EUROPEAN CENTRAL BANK

EUROSYSTEM

Working Paper Series

Lennart Dekker, Luis Molestina Vivar, Michael Wedow, Christian Weistroffer

Liquidity buffers and open-end investment funds: containing outflows and reducing fire sales

No 2825

Abstract

Using a sample of open-end corporate bond funds domiciled in the euro area, we exploit the COVID-19 market turmoil in March 2020 to examine two channels through which liquidity buffers can reduce procyclicality in the investment fund sector. First, we find that liquidity buffers reduced outflows during March 2020 only to a limited extent. Second, we find that funds entering the crisis with higher liquidity buffers were less likely to involve in cash hoarding and more likely to use cash buffers to meet outflows. Our results suggest that higher liquidity buffers can reduce procyclicality primarily through supporting the liquidity management strategies employed by fund managers.

Keywords: corporate bond funds, investor redemptions, liquidity management, COVID-19 pandemic

JEL Codes: G01, G11, G23

Non-technical Summary

Open-end corporate bond funds typically offer daily redemptions to their investors, whereas they invest in corporate bonds that are usually less liquid. This leaves these funds exposed to a liquidity mismatch, which may complicate the accommodation of large and sudden investor redemptions. In absence of appropriate liquidity management tools, the liquidity mismatch can furthermore give rise to a first-mover advantage if part of the costs associated with investor redemptions are borne by the remaining investors in the fund. This first-mover advantage may trigger run incentives and amplify outflows during crisis times. These larger outflows could then require even more procyclical asset sales by the fund manager, adversely impacting the underlying corporate bond market and other market participants. These vulnerabilities are illustrated by the recent COVID-19 episode, during which open-end corporate bond funds faced unprecedented outflows resulting in large procyclical corporate bond sales. In this paper, we zoom in on the COVID-19 crisis and study whether and how the level of pre-existing liquidity buffers affected the procyclicality of open-end corporate bond funds that are domiciled in the euro area.

Our paper contributes to the literature on run risks and liquidity management in open-end investment funds. We consider two mechanisms through which higher liquidity buffers might reduce procyclical asset sales by investment funds. First, a higher liquidity buffer improves the liquidity profile of a fund's portfolio, allowing the fund to better accommodate future outflows. Consequently, the first-mover advantage among investors is lower, and as a result the magnitude of outflows during a crisis period may be dampened. If this leads to smaller outflows for the fund manager, less corporate bond selling would be required to meet redemption requests. Second, for a given level of outflows, a higher liquidity buffer allows the fund manager to meet a larger fraction of outflows using cash or other liquid assets. As such, for a fixed level of outflows, a larger liquidity buffer reduces the need for costly liquidation of corporate bonds.

Our results suggest that funds entering the COVID-19 shock with higher liquidity buffers acted less procyclically and therefore contributed less to the instability of the underlying corporate bond market. This result can be largely attributed to the second channel, i.e. the impact of liquidity buffers on the strategies employed by fund managers to deal with outflows. The impact of liquidity buffers on the magnitude of outflows is rather limited: while higher liquidity buffers had a dampening effect on outflows during the outbreak phase of the pandemic, they did not

have a significant effect during the peak phase when outflows further accelerated. However, for a given level of outflows, we find that funds with higher pre-existing liquidity buffers were more likely to use cash and other liquid assets to meet redemption requests and sold fewer corporate bonds.

This paper is of relevance to policymakers as well. In recent years, liquidity management tools that specifically aim at reducing the first-mover advantage have become more common. Nevertheless, our results suggest that during the peak of the crisis, outflows hit funds rather indiscriminately. Hence, exogenous shocks like the COVID-19 crisis might still leave funds exposed to large redemptions. Better aligning asset liquidity with redemption terms would therefore help to improve the resilience of the investment fund sector, which could be achieved potentially through higher liquidity buffers. However, minimum liquidity requirements could reduce the intermediation capacity of investment funds and possibly impair the usability of the buffers during stress times. It is therefore important to carefully weigh the costs and benefits of such mandatory buffers.

1 Introduction

In this paper, we study how liquidity buffers affect procyclicality in open-end corporate bond funds. The risk of procyclical asset sales has been well illustrated by the COVID-19 episode. During March 2020, open-end bond funds faced unprecedented outflows reaching almost 5%, which exceeded levels seen during the global financial crisis in 2008 (International Monetary Fund, 2022). In order to meet these redemption requests, funds responded by selling bonds on a large scale. As illustrated by Figure 1, investment funds were by far the largest net sellers of debt securities in the euro area during the first quarter of 2020. This procyclical response contributed to further valuation losses and fragility in underlying bond markets (Jiang et al., 2022). As such, the COVID-19 episode illustrates how procyclical behaviour by investment funds can contribute to market volatility and thus adversely impact financial stability.

Funds act procyclically if they buy assets when returns have been high and sell assets when returns have been low. In this paper, we focus on procyclical asset sales during the onset of the COVID-19 crisis. We examine two channels through which liquidity buffers can affect such procyclical selling. First, higher liquidity buffers should reduce any mismatch between the liquidity of the fund's assets and the redemption terms offered to investors. When this liquidity mismatch is large, investor redemptions may create costs to remaining investors in the investment fund due to the cost of asset sales or a sub-optimal portfolio allocation. These negative externalities resulting from investor redemptions give rise to a first-mover advantage creating run dynamics that amplify outflows during times of stress (Chen et al., 2010; Goldstein et al., 2017). Higher liquidity buffers reduce the liquidity mismatch and the resulting first-mover advantage, which may lead to smaller outflows in response to a negative shock. This reduction in the magnitude of outflows would require less forced asset sales and hence lower procyclicality. Second, keeping the magnitude of outflows fixed, an increase in ex-ante liquidity buffers may reduce fire-sale externalities by supporting the fund's liquidity management (Di Iasio et al., 2022). Higher liquidity buffers allow fund managers to accommodate a larger part of outflows by drawing down buffers instead of costly liquidation of less liquid portfolio assets. To the extent that funds are subject to margin calls, higher liquidity buffers would also support the provision of collateral, including cash, without needing to sell less liquid assets. To the best of our knowledge, we are the first to analyse both channels through which liquidity buffers might alleviate procyclicality in the investment fund sector, notably through the dampening of outflows in a crisis as well as through less procyclical asset sales in response to a given level of outflows. We conduct our empirical tests using a sample of open-end corporate bond funds, which typically offer daily redemptions to their investors and are therefore subject to a significant liquidity mismatch (Goldstein et al., 2017).

Our main findings are as follows. First, after controlling for the flow-performance relationship and a rich set of portfolio characteristics, we find that higher liquidity buffers were associated with lower outflows during the outbreak phase of the COVID-19 crisis (between February 24^{th} and March 11^{th}). However, during the peak of the crisis (between March 12^{th} and 31^{st}), higher liquidity buffers did not attenuate outflows, suggesting that other factors played a more important role in driving outflows during the peak phase, including the wider dash for cash (i.e. reducing exposure to underlying market and credit risks). Second, we find that liquidity buffers substantially reduced procyclicality through fund managers' strategies to meet redemption requests. Using logit regressions, we find that an increase of one standard deviation in pre-existing cash buffers at February 29^{th} decreases the odds of cash hoarding by a sizable 42%, all else equal. Here, a fund is hoarding cash when it increases cash buffers despite facing outflows, implying that the fund has sold more portfolio assets than would have been necessary to meet outflows. Funds with higher pre-existing liquidity buffers used more cash and sold fewer corporate bonds to accommodate outflows, with lower fire-sale externalities as a consequence. Importantly, we control for the magnitude of outflows to rule out the explanation that funds with higher liquidity buffers acted less procyclically because they simply faced lower outflows.

This paper relates and contributes to multiple strands in the literature. First of all, we contribute to the literature on strategic complementarities in investment funds. Chen et al. (2010) and Goldstein et al. (2017) study the flow-performance relationship to show that the first mover advantage leads to elevated outflows, which leads to spillover effects in the underlying asset markets through fire-sale externalities (Coval and Stafford, 2007; Lou, 2012; Chernenko and Sunderam, 2020; Barucca et al., 2021; Fricke and Fricke, 2021; Jiang et al., 2022).[1] Consistent with this, Falato et al. (2021) show that U.S. corporate bond mutual funds with relatively less liquid portfolios faced larger outflows during the COVID-19 episode. We contribute to this literature by studying how liquidity buffers affected flow dynamics after controlling for lagged returns and a variety of fund characteristics.

[1] These vulnerabilities have also been recognized by policymakers and led to the issuance of the FSB recommendations with the aim to improve the resilience of the investment fund sector (Financial Stability Board, 2017).

Secondly, we add to the literature studying the liquidity management of bond funds. Whereas some studies document a clear pecking-order of liquidation in which fund managers first sell their more liquid assets to meet redemptions (Chernenko and Sunderam, 2016; Choi et al., 2020), others find evidence that fund managers preserve the liquidity of their portfolio to prepare for future outflows (Morris et al., 2017; Shek et al., 2018). In addition, Jiang et al. (2021) show that fund managers employ dynamic liquidity management strategies: funds mainly rely on liquid assets to accommodate flows under quiet market circumstances, whereas they proportionally scale down their holdings to preserve portfolio liquidity during times of stress. More recently, Schrimpf et al. (2021) and Ma et al. (2022) study liquidity management of bond funds during March 2020, again leading to mixed conclusions. Whereas Schrimpf et al. (2021) find that a large number of funds hoarded cash to prepare for future outflows, Ma et al. (2022) show that funds mainly sold their most liquid holdings, including Treasuries and high-quality corporate bonds. In summary, a broad range of strategies exists in responding to outflows, which is also reflected by the dispersion of empirical findings in the literature. Our contribution is to assess whether the ex ante level of liquidity buffers determines which strategy fund managers employ to meet redemption requests. We show that funds entering the COVID-19 crisis with higher liquidity buffers were less likely to involve in cash hoarding and sold fewer corporate bonds to meet outflows. Among the funds selling corporate bonds, they had a tendency to sell their more liquid corporate bonds during March 2020.

Our findings are also relevant for policymakers aiming to enhance resilience in the investment fund sector and mitigate systemic risk. A wide range of liquidity management tools have been considered from this perspective. For instance, swing pricing and anti-dilution levies may be helpful in addressing the first-mover advantage in corporate bond funds (Capponi et al., 2020; Jin et al., 2022; Dunne et al., 2022).[2] However, such antidilution tools might not be sufficient to halt outflows and mitigate procyclical asset sales during episodes of large market wide shocks. Our empirical results suggest that first-mover advantages were not the main driver of outflows during the peak of the pandemic, which renders tools that address first-mover advantages less effective in such circumstances. Deriving concrete policy conclusions is not straightforward as the design and implementation of specific policy measures can result in unintentional effects.[3]

[2] Anti-dilution levies aim to ensure that redemption costs are borne by the redeeming investors, for instance in the form of redemption fees.

[3] For instance, liquidity requirements imposed by the SEC in 2018 unintentionally led to larger flow-induced sales of less liquid bonds, as funds tried to maintain sufficient amounts of liquid assets also during crisis times

On the other hand, we find that liquidity buffers were effective in reducing procyclical asset sales during crisis times, which is also consistent with the theoretical predictions by Di Iasio et al. (2022).

2 Data Description

We obtain detailed portfolio holdings as well as daily fund flows and fund returns from Refinitiv Lipper. As of December 2019, the universe of euro area open-ended bond funds obtained from Refinitiv Lipper held total net assets of roughly 2.1 trillion euros. As our focus is on corporate bond funds, we restrict attention to funds that on average invest at least 50% of their portfolios in corporate bonds during our sample period between December 2018 and May 2020. Since Refinitiv Lipper does not contain holdings data for all funds, we identify a subset of 1938 unique funds that on average allocated at least 50% to corporate bonds. This resulting subset of funds held almost 900 billion euros in total net assets as of December 2019, accounting for over 40% of the entire euro area open-ended bond fund sector. The vast majority of the funds in our sample are domiciled in Luxembourg (Figure 2a), whereas most funds either have a global or European investment focus (Figure 2b). We define the crisis period as the period between February 24^{th} and March 31^{st}. Due to their global focus, funds' portfolios might have been subject to interventions by multiple central banks. We therefore use the announcement by the World Health Organization on March 11^{th} to split March 2020 into an outbreak and a peak phase, rather than the timing of central bank actions. We furthermore restrict our sample to funds with cash buffers between 0 and 25% as in Jiang et al. (2021), because negative or extremely high cash buffers are unlikely held for pure liquidity management purposes.[4] We merge the holdings data with additional bond characteristics from the Centralised Securities Database (CSDB) of the European System of Central Banks (ESCB). These characteristics include the bond's date of issuance, maturity date, issue size, and credit rating, as well as the industry classification of the bond's issuer.

Table 1 contains a summary of our dataset. The largest portfolio components include corporate bonds, sovereign bonds, and cash. Panel A shows that the average portfolio weight allocated to corporate bonds equals 82.80%, followed by an average weight of 5.75% invested in sovereign bonds and average cash buffers of 4.47%. Panel B of Table 1 shows that the funds in our sample

Chakraborty et al. (2022).

[4] See Table A1 in the Appendix for an overview of the items that Refinitiv Lipper classifies as cash.

on average allocate about 46% of their portfolios to investment grade corporate bonds, 33% to bonds issued by non-financial corporations, 20% to corporate bonds with an age below one year, and 17% to corporate bonds with an issue size exceeding 1 billion euros. Finally, Panel C of Table 1 contains some additional fund characteristics. The average fund in our sample manages 408 million euros, whereas the average shareclass accounts for 71 million euros in total net assets.

Figure 3a shows that the funds in our sample started facing net outflows in the final week of February 2020. The largest outflows took place after March 11^{th}, when the World Health Organization officially characterized COVID-19 as a pandemic. Outflows were sustained until the end of March, when central bank interventions stabilized the corporate bond market (Falato et al., 2021; O'Hara and Zhou, 2021; Haddad et al., 2021).

3 Determinants of outflows during March 2020

In this section, we test whether the first-mover advantage exacerbated outflows during the onset of the COVID-19 crisis in March 2020. Our analyses build on the flow-performance framework for mutual funds (see, e.g., Berk and Green, 2004), which has been studied empirically for corporate bond mutual funds by Goldstein et al. (2017).

First of all, we test whether the flow-performance relationship changed during March 2020. Goldstein et al. (2017) show that the sensitivity of outflows from corporate bond funds to poor performance is mainly driven by crisis periods and periods in which the corporate bond market is illiquid. They argue that first-mover advantages are larger during such periods, leading to larger sensitivities of outflows to poor performance. As such, we also expect to find that the sensitivity of outflows to poor returns increased in March 2020. We test this hypothesis using the following specification:

$$\begin{aligned} f_{i,t} = \alpha_t + \beta' Crisis_t + \gamma' \left(\min(0, r^i_{t-1}) \cdot Crisis_t\right) + \delta' \left(\max(0, r^i_{t-1}) \cdot Crisis_t\right) \\ + \lambda \min(0, r^i_{t-1}) + \mu \max(0, r^i_{t-1}) + \sum_{z=1}^{5} \rho_z f_{i,t-z} + \varepsilon_{i,t} \end{aligned} \tag{1}$$

Here, $f_{i,t}$ denotes the daily flow of shareclass i at day t and r^i_{t-1} is the lagged return of shareclass i ending at day $t-1$. Since there is no theoretical prior on the right horizon of lagged returns, we consider different specifications with daily, weekly, as well as monthly lagged returns. Furthermore, $Crisis_t$ denotes a vector of crisis dummies. We initially consider one dummy capturing the period between February 24^{th} and March 31^{st}, but we also split this period into an outbreak phase (February 24^{th} - March 11^{th}) and a peak phase (March 12^{th} - March 31^{st}) to allow for different dynamics during different phases of the crisis. Finally, time fixed effects are denoted by α_t. Following the standard in the literature, we conduct our analyses of flows on the shareclass level, as different shareclasses of the same fund might have different characteristics that impact flow dynamics.[5] Whereas the flow-performance relationship is often tested using monthly returns and flows, we are interested in run dynamics at a higher frequency. When investors had the possibility to redeem fund shares on a daily basis during March 2020, lagged fund returns during March 2020 were likely relevant information in determining whether to redeem or not. This more recent information would be missing from a specification exploiting a monthly frequency, where monthly outflows during March 2020 are regressed on monthly returns during February 2020. Following Falato et al. (2021), we therefore consider daily flows between January 2019 and May 2020. To allow for a concave flow-performance relationship, we distinguish between positive and negative lagged returns. We are mainly interested in the vector of coefficients denoted by γ, as this coefficient measures whether flows responded differently to negative lagged returns during the crisis relative to more quiet circumstances.

Table 2 contains the results. The coefficients corresponding to both positive as well as negative lagged returns are significantly positive irrespective of the specification, indicating that flows and lagged returns are strongly positively related. We are mainly interested in testing whether the response by investors to negative lagged returns is stronger during the COVID-19 turmoil than under more quiet circumstances. Our results using daily lagged returns in columns 1-2 do not support this hypothesis, as the coefficients on the interactions between daily lagged negative returns and the crisis dummies are statistically insignificant at the conventional significance levels. This holds irrespective whether we include one crisis dummy capturing the entire crisis period (column 1) or two crisis dummies that separately capture the outbreak and peak phases (column 2). When considering weekly lagged returns, we find some evidence that the flow-performance sensitivity increased during the outbreak phase (column 4), although this coefficient is significant at the 10% level only. Finally, when using monthly lagged returns in

[5] An example would be a fund having a separate shareclass targeting institutional investors, who might behave differently from retail investors that are targeted through a different shareclass of the same fund.

columns 5-6, we find a statistically significant increase in flow-performance sensitivities during the outbreak phase. Hence, our evidence on increased flow-performance sensitivities during the outbreak phase is stronger when using lagged returns measured over a longer horizon. Nevertheless, we cannot reject the null hypothesis of no increase in flow-performance sensitivities during the peak of the crisis, whereas the largest outflows were seen during the peak phase (Figure 3a). The results in Table 2 are robust against replacing raw returns by returns in excess of the average return by all funds with the same geographical investment focus (Table A2).

We now turn to the cross section of funds and try to relate fund-level outflows to fund characteristics. Goldstein et al. (2017) hypothesize that the first-mover advantage should be larger for more illiquid funds relative to more liquid funds. As a result, more illiquid funds should have experienced larger outflows during March 2020 than more liquid funds, all else equal. In this context, Falato et al. (2021) show that relatively less liquid US corporate bond funds faced larger outflows, but they do not control for lagged returns. We test whether funds with higher liquidity buffers experienced smaller outflows after controlling for lagged returns. Including lagged returns as a control variable is key, as returns tend be strongly correlated with future fund flows as well as the level of portfolio liquidity. We use the following specification:

$$\begin{aligned} f_{i,q,t} = \alpha_t &+ \beta' Crisis_t + \gamma' \left(\min(0, r^i_{t-1}) \cdot Crisis_t\right) + \delta' \left(\max(0, r^i_{t-1}) \cdot Crisis_t\right) \\ &+ \theta' \left(Crisis_t \cdot X_{i,q-1}\right) + \eta' X_{i,q-1} + \lambda \min(0, r^i_{t-1}) + \mu \max(0, r^i_{t-1}) \\ &+ \sum_{z=1}^{5} \rho_z f_{i,q,t-z} + \varepsilon_{i,q,t}, \end{aligned} \tag{2}$$

Here, q indicates quarters and $X_{i,q-1}$ is a vector of fund characteristics lagged by one quarter. This vector includes the fund's portfolio weight allocated to cash (w_{cash}), the portfolio weight allocated to government bonds, the portfolio weight allocated to investment grade corporate bonds, the portfolio weight allocated to bonds issued by non-financial corporations, the portfolio weight allocated to bonds with age below 1 year, the portfolio weight allocated to bonds with an issue size larger than 1 billion euros, the portfolio weight allocated to derivatives, the logarithm of lagged TNA, a dummy indicating whether the shareclass is targeting institutional investors, a dummy indicating whether the shareclass belongs to an index fund, a dummy indicating whether the fund uses financial leverage, and the maximum back load. In some specifications, we combine cash buffers with the portfolio weight allocated to government bonds with an investment-grade rating above BBB (w_{liq}), as these safe government bonds might also serve as a liquidity buffer.[6] We also interact fund characteristics with the crisis dummies to allow these characteristics to differentially impact flows during the pandemic. We include time fixed effects (α_t) but abstain from shareclass fixed effects because we are primarily interested in the variation across funds (rather than the within variation).

We hypothesize that all else equal, funds entering the crisis in March 2020 with higher cash buffers and liquid asset holdings faced smaller outflows, as the first-mover advantage should be smaller for these funds. The size of a fund's cash buffer likely depends on the liquidity of the corporate bonds held, as shown by Chernenko and Sunderam (2016). The higher the liquidity of the bonds in a fund's portfolio, the lower the need for high cash buffers to meet sudden redemptions. It is therefore important to control for the liquidity of the bonds held to prevent an omitted variable bias, as bond liquidity might simultaneously affect cash buffers as well as flows. Even though we cannot perfectly measure portfolio liquidity, we control for a number of portfolio characteristics that are correlated with a fund's asset liquidity, such as the weight allocated to bonds with large issue sizes and bonds that have been issued recently.[7] We believe this should alleviate endogeneity concerns, as it is unlikely that investors had additional information on the liquidity profiles of the investment funds in our sample beyond the characteristics we control for.

Table 3 contains the results of estimating Equation (2). We find that irrespective of the horizon at which lagged returns are measured, higher cash weights were associated with smaller outflows during the outbreak of the crisis (columns 1, 3, and 5), after controlling for portfolio characteristics and lagged returns. We find the same result when cash holdings and positions in government bonds with a credit rating higher than BBB are combined (columns 2, 4, and 6). The results thus suggest that higher liquidity buffers reduced outflows during the early stage of the COVID-19 shock. During the peak phase, we do not detect a significant relationship between pre-existing liquidity buffers and the magnitude of outflows, potentially because outflows during later parts of the crisis also reflected a wider dash for cash. Schrimpf et al. (2021), for instance, document that outflows from bond mutual funds during March 2020 were not sensitive to funds' initial cash holdings, attributing the outflows to a dash for cash that affected funds rather

[6] In this specification, we exclude the portfolio weight allocated to government bonds because of multicollinearity concerns.

[7] See Houweling et al. (2005) for an overview of liquidity proxies for euro corporate bonds.

indiscriminately.

Table A3 contains the results of estimating a variant of Equation 2 where we exclude lagged returns and their interactions with crisis dummies. Not controlling for lagged returns (interacted with crisis dummies) leads to substantially larger estimates of the coefficients corresponding to the interaction between liquidity buffers and the Outbreak dummy. Without controlling for lagged returns, the coefficient on the interaction between cash weights and the outbreak dummy equals 0.271, versus an estimate in the range of 0.171-0.218 in Table 3. Similarly, Table A3 reports a coefficient of 0.228 for the interaction between the weight invested in cash plus liquid government bonds and the Outbreak dummy, versus an estimate in the range of 0.119-0.178 in Table 3. These results highlight the importance of controlling for lagged returns, as part of the difference in outflows between funds with high versus low liquidity buffers can be attributed to differences in their respective lagged returns. Not including lagged returns would thus lead to an omitted-variables bias.

One concern could be that our results are confounded by the availability of liquidity management tools. We do control for maximum back loads, but we do not observe the availability of other liquidity management tools. A fund for which certain tools are available might hold less cash but does not need to be more vulnerable than a fund with a higher cash buffer that does not have liquidity management tools available. This could potentially work against finding a dampening effect of cash buffers on outflows. To alleviate this concern, we run two alternative specifications. First of all, we include domicile times day fixed effects (Appendix Table A4). The availability of liquidity management tools for investment funds differs across jurisdictions and also varies through time as some jurisdictions have expanded the range of liquidity management tools (European Systemic Risk Board, 2020). By including domicile times day fixed effects, we control for (time-varying) differences in the availability of such tools across jurisdictions. However, this test confirms that higher liquidity buffers reduced outflows during the outbreak phase only. Secondly, Appendix Table A5 contains a specification that includes fund family times day fixed effects. As shown by Dunne et al. (2022), the availability of liquidity management tools is typically determined at the fund-family level rather than at the individual fund or shareclass level. Hence, by including fund family times day fixed effects, we effectively eliminate variation across fund families that might be due to differences in the availability of liquidity management tools. However, the inclusion of fund family times day fixed effects in Appendix Table A5 does not lead to a stronger mitigating effect of liquidity buffers on outflows. We thus conclude that higher liquidity buffers reduced outflows only during the outbreak of the COVID-19 crisis, but not during the peak.

We finally consider outflows from exchange-traded funds (ETFs). Investors cannot redeem ETF shares as they would redeem shares of open-end funds, but need to sell their ETF shares in the secondary market instead. As a result, the first-mover advantage that is present among investors in open-end funds should be less pronounced for ETFs (Goldstein et al., 2017). On the other hand, the structure of ETFs might attract a different clientele with different liquidity preferences than investors in open-end funds (Dannhauser and Hoseinzade, 2022). For instance, institutional investors might invest a fraction of their portfolios into corporate bond ETFs to increase exposure towards corporate bonds while at the same time benefitting from the liquidity of ETF shares. If, in response to poor performance, institutional investors sell corporate bond ETFs on a large scale to manage the liquidity of their own portfolios, this might give rise to significant net outflows from ETFs during times of stress as well. Figure 3b shows that euro area corporate bond ETFs indeed faced substantial outflows during the COVID-19 market turmoil. This is consistent with the wider dash for cash being a key driver of outflows across different types of funds witnessed during the COVID-19 crisis.

4 How did funds meet redemption requests?

In this section, we study the response by fund managers to the large redemptions faced during March 2020. As shown theoretically by Di Iasio et al. (2022), fund managers might not fully internalise the impact of their forced asset sales on market prices and thereby on other market participants, resulting in inefficiently low liquidity buffers. Consistent with this, Chernenko and Sunderam (2020) show empirically that fund managers might not fully internalize the impact of their trading. They find that fund managers responsible for multiple funds rely more on cash in response to outflows if the trading externalities of one fund might hurt other funds they manage. Figure 4a plots the difference between liquidity buffers observed at February 29^{th}, 2020 and flows between March 1^{st} and March 31^{st}, 2020 for the funds in our sample. In the left-hand side of Figure 4a, we define the liquidity buffer as cash holdings. It follows that the median difference between cash holdings and flows is slightly above zero, meaning that almost half of the funds faced outflows exceeding their pre-existing cash buffers. On the right-hand side, we complement cash holdings with positions in government bonds with a credit rating exceeding BBB. By construction, this leads to a slight upwards shift in the distribution, but still a substantial set of funds had insufficient liquid holdings to meet redemption requests, thereby being forced to sell other potentially less liquid assets.

This raises the question to what extent funds relied on their liquid buffers to meet outflows. On the one hand, funds might rely heavily on cash and other liquid assets, as selling these is less costly. However, this leads to a deterioration of the fund's portfolio liquidity going forward, which might complicate the accommodation of future redemption requests. In order to preserve or even improve the fund's portfolio liquidity, the fund might therefore abstain from depleting cash buffers. Figure 4b plots the changes in cash holdings between February 29^{th} and March 31^{st}, 2020 as a percentage of total net assets at February 29^{th}, 2020 against flows in March 2020. Whereas the vast majority of the funds in our sample faced net outflows during March 2020, there is large heterogeneity in changes in cash holdings. Some fund managers clearly used cash buffers to meet at least part of the outflows, whereas others involved in cash hoarding which implies they sold more portfolio assets than necessary to meet outflows. Hence, different fund managers took different approaches in meeting outflows, and we next try to relate this heterogeneity in fund managers' strategies to meet redemption requests to the liquidity profiles of the underlying funds.

In the remainder of this section, we restrict our sample to only those funds that faced outflows during March 2020, because we are mainly interested in the way funds responded to outflows rather than inflows. We start with a logit regression to examine which fund characteristics increased the likelihood of cash hoarding:

$$\mathbb{1}(\text{Cash Hoarding}_{i,t}) = \alpha + \beta Flow_{i,t} + \gamma' X_{i,t-1} + \varepsilon_{i,t}, \tag{3}$$

where $\mathbb{1}(\text{Cash Hoarding}_{i,t})$ equals 1 if fund i hoarded cash during March 2020 and 0 otherwise. We identify a fund as hoarding cash when it 1) faced net outflows during March 2020 and 2) it increased the amount of cash held during March 2020. Note that we consider the amount of cash held rather than the portfolio weight allocated to cash, as portfolio weights are confounded by changes in the valuation of portfolio assets. As mentioned before, we focus on a subsample of funds that experienced net outflows during March 2020, so the first condition is automatically satisfied for all funds. The explanatory variable $Flow_{i,t}$ denotes the fund's flows over March 2020 scaled by the fund's total net assets of February 29^{th}, and $X_{i,t-1}$ is a vector of fund characteristics observed at February 29^{th}, 2020. This vector includes the fund's cash weight, its weight invested in government bonds, investment-grade corporate bonds, corporate bonds issued in the past year, corporate bonds with an issue size exceeding 1 billion euros, bonds issued by non-financial corporations, and its weight held in derivative positions. Moreover, it includes dummy variables indicating whether a fund uses financial leverage and whether the fund is an index fund, respectively. Finally, it includes the logarithm of the fund's total net assets. Columns 1-2 in Table 4 contain the results. We find strong evidence that higher pre-existing liquidity buffers decreased the likelihood that a fund hoarded cash in March 2020. Specifically, the results in column 1 suggest that a one standard deviation increase in pre-existing cash buffers at February 29^{th} decreases the odds of cash hoarding by 42% ($exp(-0.147 * 3.73) - 1$), keeping other factors fixed. Hence, funds with higher liquidity buffers were substantially less likely to act as shock amplifiers by selling more bonds than necessary to meet outflows. Importantly, we also control for flows, so the effect of cash buffers on the likelihood of cash hoarding is not driven by the mechanism that higher cash buffers led to a lower likelihood of cash hoarding through lower outflows.

Next, we examine the relation between the actual change in cash holdings and fund characteristics using the following cross-sectional regression:

$$\frac{\Delta Cash_{i,t}}{TNA_{i,t-1}} = \alpha + \beta Flow_{i,t} + \gamma' X_{i,t-1} + \varepsilon_{i,t} \tag{4}$$

In line with Figure 4b, the dependent variable is defined as the euro change in cash holdings by fund i between February 29^{th} and March 31^{st}, 2020, scaled by the fund's total net assets of February 29^{th}. Columns 3-4 of Table 4 contain the results. The coefficient on the fund's flow is modest and varies between 0.042 and 0.046, which reflects the large heterogeneity in the way funds responded to outflows as visible in Figure 4b. We furthermore find a significantly negative coefficient on pre-existing cash weights in column 3. This suggests that after controlling for outflows, funds with higher pre-existing cash buffers used more of those buffers to accommodate outflows. Each additional euro held in cash at February 29^{th} is associated with an average additional decrease in cash buffers of 32 cents during March. In column 4, we complement cash buffers by the weight invested in government bonds with a credit rating exceeding BBB, but the conclusion remains unchanged.

We next study portfolio rebalancing in response to outflows by examining changes in corporate bond positions directly. We define our outcome variable as follows:

$$\Delta Corp_{i,t} = \frac{\sum_{j \in C_t} Par_{i,j,t} - \sum_{j \in C_{t-1}} Par_{i,j,t-1}}{TNA_{i,t-1}} \tag{5}$$

Here, C_t denotes the set of corporate bonds held by fund i at time t, and $Par_{i,j,t}$ denotes the par value in euros that fund i holds in bond j at time t. Using par values instead of market values ensures that our measure is not confounded by changes in valuation. We then run the regression from Equation (4) with this alternative dependent variable. Columns 5-6 in Table 4 contain the results. As expected, we find that larger outflows are associated with larger decreases in the par value of corporate bonds held. An increase in outflows of 1 euro on average leads to additional corporate bond sales of about 79 cents (expressed in par value). Furthermore, we continue to find an important role for cash buffers. The significantly positive coefficient on cash weights in column 5 indicates that funds with high cash buffers sold less corporate bonds during March 2020, keeping other factors fixed. This finding is consistent with Choi et al. (2020) and Jiang et al. (2022), who find that higher liquid asset holdings alleviate flow-induced selling pressure. Again, we control for flows, so the effect of cash buffers on corporate bond selling is not driven by the mechanism that higher cash buffers led to less corporate bond selling through lower outflows. We also find that higher positions in government bonds imply lower corporate bond selling, either because the fund manager is vertically slicing a portfolio that contains a smaller position in corporate bonds, or because the manager horizontally slices the portfolio by disproportionally selling more liquid government bonds. Concluding, we find a strong link between liquidity buffers and the procyclicality of fund managers when faced with large outflows.

We consider a final cross-sectional regression to study which corporate bonds were sold by investment funds:

$$\frac{Par_{i,j,t}}{Par_{i,j,t-1}} - 1 = \alpha + \beta Flow_{i,t} + \gamma' \left(Flow_{i,t} \cdot C_{j,t-1} \right) + \delta' C_{j,t-1} + \kappa' X_{i,t-1} + \varepsilon_{i,t}, \tag{6}$$

where j indexes corporate bonds and $C_{j,t-1}$ is a vector of lagged bond characteristics, including the logarithm of issue size, bond age, time to maturity, credit rating, a dummy indicating whether the bond was issued by a non-financial corporation, and country dummies.[8] Column 1

[8]We transform credit ratings from S&P, Moody's, and Fitch to a numerical scale where a value of 1 corresponds to a rating of 'D' and a value of 22 corresponds to a AAA-rating. We then take the median across credit rating agencies to have a numerical value of a bond's credit rating.

of Table 5 shows that corporate bond selling was more pronounced for bonds with a large issue size and a small age. Since a large issue size and a small age is typically associated with higher liquidity (Houweling et al., 2005), this would point at a pecking order within the liquidation of corporate bonds, where funds predominantly sold their more liquid corporate bonds before selling their less liquid bonds. In column 2, we also include interactions between fund flows and bond characteristics. Since flows are negative, the coefficient signs of the interaction terms suggest that funds had a tendency to sell corporate bonds with a larger issue size, corporate bonds that were issued more recently, as well as higher rated corporate bonds.

Overall, these findings suggest that portfolio liquidity affects the extent to which fund managers draw down cash buffers in response to outflows (in line with Schrimpf et al. (2021)), whereas the fund manager's selection of which bonds to sell is affected by bond liquidity (in line with Ma et al. (2022)).

5 Conclusion

In this paper, we exploit the COVID-19 episode to study the liquidity management of corporate bond investment funds domiciled in the euro area. Especially funds investing in corporate bonds can be vulnerable, as corporate bonds can become illiquid in times of stress whereas the funds holding them typically offer daily redemption frequencies to their investors. This liquidity mismatch can amplify the procyclicality of the investment fund sector via two main channels: the first-mover advantage which leads to a higher sensitivity of outflows to poor performance, and the liquidity management strategies employed by fund managers to meet a given level of outflows.

As regards the first channel, we find some evidence that the flow-performance sensitivity in our sample of euro area corporate bond funds increased during the outbreak phase of the COVID-19 pandemic. While this increase in the flow-performance sensitivity could be indicative of an increased first-mover advantage, we find no such increase during the peak phase of the crisis. Our results show that higher liquidity buffers reduced outflows to some extent, namely during the outbreak of the crisis before it was officially declared a pandemic by the World Health Organization. However, this effect was absent during the peak of the crisis, suggesting that outflows at least partly reflected a wider dash for cash. Importantly, as regards the second channel, the size of liquidity buffers does affect the way fund managers deal with outflows. We find that funds with high ex-ante liquidity buffers were less likely to involve in cash hoarding. Moreover, they relied more on cash and sold less corporate bonds to meet outflows compared with funds that entered the crisis with low liquidity buffers. As such, our results suggest that the liquidity management strategies by fund managers were the main channel through which liquidity buffers led to a reduction in procyclical investment behaviour during the COVID-19 crisis in March 2020.

Our results have important policy implications. In recent years, liquidity management tools that aim at reducing the first-mover advantage, such as swing pricing, have become more common. Though helpful, these tools alone might not be sufficient to achieve a more resilient investment fund sector, as exogenous system-wide shocks like the COVID-19 market turmoil might still lead to severe outflows. This is also illustrated by the large outflows witnessed by corporate bond ETFs, assuming that ETF prices reflect asset liquidation costs more accurately compared to the net asset values of open-end funds. Our results suggest that higher liquidity buffers can help in alleviating fire-sale externalities during such times of stress, given that they play an important role in the liquidity management of funds that are invested in less liquid assets, such as corporate bonds. Deriving concrete policy conclusions is not straightforward though, also because possible unintentional effects need to be considered when devising specific measures.

For instance, minimum liquidity requirements could reduce investment funds' capacity to hold less liquid bonds, potentially leading to a higher cost of capital for the corresponding issuers. It might also impair the usability of the buffers during stress times. As such, it is important to carefully weight the costs and benefits of mandatory liquidity buffers.

References

Barucca, P., Mahmood, T., and Silvestri, L. (2021). Common asset holdings and systemic vulnerability across multiple types of financial institution. *Journal of Financial Stability*, 52:100810.

Berk, J. B. and Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of Political Economy*, 112(6):1269–1295.

Capponi, A., Glasserman, P., and Weber, M. (2020). Swing pricing for mutual funds: Breaking the feedback loop between fire sales and fund redemptions. *Management Science*, 66(8):3581–3602.

Chakraborty, I., Ferracuti, E., Heater, J. C., and Phillips, M. (2022). The consequences of fund-level liquidity requirements. *Available at SSRN*.

Chen, Q., Goldstein, I., and Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. *Journal of Financial Economics*, 97(2):239–262.

Chernenko, S. and Sunderam, A. (2016). Liquidity transformation in asset management: Evidence from the cash holdings of mutual funds. *NBER Working Paper No. 22391*.

Chernenko, S. and Sunderam, A. (2020). Do fire sales create externalities? *Journal of Financial Economics*, 135(3):602–628.

Choi, J., Hoseinzade, S., Shin, S. S., and Tehranian, H. (2020). Corporate bond mutual funds and asset fire sales. *Journal of Financial Economics*, 138(2):432–457.

Coval, J. and Stafford, E. (2007). Asset fire sales (and purchases) in equity markets. *Journal of Financial Economics*, 86(2):479–512.

Dannhauser, C. D. and Hoseinzade, S. (2022). The unintended consequences of corporate bond ETFs: Evidence from the taper tantrum. *The Review of Financial Studies*, 35(1):51–90.

Di Iasio, G., Kaufmann, C., and Wicknig, F. (2022). Macroprudential regulation of investment funds. *ECB Working Paper Series No 2695*.

Dunne, P. G., Emter, L., Fecht, F., Giuliana, R., and Peia, O. (2022). Financial fragility in open-ended mutual funds: The role of liquidity management tools. *Available at SSRN 4282841*.

European Systemic Risk Board (2020). A Review of Macroprudential Policy in the EU in 2019.

Falato, A., Goldstein, I., and Hortaçsu, A. (2021). Financial fragility in the covid-19 crisis: The case of investment funds in corporate bond markets. *Journal of Monetary Economics*, 123:35–52.

Financial Stability Board (2017). Policy recommendations to address structural vulnerabilities from asset management activities.

Fricke, C. and Fricke, D. (2021). Vulnerable asset management? the case of mutual funds. *Journal of Financial Stability*, 52:100800.

Goldstein, I., Jiang, H., and Ng, D. T. (2017). Investor flows and fragility in corporate bond funds. *Journal of Financial Economics*, 126(3):592–613.

Haddad, V., Moreira, A., and Muir, T. (2021). When selling becomes viral: Disruptions in debt markets in the covid-19 crisis and the fed's response. *The Review of Financial Studies*, 34(11):5309–5351.

Houweling, P., Mentink, A., and Vorst, T. (2005). Comparing possible proxies of corporate bond liquidity. *Journal of Banking & Finance*, 29(6):1331–1358.

International Monetary Fund (2022). Global Financial Stability Report.

Jiang, H., Li, D., and Wang, A. (2021). Dynamic liquidity management by corporate bond mutual funds. *Journal of Financial and Quantitative Analysis*, 56(5):1622–1652.

Jiang, H., Li, Y., Sun, Z., and Wang, A. (2022). Does mutual fund illiquidity introduce fragility into asset prices? Evidence from the corporate bond market. *Journal of Financial Economics*, 143(1):277–302.

Jin, D., Kacperczyk, M., Kahraman, B., and Suntheim, F. (2022). Swing pricing and fragility in open-end mutual funds. *The Review of Financial Studies*, 35(1):1–50.

Lou, D. (2012). A flow-based explanation for return predictability. *The Review of Financial Studies*, 25(12):3457–3489.

Ma, Y., Xiao, K., and Zeng, Y. (2022). Mutual fund liquidity transformation and reverse flight to liquidity. *The Review of Financial Studies*, 35(10):4674–4711.

Morris, S., Shim, I., and Shin, H. S. (2017). Redemption risk and cash hoarding by asset managers. *Journal of Monetary Economics*, 89:71–87.

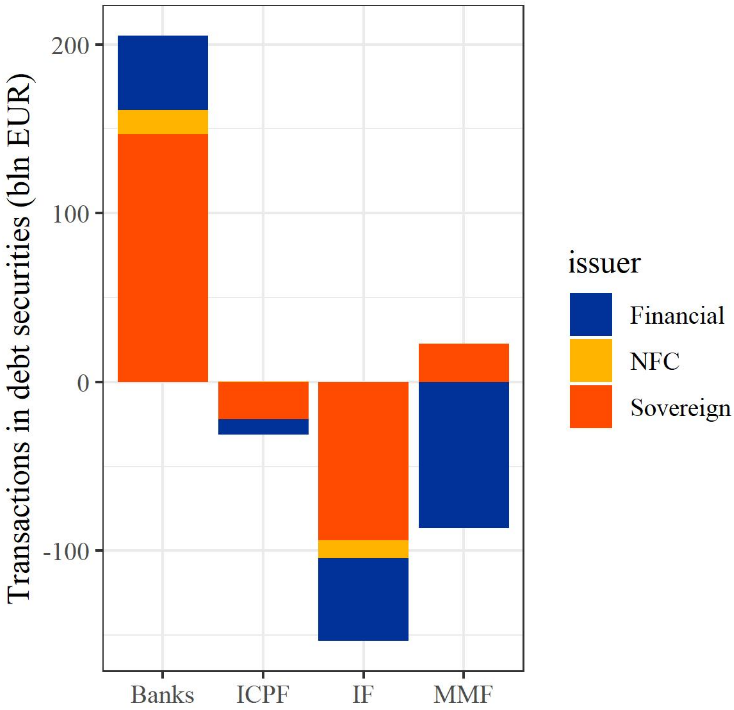
O'Hara, M. and Zhou, X. A. (2021). Anatomy of a liquidity crisis: Corporate bonds in the covid-19 crisis. *Journal of Financial Economics*, 142(1):46–68.

Schrimpf, A., Shim, I., and Shin, H. S. (2021). Liquidity management and asset sales by bond funds in the face of investor redemptions in march 2020. *Available at SSRN 3799868*.

Shek, J., Shim, I., and Shin, H. S. (2018). Investor redemptions and fund manager sales of emerging market bonds: how are they related? *Review of Finance*, 22(1):207–241.

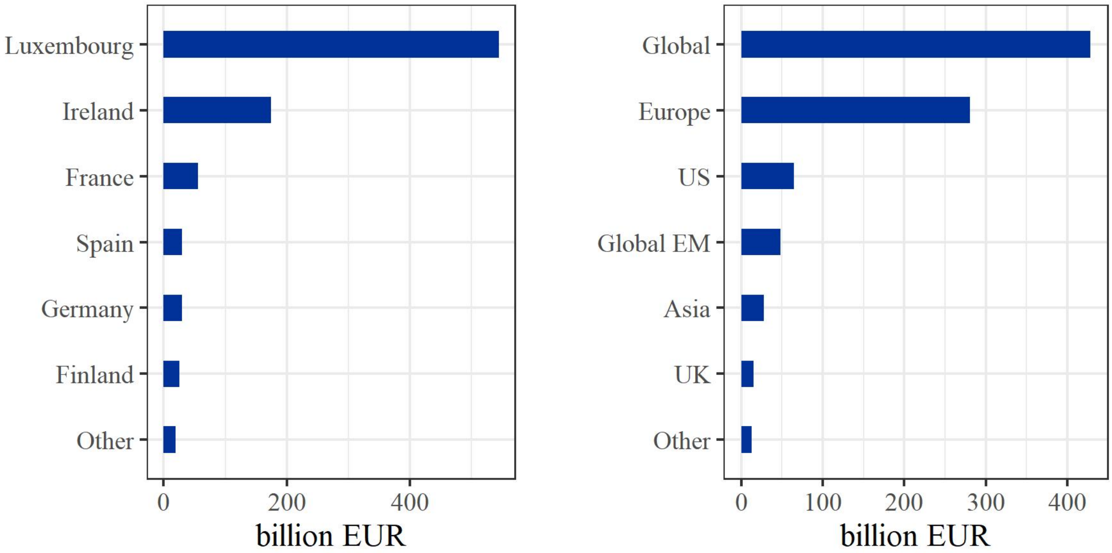
Figures

Figure 1: Transactions in debt securities during 2020Q1.



Notes: This figure shows aggregate transactions in debt securities by euro area investors broken down by investor type during the first quarter of 2020. We distinguish between Banks, Insurance Companies and Pension Funds (ICPF), Investment Funds (IF), and Money Market Funds (MMF). We also distinguish between debt issued by financial companies (Financial), non-financial corporations (NFC), and governments (Sovereign). Source: Securities Holdings Statistics.

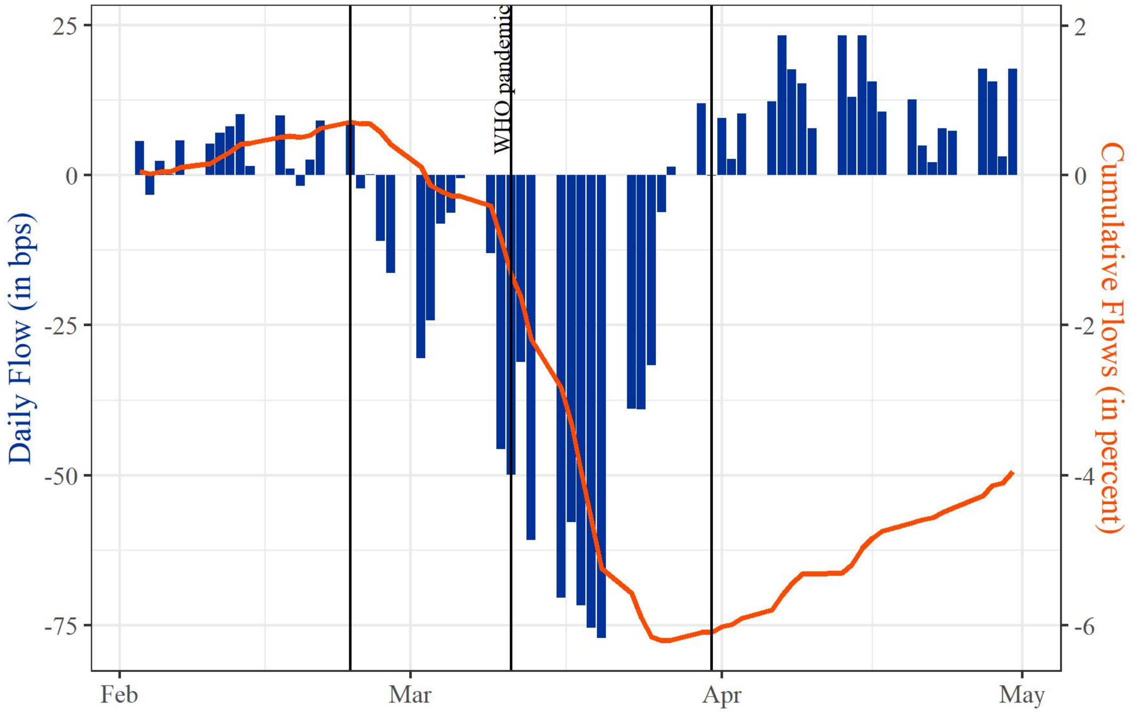
Figure 2: Total Net Assets by fund domicile and geographical investment focus.



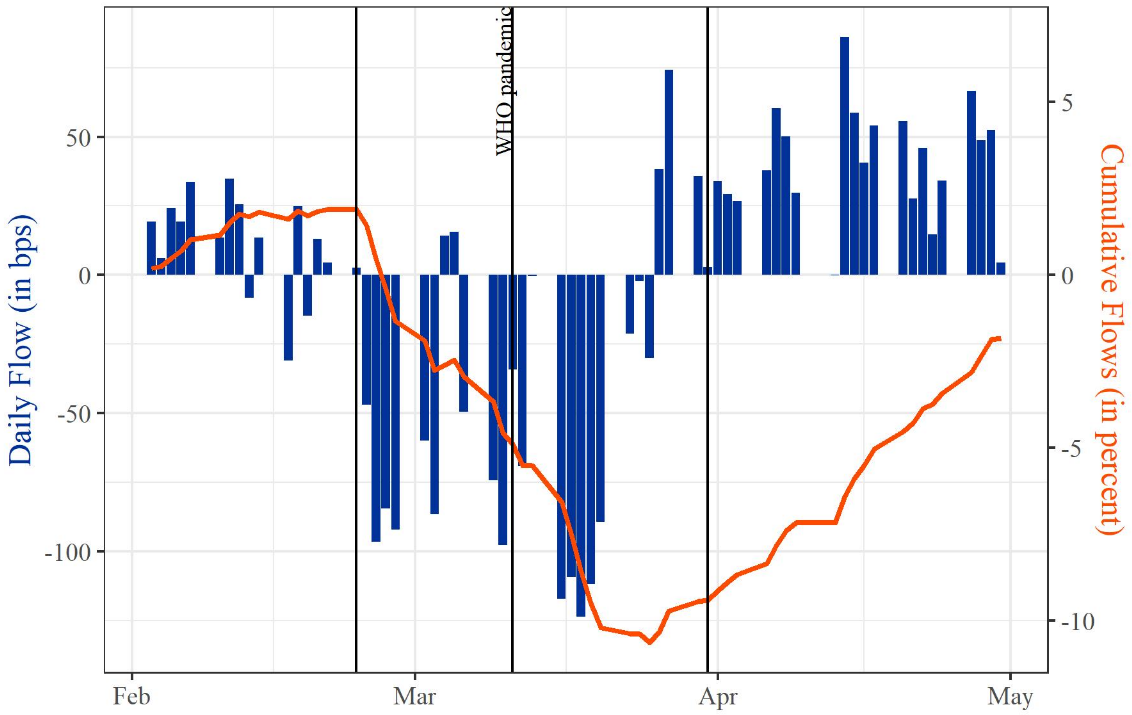
(a) Aggregate TNA by domicile. **(b)** Aggregate TNA by geographical focus.

Notes: This figure shows the combined Total Net Assets of the euro area corporate bond mutual funds in our sample by fund domicile (Panel (a)) and by geographical investment focus (Panel (b)) as of December 2019.

Figure 3: Fund flows between February and April 2020.



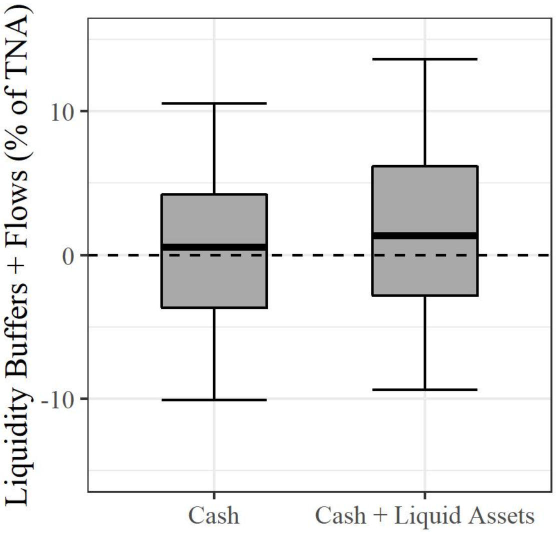
(a) Open-end corporate bond mutual funds.



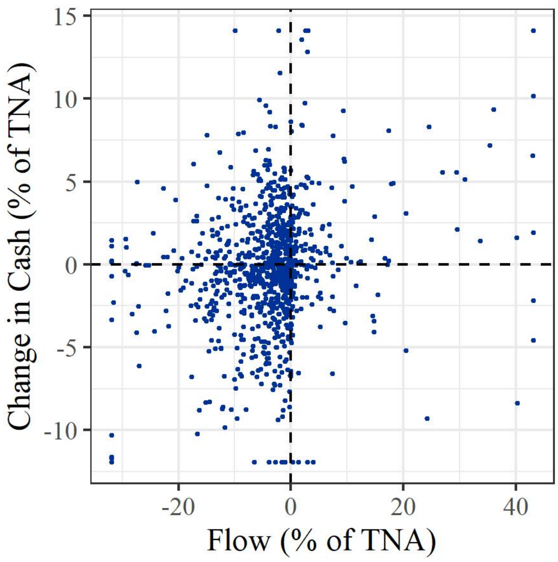
(b) Corporate bond ETFs.

Notes: This figure shows aggregate daily flows as a fraction of the previous day's total net assets, expressed in basis points (left vertical axis) as well as aggregate cumulative flows as a fraction of total net assets on January 31^{st}, 2020 in percent (right vertical axis). Panel (a) contains open-end corporate bond mutual funds and Panel (b) contains corporate bond ETFs, all domiciled in the euro area. The figure covers the period between February 1^{st}, 2020 to April 30^{th}, 2020. The vertical lines correspond to the start of our crisis period (February 24^{th}), the declaration of COVID-19 as a global pandemic by the World Health Organization (March 11^{th}), and the end of our crisis period (March 31^{st}), respectively.

Figure 4: Ex-ante liquidity buffers and fund flows.



(a) Difference between ex-ante liquidity buffers and flows.



(b) Changes in cash holdings versus flows.

Notes: Panel (a) shows the difference between funds' liquidity buffers at February 29^{th}, 2020 and fund-level outflows during March 2020, expressed as a percentage of total net assets. Liquidity buffers are defined as the funds' cash ratios (left-hand side) or funds' portfolio weights allocated to cash and government bonds with a rating exceeding BBB (right-hand side). The whisker boundaries correspond to the 10^{th} and 90^{th} percentiles. The box is drawn from the 25^{th} to the 75^{th} percentile with a horizontal line indicating the median. Panel (b) shows a scatter plot of monthly changes in cash holdings versus monthly flows during March 2020. Both changes in cash holdings as well as flows are scaled by the fund's total net assets as of February 29^{th}, 2020.

Tables

Table 1: Summary statistics.

Panel A. Asset Allocation (%)					
	Mean	St. Dev.	5%	Median	95%
Corporate	82.88	13.42	55.12	87.57	97.58
Sovereign	5.79	9.08	0.00	1.46	27.90
Cash	4.43	3.73	0.62	3.39	12.39
Panel B. Composition Corporate Bond Portfolio (%)					
	Mean	St. Dev.	5%	Median	95%
Investment Grade	46.00	29.17	1.79	48.34	88.29
NFC	33.35	16.31	4.95	33.45	59.27
Age $<$ 1 year	20.08	12.22	3.08	18.79	41.65
Issue Size $>$ 1 bln EUR	17.15	11.07	1.94	15.34	37.62
Panel C. Fund Characteristics					
	Mean	St. Dev.	5%	Median	95%
Fund Size (mln EUR)	408.29	810.71	12.03	130.37	1,880.10
Shareclass Size (mln EUR)	70.77	238.99	0.27	11.77	307.79
Daily Return (%)	0.01	0.35	-0.43	0.02	0.41
Daily Flow (%)	0.05	0.74	-0.36	0.00	0.57

Notes: This table shows descriptive statistics of our dataset. Panel A shows the overall asset allocation. Panel B shows the composition of the corporate bond investments. Panel C presents additional fund characteristics. Regarding the variables reflecting portfolio weights and fund/shareclass sizes, we first computed the time-series average for each fund/shareclass in our sample over the period between January 2019 and May 2020, after which we computed the cross-sectional statistics shown in the table.

Table 2: Flow-performance relationship open-end corporate bond funds.

Dep. Var.:	Daily flows of open-ended corporate bond funds					
Return Horizon:	Daily		Weekly		Monthly	
	(1)	(2)	(3)	(4)	(5)	(6)
$r^i_{t-1}\| < 0$	5.58**	5.58**	2.28**	2.28**	0.329*	0.329*
	(3.87)	(3.87)	(5.45)	(5.45)	(2.56)	(2.56)
$r^i_{t-1}\| < 0 \times$ Crisis	2.10		-0.242		0.286	
	(1.29)		(-0.408)		(1.09)	
$r^i_{t-1}\| < 0 \times$ Outbreak		1.11		1.46		2.52**
		(0.502)		(1.73)		(4.05)
$r^i_{t-1}\| < 0 \times$ Peak		2.40		-0.449		0.175
		(1.43)		(-0.744)		(0.676)
$r^i_{t-1}\| > 0$	13.5**	13.5**	3.82**	3.82**	1.29**	1.29**
	(11.3)	(11.3)	(9.58)	(9.58)	(6.54)	(6.54)
$r^i_{t-1}\| > 0 \times$ Crisis	-1.08		-0.172		2.84**	
	(-0.439)		(-0.228)		(3.39)	
$r^i_{t-1}\| > 0 \times$ Outbreak		-5.67*		2.82		1.81**
		(-2.19)		(1.95)		(2.81)
$r^i_{t-1}\| > 0 \times$ Peak		-0.739		-0.387		1.44
		(-0.283)		(-0.524)		(0.819)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged flows	Yes	Yes	Yes	Yes	Yes	Yes
Obs ($\times$1000)	3,018	3,018	2,994	2,994	2,879	2,879
Adjusted R^2	0.057	0.057	0.056	0.056	0.053	0.053

Notes: This table shows the results of regressing daily flows on lagged returns interacted with crisis dummies, and lagged daily flows, using shareclass-day observations during the sample period between January 2019 and May 2020. The dummy variable *Crisis* equals 1 between February 24^{th} and March 31^{st}, 2020. The dummy variable *Outbreak* corresponds to the period February 24^{th} and March 11^{th}, 2020. The dummy variable *Peak* corresponds to the the period March 12^{th} and March 31^{st}, 2020. In columns 1 and 2, lagged returns are measured on a daily horizon. In columns 3 and 4, lagged returns are measured over a weekly horizon. Finally, in columns 5 and 6, lagged returns are measured over a monthly horizon. Standard errors are clustered at the shareclass and day levels, and t-statistics are shown in parentheses. * p<0.05; ** p<0.01.

Table 3: The effect of liquidity buffers on flow dynamics.

Dep. Var.:	Daily flows of open-ended corporate bond funds					
Return Horizon:	Daily		Weekly		Monthly	
	(1)	(2)	(3)	(4)	(5)	(6)
w_{cash}	0.076**		0.078**		0.086**	
	(2.76)		(2.83)		(3.08)	
w_{cash} × Outbreak	0.218*		0.177*		0.171*	
	(2.57)		(2.39)		(2.12)	
w_{cash} × Peak	0.091		0.007		0.011	
	(0.546)		(0.055)		(0.071)	
w_{liq}		0.044*		0.048*		0.053*
		(2.14)		(2.29)		(2.50)
w_{liq} × Outbreak		0.178**		0.121*		0.119*
		(3.28)		(2.37)		(2.06)
w_{liq} × Peak		-0.051		-0.112		-0.098
		(-0.348)		(-0.965)		(-0.828)
$r^i_{t-1}\| < 0$	5.50**	5.47**	2.59**	2.59**	0.485**	0.490**
	(3.22)	(3.20)	(4.48)	(4.49)	(2.91)	(2.94)
$r^i_{t-1}\| < 0$ × Outbreak	0.172	0.367	0.364	0.503	1.82*	1.91*
	(0.078)	(0.164)	(0.383)	(0.526)	(2.29)	(2.38)
$r^i_{t-1}\| < 0$ × Peak	2.51	2.52	-0.598	-0.615	0.030	0.003
	(1.34)	(1.34)	(-0.709)	(-0.730)	(0.090)	(0.010)
$r^i_{t-1}\| > 0$	12.6**	12.7**	3.66**	3.65**	1.10**	1.10**
	(10.8)	(10.7)	(8.09)	(8.09)	(6.26)	(6.20)
$r^i_{t-1}\| > 0$ × Outbreak	-3.20	-3.22	1.35	1.69	0.852	1.10
	(-0.943)	(-0.922)	(0.945)	(1.14)	(1.14)	(1.44)
$r^i_{t-1}\| > 0$ × Peak	0.952	0.933	-0.337	-0.331	0.146	0.088
	(0.321)	(0.315)	(-0.393)	(-0.385)	(0.102)	(0.061)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs (×1000)	2,003	2,003	1,987	1,987	1,911	1,911
Adjusted R^2	0.052	0.052	0.051	0.051	0.049	0.049

Notes: This table shows the results of regressing daily flows on lagged returns and lagged portfolio characteristics, as well as their interactions with crisis dummies, using shareclass-day observations during the sample period between January 2019 and May 2020. The first crisis dummy (*Outbreak*) corresponds to the the period February 24^{th} and March 11^{th}, 2020. The second crisis dummy (*Peak*) corresponds to the the period March 12^{th} and March 31^{st}, 2020. Lagged portfolio characteristics include the fund's portfolio weight held in cash (w_{cash}) or the fund's portfolio weight held in cash and government bonds with a credit rating exceeding BBB (w_{liq}). The remaining portfolio characteristics, omitted from the table to preserve space, consist of the fund's portfolio weight invested in government bonds, investment grade corporate bonds, bonds issued by non-financial corporations, corporate bonds with an age below 1 year, corporate bonds with an issue size exceeding 1 billion euros, the fund's portfolio weight held in derivatives, the logarithm of the fund's total net assets, the fund's maximum back load, and dummies indicating whether the fund is an institutional fund, an index fund, or using financial leverage. In columns 1 and 2, lagged returns are measured on a daily horizon. In columns 3 and 4, lagged returns are measured over a weekly horizon. Finally, in columns 5 and 6, lagged returns are measured over a monthly horizon. Standard errors are clustered at the shareclass and day levels, and t-statistics are shown in parentheses. * p<0.05; ** p<0.01.

Table 4: Liquidity management during March 2020.

Dep. Var.	$1_{\Delta Cash>0}$	$1_{\Delta Cash>0}$	$\Delta Cash$	$\Delta Cash$	$\Delta Corp$	$\Delta Corp$
	Logit	Logit	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	1.493	0.660	2.831	1.217	−0.768	1.032
	(1.445)	(0.667)	(1.831)	(0.761)	(−0.300)	(0.406)
Flow	0.011	0.012	0.039*	0.045*	0.791**	0.792**
	(0.847)	(1.022)	(2.149)	(2.358)	(26.168)	(25.967)
w_{cash}	−0.147**		−0.337**		0.393**	
	(−6.252)		(−11.405)		(8.044)	
w_{liq}		−0.070**		−0.164**		0.325**
		(−4.255)		(−7.017)		(8.709)
w_{gov}	−0.019		−0.030*		0.152**	
	(−1.924)		(−1.968)		(6.074)	
w_{IG}	−0.006	−0.003	0.001	0.008	0.005	−0.001
	(−1.813)	(−0.926)	(0.296)	(1.579)	(0.584)	(−0.178)
w_{Young}	−0.003	−0.002	0.001	0.003	−0.021	−0.031*
	(−0.596)	(−0.336)	(0.124)	(0.403)	(−1.552)	(−2.293)
w_{Large}	0.013	0.013	0.007	0.005	−0.002	−0.008
	(1.906)	(1.829)	(0.633)	(0.441)	(−0.116)	(−0.456)
w_{NFC}	−0.018**	−0.015**	−0.020*	−0.016*	−0.014	−0.027*
	(−3.201)	(−2.856)	(−2.466)	(−1.965)	(−1.002)	(−2.051)
w_{Deriv}	−0.096*	−0.041	−0.142**	−0.051	0.343**	0.292**
	(−2.042)	(−1.076)	(−2.592)	(−0.899)	(3.776)	(3.249)
Leveraged	−0.208	−0.206	−1.274	−1.291	4.343**	4.165**
	(−0.380)	(−0.381)	(−1.523)	(−1.473)	(3.138)	(2.987)
Index Fund	−0.658	−0.512	−0.906	−0.583	−0.100	−0.398
	(−1.436)	(−1.130)	(−1.320)	(−0.812)	(−0.088)	(−0.348)
log(TNA)	−0.017	−0.002	−0.048	−0.022	−0.053	−0.055
	(−0.319)	(−0.039)	(−0.621)	(−0.265)	(−0.408)	(−0.422)
Adj. R^2	-	-	0.162	0.078	0.526	0.517
Pseudo R^2	0.056	0.029	-	-	-	-
Observations	767	767	767	767	767	767

Notes: This table shows the results of regressing changes in portfolio allocations on flows and portfolio characteristics. Changes in portfolio allocations, as well as fund flows, are measured over March 2020. The portfolio characteristics are evaluated at February 29^{th}, 2020 and include the fund's weight held in cash (w_{cash}), the fund's weight held in cash and government bonds with a credit rating exceeding BBB (w_{liq}), the weight in government bonds (w_{gov}), investment-grade corporate bonds (w_{IG}), corporate bonds with an age below 1 year (w_{Young}), corporate bonds with an issue size larger than 1 billion euros (w_{Large}), bonds issued by non-financial corporations (w_{NFC}), the weight held in derivatives (w_{Deriv}), dummies indicating whether the fund uses financial leverage ($Leveraged$) and whether the fund is an index fund ($IndexFund$), and the logarithm of total net assets ($log(TNA)$). In columns 1-2, the dependent variable is a binary variable equal to 1 for funds that hoarded cash in March 2020. In columns 3-5, the dependent variable is defined as the change in cash holdings relative to the fund's total net assets as of February 29^{th}, 2020. In columns 6-8, the dependent variable denotes the change in the par value of corporate bonds held relative to the fund's total net assets as of February 29^{th}, 2020. In columns 1-2, test statistics for the Wald test are shown in parenthesis. In columns 3-8 t-statistics are shown in parentheses. * p<0.05; ** p<0.01.

Table 5: Corporate bond selling during March 2020.

Dependent variable:	$\frac{Par_{i,j,t}}{Par_{i,j,t-1}} - 1$		
Model:	(1)	(2)	(3)
(Intercept)	-4.14**	13.6**	13.0**
	(-37.5)	(6.12)	(5.85)
Flow	0.810**	0.833**	0.828**
	(61.0)	(61.6)	(61.2)
log(Issue Size)		-0.905**	-0.886**
		(-10.2)	(-9.98)
Age		0.194**	0.197**
		(8.16)	(8.29)
Maturity		-0.006	-0.007
		(-1.45)	(-1.71)
Rating		-0.084**	-0.056*
		(-3.34)	(-2.24)
NFC		-0.442**	-0.448**
		(-2.64)	(-2.67)
w_{cash}		0.176**	
		(7.33)	
w_{liq}			0.218**
			(11.5)
w_{gov}		0.171**	
		(14.7)	
w_{deriv}		0.252**	0.233**
		(5.73)	(5.44)
Leveraged		3.82**	3.67**
		(5.91)	(5.68)
Index Fund		1.24**	0.956**
		(5.73)	(4.47)
log(TNA)		0.059	0.078
Country dummies	No	Yes	Yes
Adjusted R^2	0.025	0.029	0.028
Observations	144,106	144,106	144,106

Notes: This table shows the results of regressing changes in individual corporate bond positions on flows, bond characteristics, and portfolio characteristics. The unit of observation is on the fund-ISIN level. Changes in corporate bond positions, as well as fund flows, are measured over March 2020. Bond and portfolio characteristics are evaluated at February 29^{th}, 2020. The bond characteristics include the logarithm of the bond's issue size, age, time to maturity, its credit rating converted to a numerical scale, and a dummy indicating whether the bond was issued by a non-financial corporation. The portfolio characteristics include the fund's weight held in cash (w_{cash}), the fund's weight held in cash and government bonds with a credit rating exceeding BBB (w_{liq}), the weight in government bonds (w_{gov}), the weight held in derivatives (w_{Deriv}), dummies indicating whether the fund uses financial leverage ($Leveraged$) and whether the fund is an index fund ($IndexFund$), and the logarithm of total net assets ($log(TNA)$). T-statistics are shown in parentheses. * p<0.05; ** p<0.01.

Appendix

Table A1: Items classified as cash by Refinitiv Lipper.

Asset Allocation	Security Type
Cash	Cash
Cash	Currency
Cash	Foreign Exchange
Cash Equivalents	Agency Discount Notes
Cash Equivalents	Bankers Acceptance
Cash Equivalents	Cash 120 days
Cash Equivalents	Cash 30 days
Cash Equivalents	Cash 60 days
Cash Equivalents	Cash 90 days
Cash Equivalents	Cash Equivalent
Cash Equivalents	Certificate of Deposit
Cash Equivalents	Commercial Paper
Cash Equivalents	Discount Note
Cash Equivalents	Letters of Credit
Cash Equivalents	Loan Participation Note
Cash Equivalents	Repurchase Agreement
Cash Equivalents	Time / Term Deposit

Table A2: Flow-performance relationship open-end corporate bond funds using excess returns.

Dep. Var.:	Daily flows of open-ended corporate bond funds					
Return Horizon:	Daily		Weekly		Monthly	
	(1)	(2)	(3)	(4)	(5)	(6)
$r^i_{t-1}\| < 0$	5.73^{**}	5.73^{**}	2.47^{**}	2.47^{**}	0.594^{**}	0.594^{**}
	(4.14)	(4.14)	(7.42)	(7.42)	(5.16)	(5.16)
$r^i_{t-1}\| < 0 \times$ Crisis	1.08		-0.899		-0.039	
	(0.610)		(-1.23)		(-0.113)	
$r^i_{t-1}\| < 0 \times$ Outbreak		0.110		1.04		2.05^{**}
		(0.042)		(1.09)		(2.95)
$r^i_{t-1}\| < 0 \times$ Peak		1.40		-1.22		-0.244
		(0.739)		(-1.59)		(-0.720)
$r^i_{t-1}\| > 0$	15.7^{**}	15.7^{**}	4.82^{**}	4.82^{**}	1.21^{**}	1.21^{**}
	(11.2)	(11.2)	(9.07)	(9.07)	(5.18)	(5.19)
$r^i_{t-1}\| > 0 \times$ Crisis	-4.29^{*}		-1.80^{*}		-0.445	
	(-2.08)		(-2.52)		(-1.22)	
$r^i_{t-1}\| > 0 \times$ Outbreak		-8.24^{**}		-0.225		1.83^{**}
		(-4.68)		(-0.230)		(3.91)
$r^i_{t-1}\| > 0 \times$ Peak		-3.65		-1.90^{*}		-0.574
		(-1.66)		(-2.59)		(-1.55)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged flows	Yes	Yes	Yes	Yes	Yes	Yes
Obs ($\times$1000)	3,018	3,018	2,994	2,994	2,879	2,879
Adjusted R^2	0.056	0.056	0.056	0.056	0.053	0.053

Notes: This table shows the results of regressing daily flows on lagged excess returns interacted with crisis dummies, and lagged daily flows, using shareclass-day observations during the sample period between January 2019 and May 2020. Excess returns are computed as the difference between a fund's returns and the average returns of all funds with the same geographical investment focus. The dummy variable *Crisis* equals 1 between February 24^{th} and March 31^{st}, 2020. The dummy variable *Outbreak* corresponds to the period February 24^{th} and March 11^{th}, 2020. The dummy variable *Peak* corresponds to the the period March 12^{th} and March 31^{st}, 2020. In columns 1 and 2, lagged returns are measured on a daily horizon. In columns 3 and 4, lagged returns are measured over a weekly horizon. Finally, in columns 5 and 6, lagged returns are measured over a monthly horizon. Standard errors are clustered at the shareclass and day levels, and t-statistics are shown in parentheses. * p<0.05; ** p<0.01.

Table A3: The effect of liquidity buffers on flows without controlling for lagged returns.

Dep. Var.:	Daily flows	
	(1)	(2)
w_{cash}	0.066^{*}	
	(2.40)	
w_{cash} × Outbreak	0.271^{**}	
	(3.72)	
w_{cash} × Peak	0.129	
	(0.857)	
w_{liq}		0.041^{*}
		(1.97)
w_{liq} × Outbreak		0.228^{**}
		(5.36)
w_{liq} × Peak		0.003
		(0.021)
Time FE	Yes	Yes
Controls	Yes	Yes
Observations	2,003,070	2,003,070
Adjusted R^2	0.050	0.050

Notes: This table shows the results of regressing daily flows on lagged portfolio characteristics interacted with crisis dummies, using shareclass-day observations during the sample period between January 2019 and May 2020. The first crisis dummy (*Outbreak*) corresponds to the the period February 24^{th} and March 11^{th}, 2020. The second crisis dummy (*Peak*) corresponds to the the period March 12^{th} and March 31^{st}, 2020. Lagged portfolio characteristics include the fund's portfolio weight held in cash (w_{cash}) or the fund's portfolio weight held in cash and government bonds with a credit rating exceeding BBB (w_{liq}). The remaining portfolio characteristics, omitted from the table to preserve space, consist of the fund's portfolio weight invested in government bonds, investment grade corporate bonds, bonds issued by non-financial corporations, corporate bonds with an age below 1 year, corporate bonds with an issue size exceeding 1 billion euros, the fund's portfolio weight held in derivatives, the logarithm of the fund's total net assets, the fund's maximum back load, and dummies indicating whether the fund is an institutional fund, an index fund, or using financial leverage. Standard errors are clustered at the shareclass and day levels, and t-statistics are shown in parentheses. * p<0.05; ** p<0.01.

Table A4: The effect of liquidity buffers on flows: domicile times time fixed effects.

Dep. Var.:	Daily flows of open-ended corporate bond funds					
Return Horizon:	Daily		Weekly		Monthly	
	(1)	(2)	(3)	(4)	(5)	(6)
w_{cash}	0.079**		0.082**		0.091**	
	(2.85)		(2.96)		(3.22)	
w_{cash} × Outbreak	0.153*		0.103		0.092	
	(2.14)		(1.67)		(1.29)	
w_{cash} × Peak	0.027		-0.057		-0.067	
	(0.171)		(-0.459)		(-0.484)	
w_{liq}		0.041*		0.044*		0.050*
		(2.01)		(2.18)		(2.38)
w_{liq} × Outbreak		0.155**		0.096*		0.089
		(3.16)		(2.05)		(1.66)
w_{liq} × Peak		-0.057		-0.121		-0.110
		(-0.400)		(-1.06)		(-0.943)
$r^i_{t-1}\| < 0$	5.56**	5.53**	2.61**	2.62**	0.524**	0.529**
	(3.21)	(3.19)	(4.44)	(4.44)	(2.94)	(2.97)
$r^i_{t-1}\| < 0$ × Outbreak	-0.039	0.145	0.225	0.359	1.76*	1.84*
	(-0.017)	(0.064)	(0.235)	(0.372)	(2.20)	(2.28)
$r^i_{t-1}\| < 0$ × Peak	1.97	1.95	-0.676	-0.707	-0.017	-0.055
	(0.979)	(0.971)	(-0.797)	(-0.835)	(-0.053)	(-0.167)
$r^i_{t-1}\| > 0$	12.8**	12.8**	3.71**	3.70**	1.08**	1.08**
	(10.7)	(10.7)	(8.13)	(8.13)	(6.10)	(6.05)
$r^i_{t-1}\| > 0$ × Outbreak	-2.77	-2.75	1.52	1.91	1.01	1.28
	(-0.837)	(-0.803)	(1.03)	(1.24)	(1.32)	(1.62)
$r^i_{t-1}\| > 0$ × Peak	1.07	1.08	-0.302	-0.283	0.236	0.192
	(0.356)	(0.358)	(-0.354)	(-0.332)	(0.161)	(0.131)
Domicile × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs (×1000)	2,003	2,003	1,987	1,987	1,911	1,911
Adjusted R^2	0.052	0.052	0.051	0.051	0.050	0.049

Notes: This table shows the results of regressing daily flows on lagged returns and lagged portfolio characteristics interacted with crisis dummies, using shareclass-day observations during the sample period between January 2019 and May 2020. The first crisis dummy (*Outbreak*) corresponds to the the period February 24^{th} and March 11^{th}, 2020. The second crisis dummy (*Peak*) corresponds to the the period March 12^{th} and March 31^{st}, 2020. Lagged portfolio characteristics include the fund's portfolio weight held in cash (w_{cash}) or the fund's portfolio weight held in cash and government bonds with a credit rating exceeding BBB (w_{liq}). The remaining portfolio characteristics, omitted from the table to preserve space, consist of the fund's portfolio weight invested in government bonds, investment grade corporate bonds, bonds issued by non-financial corporations, corporate bonds with an age below 1 year, corporate bonds with an issue size exceeding 1 billion euros, the fund's portfolio weight held in derivatives, the logarithm of the fund's total net assets, the fund's maximum back load, and dummies indicating whether the fund is an institutional fund, an index fund, or using financial leverage. In columns 1 and 2, lagged returns are measured on a daily horizon. In columns 3 and 4, lagged returns are measured over a weekly horizon. Finally, in columns 5 and 6, lagged returns are measured over a monthly horizon. Standard errors are clustered at the shareclass and day levels, and t-statistics are shown in parentheses. * p<0.05; ** p<0.01.

Table A5: The effect of liquidity buffers on flows: fund family times time fixed effects.

Dep. Var.:	Daily flows of open-ended corporate bond funds					
Return Horizon:	Daily		Weekly		Monthly	
	(1)	(2)	(3)	(4)	(5)	(6)
w_{cash}	0.158**		0.160**		0.164**	
	(4.86)		(4.87)		(4.91)	
w_{cash} × Outbreak	0.105		0.070		0.067	
	(0.982)		(0.691)		(0.610)	
w_{cash} × Peak	-0.107		-0.168		-0.181	
	(-0.726)		(-1.27)		(-1.24)	
w_{liq}		0.069**		0.071**		0.076**
		(3.02)		(3.08)		(3.22)
w_{liq} × Outbreak		0.118*		0.063		0.068
		(2.16)		(1.36)		(1.34)
w_{liq} × Peak		-0.096		-0.157		-0.149
		(-0.761)		(-1.42)		(-1.24)
$r^i_{t-1}\| < 0$	6.38**	6.37**	2.49**	2.51**	0.536*	0.548*
	(3.46)	(3.45)	(4.14)	(4.17)	(2.44)	(2.50)
$r^i_{t-1}\| < 0$ × Outbreak	0.108	0.389	0.682	0.889	1.79*	1.93*
	(0.044)	(0.157)	(0.669)	(0.869)	(2.30)	(2.44)
$r^i_{t-1}\| < 0$ × Peak	0.627	0.578	-0.530	-0.592	-0.006	-0.067
	(0.254)	(0.235)	(-0.586)	(-0.654)	(-0.016)	(-0.175)
$r^i_{t-1}\| > 0$	14.5**	14.5**	4.32**	4.31**	1.21**	1.21**
	(11.5)	(11.4)	(8.56)	(8.57)	(5.69)	(5.68)
$r^i_{t-1}\| > 0$ × Outbreak	-5.94	-5.96	-0.792	-0.233	0.222	0.622
	(-1.55)	(-1.52)	(-0.407)	(-0.120)	(0.237)	(0.677)
$r^i_{t-1}\| > 0$ × Peak	0.001	0.033	-0.753	-0.722	-0.482	-0.552
	(0.0003)	(0.008)	(-0.760)	(-0.729)	(-0.333)	(-0.391)
Family × Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Obs (×1000)	1,942	1,942	1,926	1,926	1,854	1,854
Adjusted R^2	0.061	0.060	0.060	0.060	0.059	0.059

Notes: This table shows the results of regressing daily flows on lagged returns interacted with crisis dummies and lagged portfolio characteristics, using shareclass-day observations during the sample period between January 2019 and May 2020. The first crisis dummy (*Outbreak*) corresponds to the the period February 24^{th} and March 11^{th}, 2020. The second crisis dummy (*Peak*) corresponds to the the period March 12^{th} and March 31^{st}, 2020. Lagged portfolio characteristics include the fund's portfolio weight held in cash (w_{cash}) or the fund's portfolio weight held in cash and government bonds with a credit rating exceeding BBB (w_{liq}). The remaining portfolio characteristics, omitted from the table to preserve space, consist of the fund's portfolio weight invested in government bonds, investment grade corporate bonds, bonds issued by non-financial corporations, corporate bonds with an age below 1 year, corporate bonds with an issue size exceeding 1 billion euros, the fund's portfolio weight held in derivatives, the logarithm of the fund's total net assets, the fund's maximum back load, and dummies indicating whether the fund is an institutional fund, an index fund, or using financial leverage. In columns 1 and 2, lagged returns are measured on a daily horizon. In columns 3 and 4, lagged returns are measured over a weekly horizon. Finally, in columns 5 and 6, lagged returns are measured over a monthly horizon. Standard errors are clustered at the shareclass and day levels, and t-statistics are shown in parentheses. * p<0.05; ** p<0.01.

Acknowledgements

We thank Frank de Jong, Jasmin Gider, and seminar participants at the European Central Bank for valuable comments and suggestions.

Lennart Dekker
De Nederlandsche Bank, Amsterdam, The Netherlands; Tilburg University, Tilburg, The Netherlands;
email: l.p.dekker@tilburguniversity.edu

Luis Molestina Vivar
European Central Bank, Frankfurt am Main, Germany; Goethe University Frankfurt, Frankfurt am Main, Germany;
email: luis.molestina_vivar@ecb.europa.eu

Michael Wedow
European Central Bank, Frankfurt am Main, Germany; email: michael.wedow@ecb.europa.eu

Christian Weistroffer
European Central Bank, Frankfurt am Main, Germany; email: christian.weistroffer@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

This paper can be downloaded without charge from www.ecb.europa.eu, from the Social Science Research Network electronic library or from RePEc: Research Papers in Economics. Information on all of the papers published in the ECB Working Paper Series can be found on the ECB's website.

PDF ISBN 978-92-899-6110-3 ISSN 1725-2806 doi:10.2866/005990 QB-AR-23-062-EN-N