression (9) with increasingly comprehensive sets of fixed effects. Columns (1) and (2) show that generally there is a slightly negative correlation between the investment decisions of the banks in our sample and the trades of the rest of the investors in the funds (coefficients -0.0111 and -0.0107 of *Non-bank flows*). The correlation increases when non-bank-investors are redeeming shares (additional coefficient of -0.0171 and -0.0182 when Is Outflow = 1). However, we find that banks' contrarian behavior is by far more marked for funds affiliated to the bank, and particularly when the fund is experiencing outflows: in

this case, there is a strongly significant additional negative correlation (coefficients -0.0886 and -0.0843 of Non-bank flows×Is Outflow×Affiliated). Hence, banks seem to specifically react to outflows in affiliated funds by purchasing fund shares, thus decreasing the fund's net outflows. This correlation does not change when we add time-varying fund style fixed effects (column (3)). These control for combinations of a fund's asset type, geographical focus and benchmark, and allow us to compare bank trades of funds that are similar in terms of investment style and risk. While the R-squared indeed climbs from 7% to 20%, the statistical significance of the previous result even increases.

Next, we check the robustness of our results when we consider only bank trades where the bank held a non-zero amount both at the beginning and at the end of the quarter. This would exclude observations generated by potential reporting errors by a bank in a single period, as well as potential acquisitions by a banking group of new subsidiaries with a pre-existing portfolio of fund shares. However, this restriction also disregards those instances where the bank creates a new holding genuinely for the specific purpose of supporting an affiliated fund, as opposed to cases in which the bank intervenes because inaction would lead it to internalize losses originating on an already existing position. Column (4) shows that the correlation indicating liquidity support from the bank is still strong and highly significant, although the coefficient decreases in comparison to the full-sample estimation (from -0.09 to -0.04), notwithstanding that the sample size only shrinks by about 14%. The lower correlation suggests that banks do not provide a backstop uniquely to funds they already own.

To further investigate banks' motives, we address the question of whether banks tend to provide liquidity support in the wake of a systematic shock to their asset management business, or rather when distress is limited to a fund or sector without affecting all funds affiliated to the bank. In order to do this, for each bank we compute the aggregate flows at its affiliated funds (including those which are not part of the bank's portfolio). We define a systematic shock at a bank's asset management business when aggregate affiliated fund flows are negative. Column (5) shows that banks' interventions on the market happen mainly when there is no systematic distress (coefficient of Non-bank flows  $\times$  Is Outflow  $\times$  Affiliated increases to -0.165), while they are almost null when most of the banks' funds are experiencing outflows (offsetting coefficient of 0.151 on Non-bank flows  $\times$  Is Outflow  $\times$  Affiliated  $\times$  Sys. shock). Finally, in column (6) we saturate the regression with fund-specific time-varying fixed effects. This makes most of the estimated coefficients smaller and not statistically significant. However, it should be noted that with this restrictive specification the sample more than halves. The reason for this is that the overlap between banks' portfolios of mutual funds is limited, and it often occurs that a fund share is held by only one bank in our sample. Thus, most of the bank holdings do not contribute to the estimation when we control for fund-quarter fixed effects.

Modifying slightly our regression specification, we now investigate whether the parent bank's intervention on the market is stronger when affiliated funds are experiencing extreme

<sup>&</sup>lt;sup>7</sup>Outlier trades – for instance observations where bank trades exceed 90% of the fund value – were already dropped from the baseline sample. Also holdings which change from non-affiliated to affiliated as a result of the acquisition of an asset management company by the bank (and viceversa) are excluded.

outflows. We define

Distress<sub>jt</sub> = 
$$\begin{cases} 1 & \text{if Non-bank flows}_{jt} < \mathcal{Q}(5\%) = -16.3\%, \\ 0 & \text{otherwise,} \end{cases}$$

where Q is the quantile function associated to the variable *Non-bank flows*. In other words,  $Distress_{jt}$  marks the 5%-tail of the distribution of flows where non-bank investors of fund j withdraw more than 16.3% of TNA during quarter t. We then condition on the sample where  $Is\ Outflow_{jt}=1$ , and estimate

Bank flows<sub>ijt</sub> = 
$$\beta_1 \cdot \text{Affiliated}_{ijt} + \beta_2 \cdot \text{Distress}_{jt} \times \text{Affiliated}_{ijt} + \gamma_{ft} + \alpha_{it}$$
. (10)

Testing specification (10) on the sample of fund outflows allows us to study whether banks' contrarian behavior in trading affiliated funds' shares, which emerged from regression (9), depends on the severity of fund outflows. Columns (1)-(3) of Table 7 report the results of the baseline regression with different sets of fixed effects. On average, if a fund is experiencing extreme outflows (Distress = 1, outflows larger than -16.3%), its parent bank is responsible for an inflow of 1.42%, even when we account for bank-time and fund style-time fixed effects (coefficient of  $Distress \times Affiliated$ ). In column (4), we test the robustness specification limited to holdings which are not nil both at the start and at the end of a quarter. As before, excluding these observations reduces the estimated coefficient (0.52%) but does not invalidate the result.

Next, we look at the effect of generalised distress at the banks' mutual funds. Column (5) confirms the result in Table 6 according to which banks intervene mostly in the absence of a systematic shock: in this case, the average purchase of a distressed affiliated fund amounts to over 2% of its TNA, while a systematic shock corresponds to an offsetting coefficient of -1.16%. Again, the correlation becomes non-significant when we include a set of dummies absorbing security-time averages, and the number of observations actively used to estimate the coefficients drops from 70,782 to 33,787.

Following Hypothesis 5, we then investigate which factors may determine further heterogeneity in banks' investment decisions, and augment regression (10) with cross-sectional bank characteristics that might further explain banks' propensity to provide liquidity support to affiliated funds. Specifically, in columns (7) we introduce a dummy for whether the bank is highly capitalised. This takes the value of 1 if the bank's Tier 1 capital ratio at the end of the previous quarter is in the highest quartile of the sample, and 0 otherwise. The estimation shows that, when we isolate the investment choices of highly capitalised banks, a strong contrarian trading reaction ( $\beta = 1.54$ , p<0.05) persists in response to outflows in affiliated funds even in the most restrictive specification where we account for time-varying bank and fund fixed effects.<sup>8</sup>. Finally, we again restrict the sample to trades in shares that the bank was holding both at the start and the end of a quarter. As column (8) shows, banks' reaction appears to be on average smaller in this case, with the coefficient of Distress×Affiliated×High cap. decreasing to 0.52, but still (weakly) statistically significant

<sup>&</sup>lt;sup>8</sup>We obtain analogous but not statistically significant estimates for the effect of a high liquidity coverage ratio and a low CDS spread (not shown)

(p<0.1).

To conclude, the analysis in this section suggests that banks tend to provide a liquidity backstop to affiliated funds that are subject to abnormal outflows, but they seem less inclined to do so in periods of systematic distress, possibly because banks can do little to oppose generalised outflows driven by the fundamentals of the economy and wider financial market trends. Focusing on the smaller sample where we can compare a parent bank's reaction to fund distress directly with the reaction of another bank for the exact same fund, it emerges that it is the better capitalised parent banks which act countercyclically with respect to affiliated funds. This result reinforces the view that the solidity of the parent bank is an important factor in determining its ability to step in to support distressed affiliated funds.

#### 5.2.2 Bank support during COVID-19 shock

Our analysis of bank proprietary holdings so far has highlighted evidence of bank supporting trades to affiliated funds, in particular following idiosyncratic distress. It is interesting to investigate whether at least some banks were able to support their funds also in the event of a large exogenous systematic shock, such as the sudden outbreak of the COVID-19 crisis in the course of February and March 2020. In order to study this, we test a version of regression (10) where the role of the distress variable based on outflows is now taken by a time dummy for the quarter 2020Q1:

$$\text{Bank flows}_{ijt} = \beta_1 \cdot \text{Affiliated}_{ijt} + \beta_2 \cdot 2020 \text{Q1}_{jt} \times \text{Affiliated}_{ijt} +$$

$$\beta_3 \cdot \text{Affiliated}_{ijt} \times \text{CDS spread}_{i,t-1} + \beta_4 \cdot 2020 \text{Q1}_{jt} \times \text{Affiliated}_{ijt} \times \text{CDS spread}_{i,t-1} + \gamma_{jt} + \alpha_{it}$$
(11)

We test this regression in Table 8. In column 1, we start with a regression without fixed effects. On average, banks were decreasing their holdings of unaffiliated fund shares in 2020Q1 by 0.45% of the fund's TNA. This does not hold for affiliated shares, for which an offsetting coefficient (0.92%) is estimated. However, the size of this offset depends on the level of the bank's CDS spread: the lower the CDS, the larger a bank's contrarian behavior. This finding is strengthened by adding in sequence fund-quarter fixed effects (column 2) and bank-quarter fixed effects (column 3). In this last regression, a bank with a CDS spread of zero at the end of 2019 would be estimated to act countercyclically by an average of 1.4% of a fund's TNA, although – given the within-fund, within-bank nature of the estimation – we cannot quantify the amount due to active supporting buy trades and the amount that stems from banks selling off unaffiliated shares while taking a neutral stance vis-à-vis affiliated ones. Interestingly, the contrarian behavior is cancelled out when the bank CDS spread exceeds the value of 46 bps, which is just above the median in our sample. Above this threshold, banks are seen to even penalise their affiliated funds by selling specifically their shares. The likely reason for this is that distressed banks in a deleveraging effort may need to close positions in those funds of which they hold larger stakes, which are more likely to coincide with affiliated funds.

Admittedly, the pre-determined CDS spread may not provide the full picture as to how well banks were positioned to face the COVID-19 shockwave. We would like to check whether we come to a similar conclusion by looking at how much bank risk increased during the first three months of 2020, in order to capture the impact of the specific COVID-19 related distress on banks themselves. Hence, we replace the lag of the CDS spread with its first difference in regression (11). Columns 4 and 5 in Table 8 show that also the increase in bank risk is relevant and likely affects banks' proprietary portfolio of affiliated holdings, although there is no correlation now when both bank and fund time-varying fixed effects are included.

Finally, we repeat these tests using the first differences of the Tier 1 capital ratio and of the liquidity coverage ratio as alternative measures of bank distress. This exercise leads to mixed evidence. While the regression with the capital ratio does not yield any result (columns 6 and 7), we find the change in the LCR to positively correlate with bank supporting trades (columns 8 and 9), which suggests that those banks whose liquidity position deteriorated more as a result of the crisis were more likely to pass on this shock to their affiliated funds.

While we argue that capital and liquidity ratios are indicators of a conglomerate's financial solidity, these supervisory measures are less likely to track closely the capacity of a bank to weather the sudden COVID-19 mayhem while potentially supporting distressed business units, not least because regulators acted swiftly to release capital and liquidity buffers with the objective to provide banks with operational leeway and support their financing capacity. Given the nature of the distress in the financial system, also originating in investors' panic-driven flight to cash, a market-based perception of banks' viability such as the CDS spread should be more suited to this purpose. A correlation analysis between the three measures confirms this intuition: while the quarterly change in the CDS spread in the panel of banks has a correlation of -12% with both the change in capital ratio and the change in LCR – the market-based measure of bank risk normally aligns with capital and liquidity depletion – this correlation turns positive in 2020Q1, at resp. 51% and 52%.

#### 5.3 Affiliated funds' response to shocks and bank-fund contagion

#### 5.3.1 Italy's 2018 political uncertainty

In the middle of May 2018 tensions started to loom over Italian sovereigns due to expectations that a new populist, anti-euro government would form. As investors cut down their exposure, the spread between 10-year Italian and German government bond yields increased from 123 bps to 243 bps in the course of May and June and remained on that level over the following months. An analysis of fund flows shows that deleveraging took place also in the asset management market, with investors fleeing those mutual funds characterised by a portfolio highly tilted towards Italian sovereign bonds. To see this, we start by estimating the following fixed-effects specification at a monthly frequency on our sample of EU funds,

 $<sup>^9</sup>$ Still, lag and first difference of the CDS spread are highly correlated in 2020Q1, at 77% in the sample of holdings and 57% in the cross-section of banks.

<sup>&</sup>lt;sup>10</sup>The ECB announced on 12 March 2020 that banks could fully use capital and liquidity buffers. Cf. https://www.bankingsupervision.europa.eu/press/pr/date/2020/html/ssm.pr200312~43351ac3ac.en.html

excluding equity funds, which hold little or no sovereign bonds.

2-month flows<sub>jt</sub> = 
$$\beta_1 \cdot \text{Fund Exp}_{j,t-1}^{Ita\ sov} \times \text{May '}18_t$$
  
+ $\beta_2 \cdot \text{Fund Exp}_{j,t-1}^{Ita\ sov} \times \text{Affiliated}_{jt} \times \text{May '}18_t + Controls_{j,t-1} + \gamma_{ft} + \delta_j,$  (12)

where the dependent variable is the cumulative two-month flow of months t to t+1 at the fund level and  $Fund\ Exp_{j,t-1}^{Ita\ sov}$  is a dummy variable that is equal to 1 if the fund's stated geographical focus is Italy, more than 25% of fund j's portfolio is invested in Italian bonds, or more than 20% is invested in Italian sovereign bonds.  $^{11}\ May$  '18 takes the value of 1 for observations referred to May 2018 (where cumulative 2-month flows correspond to May and June) and 0 otherwise. The results of the estimation in column (1) of Table 9 show that Italy-exposed funds were met with abnormal outflows in May and June 2018 (-1.85%, p<0.01), but bank-affiliated funds experience less outflows compared to the others (offsetting coefficient of 0.76%, p<0.01). Given that the estimation includes fund style fixed effects, the coefficients are estimated based on a comparison between Italy-exposed and non-exposed funds – as well as between affiliated and non-affiliated funds – with an otherwise high degree of similarity.

The previous analysis of direct bank support via share purchases and of fund precautionary cash holdings revealed that differences in bank solidity help explain the average benefit yielded by bank affiliation. Following this insight, we aim to motivate the mitigated impact of the Italian crisis on exposed affiliated funds that we observe in column (1) of Table 9 by looking at the cross section of parent banks. Thus, we look at affiliated funds and add to the explanatory variables the parent banks' Tier 1 and liquidity coverage ratios, when available, in form of binary variables which take the value of 1 if the respective measure is above the median over the sample, and 0 otherwise. In columns (2) and (3) we see that both these characteristics have a significant impact on distressed mutual funds: a higher Tier 1 ratio reduces outflows at exposed funds by 1.34 percentage points over the two crisis months, while a higher LCR reduces outflows at exposed funds by 1.9 percentage points.

The results for bank capital and liquidity corroborate the view that the financial condition of the banking group played a role in determining the behavior of investors in their affiliated funds during this phase of unrest on markets. To further investigate this aspect, we check whether also banks considered safer by the market alleviated their funds' outflows, by using a dummy variable  $High\ CDS$  to mark banks with a CDS spread above the median in the sample. Column (4) of Table 9 shows that in this case we find a different result: riskier banks are in fact connected to larger outflows specifically at those affiliated funds which did not have a large exposure to Italy (-1.92 coefficient on  $May\ '18 \times High\ CDS$ ). Although this finding may at first seem unrelated to the heightened Italian sovereign risk, it is natural to ask whether the exposure of the bank itself to the shock may have negatively affected fund investors. Indeed, many among the banks with higher CDS spreads are Italian. These banks are highly exposed to shocks around the Italian sovereigns because of the home bias in their sovereign bond portfolio and because of the wider sovereign-bank nexus, which posits

<sup>&</sup>lt;sup>11</sup>To construct this measure, we primarily use the fund's portfolio allocation to Italian fixed income assets provided by Lipper. When this is missing, but full fund holdings are available, we compute directly the percentage allocation to Italian sovereign bonds. We use up to two monthly lags of both variables to fill in missing values.

that the deep dependence of banks on their sovereign means that a sovereign default would inevitably lead to a default of its banks irrespective of their financial solidity. As a consequence, the outcome of the regression with the CDS spread may largely be capturing banks' direct exposure to the shock. To shed light on this question, in column (5) we study the effect of parent banks' exposure to the shock on fund flows, distinguishing directly Italian and non-Italian groups by means of a dummy variable. First, in this sample exposed funds incur on average 1.56% more outflows during the crisis. Moreover, the estimation reveals that funds affiliated to Italian banks also suffer 2.2% higher outflows. However, this additional effect vanishes for funds themselves already exposed to the shock (offsetting coefficient of 2.9%).<sup>12</sup>

In summary, the analysis of a local shock affecting a specific section of the financial market corroborates previous evidence pointing to the fact that financially solid banking groups help affiliated funds to better withstand distress, in the sense that they are less likely to fall victim to severe outflows. However, it also reveals the existence of the opposite channel: mutual funds with an exposed parent are subject to outflows even if they do not have a direct exposure to the shock via holdings of distressed assets. This result uncovers a novel channel according to which the dependence of a business unit on expectations of a safety net within its financial conglomerate leads to financial contagion as a consequence of distress outside the unit undermining these expectations.

#### 5.3.2 Brexit referendum

The outcome of the Brexit referendum of 23 June 2016 was deemed as largely unexpected. The decision to leave the EU threw the UK financial services industry into disarray and spooked investors in UK-focused investment funds (Lewin (2016)). We study how this shock affected affiliated and unaffiliated mutual funds by estimating the following fixed-effects specification at a monthly frequency:

2-month flows<sub>jt</sub> = 
$$\beta_1$$
 · Fund  $\exp_{j,t-1}^{UK} \times \text{June '}16_t$   
+ $\beta_2$ ·Fund  $\exp_{j,t-1}^{UK} \times \text{Affiliated}_{jt} \times \text{June '}16_t + Controls_{j,t-1} + \gamma_{kt} + \delta_j$ , (13)

where the dependent variable is the cumulative two-month flows of months t and t+1 at the fund level, and  $Fund\ Exp_{j,t-1}^{UK}$  is a dummy variable that is equal to 1 if more than 30% of fund j's portfolio is invested in UK assets. June '16<sub>t</sub> takes the value of 1 for observations referred to June 2016 and 0 otherwise. When aggregating variables at the fund share class level to the fund portfolio level, we drop share classes denominated in GBP in order to abstract from exchange rate fluctuation, as the sterling depreciated starkly following the Brexit referendum.

The results of the estimation in column (1) of Table 10 confirm the hypothesis that UK-exposed funds were met with abnormal outflows in June and July 2016: for non-affiliated funds with above-threshold exposure to the UK in the wake of the referendum, the flows are estimated to be 2.38% lower after controlling for month-fund style and fund fixed effects, past

<sup>&</sup>lt;sup>12</sup>We obtain very similar results if we replace the dummy variable *Italian parent* with the exposure of a bank to the Italian sovereign relative to total assets.

performance and other fund characteristics (coefficient of  $Fund\ Exp^{UK} \times June\ '16$ , p<0.01). However, bank-affiliated funds are largely shielded from the shock: they incur 2.64% less outflows compared to their unaffiliated peers (coefficient of  $Fund\ Exp^{UK} \times Affiliated \times June\ '16$ , p<0.01).

In a further attempt to identify more precisely the funds most adversely hit by the shock, we look at their portfolio allocation in terms of industry sector. The UK financial sector was allegedly the most exposed to risks resulting from a disorderly exit from the European Union. Therefore, in the next test we repeat the estimation after taking this into account. As the portfolio allocation in terms of geography and industry reported by Lipper are independent of each other, we construct the dummy  $Fund\ Exp^{UK\ Fin}$  which is equal to 1 under the condition that both the portfolio allocation to UK assets and the portfolio allocation to the financial sector be greater than 25%. Columns (3) and (4) show that, as expected, the estimated outflows in June 2016 for unaffiliated funds with both a large exposure to UK assets and a large exposure to the financial sector are more than double those estimated previously for funds with  $Fund\ Exp^{UK}=1$  (-5.26%). However, remarkably affiliated funds are still largely insulated from the shock, with no abnormal outflows detected (offsetting coefficient of 5.54%).

As affiliated funds on average do not seem to be affected by the Brexit referendum, we next investigate whether this is also true for funds affiliated to potentially vulnerable banks. If any banks in our sample fail to meet investor expectations of providing emergency support to UK-exposed funds in the aftermath of the Brexit vote upheaval, we conjecture that they would be those presenting particularly weak balance sheet ratios. Therefore, we identify with two dummies - respectively Low Cap. and Low Liq. - those observations where respectively the bank's Tier 1 ratio and the bank's LCR lie below the lower quartile of their distribution across the sample<sup>13</sup>. The two dummies have only a 16% correlation. Columns (3) and (4) present the result of the estimation of regression (13) with the corresponding additional interactions. Interestingly, low-capital banks have an adverse effect not only on highly UK-exposed funds, but also on other funds (coefficient of -0.7% for June '16×Low Cap.). Additionally, exposed funds affiliated to less liquid and to less capitalised banks largely suffer compared to the rest of the bank-affiliated funds in the two-month period (negative coefficients of respectively -6.24% and -4.46%). As a further test, next we take the bank CDS spread as measure of bank distress. We define a dummy High CDS which is equal to 1 when the bank's CDS spread is above 120 bps, which correspond to the upper 20% of its distribution over the sample. The correlation of this dummy with Low Cap. is 22%, with Low Liq. -2%, indicating that the CDS spreads is not simply reflecting these balance sheet metrics. In column (5) we run regression (13) with High CDS and we find that funds owned by these risky banks do suffer Brexit-related distress (0.52% larger outflows for all funds plus 3.62% larger outflows for funds with large UK exposure).

These results suggest that, as was the case during the Italian crisis, the financial conditions of the banking arm – in particular for especially vulnerable institutions – influenced the investment decisions of investors in the group's funds following financial uncertainty, partly irrespective of the funds' own exposure. Thus, in our final test we address the question of

<sup>&</sup>lt;sup>13</sup>As banks started to report the LCR only in 2016Q3, in this regression we use the value in 2016Q3 to proxy for banks' LCR in 2016Q1 and 2016Q2.

whether investors withdrew their shares of funds belonging to a British financial conglomerate or to a British asset management company following the Brexit vote. We make use of a dummy variable that indicates whether the fund's ultimate parent is a UK company, and we focus directly on a sample of affiliated and unaffiliated funds that are not heavily invested in UK assets, excluding all funds with an exposure higher than 20%. Then, any outflows would be arguably motivated by the uncertainty surrounding the future prospects of the fund's company and the doubts about its continued ability to provide financial guarantees to its mutual funds business.<sup>14</sup>

Column (6) illustrates the results. Investors of funds belonging to UK companies – including banks, independent asset managers and other financial firms – withdraw on average 1.19% more of the fund's TNA in two months, compared to funds operated by non-UK companies but investing in the same asset type, with the same benchmark and geographical focus (coefficient of June ' $16\times$  UK parent). Additionally, the interaction with the Affiliated dummy shows that the fallout is more sizeable specifically for funds belonging to UK banks: in this case, average outflows increase by an additional 0.91% (coefficient of Affiliated× June ' $16\times$  UK parent).

Our findings have important implications. On one hand, the analysis of the mutual fund sector following the surprise Brexit vote shows again that funds belonging to a financially sound banking conglomerate seem to be shielded from shocks which do not affect their parent bank, arguably because these funds are perceived to be safer from investors. On the other hand, it also suggests that in case of shocks affecting directly the parent bank – such as the unexpected outcome of the Brexit vote for English financial institutions – distress can spill over to the asset management arm of a financial conglomerate, in that fund investors are induced to run to safety and withdraw capital.

## 6 Conclusion

In this paper, we showed that banks provide liquidity insurance to distressed affiliated funds by increasing their stakes in those funds that are experiencing large outflows. This dampens the severity of strategic complementarities in investors' redemptions and thus diminishes the propensity of a run among investors. As a result, investor flows of bank-affiliated funds tend to be less volatile and less sensitive to bad performance, which in turn allows these funds to hold lower precautionary cash buffers. Our further analysis shows that these beneficial effects are particularly strong if the parent bank is less risky and better capitalised. This suggests that those funds that are part of a multi-unit financial group directly benefit from the solidity of the parent institution.

Consistently with the logic above, we provided evidence that a worsening of a conglomerate's financial health or adverse shocks to the banking business may spill over to the asset management side even absent a direct link in the mutual funds in the form of portfolio exposure. First, more affected banks had to sold off affiliated fund shares during the COVID-19 outbreak in 2020, potentially jeopardizing their funds' own resilience to the crisis.

 $<sup>^{14}</sup>$ We also use the exposure of a fund's parent bank to UK assets, but we do not find this to significantly influence fund flows.

Second, although evidence indicates that funds invested in Italy and the United Kingdom were more resilient to episodes of distress in their respective market segment if they were affiliated to well capitalised and liquid banks, we also found that – conversely – investors ran on funds that were in principle not exposed to the shock following distress in the parent bank. Our findings highlight substantial dependencies between the banking system and the asset management industry and identify an important channel via which financial stability risks depend on the organizational structure of the financial sector.

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# A Figures

Figure 1: Banks' holdings of mutual fund shares.

The graph plots the market value of shares of mutual funds affiliated to the holding bank (brown line), mutual funds not affiliated to the holding bank (blue line) and total mutual fund shares (green line) in the portfolios of 26 banking groups reporting for the Securities Holdings Statistics.

2014m1 2016m1 2018m1 2020m1 Date Number of funds — Size

Figure 2: Share of EU funds affiliated to a bank.

The graph plots the share of bank-affiliated funds in the Lipper sample of mutual funds domiciled in the European Union in terms of number of primary funds (blue line) and in terms of funds' aggregate TNA (red line).

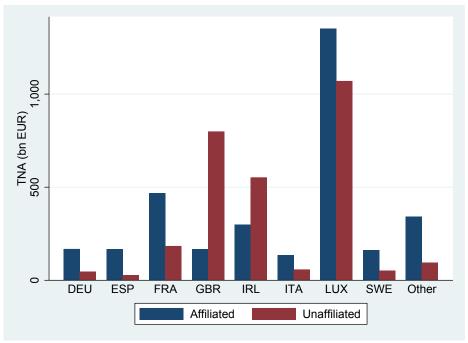


Figure 3: Domicile country of EU mutual funds.

This figure shows the aggregate TNAs of bank-affiliated funds (blue bars) and unaffiliated funds (red bars) broken down by country of domicile in the Lipper sample of mutual funds domiciled in the European Union in June 2016.

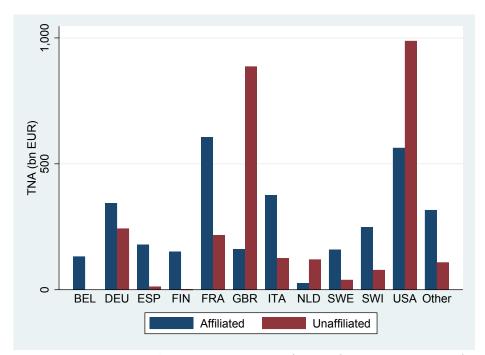


Figure 4: Country of EU mutual funds' ultimate parents.

This figure shows the aggregate TNAs of bank-affiliated funds (blue bars) and unaffiliated funds (red bars) broken down by country of their ultimate parent in the Lipper sample of mutual funds domiciled in the European Union in June 2016.

# B Tables

Table 1: Definition of dependent and independent variables.

Dependent variables	
Fund flows $_{jt}$	Percent flows for fund $j$ in month $t$ (see definition (2)).
$\sigma(\mathrm{Flows})_{jt}$	Standard deviation of monthly flows for fund $j$ computed over a
	12-month period from $t-11$ to $t$ if at least 5 data points are not
	missing.
Cash $\%_{jt}$	Percent portfolio allocation to cash and cash-like instruments for
	fund $j$ at the end of month $t$ .
Bank flows $_{ijt}$	Percent fund flows originated by bank $i$ trading fund $j$ during
•	quarter $t$ (see definition (3)). This variable exists if fund $j$ is in
	bank i's portfolio in at least quarter $t-1$ or quarter $t$ .
$2 \text{m flows}_{jt}$	Cumulative percent flows for fund $j$ in months $t$ and $t+1$ .
Independent variables	
$Affiliated_{ijt}$	In the bank-holdings sample, binary variable which is equal to 1
<i>y</i>	if mutual fund $j$ is affiliated to bank $i$ at the end of quarter $t$ and
	0 otherwise; in the mutual funds sample (without index $i$ ), it is
	equal to 1 if fund $j$ in month $t$ is part of a bank holding company
	or a financial conglomerate which includes banking activities.
Non-bank flows <sub><math>jt</math></sub>	Percent flows for fund $j$ in quarter $t$ , net of flows originating from
ron sam nows <sub>ji</sub>	banks in the bank-holdings sample (see definition (4)).
Is $\operatorname{outflow}_{jt}$	Binary variable which is equal to 1 if Non-bank flows $it$ is strictly
is oddiow <sub>jt</sub>	negative, 0 otherwise.
Distross	Binary variable which is equal to 1 if Non-bank flows $it$ is below
$\mathrm{Distress}_{jt}$	
IIimh camital	the 5th percentile in the corresponding sample, 0 otherwise.
$High \ capital_{ijt}$	Binary variable which is equal to 1 if bank i's Tier 1 ratio is above
Creatementic about	the upper quartile in the corresponding sample, 0 otherwise.
Systematic shock <sub>it</sub>	Binary variable which is equal to 1 if the aggregate flows of funds
C tl l l	affiliated to bank <i>i</i> during quarter <i>t</i> are negative, 0 otherwise.
6-month $alpha_{jt}$	Jensen's alpha of fund $j$ over months $t-6$ to $t-1$ , computed
(D. )	based on the fund's Lipper Global classification benchmark.
$\sigma(\text{Return})_{jt}$	Standard deviation of fund j's monthly returns computed over
	a 12-month period from $t-12$ to $t-1$ if at least 5 data points
(=1	are not missing.
$\sigma(\text{Flows})_{jt}$	See Dependent variables.
$Log(TNA)_{jt}$	Natural logarithm of fund j's Total Net Assets (in $\in$ million) at
	the end of month $t$ .
Fund $TER_{jt}$	Total expense ratio of fund $j$ in month $t$ .
$Log(Age)_{jt}$	Natural logarithm of fund $j$ 's age (expressed in months) at month
	t.
Institutional ownership $_{jt}$	Value-weighted fraction of fund $j$ 's share classes reserved for in-
	stitutional investors in month $t$ .
Capital ratio $_{it}$	Tier 1 capital ratio of the parent bank of fund $j$ in month $t$ .
Good capital $_{it}$	Binary variable which is equal to 1 if the Tier 1 ratio of the
<b>1</b>	parent bank of fund $j$ is above the median in the corresponding
	sample, 0 otherwise.
Good liquidity <sub>it</sub>	Binary variable which is equal to 1 if the liquidity coverage ratio
1 - J Jt	of the parent bank of fund $j$ is above the median in the corre-
	sponding sample, 0 otherwise.
Low capital $_{it}$	Binary variable which is equal to 1 if the Tier 1 ratio of the parent
$\mathbf{L}_{o}$ $\mathbf{L}_{a}$	bank of fund $j$ is below the lower quartile in the corresponding

Table 1: Definition of dependent and independent variables.

Low liquidity $jt$	Binary variable which is equal to 1 if the liquidity coverage ratio
1	of the parent bank of fund $j$ is below the lower quartile in the corresponding sample, 0 otherwise.
CDS spread <sub><math>jt</math></sub>	5-year CDS spread of the parent bank of fund $j$ in month $t$ (normally 2014 modified-modified restructuring contracts in Euro).
$\mathrm{High}\ \mathrm{CDS}_{jt}$	Binary variable which is equal to 1 if the parent bank of fund $j$ has a CDS spread higher than 120 bps at the end of month $t$ , 0 otherwise.
Alternatives $\operatorname{fund}_{j}$	Binary variable which is equal to 1 if fund $j$ is classified as an alternative assets fund, 0 otherwise.
Bond $\operatorname{fund}_j$	Binary variable which is equal to 1 if mutual fund $j$ is classified as a bond fund, 0 otherwise.
Equity $\operatorname{fund}_{j}$	Binary variable which is equal to 1 if mutual fund $j$ is classified as an equity fund, 0 otherwise.
Mixed $\operatorname{fund}_j$	Binary variable which is equal to 1 if mutual fund $j$ is classified as a mixed assets fund, 0 otherwise.
Fund Exp. $_{jt}^{Ita\ Sov}$	Binary variable which is equal to 1 if fund $j$ 's portfolio is invested for at least 20% in Italian sovereign bonds (for those funds reporting securities holdings) or at least 25% in Italian bonds (for those funds reporting a geographical portfolio allocation) at the end of month $t$ , or if the geographical focus in the fund prospectus is Italy; 0 otherwise.
Bank $\operatorname{Exp}_{jt}^{Ita\ Sov}$	Balance sheet exposure of the parent bank of fund $j$ to Italian sovereign bonds at the end of month $t$ , expressed as a percent of the bank's total assets.
Italian $parent_{jt}$	Binary variable which is equal to 1 if the ultimate parent of fund j's asset management company is Italian; 0 otherwise.
Fund $\operatorname{Exp}_{jt}^{UK}$	Binary variable which is equal to 1 if fund $j$ 's portfolio is invested for at least 30% in United Kingdom securities (according to reported securities holdings or geographical portfolio allocation) at the end of month $t$ , or if the geographical focus in the fund prospectus is the United Kingdom; 0 otherwise.
Fund $\operatorname{Exp}_{jt}^{UK\ Fin}$	Binary variable which is equal to 1 if at least 25% of the portfolio of fund $j$ is invested in United Kingdom securities and at least 25% of the portfolio is invested in financial sector assets at the end of month $t$ ; 0 otherwise.
UK parent $_{jt}$	Binary variable which is equal to 1 if the ultimate parent of fund $j$ 's asset management company is from the United Kingdom; 0 otherwise.
June ' $16_t$	Binary variable which is equal to 1 if $t$ is June 2016, 0 otherwise.
May ' $18_t$	Binary variable which is equal to 1 if $t$ is May 2018, 0 otherwise.

 ${\it Table 2: Summary statistics for main dependent and independent variables.}$ 

 $Panel\ A:\ sample\ of\ bank\ holdings\ of\ mutual\ fund\ shares.$ 

	Mean	St. dev.	p1	p5	p25	Median	p75	p95	p99	N
Bank flows (%)	-0.05	3.37	-5.19	-0.22	-0	0	0	0.19	3.50	122416
Non-bank flows (%)	-0.28	13.84	-32.63	-16.38	-5.12	-1.27	2.41	19.21	49.88	122416
Is outflow	0.62	0.49	0	0	0	1	1	1	1	122416
Distress	0.05	0.22	0	0	0	0	0	1	1	122416
Affiliated	0.17	0.38	0	0	0	0	0	1	1	122416
T1 capital ratio (%)	13.13	2.09	9.04	10.18	11.35	13.35	14.31	17.30	18.02	122204
Systematic shock	0.40	0.49	0	0	0	0	1	1	1	122117
Bank holding (% of TNA)	2.18	11.28	-0	0	0	0	0.06	7.27	80.90	122416

 $Panel\ B:\ sample\ of\ European\ mutual\ funds.$ 

	Mean	St. dev.	р1	р5	p25	Median	p75	p95	p99	N
Affiliated funds										
Fund flows (%)	-0.19	7.49	-20.46	-7.33	-1.55	-0.29	0.55	7.22	22.65	874642
Return (%)	0.27	2.45	-7.95	-3.93	-0.49	0.16	1.24	4.34	7.72	874642
6-month alpha (%)	0.15	2.37	-7.10	-3.64	-0.90	0.04	1.20	4.12	7.77	874642
Cash (%)	5.71	9.47	-9.23	-0.25	1.25	3.17	6.87	19.75	46.09	359636
Fund Exp. Ita Sov	0.06	0.24	0	0	0	0	0	1	1	491497
Fund Exp. $UK$	0.01	0.09	0	0	0	0	0	0	0	493836
Fund Exp. $UK Fin$	0.01	0.08	0	0	0	0	0	0	0	291290
UK parent	0.02	0.15	0	0	0	0	0	0	1	832213
Italian parent	0.09	0.29	0	0	0	0	0	1	1	864927
Log(TNA)	4.36	1.51	1.71	2.07	3.20	4.26	5.37	6.99	8.18	874642
Fund TER (%)	1.34	0.71	0.09	0.28	0.81	1.29	1.80	2.55	3.29	823232
Log(Age)	4.40	0.95	2.08	2.64	3.76	4.54	5.15	5.69	6.00	874563
Institutional ownership	0.16	0.32	0	0	0	0	0	1	1	874642
Bond fund	0.28	0.45	0	0	0	0	1	1	1	874642
Equity fund	0.33	0.47	0	0	0	0	1	1	1	874642
Mixed fund	0.31	0.46	0	0	0	0	1	1	1	874642
Bank exposure to Ita. sov.	1.86	2.96	0	0.03	0.24	0.80	1.26	8.42	12.39	457214
T1 capital ratio (%)	14.22	2.61	9.49	10.33	12.53	13.86	15.71	18.61	21.27	512732
LCR	1.63	0.73	0.94	1.20	1.35	1.42	1.60	3.17	4.66	348933
CDS spread	84.77	66.23	22.08	28.32	53.19	71.93	98.03	175.04	254.51	434469
Unaffiliated funds										
Fund flows (%)	0.22	7.57	-18.95	-6.73	-1.26	-0.06	1.01	7.72	23.33	563469
Return (%)	0.32	2.70	-8.34	-4.50	-0.69	0.29	1.59	4.80	7.91	563469
6-month alpha (%)	0.21	2.53	-7.40	-3.90	-1	0.10	1.40	4.50	8.08	563469
Cash (%)	5.87	9.46	-10	-0.16	1.23	3.25	7.17	20.55	46.59	276916
Fund Exp. Ita Sov	0.04	0.19	0	0	0	0	0	0	1	346773
Fund Exp. $UK$	0.02	0.15	0	0	0	0	0	0	1	275809
Fund Exp. $UK Fin$	0.01	0.10	0	0	0	0	0	0	0	179432
UK parent	0.16	0.37	0	0	0	0	0	1	1	420931
Italian parent	0.08	0.27	0	0	0	0	0	1	1	546339
Log(TNA)	4.63	1.60	1.73	2.16	3.41	4.54	5.73	7.40	8.51	563469
Fund TER (%)	1.39	0.74	0.07	0.26	0.86	1.37	1.81	2.64	3.58	534490
Log(Age)	4.40	0.93	2.08	2.64	3.80	4.52	5.10	5.72	6.05	563072
Institutional ownership	0.24	0.38	0	0	0	0	0.45	1	1	563469
Bond fund	0.24	0.43	0	0	0	0	0	1	1	563469
Equity fund	0.40	0.49	0	0	0	0	1	1	1	563469
Mixed fund	0.30	0.46	0	0	0	0	1	1	1	563469
Bank exposure to Ita. sov.										0
T1 capital ratio (%)										0
LCR										0
CDS spread										0

Table 3: Sensitivity of fund flows to negative performance. Test of Hypothesis 1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Fund flows	Fund flows	Fund flows	Fund flows	Fund flows	Fund flows
6-month alpha $\times \mathbb{1}_{6\text{-month alpha}>0}$	0.167***	0.170***	0.303***	0.141***	0.313***	1.407**
	(10.58)	(9.01)	(6.01)	(6.61)	(3.86)	(2.15)
6-month alpha $\times \mathbb{1}_{\text{6-month alpha}>0} \times$ Affiliated	-0.0447***	-0.0938***	-0.0396	-0.0317	-0.0329	-1.297*
	(-2.90)	(-4.57)	(-0.86)	(-1.42)	(-0.35)	(-1.90)
6-month alpha $\times \mathbb{1}_{6\text{-month alpha}<0}$	0.184***	0.164***	0.210***	0.164***	0.352***	0.367
	(17.13)	(12.31)	(4.37)	(9.15)	(4.10)	(0.90)
6-month alpha $\times \mathbb{1}_{\text{6-month alpha} < 0} \times$ Affiliated	-0.0690***	-0.0298*	-0.101**	-0.0386*	-0.276**	-0.0229
	(-5.05)	(-1.91)	(-2.08)	(-1.72)	(-2.12)	(-0.05)
Affiliated	-0.179*** (-5.69)	0.00679 $(0.15)$	-0.245*** (-3.69)	-0.189*** (-4.37)	-0.522** (-2.41)	-0.670*** (-2.96)
Log(TNA)	0.00293 $(0.33)$	-0.000457 (-0.04)	-0.0317 (-1.60)	0.0170 $(1.30)$	0.119** (2.49)	0.0140 $(0.22)$
Fund TER	-0.104*** (-4.50)	0.0334 $(1.15)$	-0.186*** (-2.83)	-0.154*** (-5.45)	-0.242** (-2.52)	-1.065*** (-2.84)
Log(Age)	-0.394***	-0.389***	-0.315***	-0.402***	-0.474***	-0.379**
	(-19.84)	(-13.65)	(-10.03)	(-15.38)	(-5.10)	(-2.43)
Institutional ownership	-0.142 (-0.95)	-0.568*** (-2.67)	0.209 $(0.77)$	0.500 (1.40)	0.361 $(0.39)$	-0.596 (-0.68)
L(Fund flows)	0.209***	0.163***	0.216***	0.315***	0.270***	0.0219
	(27.98)	(23.50)	(22.13)	(19.32)	(9.85)	(0.89)
Month-fund style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations $R^2$ Fund type	1018915	366765	244061	346374	32064	29651
	0.113	0.086	0.130	0.161	0.211	0.052
	All	Equity	Bond	Mixed assets	Alternatives	Money market

This table reports coefficient estimates of regression (5), where the dependent variable is monthly percent fund flows. The sample includes funds where retail share classes exceed 70% of the TNA. In column (2) the sample is restricted to equity funds, in column (3) to bond funds, in column (4) to mixed-assets funds, in column (5) to alternatives funds, and in column (6) to money market funds. Month-fund style fixed effects represent a set of dummies for each combination of month and fund's asset type, Lipper Global classification scheme and geographical focus. The t-statistics reported in parentheses use standard errors clustered at the fund level and at the month level.

t statistics in parentheses \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table 4: Volatility of fund flows. Test of Hypothesis 2.

	$\sigma(1)$ $\sigma(\text{Flows})$	$\frac{(2)}{\sigma(\text{Flows})}$	$\begin{array}{c} (3) \\ \sigma(\text{Flows}) \end{array}$	$\frac{(4)}{\sigma(\text{Flows})}$	$\begin{array}{c} (5) \\ \sigma(\text{Flows}) \end{array}$
Affiliated $_{t-12}$	-0.272*** (-5.31)	-0.132** (-2.62)	-0.354** (-2.53)	-0.366*** (-2.72)	-0.258* (-1.79)
$\sigma(\text{Return})$	$0.170^{***}$ $(7.42)$	0.195*** (5.82)	0.0162 $(0.66)$	0.0387 $(1.28)$	$0.0678^{**}$ $(2.02)$
Affiliated $_{t-12} \times \sigma(\text{Return})$					-0.0482* (-1.75)
Institutional ownership $_{t-12}$	4.894*** (17.98)	2.695*** (10.78)	$1.676^{***}$ $(3.55)$	1.882*** (3.94)	1.886*** (3.95)
$Log(TNA)_{t-12}$	-0.217*** (-14.26)	-0.323*** (-20.98)	-1.529*** (-19.00)	-1.587*** (-18.24)	-1.587*** (-18.24)
Fund TER $_{t-12}$	-0.798*** (-19.68)	-0.437*** (-10.52)	$0.203^{**}$ $(2.62)$	0.148* (1.89)	$0.147^*$ (1.89)
$Log(Age)_{t-12}$	-0.257*** (-10.08)	-0.523*** (-20.60)	-0.224*** (-3.19)	-0.185** (-2.31)	-0.185** (-2.32)
Month fixed effects	Yes	No	Yes	No	No
Month-fund style fixed effects	No	Yes	No	Yes	Yes
Fund fixed effects	No	No	Yes	Yes	Yes
Observations $R^2$	813882 0.028	$796346 \\ 0.155$	813601 0.525	796069 0.547	796069 0.547

 $<sup>\</sup>boldsymbol{t}$  statistics in parentheses

This table reports coefficient estimates of different versions of regression (6) where the dependent variable is the volatility of monthly fund flows over the previous 12 months. The sample includes funds where retail share classes exceed 70% of the TNA. All regressors except  $\sigma(Return)$  are at month t-12.  $\sigma(Return)$  is the volatility of monthly fund returns over months from t-12 to t-1. Month-fund style fixed effects represent a set of dummies for each combination of month and fund's asset type, Lipper Global classification scheme and geographical focus. The t-statistics reported in parentheses use standard errors clustered at the fund level and at the month level.

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table 5: The influence of parent banks on funds' cash buffers. Test of Hypothesis 3.

	(1) Cash %	(2) Cash %	(3) Cash %	(4) Cash %	(5) Cash %	(6) Cash %	(7) Cash %	(8) Cash %	(9) Cash %
Alternative fund	13.59*** (8.84)								
Bond fund	1.805*** (7.57)								
Mixed fund	5.007*** (18.99)								
Affiliated $\times$ Alternative fund	-4.945** (-2.49)	-3.169* (-1.78)	5.454 (1.60)						
Affiliated $\times$ Bond fund	0.369 (1.49)	-0.0101 (-0.03)	-1.372** (-2.23)						
Affiliated $\times$ Equity fund	-0.374*** (-2.77)	-0.248** (-2.09)	-0.206 (-0.46)						
Affiliated $\times$ Mixed fund	-0.329 (-1.26)	-1.207*** (-3.99)	-0.619 (-1.42)						
Capital ratio $\times$ Alternative fund				-0.771 (-1.49)	-0.706 (-1.36)	-0.131 (-0.27)			
Capital ratio $\times$ Bond fund				-0.194*** (-2.82)	-0.0949 (-1.31)	0.0156 $(0.16)$			
Capital ratio $\times$ Equity fund				0.00419 (0.10)	0.0844 (1.66)	-0.00289 (-0.06)			
Capital ratio $\times$ Mixed fund				-0.176** (-2.28)	-0.121 (-1.55)	-0.0736 (-0.86)			
Capital ratio $\times \sigma(\text{Flows})$					-0.0225*** (-2.77)	-0.0147*** (-3.20)			
CDS spread $\times$ Alternative fund							-0.00923 (-0.43)	-0.0146 (-0.67)	-0.0226 (-1.02)
CDS spread $\times$ Bond fund							0.0252*** (4.94)	0.0181*** (3.73)	0.00340 (1.18)
CDS spread $\times$ Equity fund							0.00144 $(0.53)$	-0.00299 (-1.03)	-0.00259 (-1.49)
CDS spread $\times$ Mixed fund							0.00420 $(0.75)$	-0.000453 (-0.08)	-0.00115 (-0.29)
CDS spread $\times \sigma(\text{Flows})$								0.00162*** (3.42)	0.000710** (2.25)
$\sigma(\text{Flows})$	0.0805*** (5.98)	0.0815*** (5.90)	0.0542*** (6.78)	0.123*** (4.29)	0.442*** (3.34)	0.309*** (4.26)	0.0829*** (3.17)	-0.0453 (-1.44)	0.00419 (0.19)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month fixed effects	Yes	No	No	No	No	No	No	No	No
Month-fund style fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	No	No	Yes	No	No	Yes	No	No	Yes
$\frac{N}{R^2}$	457099 0.101	443114 0.231	442250 0.705	124899 0.269	124899 0.269	124389 0.673	125287 0.280	125287 0.281	124819 0.708

This table reports coefficient estimates of regressions (7) and (8) where the dependent variable is a fund's percent portfolio allocation to cash. The sample includes funds where retail share classes exceed 70% of the TNA. Fund controls include the contemporaneous percent flows, the log of TNA, the log of fund age in months, the total expense ratio, the proportion of institutional ownership and the alpha over the previous six months. Month-fund style fixed effects represent a set of dummies for each combination of month and fund's asset type, Lipper Global classification scheme and geographical focus. The t-statistics reported in parentheses use standard errors clustered at the fund level and at the month level.

t statistics in parentheses \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table 6: Bank purchases of affiliated fund shares. Test of Hypotheses 4 and 5 based on model (9).

	(1) Bank flows	(2) Bank flows	(3) Bank flows	(4) Bank flows	(5) Bank flows	(6) Bank flows
Affiliated	-0.551*** (-3.94)	-0.594*** (-3.80)	-0.560*** (-3.94)	-0.350** (-2.57)	-0.685*** (-4.50)	-0.215* (-1.93)
Non-bank flows	-0.0111** (-2.60)	-0.0107** (-2.64)	-0.00718 (-1.47)	-0.00157 (-0.91)	-0.00708 (-1.40)	
Is Outflow	-0.273** (-2.69)	-0.273** (-2.70)	-0.189** (-2.21)	-0.0586 (-1.44)	-0.172* (-2.07)	
Non-bank flows $\times$ Is Outflow	-0.0171** (-2.66)	-0.0182** (-2.76)	-0.0160*** (-2.90)	-0.0113** (-2.50)	-0.0148** (-2.18)	
Non-bank flows $\times$ Affiliated	-0.0324** (-2.26)	-0.0325** (-2.29)	-0.0269* (-1.98)	-0.0103* (-1.74)	0.00483 $(0.37)$	0.00743 $(0.39)$
Non-bank flows $\times$ Is Outflow $\times$ Affiliated	-0.0886*** (-2.80)	-0.0843*** (-2.82)	-0.0881*** (-2.94)	-0.0415** (-2.16)	-0.165*** (-4.07)	-0.0403 (-1.24)
Affiliated $\times$ Sys. shock					0.252 $(1.38)$	0.180 (1.55)
Non-bank flows $\times$ Sys. shock					0.00292 $(0.60)$	0.00540 $(1.54)$
Is Outflow $\times$ Sys. shock					-0.0381 (-0.72)	0.00331 $(0.08)$
Non-bank flows $\times$ Is Outflow $\times$ Sys. shock					-0.00470 (-0.78)	-0.0000254 (-0.00)
Non-bank flows $\times$ Affiliated $\times$ Sys. shock					-0.0699** (-2.53)	-0.0424* (-1.80)
Non-bank flows $\times$ Is Outflow $\times$ Affiliated $\times$ Sys. shock					0.151*** (2.85)	0.0678* (1.85)
Constant	Yes	No	No	No	No	No
Bank-quarter fixed effects	No	Yes	Yes	Yes	Yes	Yes
Fund style-quarter fixed effects	No	No	Yes	Yes	Yes	No
Fund-quarter fixed effects	No	No	No	No	No	Yes
Observations $$R^2$$ Sample	120742 0.036 Full	120716 0.072 Full	115631 0.196 Full	99531 0.158 No zero hold.	115357 0.202 Full	54254 0.469 Full

This table reports coefficient estimates of different versions of regression (9) where the dependent variable Bank flows is a bank's net purchase/sale of a mutual fund share expressed in percent of the fund's TNA. Column (4) includes only observations where the bank holding is positive in both the consecutive periods used to calculate bank trades. Fund style-quarter fixed effects represent a set of dummies for each combination of quarter and fund's asset type, benchmark technical indicator and geographical focus. The t-statistics reported in parentheses use standard errors clustered at the fund level and at the bank level.

t statistics in parentheses  $\label{eq:problem} ^* \ p < 0.10, \ ^{**} \ p < 0.05, \ ^{***} \ p < 0.01$ 

Table 7: Bank purchases of affiliated fund shares. Test of Hypotheses 4 and 5 based on model (10).

	(1) Bank flows	(2) Bank flows	(3) Bank flows	(4) Bank flows	$(5)$ $X=Sys.\ shock$	$ \begin{array}{c} (6) \\ X = Sys. \ shock \end{array}$	$ \begin{array}{c} (7) \\ X = High \ cap. \end{array}$	$(8)$ $X=High\ cap.$
Affiliated	-0.0677 (-1.07)	-0.119 (-0.92)	-0.0742 (-0.75)	-0.0530 (-0.58)	-0.0339 (-0.47)	-0.00164 (-0.02)	-0.0438 (-0.67)	-0.0130 (-0.28)
Distress	$0.285^{***}$ $(3.16)$	$0.291^{***}$ $(3.35)$	$0.247^{***}$ (2.81)	$0.160^{***}$ $(3.27)$	$0.256^{**} $ $(2.74)$			
Distress $\times$ Affiliated	1.971** (2.77)	1.847*** (3.01)	1.422*** (3.11)	0.515** (2.26)	2.146*** (3.15)	0.775 (1.38)	-0.137 (-1.22)	-0.0785 (-1.20)
Affiliated $\times$ Variable $X$					-0.0810 (-0.53)	-0.0417 (-0.62)	0.136 $(1.00)$	-0.0409 (-0.67)
$\text{Distress} \times \textit{Variable } X$					-0.0499 (-0.79)	-0.142 (-1.35)	-0.103 (-0.99)	-0.00446 (-0.07)
$\text{Distress} \times \text{Affiliated} \times \textit{Variable} \ X$					-1.163** (-2.14)	-0.786 (-1.43)	1.541** (2.19)	0.519* (1.89)
Constant	Yes	No	No	No	No	No	No	No
Bank-quarter fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund style-quarter fixed effects	No	No	Yes	Yes	Yes	No	No	No
Fund-quarter fixed effects	No	No	No	No	No	Yes	Yes	Yes
Observations $R^2$ Sample	75062 0.012 Outflows	75013 0.067 Outflows	70944 0.213 Outflows	61604 0.180 No zero hold.	70782 0.214 Outflows	33787 0.485 Outflows	32251 0.484 Outflows	23941 0.483 No zero hold.

t statistics in parentheses

This table reports coefficient estimates of different versions of regression (10) where the dependent variable Bank flows is a bank's net purchase/sale of a mutual fund share expressed in percent of the fund's TNA. The sample contains only observations where Is Outflow = 1. Columns (4) and (8) include only observations where the bank holding is positive in both the consecutive periods used to calculate bank trades. Fund style-quarter fixed effects represent a set of dummies for each combination of quarter and fund's asset type, benchmark technical indicator and geographical focus. The t-statistics reported in parentheses use standard errors clustered at the fund level and at the bank level.

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table 8: Bank support to affiliated funds during COVID-19 shock.

			$ (3) \\ X = CDS $	$X = \Delta CDS$	$X = \Delta CDS$	$X = \Delta Capital$	$X = \Delta Capital$	$X = \Delta LCR$	$X = \Delta LCR$
Affiliated	-0.654* (-1.83)	-0.0237 (-0.31)	-0.0684 (-0.94)	-0.0294 (-0.61)	-0.0580 (-1.19)	-0.0990 (-1.47)	-0.114 (-1.70)	-0.00658 (-0.11)	-0.0889 (-1.26)
Q1'20	-0.448* (-1.76)								
Q1'20 $\times$ Affiliated	$0.921^*$ (1.87)	2.153*** (3.68)	1.412** (2.26)	0.850* (1.85)	0.125 $(0.33)$	-0.213 (-0.28)	0.180 $(0.27)$	-0.0933 (-0.27)	0.328** (2.25)
$Variable\ X$	0.000203 $(1.14)$	-0.000150 (-0.60)		-0.0000219 (-0.02)		0.00208 $(0.22)$		0.0753 $(1.61)$	
Affiliated $\times$ Variable $X$	0.00328 $(1.25)$	-0.000109 (-0.24)	0.0000684 $(0.15)$	-0.000446 (-0.23)	0.00267 $(1.50)$	0.0906 $(1.20)$	0.0373 $(0.57)$	-0.170 (-0.42)	-0.0639 (-0.19)
Q1'20 $\times$ Variable X	0.00349 $(1.04)$	0.00541** (2.81)		0.00314* (1.88)		0.128** (2.19)		-0.498 (-1.69)	
Q1'20 × Affiliated × Variable X	-0.0190 (-1.37)	-0.0507*** (-3.33)	-0.0308** (-2.15)	-0.0217** (-2.46)	0.00304 $(0.36)$	-0.568 (-0.94)	-0.653 (-0.91)	3.831* (1.84)	2.845** (2.15)
Constant	Yes	No	No	No	No	No	No	No	No
Bank-quarter fixed effects	No	No	Yes	No	Yes	No	Yes	No	Yes
Fund-quarter fixed effects	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	104297	43947	43900	43947	43900	51790	51703	28918	28841

t statistics in parentheses

This table reports coefficient estimates of regressions based on (11). Q1'20 is a dummy variable for observations in quarter 2020Q1. The dependent variable is a bank's net purchase/sale of a mutual fund share expressed in percent of the fund's TNA. The variable "X" in columns 1-3 is the lagged value of the bank's CDS spread, in columns 4-5 the first difference of the CDS spread, in columns 6-7 the first difference of the bank's Tier 1 capital ratio, in columns 8-9 the first difference of the bank's liquidity coverage ratio. The t-statistics reported in parentheses use standard errors clustered at the fund level and at the bank level.

<sup>\*</sup> p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table 9: The effect of the government and political crisis in Italy on fund flows.

	X = Affiliated	$X = \begin{array}{c} (2) \\ X = Good \ cap. \end{array}$	X = Good liq.	$X = High \ CDS$	$X = Italian \ parent$
Fund Exp. $^{Ita\ sov}$	-1.018**	0.571	-1.105	-0.542	-0.0115
	(-2.08)	(1.06)	(-1.50)	(-0.81)	(-0.03)
Fund Exp. $^{Ita\;sov}$ $\times$ May '18	-1.845***	-2.079***	-2.541***	-1.728***	-1.557***
	(-8.18)	(-8.31)	(-5.33)	(-4.53)	(-8.60)
$Variable\ X$	-0.781***	0.403**	-0.0549	-0.185	2.119***
	(-3.41)	(2.13)	(-0.35)	(-1.11)	(3.22)
Fund Exp. $^{Ita\;sov}$ $\times$ $Variable$ $X$	1.154*	-0.633	0.900	0.794*	0.283
	(1.96)	(-1.32)	(1.51)	(1.76)	(0.31)
May '18 × Variable X	0.0840	-0.283*	-0.333*	-1.918***	-2.201***
	(1.16)	(-1.90)	(-1.87)	(-10.02)	(-12.47)
Fund Exp. $^{Ita\;sov}$ $\times$ May '18 $\times$ $Variable~X$	0.762***	1.339***	1.899***	2.071***	2.914***
	(3.21)	(4.72)	(4.12)	(4.66)	(11.46)
Fund controls	Yes	Yes	Yes	Yes	Yes
Month-fund style fixed effects	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes
$\frac{N}{R^2}$ Sample	480111	162293	97027	145178	288609
	0.276	0.314	0.354	0.320	0.291
	Full	Affiliated	Affiliated	Affiliated	Affiliated

This table reports coefficient estimates of different versions of regression (12) where the dependent variable represents cumulative percent fund flows for months t and t+1. The sample contains bond funds and mixed-asset funds. The sample in columns (2)-(5) is restricted to bank-affiliated funds. In the estimation of column (5), funds with an Italian parent bank are excluded. Fund controls include 6-month alpha, Log(TNA), Log(Age), 2-month flows and institutional ownership, all lagged at time t-1, with the exception of the lag of 2-month flows which represents cumulative flows at time t-2 and t-1. Month-fund style fixed effects represent a set of dummies for each combination of month and fund's asset type, Lipper Global classification scheme and geographical focus. The t-statistics reported in parentheses use standard errors clustered at the fund level and at the month level.

t statistics in parentheses \* p < 0.10, \*\* p < 0.05, \*\*\* p < 0.01

Table 10: The effect of the Brexit referendum on fund flows.

	X = Affiliated	X = Affiliated	$X = Low \ Cap.$	$X = Low \ Liq.$	$X = High \ CDS$	X = UK parent
Fund Exp. $^{UK}$	-0.139 (-0.34)		0.251 (0.23)	0.876 (0.49)	-0.0384 (-0.04)	
Fund Exp. $UK \times June$ '16	-2.377*** (-6.63)		6.290*** (5.88)	5.512*** (2.88)	0.755 (1.00)	
Variable X	-0.469** (-2.54)	-0.712*** (-3.25)	0.148 (0.82)	-0.00149 (-0.01)	-0.189 (-1.32)	0.570 (1.23)
Fund Exp. $UK \times Variable X$	0.626 (0.99)		0.123 (0.10)	-1.352 (-0.63)	1.521 (1.19)	
June '16 × Variable X	-0.304*** (-4.65)	-0.784*** (-9.25)	-0.697*** (-7.18)	0.0761 $(0.71)$	-0.521*** (-5.87)	-1.188*** (-8.17)
Fund Exp. $^{UK}$ × June '16 × $Variable~X$	2.640*** (6.52)		-6.239*** (-5.90)	-4.457** (-2.38)	-3.624*** (-3.31)	
Fund Exp. $^{UK\ Fin}$ .		0.451 (0.58)				
Fund Exp. $^{UK\ Fin.}$ × Variable X		-0.239 (-0.26)				
Fund Exp. $UK Fin. \times June$ '16		-5.260*** (-13.00)				
Fund Exp. $^{UK\ Fin.}$ × June '16 × $Variable\ X$		5.537*** (9.97)				
Affiliated						-0.0427 (-0.13)
Affiliated $\times$ June '16						-0.400*** (-5.50)
Affiliated $\times$ June '16 $\times$ Variable X						-0.911*** (-4.40)
Fund controls	Yes	Yes	Yes	Yes	Yes	Yes
Month-fund style fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Fund fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
$rac{N}{R^2}$ Sample	703990 0.246 Full	429433 0.254 Full	236970 0.282 Affiliated	183694 0.296 Affiliated	219088 0.282 Affiliated	663693 0.249 Not UK-expose

This table reports coefficient estimates of different versions of regression (13). The dependent variable represents cumulative percent fund flows for months t and t+1. All models exclude share classes denominated in GBP. The sample in columns (3)-(5) is restricted to bank-affiliated funds, and in column (6) funds with an exposure to UK assets higher than 20% are excluded. Fund controls include 6-month alpha, Log(TNA), Log(Age), 2-month flows and institutional ownership, all lagged at time t-1, with the exception of the lag of 2-month flows which represents cumulative flows at time t-2 and t-1. Month-fund style fixed effects represent a set of dummies for each combination of month and fund's asset type, Lipper Global classification scheme and geographical focus. The t-statistics reported in parentheses use standard errors clustered at the fund level and at the month level.

t statistics in parentheses \* p < 0.10, \*\*\* p < 0.05, \*\*\* p < 0.01