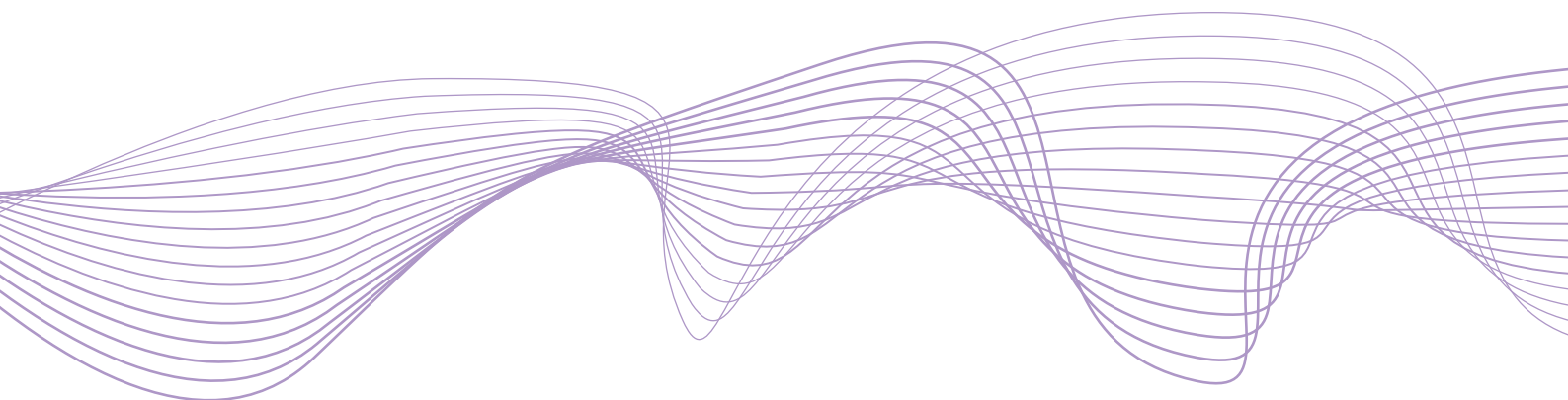


# Working Paper Series

No 140 / March 2023

## Financial fragility in open-ended mutual funds: the role of liquidity management tools

by  
Peter Dunne  
Lorenz Emter  
Falko Fecht  
Raffaele Giuliana  
Oana Peia



**ESRB**  
European Systemic Risk Board  
European System of Financial Supervision

## **Abstract**

We study the role of liquidity management tools (LMTs) in mitigating financial fragility in investment funds during the COVID-19 market distress. We employ a unique dataset that reports the availability of different types of LMTs in a sample of Irish-domiciled corporate bond funds. We find that funds with access to price-based tools such as redemption fees or anti-dilution levies experienced lower net outflows in March 2020, as compared to funds with only quantity-based tools such as redemption gates, temporary suspensions or redemption in kind. This difference is stronger among funds with a high sensitivity of flows to past-performance and reflects both higher gross inflows and lower gross outflows during this episode. Funds with price-based LMTs also rebalance their portfolios towards less liquid bonds, which results in lower price fragility among bonds held disproportionately by our sample of Irish-domiciled funds.

*Keywords:* liquidity management tools, investment funds, COVID-19, financial fragility.

*JEL Classification:* G2, G23.

# 1 Introduction

In March 2020 concerns about the looming COVID-19 pandemic caused severe financial market distress accompanied by an unprecedented run on open-ended investment funds by investors worldwide. Figure 1a depicts the net flows into open-ended funds domiciled in Ireland, which hosts the second largest investment funds sector in Europe (Cima et al. 2019). The sector saw a total of more than 72 billion euros of net redemptions in March 2020, with funds investing in corporate bonds experiencing the highest distress (see Figure 1a and 1b).

Funds investing in corporate bonds are known to be particularly fragile and susceptible to runs as their pricing mechanism brings about strategic complementarities in investors' redemption decisions (Chen et al. 2010, Goldstein et al. 2017). This is because withdrawing investors can typically redeem their shares at a daily fixed net asset value (NAV), while the subsequent costs of portfolio adjustments are born by investors who keep their money in the fund. As such, large withdrawals can impose a negative externality on remaining investors, which is particularly high during episodes of market-wide distress and in funds investing in relatively illiquid assets such as corporate bonds. In order to contain these externalities and mitigate the resulting fragility of open-ended funds, various liquidity management tools (LMTs) have been proposed by regulators and, in some cases, already been introduced.<sup>1</sup> However, evidence on the effectiveness of these different LMTs is still very scarce.

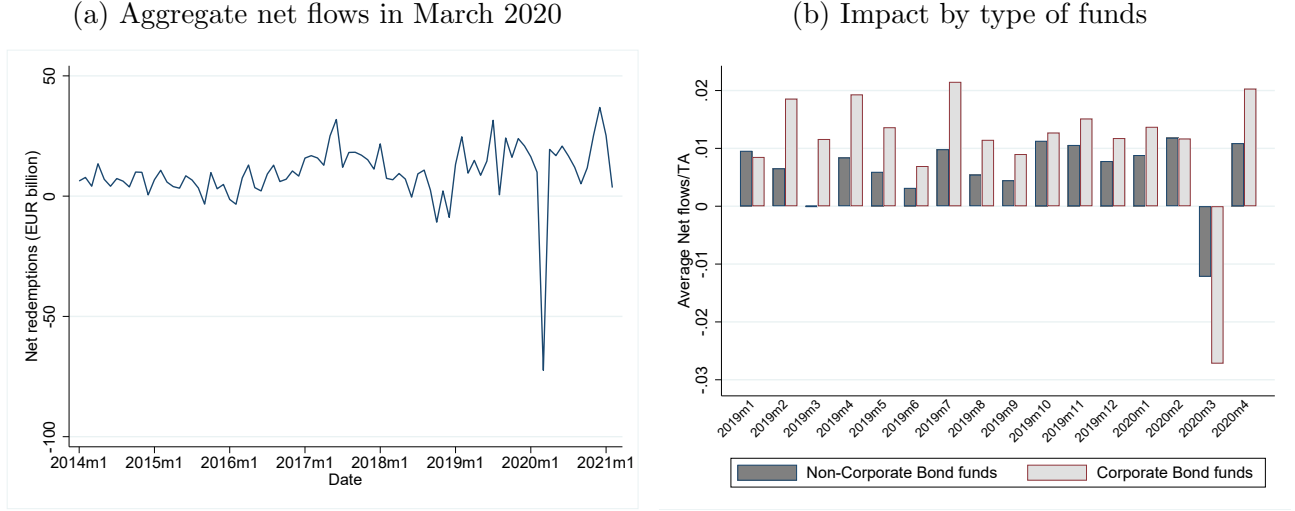
In this paper, we provide the first systematic analysis of the effectiveness of a wide-range of liquidity management tools, using the context of corporate bond funds in Ireland during the COVID-19 shock in March 2020. We employ a unique dataset collected by the Central Bank of Ireland, which combines information on monthly fund flows with data on the availability of liquidity management tools (LMTs). Irish-domiciled investment funds were among the first to introduce a wide range of LMTs (ESRB 2017) and, since 2018, report to the regulator on the availability of six types of tools: anti-dilution levies, redemption fees, redemption gates, temporary suspension of dealing, redemption in kind and side-pockets.

We find that, in the entire sample of equity, bond and mixed funds domiciled in Ireland, most funds (94% at the end of 2020) report the availability of at least one type of tool.

---

<sup>1</sup>See, for example, the recommendation of the European Systemic Risk Board of 7 December 2017 on liquidity and leverage risks in investment funds (ESRB/2017/6).

Figure 1: Net flows into open-ended funds domiciled in Ireland



Moreover, there is an increase in the availability of most LMTs over the three years covered in our dataset. Tools such as suspensions, redemption gates or redemptions in kind are widely present, although survey evidence suggests they are rarely employed in practice (ESMA 2020). On the other hand, redemption fees are available in around 30% of funds, while the presence of anti-dilution levies increased from 54% to 60% of funds over the period considered. Funds report, on average, four different tools, with bond and mixed funds having more LMTs, on average.

Moreover, the availability of certain tools tends to be highly correlated: for example, funds that have redemption gates are more likely to also report suspensions, while the availability of redemption fees is negatively correlated with that of anti-dilution levies. As such, we focus our analysis on the effectiveness of so-called price-based tools such as fee or levies in addition to the more widespread quantity-based tools such as gates, suspensions and redemptions in kind. We compare funds reporting a combination of price- and quantity-based tools (treatment group) to a control group with only quantity-based tools.

We classify according to this definition a sample of 521 funds that invest in corporate bonds, including bond funds as well as mixed funds. We then use a difference-in-difference approach to investigate the effectiveness of price-based LMTs in mitigating investor outflows in March 2020. Causal identification in such a diff-in-diff approach relies on several assumptions. First, we need to assume that the shock was not anticipated, i.e. that investors with different

sensitivities to stress events did not select out of treated funds prior to the shock. We show that this assumption holds, as there are no clear trends in net flows in the two groups of funds prior to March 2020. Second, we assume that the selection in control and treatment groups is random or at least not related to other characteristics affecting funds' susceptibility to performance shocks and large scale withdrawals. In this regard, it is key to our analysis that LMTs are introduced not at the fund but at the fund-family level. To further mitigate concerns about unobservable heterogeneity between treated and non-treated funds, we split the sample of funds according to their sensitivity of flows-to-performance prior to the COVID-19 shock. By focusing on the sample of funds that have a high sensitivity of flows-to-performance, we reduce the concern that investors in the treated group are less sensitive to shocks and that treated funds have (endogenously) more or less liquid asset holdings. In addition, we control for heterogeneity across funds in the treatment and control group not only using a wide array of time-varying fund characteristics, but also by including fund and month fixed effects.

We find that funds with access to fees or levies experienced lower net outflows in March 2020, as compared to funds with only quantity-based tools. This difference is statistically significant for funds with an above median past flow-to-performance sensitivity, but not in the sample with a below median sensitivity, suggesting that access to price-based LMTs is effective in mitigating financial fragility, particularly among funds most prone to panic induced distress. The effect is economically significant: funds in the treated group have 5% lower net outflows to total assets as compared to funds in the control group (average net outflows to total assets in March 2020 is around 3%).

We also find that this differential effect is due to both lower gross outflows and higher gross inflows, suggesting that the availability of price-based LMTs mitigates the observed negative correlation between outflows and inflows during periods of distress. This means that fees and levies not only contain incentives to withdraw in a crisis, but also make it more attractive to purchase fund shares as new investors' return will be less impaired by portfolio adjustment costs induced by current outflows.

In line with this reasoning, we also find that treated funds have a better performance after the shock and that they experience a lower outflows-induced selling pressure, particularly among their more illiquid bond holdings. Specifically, we investigate the change in the port-

folio shares of different asset classes between December 2019 and March 2020 using ISIN-level data of asset holdings in our sample of Irish-domiciled funds. We show that funds with price-based LMTs saw a larger increase in their share of illiquid corporate bonds, but a smaller one in that of cash holdings, relative to quantity-based LMTs funds. This suggests treated funds sold relatively fewer illiquid assets during this episode of severe financial distress.

We then investigate whether the lower outflows-induced selling pressure had an effect on the fragility of bonds' prices around March 2020. In a sample of bonds held by both treatment and control groups, we build a measure of a bond's exposure to selling pressure as the fraction of its total outstanding amount held across the two types of funds in our sample. We show that bonds that were held disproportionately more by the sample of price-based LMT funds experienced smaller changes in yield during March-April 2020. This suggests that, by mitigating outflow-induced selling pressures, the availability of LMTs can also impact portfolio re-balancing decisions and, consequently, the fragility of funds' asset portfolios.

Our results are robust to a variety of specifications including alternative definitions for the treatment and control groups, as well as for the sample of funds investing in corporate bonds. We also control for the effect of a wide-range of fund characteristics that might affect net flows during March 2020, such as size, liquidity, investor base, ownership of the asset management company, past volatility of flows or past performance.

Our results contribute to several strands of the literature. First, there is, by now, a large literature documenting the extent of financial market distress in March 2020 in bond markets, and particularly corporate bonds (Haddad et al. 2020, Kargar et al. 2020). Several papers look specifically at open-ended funds during the COVID-19 crisis.<sup>2</sup> Closely related to our paper is Ma et al. (2020) who find that the liquidity transformation of fixed-income funds and their exposure to large scale withdrawals during the COVID-19 crisis induced those funds to primarily sell liquid sovereign and corporate bonds contributing to the huge selling pressure in those securities markets. Falato et al. (2021) analyse daily flows of US bonds funds around March 2020 and show that some fund characteristics such as illiquidity or vulnerability to fire-sales were important in explaining the fragility of outflows. Similarly, Grill et al. (2022) investigate the determinants of suspensions of redemptions during the COVID-19 market

---

<sup>2</sup>For example, Pástor & Vorsatz (2020) show that during the crisis passive funds outperformed actively managed funds and funds with high sustainability rating experienced lower outflows.

turmoil and find that illiquid funds investing in real estate were substantially more likely to suspend than other funds. We complement this evidence by looking at the effectiveness of liquidity management tools in mitigating outflows. Dunne & Giuliana (2021) also provide evidence on the effects of liquidity management tools in a sample of Irish-domiciled Money Market Funds. They exploit legal liquidity requirements imposed on this type of funds and show that tools such as gates can exacerbate outflows during periods of distress if the fund is close to the legal threshold. Several works also study the implications of funds' portfolios liquidity structure on the fragility of the assets they hold. Chiefly, Jiang et al. (2022) shows that bonds held by funds with more illiquid portfolios experienced more negative returns and larger reversals around March 2020.

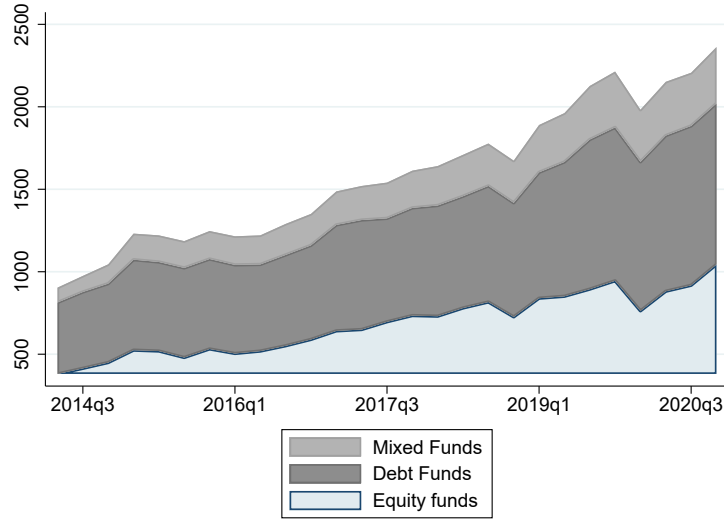
Our work is also related to a large literature on financial stability and runs on financial institutions. While most of the focus has been on the banking sector, recent work has highlighted how the liquidity transformation performed by open-ended funds makes them prone to similar run-type behavior. Chen et al. (2010) develop a model of runs in a global-games framework and show how complementarities in investors' actions will generate an amplification of outflows following bad performance, especially if the fund is illiquid. Consistent with this prediction, they show that the sensitivity of outflows to bad performance is higher in equity funds that hold less liquid assets. Goldstein et al. (2017) complement this evidence in a sample of bond mutual funds by showing that they exhibit a concave flow-to-performance relationship where outflows are sensitive to bad performance more than their inflows are sensitive to good performance. We provide the first systematic evidence consistent with the effectiveness of different liquidity management tools in reducing this first mover advantage. In this regards, closest to our work is Jin et al. (2022), who investigate the effectiveness of one particular LMT, swing pricing, in a sample of 299 UK corporate bond funds.<sup>3</sup> They show that swing pricing eliminates the first-mover advantage arising from the traditional pricing rule and significantly reduces outflows during market stress. However, they do not focus on episodes of severe market distress such as the COVID-19 shock or other types of LMTs.

The remainder of this paper is organized as follows. Section 2 describes the institutional

---

<sup>3</sup>While the data collected by the Central Bank of Ireland does not explicitly distinguish between swing pricing and anti-dilution levies, both tools work in the same way though adjusting the share price to incorporate the costs associated with a transaction. As such, funds in our sample employing swing pricing would report and be included in the anti-dilution levy category of liquidity management tools.

Figure 2: Assets under management (mil euro) of Irish-domiciled IF



background and data. Section 3 presents the empirical strategy, section 4 the results and the last section concludes.

## 2 Institutional background and data

Ireland is home to a large number of open-ended funds with a total of assets under management (AUM) amounting to over 3.2 trillion euro in 2020. The majority of these funds are equity, bond and mixed open-ended funds, which have seen a dramatic growth in their AUM from 2014 to 2020 (see Figure 2).

Irish-domiciled investment funds report annually to the Central Bank of Ireland on a wide-range of fund characteristics including liquidity management tools available to the fund.<sup>4</sup> Investors must be informed about the availability of all LMTs at a fund's disposal and, in Ireland, this is made explicit in the prospectus of the fund's family. The report inquires about the availability of six types of tools detailed in Table 1 and the data is available over the period 2018-2020. Funds domiciled in Ireland were among the first to introduce a wide variety of LMTs (ESRB 2017, Daly et al. 2017) and we observe an increase in the availability of these tools from the end of 2018 to the end of 2020. Specifically, Figure 3 shows the availability of

---

<sup>4</sup>Readers should note that the Fund Profile is not a regulatory return and the reported data is not subjected to the same level of validation as data from a regulatory return.



Table 1: Liquidity Management Tools

Tool	Definition
Anti-dilution levy	Costs (transaction costs, taxes or stamp duties) corresponding to the sale of underlying assets in case of redemption (or acquisition in case of new subscription) are charged to the investors executing the redemption/subscription.
Redemption fee	Fee typically charged as a percentage of the NAV of the shares being redeemed.
Redemption gate	Usually applied once redemption requests in a dealing day exceed a certain percentage of the NAV or total number of shares.
Suspension	Temporary suspension of dealing/calculation of NAV.
Redemption in kind	Transfer of an underlying asset to a redeeming investor.
Side pocket	Creation of side pocket share classes into which assets that become illiquid or difficult to value are placed. Investors receive shares in that side pocket class, thus avoiding the need to redeem less liquid assets at heavily discounted prices in order to meet redemption requests (not permitted for retail funds).

different tools across the entire population of Irish-domiciled funds in 2018 (5,506 funds) and 2020 (5,869 funds), while Figure 4 focuses on the sample of equity, bond and mixed mutual funds (a total of 4,070 funds in December 2019).

Only 6% of funds in the entire population do not report any tool at the end of 2020 and funds can employ, on average, four types of liquidity management tools. LMTs can be intuitively split in two categories: (i) quantity-based LMTs, which include suspensions, gates and redemptions in kind, and impact the ability to redeem fund shares during periods of distress and (ii) price-based LMTs such as anti-dilution levies and redemption fees, which impact the prices of the shares redeemed.<sup>5</sup> As evident from Figures 3 and 4, the quantity-

<sup>5</sup>Side-pockets would also be included in this category, however, we will not consider this tool in the rest of the analysis, as funds that cater retail customers, which represent the large majority of our sample, are not legally allowed to employ this tool in Ireland. Moreover, the percentage of funds reporting this tool is very

Figure 3: Availability of liquidity management tools (entire sample)

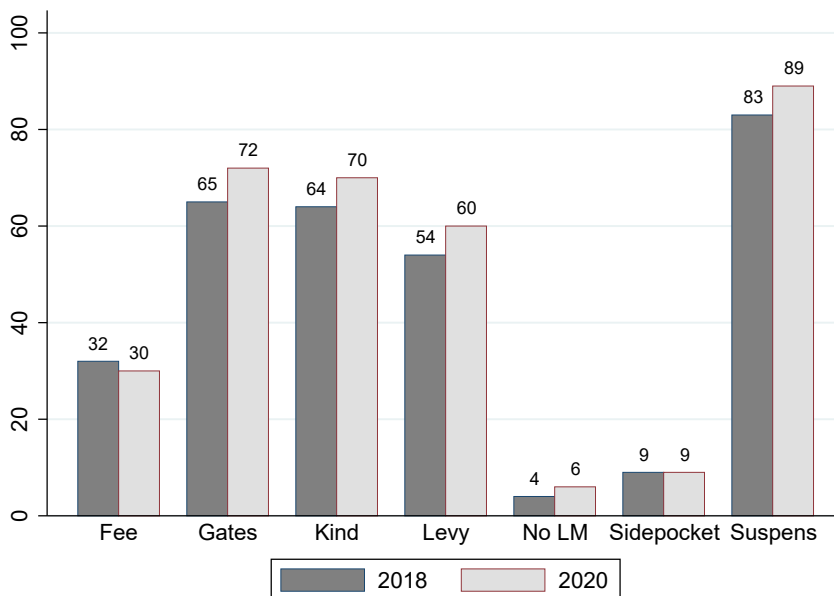


Figure shows the proportion of funds reporting availability of different liquidity management tools in December 2018 as compared to December 2020 in the entire population of Irish-domiciled mutual funds (a sample of 5,506 funds in December 2018 and 5,869 in December 2020). Changes in percentages reflect both entry of new funds, as well as the switch to new tools by existing funds.

based LMTs (QLMTs) are widely available across all types of investment funds. However such tools are usually considered “extraordinary” and are rarely employed in practice due to reputational concerns.<sup>6</sup> On the other hand, price-based LMTs (PLMTs) are less frequent. For example, redemption fees are present in around 30% of funds, while anti-dilution levies become more prevalent over time (with an increase from 54% to 60% of all funds from 2018 to 2020). Bond and mixed funds also tend to report, in general, more LMTs, and, in particular, tools such as anti-dilution levies and redemption fees are more widespread among these funds (see Figure 4).

Our dataset allows us to observe the introduction of different liquidity management tools over time at the individual fund level. However, the decision to introduce a liquidity management tool generally occurs at the fund family or asset management company level.<sup>7</sup> While low (around 9% in the entire population of Irish-domiciled funds).

<sup>6</sup>For example, a survey among European funds conducted by the European Securities and Markets Authority (ESMA) found that, in a sample of 541 funds that experienced significant distress in March 2020, only six suspended redemptions due to large outflows (ESMA 2020).

<sup>7</sup>Investment funds are registered in Ireland as ICAVs (Irish collective asset management vehicles) which constitute an umbrella fund (or a family of funds). The availability of liquidity management tools is detailed

Figure 4: Percentage of funds with different LM tools (sample of equity, bond and mixed funds)

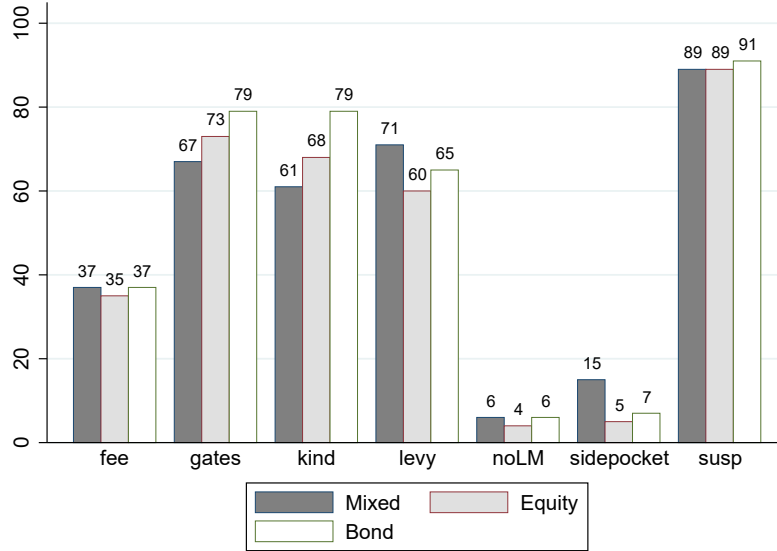


Figure show the proportion of funds reporting availability of different liquidity management tools in 2019m12. The sample is: 1,132 Bond funds, 2,018 Equity Funds, and 920 Mixed.

this is very helpful for our identification strategy as it ensures that the introduction of a LMTs is not an endogenous decision of the individual fund (on average a fund-family comprises 20 different funds), characteristics at the fund-family level are still likely to determine whether and when a particular LMT is introduced.

We investigate several fund-family characteristics that are potentially correlated with the probability of introducing a new LMT. For that purpose, we construct several fund family characteristics that capture institutional ownership, size, liquidity, as well as flow-related measures such as past volatility of flows, sensitivity of flows to performance or the average number of funds in the family that are in the lowest decile of net flows in a given month in a given class of funds (i.e., distressed funds). Appendix Table A details the construction of fund-family variables.

Table 2 shows the results of a series of cross-sectional probit models where the dependent variable is an indicator equal 1 if the fund family has introduced a new tool from December

---

in the umbrella fund prospectus and should normally apply to all funds in the family (unless, for legal requirements, this is not allowed, such as in the case of side pockets). Moreover, we cross-check that in our sample of funds the introduction of a new tool occurs across all funds within a family (Umbrella Fund). This is indeed the case for almost all introductions of new tools (small exceptions refer to the introduction of side pockets and potential misreporting due to the timing of reporting to the regulator).

Table 2: Introduction of Liquidity Management Tools

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Ln(Assets)	0.143*** (0.033)	0.161*** (0.035)	0.166*** (0.035)	0.181*** (0.037)	0.163*** (0.036)	0.174*** (0.038)	0.165*** (0.035)	0.162*** (0.035)	0.166*** (0.035)	0.172*** (0.037)	0.157*** (0.036)
Nb funds	0.010* (0.006)	0.009 (0.006)	0.008 (0.006)	0.010 (0.006)	0.009 (0.006)	0.008 (0.006)	0.008 (0.006)	0.009 (0.006)	0.009 (0.006)	0.009 (0.006)	0.009 (0.006)
Median Age	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Liquidity/TA		-1.090* (0.635)	-1.133* (0.642)	-1.247* (0.678)	-1.109* (0.644)	-1.086* (0.635)	-1.257* (0.690)	-1.091* (0.635)	-1.114* (0.659)	-1.173* (0.665)	-1.094* (0.643)
High sensitivity		0.092 (0.166)	0.139 (0.172)	-0.058 (0.165)	0.075 (0.183)	0.108 (0.166)	0.079 (0.166)	0.091 (0.167)	0.078 (0.167)	0.039 (0.165)	0.094 (0.166)
Share Pension & Insurance			-0.987* (0.504)								
Share Banks & IF				0.429** (0.169)							
Volatility					0.562 (2.188)						
Share distressed						-2.066 (1.908)					
Share equity funds							-0.033** (0.013)				
Share bond funds								-0.002 (0.018)			
Share mixed funds									0.019 (0.017)		
Share retail funds										-0.018 (0.011)	
BHC											0.159 (0.189)
Observations	1,149	934	934	934	934	934	934	934	934	934	934

The table shows a series of cross-sectional probit regressions where the dependent variable is an indicator equal to one if the fund family introduced a LMT in 2019. All explanatory variables are weighted averages at fund-family level by using the share of assets of the fund in the total assets of the fund family as a weight. Liquidity/TA is the average cash and liquid bonds to total assets in the fund family. High sensitivity is the average sensitivity of flows to performance during 2017-2018. Share Pension & Insurance is the average share of ownership by pensions and insurance companies. Share Banks & IF is the average share ownership by banks and investment funds. Volatility is the average family volatility of flows over the last 12 months. Share of distressed is the average number of funds that rank in the lowest decile of net flows to total assets in any given month during 2017-2018. BHC is an indicator equal 1 if the asset management company is owned by a bank holding corporation. Robust standard errors in parenthesis. \*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

2018 to December 2019.<sup>8</sup> We find that several fund-family characteristics are correlated with the probability of introducing LMTs. Chiefly, large fund families, measured by the log of total assets under management, are more likely to add LMTs. On the other hand, families with higher average levels of liquidity, measured as the average level of cash and liquid government bonds to total assets, are less likely to introduce new liquidity management tools. This is intuitive as funds with larger cash buffers can more easily meet redemptions. We also find that the investor base matters in the decision to introduce new LMTs, with families with higher shares of banks and investment funds being more likely to adopt LMTs, while those with a higher share of pension funds and insurance companies being less likely.<sup>9</sup> We also find that families with a larger share of equity funds are less likely to adopt LMTs, which

<sup>8</sup>We exclude 2020 from this analysis as the COVID-19 shock might explain the introduction of tools in 2020.

<sup>9</sup>The negative correlation between high ownership by pension funds and the introduction of LMTs can be due to the documented counter-cyclical investment behavior of pension funds, which makes them less likely to redeem in periods of market distress (Timmer 2018).

is expected given that equity funds are less likely to face the liquidity mismatch problems that LMTs aim to address. Finally, note that the past volatility of flows, the past sensitivity of flows to performance, or the average number of distressed funds are not correlated with the decision to introduce a new LMTs. This suggests that the decision to introduce LMTs is not necessarily related to an individual funds’ redemption experiences, which is our main outcome variable of interest.

## 2.1 Sample construction

The descriptive statistics presented in the previous section show that quantity-based LMTs are not only available for the vast majority of funds, but, as Table 3 shows, funds typically report most of these tools together: the availability of suspensions, redemption gates and redemption in kind tends to be highly correlated in the sample of equity, bond and mixed funds. Various surveys conducted by the ESRB show that, although these tools have historically been available to funds, their actual usage is limited due to the significant reputational concerns (ESRB, 2017; 2020). In contrast, the introduction of anti-dilution levies and redemption fees is not only more recent, but Table 3 shows that their availability across funds is negatively correlated, suggesting they are viewed as substitute tools.<sup>10</sup>

Table 3: Pairwise correlations

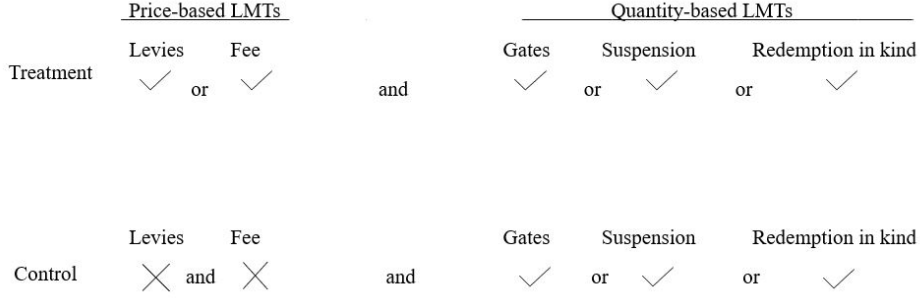
Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) Levy	1					
(2) Gates	0.16 (0.000)	1				
(3) Redemption in kind	0.097 (0.000)	0.587 (0.000)	1			
(4) Suspension	0.205 (0.000)	0.512 (0.000)	0.45 (0.000)	1		
(5) Redemption fees	-0.021 (0.119)	0.095 (0.000)	0.086 (0.000)	0.14 (0.000)	1	
(6) Side pocket	0.01 (0.477)	0.112 (0.000)	0.092 (0.000)	0.022 (0.111)	-0.13 (0.000)	1

Correlations are based on a sample of 1,132 Bond funds, 2,018 Equity Funds, and 920 Mixed funds in 2019m12. P-values in parenthesis.

Consequently, our main empirical investigation will focus on the “add-on effect” that price-

<sup>10</sup>Irish domiciled funds were among the first to use redemption fees and anti-dilution levies to mitigate liquidity risk (ESRB 2017, Daly et al. 2017). For example, in a survey of 283 Irish-domiciled funds, Daly et al. (2017) document that around 19% of funds report employing an anti-dilution levy during 2007-2015.

Figure 5: Treatment definition



based LMTs have over and above quantity-based LMTs on funds' resilience. To this end, we classify funds into treatment and control groups as depicted in Figure 5. Specifically, we include in the treatment group (PLMT) funds that report the availability of either redemption fees or levies and *at least one* of the QLMTs: suspensions, gates, and redemption in kind. The control group is represented by funds that do not report either fees or levies, but have at least one of QLMT. This classification of funds allows us to take into account the fact that the QLMTs are reported as available in a large proportion of funds and classifies the largest number of funds into the treatment and control groups. We perform, however, robustness tests where we consider alternative definitions.

Since corporate bonds are comparably illiquid, corporate bond holdings of open-end mutual funds drive their liquidity transformation and their exposure to panic-driven runs (Ma et al. 2020). Thus, we focus our analysis on a sample of funds that invest in corporate bonds. These funds experience liquidity mismatch and were most susceptible to investor runs (Figure 1b). The classification is based on the funds' self reported data collected by the Central Bank of Ireland.<sup>11</sup> As of December 2019, 521 funds in the dataset are classified as a corporate bond fund and will constitute the main sample in our analysis. Figure 6 shows the availability of different LMTs in the sample of corporate bond funds. Overall, it shows similar patterns as in the overall sample, with gates, redemption in kind and suspensions being widely present. It also shows an increase in availability of most tools in the three years of reporting available.

In the sample of corporate bond funds considered, 68% are included in the treatment

<sup>11</sup>Precisely, we include pure bond funds that self-report to the CBI as corporate bond funds. We also include mixed funds that hold corporate bonds in their portfolio. The average share of corporate bond holdings in the sample of pure bond funds is 45%, while in the sample of mixed funds is 17%. We present robustness tests where we vary these definitions and the sample of funds classified as corporate bond funds.

Figure 6: Percentage of funds with different LM tools in the sample of funds investing in corporate bonds

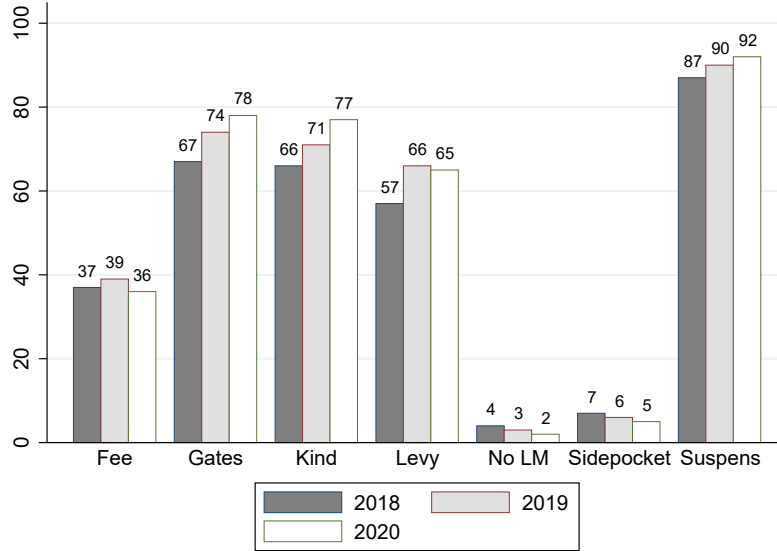


Figure show the proportion of funds reporting availability of different liquidity management tools in the sample of corporate bond funds in December 2018 (507 funds), 2019 (521 funds) and 2020 (530 funds).

group, while 32% have only quantity based LMTs available. Table 4 shows some descriptive statistics for the fund characteristics split for the treatment and control group over the period January-December 2019. Overall, funds in the two groups have comparable characteristics, although funds in the PLMT group tend to be larger, in terms of total assets. They do not, however, necessarily belong to larger fund families or are older. Importantly, the average monthly returns and volatility of flows over the period January 2019-December 2019 are comparable. Liquidity, measured as cash and liquid government bonds to total assets, is, however, notably higher in the control group. This is intuitive as funds employing fees or redemption levies need to hold less liquidity to meet redemption demands. We also construct several measures of ownership by different institutional groups, i.e. banks and investment funds or pension and insurance companies.<sup>12</sup> These ownership shares are also comparable across the two groups, as is the share of funds that are leveraged.

<sup>12</sup>We do not control for the share of ownership by households as this is not perfectly observed in our data that only identifies households residing in Ireland. Foreign households' ownership is measured through the custodian bank.

Table 4: Descriptive Statistics

Variable	PLMT		QLMT		t-test
	Mean	Std. Dev.	Mean	Std. Dev.	
Funds in family	21.99	17.90	19.65	16.33	-1.04
ln Assets	18.77	1.87	18.21	1.68	-2.95***
Return	0.00	0.06	0.00	0.08	0.003
Fund age	5.15	4.56	5.93	6.04	6.83***
BHC belong	0.21	0.40	0.22	0.41	1.37
Volatility flows	0.05	0.05	0.05	0.05	0.69
Leverage dummy	0.57	0.50	0.59	0.49	1.64
Liquidity	0.04	0.08	0.07	0.17	13.99***
Share Households	0.01	0.05	0.012	0.07	-0.12
Share Banks & Funds	0.35	0.41	0.36	0.70	0.07
Share Pension & Insurance Funds	0.12	0.24	0.09	0.25	0.78

Table presents descriptive statistics for the period 2018m1-2020m2. The last column shows the t-statistic of a t-test on the difference in means between PLMT and QLMT funds.\*\*\* shows significance at 1% level.

### 3 Empirical strategy

Our main empirical investigation aims at understanding if and what types of liquidity management tools were effective in mitigating the fragility of flows during the COVID-19 episode of market distress. The baseline analysis looks at the net flows to total assets of individual funds at a monthly frequency:

$$\frac{\text{Net Flow}_{i,t}}{\text{Total Assets}_{i,t-1}} = \alpha_i + \mu_t + \beta_1 \text{PLMT}_{i,t} \times \text{March2020}_t + \beta_2 \text{PLMT}_{i,t} + \beta_3 \text{March2020}_t + \theta' X_{i,t-1} + \gamma' X_{i,t-1} \times \text{March2020}_t + \epsilon_{i,t} \quad (1)$$

where  $\text{Net Flow}_{i,t}/\text{Total Assets}_{i,t-1}$  is defined as monthly inflows less outflows of shares at the market price at the time of the transaction divided by the fund's total assets in the previous month.<sup>13</sup>  $\text{PLMT}_i$  is an indicator variable equal to 1 if fund  $i$  is in the treatment group, as defined in Figure 5, while March 2020 is a dummy equal 1 in March 2020 and zero from January 2018 to February 2020.  $X_{i,t-1}$  is a vector of lagged fund characteristics, which include measures of size, liquidity, past performance and flow volatility, as well as ownership shares. Appendix A provides details on variable definitions. In most specifications, we also include interactions between these other fund characteristics and the March 2020 dummy to alleviate

<sup>13</sup>As the data available at the Central Bank of Ireland records inflows and outflows at the market price of the transaction, our measure of net flows is directly computed, rather than the indirect measure imputed from changes in portfolio size and asset prices as it is common in the literature.



concerns that underlying fund differences in, for example, liquidity or the investor base might explain flows in March 2020. Finally, we control, throughout all specifications, for month and fund fixed effects to absorb aggregate shocks in a given period, as well as time-invariant fund characteristics. Time fixed-effects will also absorb the coefficient of the March 2020 dummy variable and allow us to obtain identification from differences in net flows across funds in the same month.

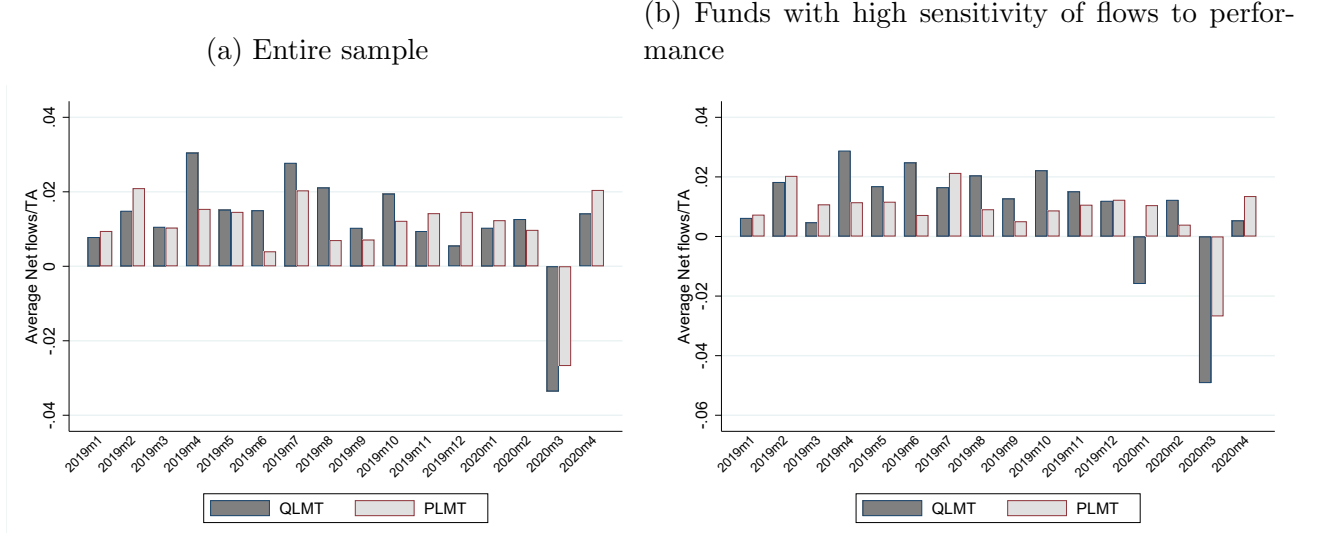
The coefficient of interest is  $\beta_1$ . A positive coefficient implies that the difference in net flows in March 2020 compared to the pre-shock period was higher among funds with levies or fees as compared to the control group. In other words, PLMTs funds experienced lower net redemptions during March 2020, as compared to funds that with only QLMTs. Causal identification relies on several assumptions.

The first is that the market distress in March 2020 was not anticipated, causing investors with different sensitivities to stress events selecting into funds that do not have access to redemption fees or levies prior to the shock. There is significant evidence documenting the distress in the bond markets, which shows that the periods of turmoil started in early March and ended towards the end of March when major central banks announced asset purchase programs (Kargar et al. 2020, Falato et al. 2021, Haddad et al. 2020). Figure 7a confirms this in our sample of bonds funds by showing the average net flows to total in the treated and control groups from January 2019 to April 2020. In the first months of 2020, both groups experience net inflows with no clear shift of investors towards funds without fees or levies prior to March 2020. There are also no clear pre-trends in the longer run average monthly net flows between the two groups.

Second, we also need to assume that selection into the treatment and control groups is random and not related to the outcome variable of interest, i.e., differences in net flows. As we have argued in the previous section the introduction of LMTs occurs at the family level and is not related to funds' flow volatility or the sensitivity of flows to performance. To further mitigate concerns that other fund characteristics that might be correlated with the availability of PLMTs might explain differences in net flows in March 2020, we saturate the model with a wide array of fund observable characteristics and fund fixed effects.

Yet, one remaining concern is that of unobservable matching between investors and funds,

Figure 7: Average Net flows/TA



such that investors who are more prone to withdraw during market distress select out of funds that apply fees or levies. To alleviate this concern, we split the sample of funds according to their past sensitivity of flows to performance. By focusing on a sample of funds that have a high sensitivity of flows to performance, we mitigate the role of investor selection in explaining the results. More precisely, we estimate Eq. (1) separately for funds to a high versus low sensitivity of flows to performance. We classify funds following the flow-to-performance literature (Chevalier & Ellison 1997, Sirri & Tufano 1998, Huang et al. 2007) by relating net flows in a fund to its past return, as follows:

$$\frac{\text{Net flows}_{i,t}}{TA_{i,t-1}} = \alpha + \beta \text{Return}_{i,t-1} + \epsilon_{i,t}, \quad (2)$$

where  $\text{Return}_{i,t-1}$  is fund return in the previous month, computed as the percentage change in its NAV. We estimate Eq. (2) for each fund in every month over the period January 2014 - December 2018. We then rank funds based on the estimated  $\beta_i$ s into those with an above median sensitivity of flows to performance and those below. We then perform a split sample analysis where we estimate Eq.(1) for funds with an above the median sensitivity and those with a below the median one.

Simple descriptive statistics point to the impact of LMTs being stronger in the high sensitivity group. Figure 7b shows the average monthly net flows in the sample of high

sensitivity funds by treatment and control groups. The differential impact is even stronger in this sub-sample as compared to the entire sample of corporate bond funds depicted in Figure 7a. The empirical analysis in the next section confirms this result in a more rigorous econometric model.

## 4 Results

The results from the baseline model in (1) are presented in Table 5. We first present the results of the split sample analysis, with columns (1) and (2) corresponding to the sample of funds with an above the median past sensitivity of flows to performance, while columns (3)-(4) with a below the median sensitivity. We find that price-based LMT funds have a significantly higher net flow (lower net outflows) during March 2020 as compared to funds with only quantity-based LMTs. This effect is present among funds with a high sensitivity of flows to performance (column (1)) and less so among those with a low sensitivity (column (3)). This suggests that tools such as redemption fees or anti-dilution levies were effective in mitigating net outflows during the COVID-19 shock to financial markets particularly in the sample of funds that are more susceptible to liquidity shocks. The effect is also economically significant. Looking at the estimates in column (1), PLMT funds have 5.2% higher net flows to total assets as compared to control funds (the average in March 2020 is around -3%).

In all models, we control for a rich set of observable fund characteristics such as size, past volatility of flows, past returns, liquidity, leverage and ownership measures. Moreover, in columns (2) and (4), we include interactions between these fund characteristics and the March 2020 dummy to account for alternative factors that might explain differences in net flows in March 2020. The results are even more robust in this more stringent specification and we present the coefficient estimates of the additional controls in Appendix Table 10. Notably, we find that bigger funds and those with a higher past volatility of flows experienced lower net flows in March 2020. At the same time, leveraged funds and those with higher ownership by banks, investment funds or pensions and insurance corporations experienced lower net outflows in March 2020.

Finally, all estimations include fund and month fixed effects, which absorb all unobservable fund time-invariant characteristics as well as the aggregate impact of the March 2020 stress

Table 5: Fund Flows during March 2020

<i>Dependent variable: Net flow/TA</i>	High sensitivity		Low sensitivity		Full sample	
	(1)	(2)	(3)	(4)	(5)	(6)
PLMT× March 2020	0.052** (0.022)	0.064*** (0.017)	-0.025 (0.017)	-0.003 (0.018)	-0.023 (0.198)	-0.004 (0.020)
PLMT × High Sensitivity× March 2020					0.070*** (0.011)	0.068*** (0.020)
High Sensitivity× March 2020					-0.064*** (0.018)	-0.059*** (0.016)
PLMT × High Sensitivity					0.028 (0.024)	0.030 (0.023)
Fund-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-level controls X March 2020	No	Yes	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,049	5,049	4,338	4,338	9,387	9,387
R-squared	0.287	0.300	0.210	0.222	0.251	0.263

The dependent variable is *Net Flow/TA*, defined as the net monthly capital flow into a fund divided by the fund's total net assets in the previous month. PLMT is an indicator variable equal 1 for funds with fees or levies and at least one of the QLMTs (suspensions, gates or redemption in kind) and 0 for funds with neither fees nor levies, but at least one of the QLMTs. March 2020 a dummy variable equal to 1 in March 2020 and zero from January 2018 to February 2020. High Sensitivity<sub>*i*</sub> is an indicator variable equal to 1 if a fund has an above the median sensitivity of flows to performance over the period 2014-2018. Fund-level controls include: the lag of net flows to total assets, lag of monthly return, number of funds in family, lag of log of total assets, lag of volatility of flows, lag of leverage, a dummy variable for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations. Fund-level controls X March 2020 represents an interaction between the controls and the March 2020 dummy variable. Standard errors clustered at the fund family in parenthesis.

\*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

across the Irish domiciled fund industry. We cluster standard errors at the family level in the main specifications as this is the treatment assignment level (see Bertrand et al. 2004). This, together with the rich set of fund controls, mitigates to a great extent concerns of omitted variable bias.

Furthermore, while we will present split sample analysis throughout the remainder of the paper, in columns (5)-(6) of Table 5, we show that our results remain unchanged if we estimate the model on the entire sample and introduce a triple interaction term between: (i) the treatment condition, (ii) the March 2020 dummy variable and (iii) an indicator variable equal to one for funds above the medium sensitivity of flows to past performance and zero for

those below (High Sensitivity). Specifically the model estimated is:

$$\begin{aligned} \frac{\text{Net Flow}_{i,t}}{\text{Total Assets}_{i,t-1}} = & \alpha_i + \mu_t + \beta_1 \text{PLMT}_{i,t} \times \text{March2020}_t \times \text{High Sensitivity}_i + \\ & \beta_2 \text{PLMT}_i \times \text{March2020}_t + \beta_3 \text{March2020}_t \times \text{High Sensitivity}_i + \\ & \beta_4 \text{PLMT}_{i,t} \times \text{High Sensitivity}_i + \gamma' X_{i,t-1} \times \text{March2020}_t + \epsilon_{i,t} \quad (3) \end{aligned}$$

The coefficient  $\beta_1$  in Eq. (3) of the triple interaction term captures the differential net flows in March 2020 in treatment versus control funds, in the sample of high sensitivity funds as compared to the low sensitivity ones. The baseline results are confirmed in this alternative specification. Moreover, the negative coefficient of the interaction between High Sensitivity  $\times$  March 2020 confirms that funds with a more stringent complementarity of actions among investors were also the ones experiencing lower net flows in March 2020.

One concern with the results in Table 5 is that investors anticipated the stress event and shifted their funds into investment funds that do not apply redemption fees or levies. While the descriptive statistics in Figure 7a suggest that this is unlikely, we further validate this identifying assumption by showing the difference in net flows in the treatment and control groups in each month from March 2019 to May 2020. Specifically, we estimate the following model:

$$\begin{aligned} \frac{\text{Net Flow}_{i,t}}{\text{Total Assets}_{i,t-1}} = & \alpha_i + \mu_t + \beta_q \sum_{q=2019m3}^{2020m5} 1_{t=q} \times \text{PLMT}_i \times \text{High sensitivity}_i \\ & + \theta' X_{i,t-1} + \epsilon_{it} \quad (4) \end{aligned}$$

where  $\text{PLMT}_i \times \text{High sensitivity}_i$  is interacted with a series of indicator variables equal to 1 in each month  $q$  and zero otherwise. Figure 8 shows the coefficient estimates of this triple interaction term (with January 2020 as the baseline. This figure also confirms the conditional parallel trends assumption by showing no significant difference before and after March 2020 between the treatment and control groups.

The baseline results in Table 5 are robust to a series of alternative specifications and samples. First, in Appendix Table 11, we show that the results hold for both the sample of bond funds and mixed funds separately. Second, we consider alternative definitions for the

Figure 8: Timing of effects

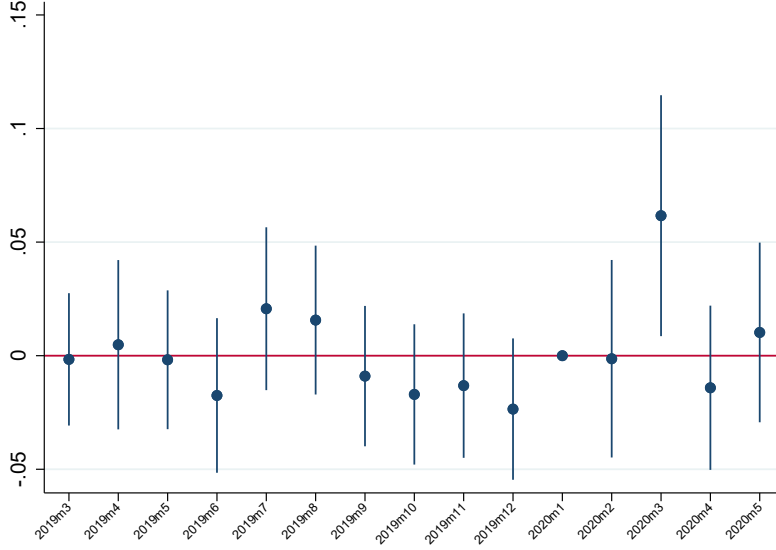


Figure shows the estimated coefficient  $\beta_q$  in Eq. (4) for the subsample of funds with a high sensitivity of flows to performance. March 2019 is considered as the baseline month and is dropped. 95% confidence intervals are shown.

treatment and control groups. In Appendix Table 12, PLMT2 considers as treatment group funds that have either fee or levies and *all* QLMTs, i.e., gates, suspensions and redemptions in kind. The control group includes funds that have all QLMTs. As focusing on funds that report all the quantity-based tools restricts our sample considerably, we also consider the alternative PLMT3, where we employ the same definition as PLMT2, but we exclude the redemptions in kind tool from both the treatment and control groups. Again, the results are robust under these alternative definitions.

Next, we consider the robustness of our results to model specification. For instance, Roth et al. (2022) recommend clustering standard errors in diff-in-diff models at the unit of observation level whenever the number of clusters at the level at which treatment is independently assigned (fund family, in our case) is not very large. At the same time, clustering at the fund level also allows us to account for the correlation in fund flows across time. We also consider the robustness of our results to the definition of funds investing in corporate bonds. Our main sample includes bond funds that self-identify as corporate bond funds in their yearly reporting to the Central Bank of Ireland. We consider two alternative definitions. First, we follow Chakraborty et al. (2022) and include funds that hold at least 15% of their portfolio in

corporate bonds. This results in a sample of 606 bond and mixed funds. Second, we consider a larger sample of funds that hold at least one corporate bond in their portfolio. This results in a sample of 1,011 bond and mixed funds. Appendix Figure 13 presents the coefficient  $\beta_1$  in Eq.(3) of the triple interaction term  $\text{PLMT} \times \text{March 2020} \times \text{High Sensitivity}$  for these alternative specifications and samples. Results are robust across all models, albeit less precisely estimated for the largest sample that includes all funds that hold at least one corporate bond.

Finally, we check the sensitivity of our results to the sample split between high and low sensitivity funds. In our baseline results, we estimate the flow to performance relationship over the period 2014-2018 to classify funds. However, one concern is that, for funds already employing fees or levies during that period, this relationship is affected by the presence of these liquidity management tools. This would, however, create a downward bias in the estimate of  $\beta$  in Eq. 2, making funds that have employed the tools for a longer period to be classified with a below the median sensitivity. Nonetheless, to overcome this concern, we check the robustness of our main results to restricting the sample of funds to only those that introduce either fees or levies during 2019. For this sample, the estimated flow-to-performance sensitivity during the period 2014-2018 is not biased by the presence of the LMTs. As such the new treatment group includes only the funds for which we observe the introduction of levies or fees in December 2019 (35 corporate bond funds). The control group remains the same as in the baseline definition: funds that do not have access to fees or levies, but have at least one of the QLMTs. The results of the baseline model in Eq. (1) using this alternative model are presented in Appendix Table 13 and shows that our main results are robust even in this restricted sample of switchers.

## 4.1 Outflow and inflows

The results in the previous section show that funds with anti-dilution levies or redemption fees experience higher net flows during March 2020. One natural question is to investigate whether the higher net flows are due to lower outflows or higher inflows or both. The analysis in Table 6 estimates Eq. (1) by considering as dependent variables outflows to total assets, as well as inflows to total assets. Similar to previous results we present the estimates for the low versus the high sensitivity funds separately. Outflows and inflows are both positive numbers,

Table 6: Outflows versus inflows

<i>Dependent variable</i>	High sensitivity			Low sensitivity		
	(1) $\frac{Outflows}{TA}$	(2) $\frac{Inflows}{TA}$	(3) Prob Negative net flows	(4) $\frac{Outflows}{TA}$	(5) $\frac{Inflows}{TA}$	(6) Prob Negative net flows
PLMT $\times$ March 2020	-0.033* (0.093)	0.042*** (0.003)	-0.307*** (0.001)	-0.006 (0.814)	-0.020 (0.455)	0.050 (0.563)
Fund Controls	Yes	Yes	Yes	Yes	Yes	Yes
Controls X March 2020	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,049	5,049	5,049	4,338	4,338	4,338
R-squared	0.212	0.313	0.332	0.187	0.220	0.440

The dependent variable in columns (1) and (4) is  $Outflows/TA$ , defined as the monthly redemptions from a fund divided by the fund's total net assets in the previous month. The dependent variable in columns (2) and (5) is  $Inflows/TA$ , defined as the monthly new subscriptions into a fund divided by the fund's total net assets in the previous month, while in columns (3) and (6) it is a dummy equal 1 if the fund experienced a negative net flow in a given month, and 0 otherwise. PLMT is an indicator variable equal 1 for funds with fees or levies and at least one of the QLMTs (suspensions, gates or redemption in kind) and 0 for funds with neither fees nor levies, but at least one of the QLMTs. March 2020 a dummy variable equal to 1 in March 2020 and zero from January 2018 to February 2020. High Sensitivity is the sample of funds with an above the median sensitivity of flows to performance over the period 2014-2018. Fund-level controls include: the lag of net flows to total assets, lag of return, number of funds in family, lag of ln of assets, lag of volatility of flows, lag of leverage, a dummy for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations. Fund-level controls X March 2020 represents an interaction between the controls and the March 2020 dummy variable. Standard errors clustered at the fund family in parenthesis. \*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

with zeros recorded for funds that experienced no outflows or inflows in a given month.

We find that PLMT funds had both relatively lower outflows (column(1)) and higher inflows (column (2)) in March 2020 as compared to the control group. Moreover, column (3) shows that these funds also have a disproportionally lower probability of having negative net flows, where the dependent variable in this column is an indicator variable equal to 1 if net flows are negative and 0 if they are positive. Furthermore, as before, this effect is only observed on the high sensitivity sample of funds.

The findings in Table 6 suggest that the presence of PLMTs affects both inflows and outflows in periods of distress. One channel through which this happens is via changes in the correlation between inflows and outflows. Specifically, in periods of distress we might expect a negative correlation between inflows and outflows, as potential investors are concerned about



Table 7: Correlation between outflow and inflows

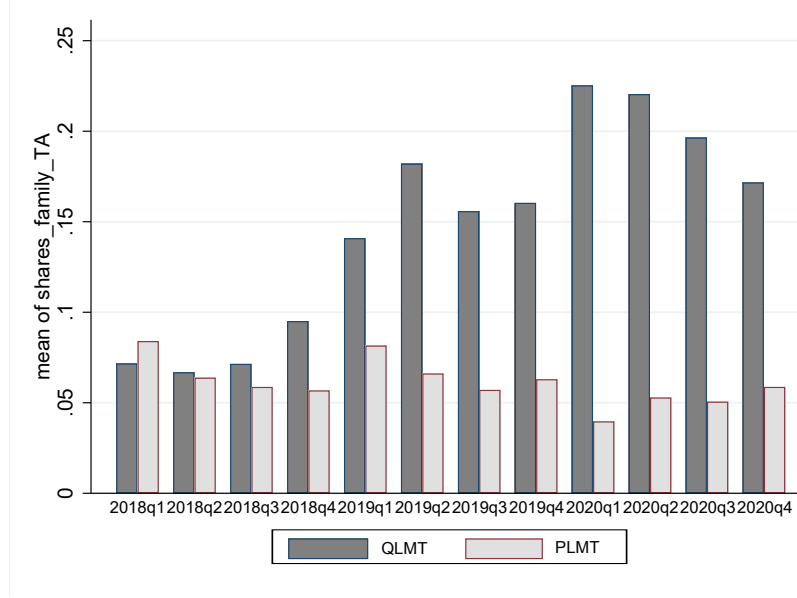
Dependent variable: Inflows/TA	(1)	High sensitivity (2)	Low sensitivity (3)
Outflows/TA	0.447*** (0.000)	0.310*** (0.102)	0.258** (0.118)
Outflows/TA $\times$ March 2020	-0.139* (0.073)	-0.417*** (0.131)	0.370 (0.302)
PLMT $\times$ Outflows/TA $\times$ March 2020		0.312* (0.179)	-0.675** (0.336)
Outflow $\times$ PLMT		0.206* (0.116)	0.174 (0.140)
PLMT $\times$ March 2020		-0.019 (0.023)	0.021 (0.018)
Fund-level controls	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
Observations	12,062	5,538	4,732
R-squared	0.375	0.377	0.300

The dependent variable is *Inflows/TA*, defined as the net monthly inflows of capital into a fund divided by the fund's total net assets in the previous month. PLMT is an indicator variable equal 1 for funds with fees or levies and at least one of the QLMTs (suspensions, gates or redemption in kind) and 0 for funds with neither fees nor levies, but at least one of the QLMTs. March 2020 a dummy variable equal to 1 in March 2020 and zero from January 2018 to February 2020. High Sensitivity is the sample of funds with an above the median sensitivity of flows to performance over the period 2014-2018. Fund-level controls include: lagged net flows to total assets, lagged return, number of funds in family, lagged log of assets, lagged volatility of flows, lagged leverage, a dummy for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations. Standard errors clustered at the fund family in parenthesis. \*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

the impact that outflows will have on the fund's NAV. However, in funds where the cost of withdrawals is more likely to be borne by the investors who execute the transaction, this concern is reduced.

Table 7 presents evidence of this mechanism. In column (1), we find that the correlation between inflows and outflows is generally positive, but significantly lower in March 2020, consistent with a first mover advantage reasoning. However, when we include an interaction term with the treatment condition, we find that among funds with fees or levies, the correlation becomes positive again (column (2)). This suggests that the presence of PLMTs affects the strategic complementarities in investors' actions. Again, the results hold for funds that are more likely to be characterized by such strong complementarities, i.e. the high sensitivity

Figure 9: Proportion of fund share held by other funds in the same family



The figure shows the proportion of fund share held by other funds in the same family. 1 corresponds to treated fund and zero to the control group.

ones.

One concern with the results above it that the observed increase in inflows is the result of intra-family liquidity support. For example, Bhattacharya et al. (2013) show that affiliated funds of mutual funds provide an insurance pool against temporary liquidity shocks to other funds in the family. While we do not observe investor level information in our dataset, we can compute, for each individual fund, the share of assets owned by other funds in the same family.

Specifically, for each fund belonging to a fund family, we can compute the proportion of its fund shares that are held by other funds in the same family. We then plot the evolution of the average proportion of fund shares held by other funds in the family for the treated and control funds. Figure 9 shows that, over the period 2018-2020, funds in the control group have, on average, a higher share of their equity held by other funds in the family. We observe asset ownership only at the quarterly level, so to compare the increase in cross-family ownership we compare the last quarter of 2019 to the first quarter of 2020 (ending in March). We observe that funds in the treated group did not experience an average increase in intra-family ownership, if anything the ratio appears to be decreasing in 2020Q1 as compared to 2019Q4

in this group. On the other hand, the proportion of shares held within the family increases visibly in the control group suggesting an increased liquidity support in this group. These descriptive statistics suggest that the increase in inflows observed among PLMT funds is not likely the result of cross-family liquidity support.<sup>14</sup>

## 4.2 Fund performance

A large literature documents that portfolio adjustments due to redemptions are costly and they can dilute fund performance (Goldstein et al. 2017). Given the mitigating effect on outflows that we have documented in this paper, this would suggest that PLMT funds also see superior returns following the shock. To test this hypothesis, we estimate the following cross-sectional model in each month from July 2019 to July 2020:

$$\% \Delta \text{NAV}_i = \alpha + \beta \text{PLMT}_i + \theta' X_i + \epsilon_i, \quad (5)$$

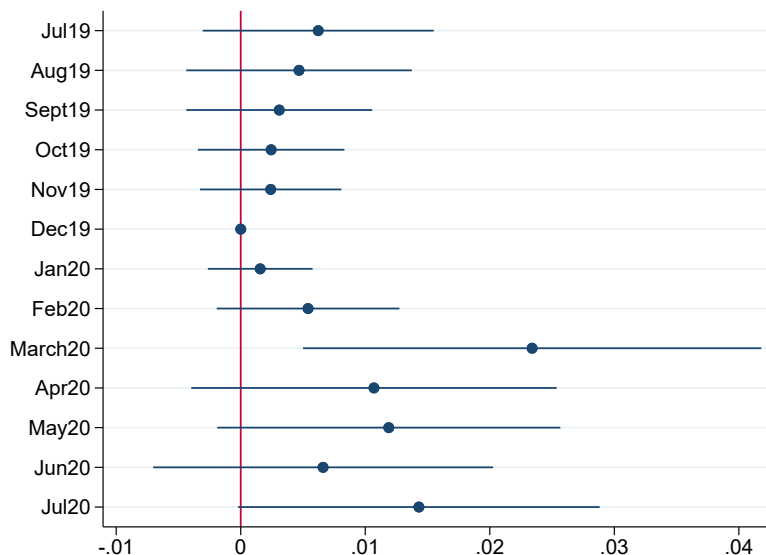
where  $\% \Delta \text{NAV}_{i,t}$  is the change in NAV in month  $t$  with respect to December 2019, which is taken as baseline. The coefficient  $\beta$  captures the difference in returns between PLMT and QLMT funds in each month and is presented in Figure 10. Eq. (5) controls for several fund characteristics, which include the lag of total assets, as well as a series of dummy variables that reflect investment strategy: investment rating, an indicator for bond funds (as opposed to mixed), as well as regional strategy (regions included being Europe, Americas, Emerging Markets, Asia Pacific).

We observe that prior to March 2020, there are no statistically significant differences in performance between the two groups. However, during March 2020, PLMT funds see a significantly higher performance. This appears persistent over subsequent months although not always robustly estimated.

---

<sup>14</sup>It should be noted that we only considered ownership by funds in the same family that are domiciled in Ireland. If there are funds in the same family legally domiciled in another country, we do not observe this ownership data. However, this not likely to be a significant number of funds, as management companies incorporate umbrella funds (fund families) as ICAVs under Irish law.

Figure 10: Fund performance



The figure shows the coefficient estimates of  $\beta$  in Eq. (5) in each quarter.

### 4.3 Selling pressure and portfolio rebalancing

We turn next to the impact of the COVID-19 shock on the asset holdings of mutual funds with different types of LMTs. Recent evidence shows that, when faced with redemption risk, asset managers actively manage the liquidity of funds' portfolios. For example, Morris et al. (2017) show that bond funds do not necessarily reduce cash holding to meet investor outflows, but would very often sell other less liquid assets. This cash hoarding behavior is more pronounced among less liquid funds and can amplify fire sales during periods of market distress (see also Chakraborty et al. 2022, Jiang et al. 2022). Similarly, Jiang et al. (2021) show that, during tranquil market conditions, corporate bond funds reduce liquid asset holdings to meet redemptions, whereas during market turmoil they tend to scale down their liquid and illiquid assets proportionally to preserve portfolio liquidity. This also suggests that funds' liquidity management can introduce fragility into asset prices. For instance, Jiang et al. (2022) show that bonds held disproportionately by more illiquid funds experienced more negative returns and larger reversals around March 2020.

As our evidence thus far suggests that price-based LMTs mitigate redemption risk, we expect this to also have consequences in terms of the liquidity structure of funds' portfolios following the COVID-19 shock. Specifically, facing a lower redemption risk, PLMT funds

should experience a lower pressure to build up cash reserves or hold more liquid assets to meet future outflows. At the same time, given the severe distress in the corporate bond market during March 2020 (Haddad et al. 2020, Kargar et al. 2020), we expect PLMT funds to sell less bonds that traded at a discount, such as more illiquid corporate bonds. This, in turn, can have implications for the price fragility of the assets held by these funds at the peak of market distress.

To address these questions, we extend our dataset to include the asset holdings of our sample of funds. We focus on this subsection on the sample of corporate bond funds only i.e., excluding the mixed funds, since our main focus will be on the liquidity structure of the funds' bond portfolios and on the subsequent consequences of portfolio rebalancing on bond yields. We obtain data on quarterly asset holdings reported by Irish-domiciled funds to the Central Bank of Ireland (Money Market and Investment Funds statistics). This database contains ISIN-level information on all the asset holdings of reporting funds. For each bond  $i$  we collect information on the holding amount by each fund  $j$  at the end of March 2020 (Q1) and end of December 2019 (Q4) and compute the change in portfolio share within this period.

We start by investigating portfolio rebalancing across assets with different levels of liquidity from December 2019 to March 2020. Specifically, we look at the change in the portfolio share of five types of assets: cash, government and corporate bonds, as well as illiquid corporate and government bonds, respectively. To this end, we estimate a cross-sectional model where we regress the percentage change in the share of asset class  $c$  in fund  $j$ 's portfolio on our treatment dummy, as follows:

$$\% \Delta Share_{c,j} = \alpha + \beta_1 PLMT_j + \theta' X_j + \epsilon_j, \quad (6)$$

where  $\% \Delta Share_{c,j}$  is measured as  $\ln(Share_{c,j, March} / Share_{c,j, Dec19})$  and the portfolio share is computed as  $Share_{c,j,t} = \frac{\sum_{i \in c} \text{Holding amount}_{i,j,t}}{\text{Total Assets}_{j,t}}$ . We estimate the model in (6) separately for each asset class  $c$ . We capture a bond's liquidity through their IHS Markit liquidity score (which is a score from 1 to 5, with 1 being the most liquid and 5 being least liquid). We define a bond to be illiquid if it has a Markit score of 2 or higher and liquid if the score is 1.<sup>15</sup>

---

<sup>15</sup>The liquidity threshold is driven by the distribution of bonds in our sample, as 71% of these bonds have a score of 1.

Table 8: Portfolio rebalancing

Dependent variable	$\Delta\text{Cash/TA}$	$\Delta\text{Corporate Bonds/TA}$	$\Delta\text{Illiquid Corporate Bonds/TA}$	$\Delta\text{Gov Bonds/TA}$	$\Delta\text{Illiquid Gov Bonds/TA}$	$\Delta\text{Bonds/TA}$	$\Delta\text{Corporate bond/TA}$	$\Delta\text{Government bond/TA}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PLMT	-3.591** (1.784)	0.087** (0.035)	0.093* (0.049)	-0.021 (0.053)	-0.042 (0.097)			
PLMT $\times$ Illiquid bond						0.036*** (0.011)	0.038*** (0.011)	0.015 (0.049)
Fund-level controls	Yes	Yes	Yes	Yes	Yes	No	No	No
Bond FE	No	No	No	No	No	Yes	Yes	Yes
Fund FE	No	No	No	No	No	Yes	Yes	Yes
Observations	422	423	423	423	423	94,454	89,070	5,331
R-squared	0.08	0.11	0.07	0.04	0.04	0.39	0.39	0.49

The dependent variable in columns (1)-(5) is the percentage change in the share of asset class  $c$  in fund  $j$ 's portfolio, while in columns (6)-(8) it is the change in portfolio share of asset  $i$  from December 2019 to March 2020. Column (7) includes a subsample of corporate bond funds, while column (8) of government bonds, respectively. PLMT is an indicator variable equal 1 for funds with fees or levies and at least one of the QLMTs (suspensions, gates or redemption in kind) and 0 for funds with neither fees nor levies, but at least one of the QLMTs. Fund-level controls are measure in December 2019 and include: fund return, number of funds in family, log of assets, volatility of flows, leverage, a dummy for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations. Robust standard errors in parenthesis. \*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

We also control for the same fund-level characteristics as in previous sections, which include fund return, number of funds in family, total assets, volatility of flows, leverage, a dummy for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations, all measured in December 2019.

The results are presented in columns (1)-(5) of Table 8 and point to significant differences in portfolio rebalancing between PLMT and QLMT funds. Specifically, PLMT funds experience a significantly lower increase in Cash/TA, which suggests that the presence of anti-dilution levies or redemption fees is associated with less pressure to increase the share of cash to Total assets to meet redemptions after the COVID-19 shock. Aggregate evidence shows that the share of cash to total assets in bond funds went up in March 2020, which implies that funds sold more assets than needed to meet redemptions thereby putting additional pressure on bond prices (Schrimpff et al. 2021). This was also the case in our sample, with both treatment and control groups holding a higher average share of cash to TA at the end of March compared to the previous quarter. However, the evidence in Table 8 suggests PLMT funds increased their share of cash holding to a lesser extent. As a consequence, they rebalanced their portfolios towards holding more corporate bonds (column (2)), and, in particular, illiquid one (column (3)). At the same time, we do not observe any disproportionate change in the share of government and illiquid government bonds in columns (4) and (5).

We then confirm these cross-section results at the bond-fund level, which allows us to also

control for bond and fund fixed effects. Specifically, the dependent variable in columns (6)-(7) is the change in the share of bond  $i$  in fund  $j$ 's portfolio from December to March, computed as  $\Delta Share_{i,j} = \frac{Holdings_{i,j, March}}{TA_{j, March}} - \frac{Holdings_{i,j, Dec}}{TA_{j, Dec}}$ . We regress this on an interaction term between our treatment indicator and the Illiquid bonds indicator. The results are consistent with the fund-level analysis. Specifically, in the entire sample of bonds (column (6)), the interaction term is positive, suggesting PLMT increased the share of Illiquid bonds disproportionately more than QLMT funds. Furthermore, this result is driven by the sub-sample of corporate bonds (column (7)) and less so by government bonds (column (8)).<sup>16</sup> It should also be noted that the results in Table 8 are significant in the entire sample of PLMT funds, and, in unreported results, we find no statistically significant difference between high versus low sensitivity funds. This is intuitive as low sensitivity PLMT funds would also have fewer incentives to re-balance their portfolios towards more liquid assets.

The results in Table 8 suggest QLMT funds sold disproportionately more illiquid bonds as a share of total assets and, consequently, held more liquid portfolios afterwards. However, the implications for the price fragility of their asset holdings is not straightforward, particularly if QLMT funds held larger cash buffers en-ante to meet redemptions, as suggested by the descriptive evidence in Table 4. As such, we document the selling pressure on asset holdings by looking at the overall change in the holding amount of bond  $i$  by fund  $j$  from December 2019 to March 2020. Specifically, we estimate the following cross-sectional model:

$$\% \Delta Holdings_{i,j} = \alpha_i + \beta_1 PLMT_j + \theta' X_j + \epsilon_{i,j}, \quad (7)$$

where  $\% \Delta Holdings_{i,j}$  is either the percentage change in holdings of bond  $i$  by fund  $j$  from December 2019 to March 2020 (i.e.,  $\ln(Holdings_{i,j, Mar}/Holdings_{i,j, Dec})$ ) or the change in holdings during the period scaled by the total amount outstanding of bond  $i$ :  $\frac{\Delta Holdings_{i,j}}{Amount\ Outstanding_i}$ . The second definition puts more weight on bonds which are held in large amounts by our sample of Irish-domiciled funds. Our main independent variable is the treatment variable,  $PLMT_j$ , and we control for the same set of fund-level characteristics as in the flow level analysis measured in December 2019. We also include the change in total assets from December to

---

<sup>16</sup>Note though, that since this is a sample of corporate bond funds, they hold a significantly lower number of government bonds.

Table 9: Changes in bond holdings

Dependent variable	%Δ Holdings					Δ Holdings/Outstanding Amount				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
PLMT	0.0344*** (0.0058)	0.0033 (0.0068)				0.0001*** (0.0000)	0 (0.0000)			
PLMT × High Sensitivity		0.0525*** (0.0073)					0.0003*** (0.0001)			
PLMT × Illiquid Bond			0.0328*** (0.0105)	0.0317*** (0.0108)	0.036 (0.0497)			0.0002*** (0.0001)	0.0002*** (0.0001)	0.0002 (0.0002)
High Sensitivity		-0.0065 (0.0063)					-0.0005*** (0.0000)			
Fund-level controls	Yes	Yes	No	No	No	Yes	Yes	No	No	No
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	No	No	Yes	Yes	Yes	No	No	Yes	Yes	Yes
Observations	95,287	95,287	95,282	89,960	5,269	95,287	95,287	95,282	89,960	5,269
R-squared	0.37	0.38	0.44	0.44	0.49	0.58	0.58	0.63	0.63	0.7

The dependent variable in columns (1)-(5) is the percentage change in holdings of bond  $i$  by fund  $j$  from December 2019 to March 2020, while in column (6)-(10) it is the change in holdings during December 2019- March 2020 scaled by the amount outstanding of the bond. PLMT is an indicator variable equal 1 for funds with fees or levies and at least one of the QLMTs (suspensions, gates or redemption in kind) and 0 for funds with neither fees nor levies, but at least one of the QLMTs. High Sensitivity is an indicator variable equal 1 if the fund has an above the median sensitivity of flows to performance over the period 2014-2018. Illiquid Bond is an indicator variable equal 1 if a bond is illiquid based on its Markit liquidity score. Columns (4) and (5) are estimated on a subsample of corporate bonds only, while columns (9) and (10) on the subsample of government bonds, respectively. Fund-level controls include the change in total assets from December 2019 to March 2020, as well as fund return, number of funds in family, ln of assets, volatility of flows, leverage, a dummy for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations measured in December 2019. Robust standard errors in parenthesis.\*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

March to account for the differences in net flows during the period. All specifications include bond-fixed effects ( $\alpha_i$ ), which control for the riskiness and performance of the bond during the period, allowing us to obtain identification from within bond variation across funds with different LMTs.

The results from this baseline specification are presented in columns (1) and (5) of Table 9 and confirm our flow-level analysis in the previous section: PLMT funds, which experienced fewer net redemptions, reduce their bond holdings by less as compared to QLMT funds holding the same bonds in their portfolio. Moreover, the change in bond holdings is even larger among the sample of high sensitivity funds, which is in line with the results in previous sections (see columns (2) and (7)).

We then turn to the liquidity of the bonds sold. In column (3) and (5) we interact the PLMT indicator with a dummy variable equal one if a bond is illiquid and zero otherwise. We find that PLMT funds sold, on average a lower amount of illiquid bonds (the change in holding from March 2020 to December 2019 is higher) as compared to QLMT funds. Moreover, this result is mainly driven by the sample of corporate bonds. In columns (4) and (9) we estimate Eq. (7) for the subsample of corporate bonds, while in columns (5) and (10) for the subsample of government bonds, respectively. The interaction between PLMT and



the Illiquid bond indicator is positive and significant only in the sample of corporate bonds. Importantly, the inclusion of the interaction term  $PLMT \times \text{Illiquid Bond}$  in columns (4)- (5) and (9)-(10) also allows us to control for fund fixed effects.

The results in Table 9 suggest that the availability of price-based liquidity management tools mitigates the selling pressure on the bonds held by the funds with access to them, particularly on the more illiquid bonds. This lower outflows-induced selling pressure can, in turn, reduce the fragility of bonds' prices around March 2020, in particular for those held disproportionately by our sample of Irish funds. To investigate this effect, we follow Jiang et al. (2022) and compute a measure of the exposure of a bond to outflows-induced selling based on a holdings-weighted average across funds with PLMTs versus QLMTs as follows:

$$Exposure_{i,j,t} = \frac{\sum_{j=1}^J \text{Holding amount}_{i,j,t} \times PLMT_j}{\text{Outstanding Amount}_i}, \quad (8)$$

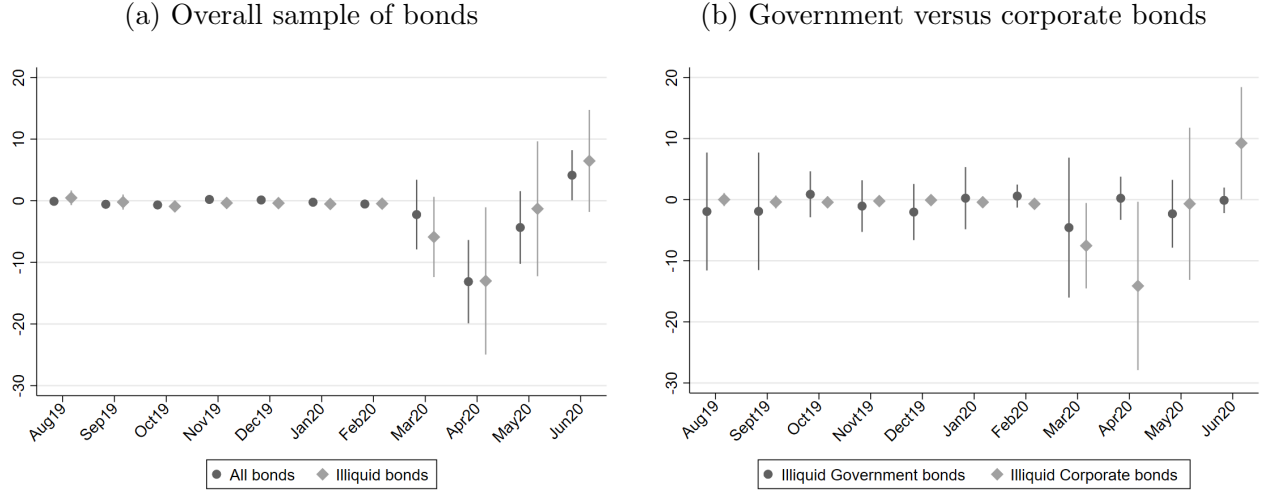
As such, the measure in (8) implies that bonds with high *Exposure* are held disproportionately by the sample of Irish funds that report having PLMTs. Given the lower outflows-induced selling pressure documented in Table 9, we then expect bonds with a high *Exposure* measure to also exhibit a lower change in yield around March 2020. To show this, we look at the average monthly changes in yields in the sample of bonds held by both treatment and control funds and estimate the following cross-sectional regressions in each month:

$$\Delta Yield_{i,t} = \alpha_{Issuer} + \beta Exposure_{i,j,t} + \theta' X_{i,j,t} + \epsilon_{i,t}, \quad (9)$$

where  $\Delta Yield_{i,t}$  is the average monthly change in yield of bond  $i$  in the period August 2019-June 2020. In  $X_{i,j,t}$ , we control for the fraction of a bond's outstanding amount held by all the Irish-domiciled funds in our sample (i.e.,  $\frac{\sum_{j=1}^J \text{Holding amount}_{i,j,t}}{\text{Outstanding Amount}_i}$ ), as well as the share of a bond  $i$  held by the sample of PLMT funds in the total holdings of Irish domiciled funds (i.e.,  $\frac{\sum_{j=1}^J \text{Holding amount}_{i,j,t} \times PLMT_j}{\sum_{j=1}^J \text{Holding amount}_{i,j,t}}$ ). The latter variable controls for the selection of Irish PLMT funds into more pro-cyclical or illiquid bonds (given that the presence of the price-based tools mitigates investor runs). Additionally, we include indicator variables for a bond's investment grade rating and liquidity (captured by the Markit score).

The coefficient  $\beta$  in (9) captures the change in yield of bonds that are disproportionately

Figure 11: Impact on bond yields

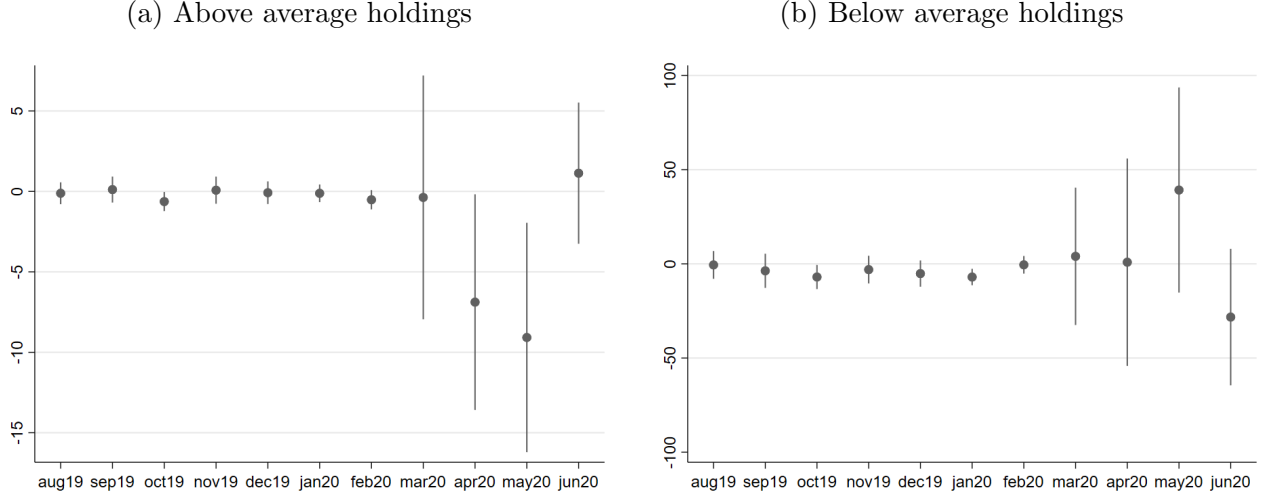


The figure shows the coefficient estimates of  $\beta$  in Eq.(9) in each month. Figure b) presents a split sample analysis on the sample of illiquid corporate and government bond, respectively. 90% confidence intervals are presented.

held by Irish funds with PLMTs and is presented in Figure 11. Figure 11a) shows the effect of PLMT exposure on the sample of bonds held by Irish-domiciled funds, as well as on the subsample of illiquid bonds as measured by their Markit liquidity score. The figure suggests that bonds held by PLMTs experienced a lower change in yield during March-May 2020, with the strongest impact in April 2020. Importantly, there is no difference in yields before March 2020, with the coefficient estimate being very close to zero in all prior months. The vertical axis is expressed in percentage points, so considering the average measure of exposure of 1.01% of the amount outstanding, the coefficient estimate in April 2020 implies, on average, a  $13\% \times 1.01\% = 0.13\%$  lower yield across all bonds in the sample. Alternatively, if we consider the standard deviation of the exposure measure of 0.02, then one standard deviation increase in exposure is equivalent to a 0.26 basis points lower yield for bonds held by PLMT funds. Similarly, Figure 11b) shows the estimate of  $\beta$  on the sub-sample of illiquid corporate and government bonds, respectively. It suggests that the differential impact on yields is largest among the sample illiquid corporate bonds.

The evidence in Figure 11 suggests that the significantly lower selling pressure documented in Table 9 resulted in lower price volatility (smaller change in yields) for bonds held by Irish PLMT funds, particularly if these funds held a larger fraction of the bond's outstanding

Figure 12: Impact on bond yields: split sample analysis



The figure shows the coefficient estimates of  $\beta$  in Eq.(9) in each month. Figure a) is estimated on the subsample of funds with an above the average fraction of holdings in the total amount outstanding, while Figure b) for those with a below the average, respectively. 90% confidence intervals are presented.

amount. The magnitude of the effect is small since our sample of Irish-domiciled mutual funds holds a rather small fraction of the total amount outstanding of the bonds in their portfolio. In Figure 12, we repeat the analysis by splitting the sample of bonds around the average fraction of amount outstanding that is held by our sample of funds. Specifically, Figure 12a) shows the estimate of  $\beta$  in Eq. (9) for the sample of funds with an above the average fraction of holdings in the total amount outstanding ( $\frac{\sum_{j=1}^J \text{Holding amount}_{i,j,t}}{\text{Outstanding Amount}_i}$ ), while Figure 12b) for those below the average, respectively. As expected, the effect is observed only in the former subsample and the magnitude is larger: in this subsample the average holdings is 3% of the amount outstanding, implying a  $6.88\% \times 0.03 = 0.2\%$  lower yield for bonds held by PLMT as compared to those held by QLMT.

Overall, the results in Table 9 and Figures 11-12 point to an important effect of funds' liquidity management strategy on the fragility of the assets held in their portfolio during episodes of market distress such as the COVID-19 shock. We show that PLMT funds not only sold fewer illiquid bonds, but this also translated into less price fragility of the bonds that were disproportionately held by these funds.

Overall, the results in this subsection suggest that the presence price-based LMTs has important consequences on portfolio rebalancing following episodes of market distress. Our

treated group rebalance their portfolio towards less liquid assets suggesting that the mitigating effect of PLMTs on net flows is also associated with a lower selling pressure on illiquid assets and price volatility of these assets. This suggests that the availability of price-based liquidity management tools in open-ended funds can have important implications for financial stability. Similar evidence is provided in King & Semark (2022) who perform a simulation exercise on the universe of UK corporate bond funds and find that a widespread use of swing pricing among these funds would reduce the amplification of outflow-induced shocks to investment grade bond spreads by around 8%, and by around 22% for high yield bonds.

## 5 Conclusions

The investment fund sector has seen a dramatic growth of its assets under management over the last two decades, which has raised concerns over its financial stability. As a result, regulators have encouraged the use of liquidity management tools to mitigate the pressure on funds' liquidity during episodes of massive investors withdrawals. However, there is limited empirical evidence into the effectiveness of such tools.

In this paper, we investigate the role of different liquidity management tools in mitigating financial fragility in the investment fund industry during the COVID-19 episode of market distress in March 2020. We document the availability of five types of LMTs in a sample of Irish-domiciled funds investing in corporate bonds. We show that the availability of tools has increased since 2018 and a large majority of funds report quantity-based tools such as redemption gates, suspension of dealings and redemption in kind. However, since these tools are less frequently employed, we focus our analysis on the effectiveness of price-based tools such as anti-dilution levies or redemption fees.

We show that funds with access to redemption fees or levies experienced higher net flows during March 2020 as compared with funds with only price-based tools. This effect is driven by a sample of funds with a high sensitivity of flows to performance, which are more susceptible to investor runs. Moreover, we document that the presence of liquidity management tools also has important consequences on portfolio rebalancing following episodes of market distress. Funds with price-based LMTs rebalance their portfolio towards less liquid assets suggesting that the mitigating effect of such tools on net flows is also associated with a lower selling

pressure on illiquid assets.

## References

- Bertrand, M., Duflo, E. & Mullainathan, S. (2004), ‘How much should we trust differences-in-differences estimates?’, *The Quarterly journal of economics* **119**(1), 249–275.
- Bhattacharya, U., Lee, J. H. & Pool, V. K. (2013), ‘Conflicting family values in mutual fund families’, *The Journal of Finance* **68**(1), 173–200.
- Chakraborty, I., Ferracuti, E., Heater, J. C. & Phillips, M. (2022), ‘The consequences of fund-level liquidity requirements’, *Available at SSRN*.
- Chen, Q., Goldstein, I. & Jiang, W. (2010), ‘Payoff complementarities and financial fragility: Evidence from mutual fund outflows’, *Journal of Financial Economics* **97**(2), 239–262.
- Chevalier, J. & Ellison, G. (1997), ‘Risk taking by mutual funds as a response to incentives’, *Journal of Political Economy* **105**(6), 1167–1200.
- Cima, S., Killeen, N., Madouros, V. et al. (2019), Mapping market-based finance in ireland, Technical report, No. 17/FS/19, Central Bank of Ireland.
- Daly, P., Moloney, K. et al. (2017), ‘Liquidity & risk management: Results of a survey of large irish-domiciled funds’, *Central Bank of Ireland Quarterly Bulletin* **3**, 48–62.
- Dunne, P. G. & Giuliana, R. (2021), ‘Do liquidity limits amplify money market fund redemptions during the covid crisis?’.
- ESMA (2020), Recommendation of the european systemic risk board (esrb) on liquidity risk in investment funds, Technical report, ESMA34-39-1119/ November 2020.
- ESRB (2017), Eu shadow banking monitor, Technical report, No 2 / May 2017.
- Falato, A., Goldstein, I. & 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.
- Goldstein, I., Jiang, H. & Ng, D. T. (2017), ‘Investor flows and fragility in corporate bond funds’, *Journal of Financial Economics* **126**(3), 592–613.

- Grill, M., Vivar, L. M. & Wedow, M. (2022), ‘Mutual fund suspensions during the covid-19 market turmoil-asset liquidity, liquidity management tools and spillover effects’, *Finance Research Letters* **50**, 103249.
- Haddad, V., Moreira, A. & Muir, T. (2020), When selling becomes viral: Disruptions in debt markets in the covid-19 crisis and the fed’s reponse, Technical report, National Bureau of Economic Research.
- Huang, J., Wei, K. D. & Yan, H. (2007), ‘Participation costs and the sensitivity of fund flows to past performance’, *The Journal of Finance* **62**(3), 1273–1311.
- Jiang, H., Li, D. & 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. & 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. & Suntheim, F. (2022), ‘Swing pricing and fragility in open-end mutual funds’, *The Review of Financial Studies* **35**(1), 1–50.
- Kargar, M., Lester, B., Lindsay, D., Liu, S., Weill, P.-O. & Zúñiga, D. (2020), Corporate bond liquidity during the covid-19 crisis, Technical report, National Bureau of Economic Research.
- King, B. & Semark, J. (2022), ‘Reducing liquidity mismatch in open-ended funds: a cost-benefit analysis’.
- Ma, Y., Xiao, K. & Zeng, Y. (2020), ‘Mutual fund liquidity transformation and reverse flight to liquidity’, *Available at SSRN 3640861* .
- Morris, S., Shim, I. & Shin, H. S. (2017), ‘Redemption risk and cash hoarding by asset managers’, *Journal of Monetary Economics* **89**, 71–87.
- Pástor, L. & Vorsatz, M. B. (2020), ‘Mutual fund performance and flows during the covid-19 crisis’, *The Review of Asset Pricing Studies* **10**(4), 791–833.

- Roth, J., Sant'Anna, P. H., Bilinski, A. & Poe, J. (2022), 'What's trending in difference-in-differences? a synthesis of the recent econometrics literature', *arXiv preprint arXiv:2201.01194* .
- Schrimpf, A., Shim, I. & 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* .
- Sirri, E. R. & Tufano, P. (1998), 'Costly search and mutual fund flows', *The journal of finance* **53**(5), 1589–1622.
- Timmer, Y. (2018), 'Cyclical investment behavior across financial institutions', *Journal of Financial Economics* **129**(2), 268–286.



# Appendix

## A Variable definitions

Variable name	Definition
<b>Fund-level variables</b>	
$Netflow_t/TA_{t-1}$	Net flow in month $t$ computed gross inflows minus outflows scaled by lagged total assets: $\frac{Inflows_t - Outflows_t}{TA_{t-1}}$
$Return_t$	Monthly fund return computed as the changed in NAV: $ln\left(\frac{NAV_t}{NAV_{t-1}}\right)$
PLMT	Dummy equal to 1 if a fund has access to either redemption fees or levies and at least one of the QLMT tools (suspensions, gates, and redemption in kind) and zero if the fund does not report either fees or levies, but at least one of the QLMT tools .
High Sensitivity	Dummy equal to 1 if a fund has an above the median flow-to-performance sensitivity during from 2014 (or date of creation) to 2018 and zero otherwise.
Nb funds in family	The number of funds in the fund family
Ln Assets	Log of Total Assets
Volatility	Past volatility of fund flows computed as the rolling standard deviation of net flows to TA over the past 12 months
Liquidity/TA	A quarterly measure of fund liquidity computed as the ratio of cash & equivalents plus holdings of US & German government bonds to TA
Leverage	An indicator variable equal to one if the fund uses leverage and zero otherwise (self reported by fund)
Share of Banks & IF	Percentage of fund shares owned by banks and other investment funds
Share of Pension & Insurance	Percentage of fund shares owned by pension funds and insurance corporations
Investment grade	An indicator variable equal to 1 if the fund has investment grade rating
BHC	An indicator equal to 1 if the fund's asset management company belongs to a bank holding corporation (based on ultimate ownership data in Orbis Bureau Van Dijk)
<b>Family family-level variables*</b>	
Ln(Assets)	Log of Total Assets in fund family
Nb funds in family	The number of funds in the fund family
Liquidity/TA	Weighted average level of liquidity measured as a fund's ratio of cash & equivalents plus holdings of US & German government bonds to TA
High Sensitivity	Weighted average share of high flow-to-performance sensitivity funds in the family.
Share of Banks & IF	Weighted average percentage of fund shares owned by banks and other investment funds
Share of Pension & Insurance	Weighted average of percentage of fund shares owned by pension funds and insurance corporations
Share of distressed	Weighted average of percentage of funds that are in the lowest decile of net flows in a given month in a class of funds, i.e., equity, bond and mixed funds.
Family-level variables are weighted averages, where the weights are represented by the share of an individual's funds assets in the total assets of the family.	

## B Additional results

Table 10: Additional Control Variables for estimations in Table 5

<i>Dependent variable: Net flow/TA</i>	High sensitivity		Low sensitivity		Full sample	
Net flows/TA <sub>t-1</sub> ,	0.134*** (0.029)	0.127*** (0.029)	0.119*** (0.041)	0.119*** (0.042)	0.132*** (0.026)	0.128*** (0.027)
PLMT	0.006 (0.014)	0.011 (0.015)	-0.022 (0.024)	-0.020 (0.022)	-0.023 (0.022)	-0.020 (0.020)
Return <sub>t-1</sub>	-0.015 (0.015)	-0.024 (0.045)	0.000 (0.005)	0.001 (0.005)	-0.006 (0.006)	-0.003 (0.007)
Fund age	-0.001 (0.003)	-0.001 (0.003)	-0.009* (0.005)	-0.008 (0.005)	-0.007 (0.006)	-0.007 (0.005)
Nb funds in family	-0.001 (0.001)	-0.000 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)
Log Total Assets <sub>t-1</sub>	-0.051*** (0.007)	-0.048*** (0.007)	-0.033*** (0.008)	-0.031*** (0.008)	-0.045*** (0.005)	-0.043*** (0.005)
Volatility <sub>t-1</sub>	0.030 (0.049)	0.045 (0.048)	-0.013 (0.081)	-0.018 (0.085)	0.022 (0.044)	0.031 (0.045)
Leverage <sub>t-1</sub>	-0.005 (0.009)	-0.007 (0.009)	0.012 (0.009)	0.003 (0.011)	-0.002 (0.008)	-0.007 (0.008)
Investment Grade	-0.031** (0.013)	-0.026 (0.020)	-0.027*** (0.009)	-0.026*** (0.009)	-0.029*** (0.010)	-0.027** (0.012)
Share of Banks&IF <sub>t-1</sub>	0.104*** (0.013)	0.099*** (0.015)	0.045** (0.018)	0.043** (0.017)	0.083*** (0.013)	0.079*** (0.013)
Share of Pension & Insurance <sub>t-1</sub>	0.139*** (0.022)	0.139*** (0.024)	0.015 (0.029)	0.012 (0.028)	0.083*** (0.022)	0.081*** (0.022)
Return <sub>t-1</sub> × March2020		0.015 (0.045)		-0.030 (0.113)		-0.007 (0.008)
Fund age <sub>t-1</sub> × March2020		-0.000 (0.001)		-0.000 (0.002)		-0.000 (0.001)
Nb funds <sub>t-1</sub> × March2020		0.000 (0.000)		-0.000 (0.000)		-0.000 (0.000)
Log TA <sub>t-1</sub> × March2020		-0.016*** (0.003)		-0.017** (0.007)		-0.017*** (0.003)
BHC <sub>t-1</sub> × March2020		-0.008 (0.011)		-0.006 (0.029)		-0.006 (0.013)
Volatility <sub>t-1</sub> × March2020		-0.603*** (0.166)		-0.263 (0.323)		-0.438** (0.188)
Leverage <sub>t-1</sub> × March2020		0.036*** (0.012)		0.034* (0.019)		0.036*** (0.012)
Liquidity/TA <sub>t-1</sub> × March2020		-0.020 (0.048)		0.057 (0.053)		-0.003 (0.034)
Investment grade <sub>t-1</sub> × March2020		-0.009 (0.013)		-0.006 (0.022)		-0.006 (0.014)
Share Banks&IF <sub>t-1</sub> × March2020		0.026** (0.011)		0.008 (0.018)		0.026*** (0.009)
Share of Pension <sub>t-1</sub> × March2020		0.055*** (0.021)		0.048 (0.044)		0.050** (0.024)
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,049	5,049	4,338	4,338	9,387	9,387
R-squared	0.287	0.300	0.210	0.222	0.251	0.263

Table 11: Net flows for Bond and Mixed funds separately

	Bond funds			Mixed funds		
	(1) High sensi- tivity	(2) Low sensi- tivity	(3) Full sample	(4) High sensi- tivity	(5) Low sensi- tivity	(6) Full sample
PLMT $\times$ March 2020	0.074*** (0.027)	-0.033 (0.026)	-0.005 (0.024)	0.068*** (0.018)	-0.005 (0.020)	-0.012 (0.019)
PLMT $\times$ High Sensitivity $\times$ March 2020			0.067** (0.029)			0.078*** (0.029)
High Sensitivity $\times$ March 2020			-0.058** (0.023)			-0.060** (0.026)
PLMT $\times$ High Sensitivity			0.088*** (0.032)			-0.008 (0.015)
PLMT	0.027 (0.032)	-0.079*** (0.016)	-0.067*** (0.009)	-0.003 (0.004)	0.008 (0.014)	0.007 (0.017)
Fund-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Fund-level controls X March 2020	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,856	2,643	5,499	2,347	1,804	4,151
R-squared	0.297	0.217	0.260	0.312	0.240	0.268

The dependent variable is *Net Flow/TA*, defined as the net monthly capital flow into a fund divided by the fund's total net assets in the previous month. PLMT is an indicator variable equal 1 for funds with fees or levies and at least one of the QLMTs (suspensions, gates or redemption in kind) and 0 for funds with neither fees nor levies, but at least one of the QLMTs. March 2020 a dummy variable equal to 1 in March 2020 and zero from January 2018 to February 2020. High Sensitivity is the sample of funds with an above the median sensitivity of flows to performance over the period 2014-2018. Fund-level controls include: the lag of net flows to total assets, lag of return, number of funds in family, lag of ln of assets, lag of volatility of flows, lag of leverage, a dummy for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations. Fund-level controls X March 2020 represents an interaction between the controls and the March 2020 dummy variable. Standard errors clustered at the fund family in parenthesis. \*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

Table 12: Alternative treatment definitions

	High Sensitivity		Low Sensitivity	
	(1)	(2)	(3)	(4)
PLMT2 $\times$ March 2020	0.054** (0.023)		0.016 (0.644)	
PLMT3 $\times$ March 2020		0.060*** (0.004)		-0.006 (0.826)
Observations	3,449	3,895	2,586	2,927
R-squared	0.308	0.323	0.221	0.209
Fund-level controls	Yes	Yes	Yes	Yes
Fund-level controls X March 2020	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes

The dependent variable is Net Flow/TA. PLMT2 is an indicator variable equal 1 if a fund reports fees or levies and *all* QLMTs (suspensions, gates or redemption in kind) and 0 if a fund has access to *all* QLMTs. PLMT3 is an indicator variable equal 1 if a fund reports fees or levies and suspensions and gates and 0 if the fund does not report neither fees nor levies, but reports having access to suspensions and gates. March 2020 a dummy variable equal to 1 in March 2020 and zero from January 2018 to February 2020. High Sensitivity is the sample of funds with an above the median sensitivity of flows to performance over the period 2014-2018. Fund-level controls include the lags of: net flows to total assets, return, number of funds in family, ln of assets, volatility of flows, a dummy for leveraged funds, a dummy for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations. Fund-level controls X March 2020 represents an interaction between the controls and the March 2020 dummy variable. Standard errors clustered at the fund family in parenthesis. \*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

Table 13: Sample of switchers

Dependent variable	High sensitivity			Low sensitivity				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Net flow/TA	Dummy outflows	Outflows/TA	Inflows/TA	Net flow/TA	Dummy outflows	Outflows/TA	Inflows/TA
PLMT Switch $\times$ March 2020	0.105*** (0.039)	-0.219 (0.219)	-0.110** (0.051)	0.005 (0.025)	-0.056 (0.051)	-0.068 (0.310)	0.074 (0.055)	0.024 (0.054)
Net flows/TA <sub><i>t</i>-1</sub>	0.233*** (0.044)	-0.601*** (0.146)			0.121** (0.051)	-0.403** (0.189)		
Outflows/TA <sub><i>t</i>-1</sub>			0.033 (0.055)				-0.033 (0.045)	
Inflows/TA <sub><i>t</i>-1</sub>				0.213*** (0.056)				0.190** (0.082)
Observations	1,270	1,270	1,270	1,270	1,103	1,103	1,103	1,103
R-squared	0.392	0.390	0.269	0.435	0.257	0.428	0.193	0.284
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

PLMT Switch is a sample of funds that introduced levies or fees in December 2019, and have at least one of the QLMT tools available. March 2020 a dummy variable equal to 1 in March 2020 and zero from January 2018 to February 2020. High Sensitivity is the sample of funds with an above the median sensitivity of flows to performance over the period 2014-2018. Fund-level controls include the lags of: net flows to total assets, return, number of funds in family, ln of assets, volatility of flows, a dummy for leveraged funds, a dummy for investment grade funds, the share of assets owned by banks and investment funds, as well as the share owned by pension funds and insurance corporations. Fund-level controls X March 2020 represents an interaction between the controls and the March 2020 dummy variable. Standard errors clustered at the fund family in parenthesis. \*\*\* represents significance at 1% level, \*\* at 5% level and, \* at 10% respectively.

Figure 13: Alternative clustering and sample definitions

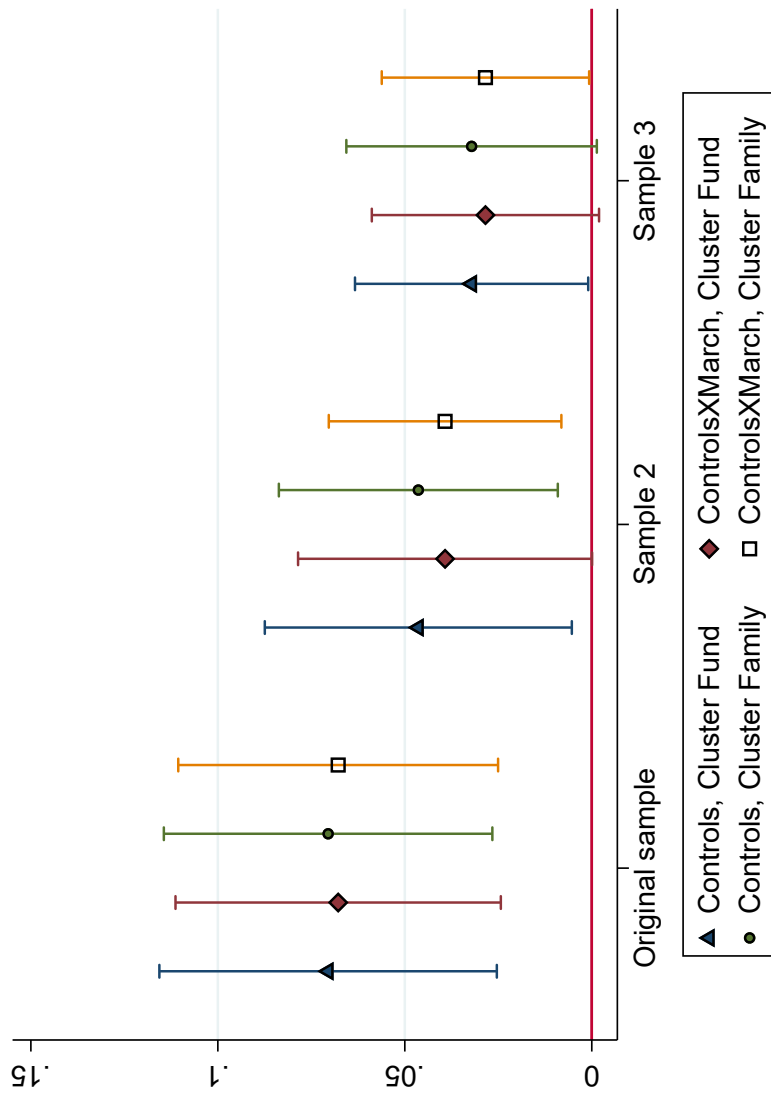


Figure shows the estimates of the coefficient  $\beta_1$  in Eq. (3). The Original sample includes 521 funds, Sample 2 includes 606 funds, while Sample 3, 1,011, respectively. For the Original sample estimates, the first two estimates presented assume clustering at the Fund level, while the last two are robust standard errors. For Samples 2 and 3, the first two estimates presented assume clustering at the Fund level, while the last two at the Fund Family level.

## Imprint and acknowledgements

We would like to thank Vasileios Madouros, Cian Murphy, Andrew Metrick (discussant), Karl Whelan, Nima Fazeli (discussant), Kitty Moloney, Catharine Dwyer, Naoise Metadger, Ashley Nanton, James Leen, Barbara Casu, Ana-Maria Fuertes, Francesc Rodriguez-Tous, participants to the Financial Stability Board conference on “Systemic risks in non-bank financial intermediation (NBF1) and policies to address them”, IFABS 2022 Naples Conference and 1st PSB Workshop on Banks and Financial Markets, as well as seminar participants at Bayes Business School, Smurfit Business School, Bank of England, European Central Bank, Central Bank of Ireland, University College Dublin and Maynooth University for useful comments. Views expressed are those of the authors and do not reflect views of the Central Bank of Ireland or the European Central Bank.

### **Peter Dunne**

Central Bank of Ireland, Dublin, Ireland; email: [peter.dunne@centralbank.ie](mailto:peter.dunne@centralbank.ie).

### **Lorenz Emter**

Central Bank of Ireland, Dublin, Ireland; European Central Bank, Frankfurt am Main, Germany; email: [lorenz.emter@ecb.europa.eu](mailto:lorenz.emter@ecb.europa.eu)

### **Falko Fecht**

Deutsche Bundesbank, Frankfurt am Main, Germany; email: [falko.fecht@bundesbank.de](mailto:falko.fecht@bundesbank.de)

### **Raffaele Giuliana**

Central Bank of Ireland, Dublin, Ireland; European Systemic Risk Board, Frankfurt am Main, Germany; email: [Raffaele.giuliana@ecb.europa.eu](mailto:Raffaele.giuliana@ecb.europa.eu)

### **Oana Peia**

University College Dublin, Dublin, Ireland; email: [oana.peia@ucd.ie](mailto:oana.peia@ucd.ie)

### **© European Systemic Risk Board, 2021**

Postal address	60640 Frankfurt am Main, Germany
Telephone	+49 69 1344 0
Website	<a href="http://www.esrb.europa.eu">www.esrb.europa.eu</a>

All rights reserved. Reproduction for educational and non-commercial purposes is permitted provided that the source is acknowledged.

### **Note:**

**The views expressed in ESRB Working Papers are those of the authors and do not necessarily reflect the official stance of the ESRB, its member institutions, or the institutions to which the authors are affiliated.**

ISSN	2467-0677 (pdf)
ISBN	978-92-9472-327-7 (pdf)
DOI	10.2849/883866 (pdf)
EU catalogue No	DT-AD-23-001-EN-N (pdf)