INTERNATIONAL MONETARY FUND

Derivative Margin Calls: A New Driver of MMF Flows

Maddalena Ghio, Linda Rousova, Dilyara Salakhova, and Germán Villegas-Bauer

WP/23/61

2023
MAR

WORKING PAPER

 WP/23/61

IMF Working Paper
Research Department

Derivative Margin Calls: A New Driver of MMF Flows
Prepared by Maddalena Ghio, Linda Rousova, Dilyara Salakhova, and Germán Villegas-Bauer*

Authorized for distribution by Maria Soledad Martinez Peria
First version: March 2023
Current version: November 2024

ABSTRACT: During the March 2020 market turmoil, euro area money-market funds (MMFs) experienced significant outflows, reaching almost 8% of assets under management. Using highly granular data on derivative contracts and MMFs, we construct a daily fund-level panel spanning from February to April 2020 and unearth a new channel through which shocks from the derivative market propagated to MMFs. This channel are investors' liquidity needs related to derivative margin payments, which have significantly increased in recent years owing to the derivatives reforms enacted after the GFC. Our findings suggest that variation margin payments faced by euro area non-bank financial sectors could have driven almost half of the aggregate outflows from EUR-denominated MMFs domiciled in the euro area.

JEL Classification Numbers:	G13, G15, G23
Keywords:	Liquidity Risk; Money Market Funds; Big Data; Interconnectedness; Non-Bank Financial Intermediaries
Author’s E-Mail Address:	Maddalena.Ghio@gmail.com, Linda.Rousova@ecb.europa.eu, Salakhova.Dilyara@gmail.com, gvillegasbauer@imf.org

* Maddalena Ghio, Dilyara Salakhova, and Germán Villegas Bauer worked on the paper while affiliated with the European Central Bank. We are grateful to Simon Kördel and Sebastiano Michele Zema for their generous help with some of the data used in this paper. We would also like to thank the participants in internal ECB seminars, the 2022 FSB conference entitled “Understanding and addressing systemic risks in non-bank financial intermediation", the EEA-ESEM 2022 conference, the referee and editor of the Working Paper Series of the ECB, and Kelly Eckhold for their insightful comments.

1 Introduction

The complexity of the financial system, reflected in multiple intricate connections among financial institutions, facilitates shock propagation during market turmoils. Each new stress episode usually leads to the detection of new channels of shock transmission. During the Great Financial Crisis (GFC), risk-taking behaviour in money-market funds (MMFs) and high credit risk in opaque derivatives markets amplified the financial stress via runs on MMFs and defaults on derivative contacts (e.g., Kacperczyk and Schnabl, 2010; McDonald and Paulson, 2015). Since then, the regulation on MMFs has introduced restrictions on the type of assets that MMFs are allowed to hold (Szczepanski, 2016), while the OTC derivatives reform imposed stricter collateralisation requirements on derivative trading (ECB, 2016). These and other reforms enacted after the GFC have fundamentally changed the functioning of some parts of the financial system.

The first serious test of the reforms occurred during the Covid19-related market turmoil in March 2020, when investors scrambled for cash, notably during the acute 'dash for cash' phase (FSB, 2020). Despite the reforms, both MMFs and derivatives made news headlines again. In particular, MMFs across the globe experienced significant outflows, which for some exceeded the outflows during the GFC. In the US, publicly-offered institutional prime MMFs recorded outflows of 30% of their assets between March 11 and 24 (PWG, 2020), while euro area MMFs faced outflows of nearly 8% of assets under management within a week from March 13 to 20 (Boucinha et al., 2020).

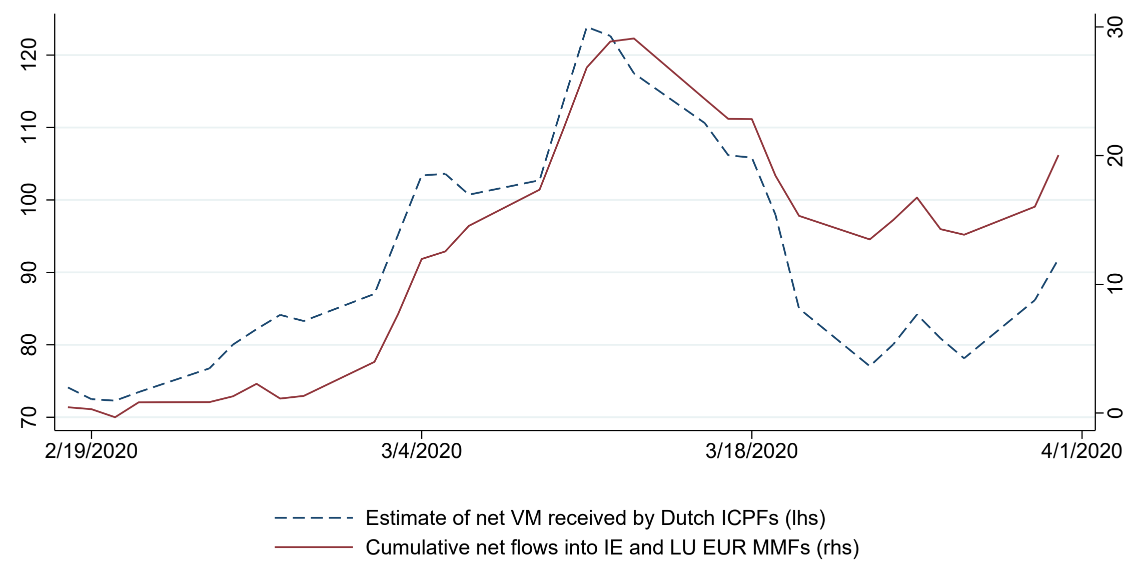
Euro area MMFs – with over EUR 1.5 trillion of assets – are an important source of short-term funding to banks and non-financial firms.[1] However, in March 2020, a number of MMFs had difficulties in raising sufficient cash to meet redemptions, which led them to request banks to buy back their issued commercial paper. As a result, bank access to short-term funding became impaired, with potential negative repercussions for other parts of the financial system and the real economy at a time when liquidity was in high demand (see Aldasoro et al., 2020; Garcia Pascual et al., 2021). Central banks' unprecedented response coupled with other public policy actions helped stabilise the MMF outflows. The stress episode raises questions about the potential drivers and amplifiers of such volatility in MMF flows.

In this paper, we investigate one such potential driver – the liquidity needs faced by MMF investors and particularly those related to the collateralisation of derivative contracts. Since

[1]Euro area MMF assets are based on ECB's Balance Sheet Items statistics for mid-2023.

MMF investors tend to rely on MMFs' cash-like properties and redeem MMF shares to obtain liquidity when needed (FSB, 2021), their liquidity needs might indeed pose significant strains on MMFs. Looking at the March 2020 market turmoil, Figure 1 documents a strikingly strong correlation (over 80%) between variation margin (VM) payments on derivative portfolios of euro area insurance companies and pension funds (ICPFs) and MMF flows held by ICPFs facing these payments (Fache Rousová et al., 2020). Market intelligence also suggests that VM payments did play a role in MMF flow dynamics during the March 2020 market turmoil (BlackRock, 2020; Bank of England, 2020). Our paper is the first – to our knowledge – to investigate this role quantitatively and systematically.

Figure 1
Co-movement of ICPFs' VM payments and flows in EUR-denominated MMFs domiciled in Ireland and Luxembourg.



Notes: Values in EUR bn. "Net VM received" is the difference between the stock variables "VM received" and "VM posted" reported in EMIR. See Section 2 for more details.
Sources: EMIR data, EPFR Global and authors' calculations.

Studying the effects of margin payments on the financial system in general and MMFs in particular is of key importance, particularly in view of the recent regulatory reform which introduced daily exchange of (initial and variation) margin for the vast majority of derivative exposures, thereby profoundly changing the functioning of derivative markets. The new requirements reduce counterparty credit risk, but they also increase liquidity risk as counterparties need to meet margin calls with high-quality collateral at a short notice (typically within one or two days). More specifically, VM is collateral exchanged between the two counterparties to a derivative transaction, which reflects the price movement of such transaction, and during the

March 2020 market turmoil, daily VM calls rose more than fivefold (BCBS, CPMI, IOSCO, 2022; Fache Rousová et al., 2020). By contrast, prior to the GFC, VM payments were infrequent and not subject to regulation (see e.g. McDonald and Paulson, 2015; Paddrik et al., 2020).

To study the relationship between VM payments and MMF flows, we estimate the effects of VM paid and received by the largest holders of EUR-denominated MMFs on flows of these MMFs. We combine three granular data sources: (i) transaction-by-transaction derivatives data collected under the European Market Infrastructure Regulation (EMIR), which can be classified as *big data* (also known as trade repository, or TR, data), (ii) investors' holdings of MMF shares from Securities Holdings Statistics by Sector (SHSS) and (iii) MMF flows data from Refinitiv Lipper. The resulting dataset contains a daily fund-level panel where the dependent variable is daily flows in individual MMFs domiciled in France, Ireland and Luxembourg, and the explanatory variables of interest are VM posted or received by major investor groups (country-sectors) holding the respective MMFs. The panel spans over three months: February, March and April 2020.

Since margin payments in EUR (as opposed to USD or GBP) are the largest in our dataset, we focus on these margin payments and on EUR-denominated MMF flows. Furthermore, we study the effects of VM payments (as opposed to initial margin payments) as VM is typically paid in cash, while inital margin payments can also be met with non-cash collateral (e.g., high-quality government debt). Focusing on VM payments is also in line with the results of the ECB's June 2020 SESFOD survey which indicate that VM payments led to a strained liquidity situation in some insurance companies, hedge funds and investment funds, while initial margin had almost no impact on their liquidity situation (ECB, 2020).

Our results suggest that VM payments experienced by some investors holding MMFs were an important driver of the flows of EUR-denominated MMFs domiciled in the euro area. We estimate that, in aggregate, VM payments faced by euro area non-bank financial sectors were responsible for 30% to 60% of total outflows from the funds in our sample. In line with expectations, the results are typically more pronounced for MMF investors facing large margin payments, notably investment funds and pension funds, than MMF investors facing relatively limited margin payments. Specifically, distinguishing between MMF outflows and inflows and VM posted and received, we show that the need to post margin tends to increase MMF outflows, indicating that some MMF investors quickly redeemed MMF shares to meet the margin payments. By the same token, margin received is found to increase inflows into MMFs.

Overall, the results indicate that some non-bank financial intermediaries such as investment funds and pension funds used MMFs to manage liquidity related to margin calls in the March

2020 market turmoil. The results are robust across all three countries where EUR-denominated MMFs are domiciled (i.e., France, Ireland and Luxembourg) and various model specifications. Moreover, we find these results despite the lack of sufficient data granularity, having to conduct the analysis at the less accurate country-sector-to-MMF level and not the firm-to-MMF level.

Our paper contributes to two strands of literature. First, it expands the literature on MMF runs by unearthing a new driver of MMF outflows in stress periods. Second, it contributes to the emerging studies on liquidity risk stemming from margin and collateral calls by showing how such risk can materialise and spillover to the wider financial system.

Regarding the first strand of literature, we highlight the importance of investors' liquidity needs in driving MMFs flows by documenting and quantifying a new channel of shock propagation, where a shock to the derivative market is transmitted to MMFs through investors facing derivative margin calls. Unearthing this channel is novel in the literature, which so far focused on drivers of MMF flows related to MMF characteristics such as their riskiness and threshold effects (Bouveret et al., 2022).

In particular, several studies show that MMF investor redemptions were concentrated among risky funds during the 2007-2009 financial crisis (Strahan and Tanyeri, 2015; McCabe, 2010) and during the Eurozone banking crisis in mid-2011 (Chernenko and Sunderam, 2014). Existing studies on MMF outflows during the March 2020 market turmoil suggest that the outflows from USD-denominated MMFs domiciled in the euro area were driven by flight-to-safety reasons as investors withdrew particularly from riskier low-volatility net asset value (LVNAV) funds and moved investments into safer USD-denominated constant net asset value (CNAV) funds (de Guindos and Schnabel, 2020; Boucinha et al., 2020). Similarly, Capotă et al. (2022) underlines the role of a number of weaknesses in the European MMF regulatory framework, including the LVNAV structure, while Li et al. (2021) provides evidence that liquidity restrictions on investors introduced in the 2016 US MMF reform, such as redemption gates and liquidity fees, exacerbated the run on US prime MMFs. Only a few recent studies point at the role that MMF investors or their characteristics can play in explaining MMF flows (Avalos and Xia, 2021; Cipriani and La Spada, 2021; Darpeix, 2021; Epstein and Li, 2022) but none of them uncovers the link between MMFs and derivative markets as our paper does.

Turning to the second strand of literature, our paper contributes to the emerging studies on liquidity risk stemming from derivative exposures, which might spillover to the wider financial system or even the real economy. In this respect, our paper is the closest to Czech et al. (2021), which shows that UK-based ICPFs heavily sold gilts to meet VM calls on their FX hedges in the March 2020 market turmoil. A similar fire-selling spiral emerged in the UK gilt market in September 2022, when Liability-Driven Investment (LDI) funds faced margin calls on their interest rate hedges and collateral calls on secured borrowing (Bank of England, 2022; Chen and Kemp, 2023). Furthermore, Biais et al. (2020) provides a theoretical framework, which links VM payments to asset sales and depression of asset prices. We contribute to this literature by establishing a link between VM and MMFs flows.

A number of other papers (Bardoscia et al., 2021; Paddrik et al., 2020; Bardoscia et al., 2019; Glasserman and Wu, 2018; de Jong et al., 2019; Jensen and Achord, 2019; Fache Rousová et al., 2020; Jukonis et al., 2022) also investigate the risks stemming from derivative margin payments, but they typically rely on margin simulations rather than actual data or consider a limited number of derivative contract types and/or simplistic market shocks. They also tend to compare the simulated margin demands to static (e.g., pre-crisis) liquidity buffers and thus do not capture the evolving market dynamics and the actual impact on the wider financial system such as our paper does.

The rest of the paper is structured as follows. Section 2 describes the data and provides some key descriptive statistics with focus on the March 2020 market turmoil. Section 3 presents the empirical model. Section 4 discusses the results. Section 5 concludes.

2 Data

In this paper, we combine three highly granular, voluminous and unique data sets. First, we use transaction-by-transaction EMIR data on derivatives to compute VM payments of investors. We further enrich these data using sector classification developed by Lenoci and Letizia (2021). Second, we use Refinitiv Lipper data to obtain daily MMF flows at the fund level. We then link the VM payments and MMF flows data using Securities Holdings Statistics by Sector (SHSS) data, which provide information on sectors that hold individual MMFs. Since SHSS data include investor information only at country-sector level (e.g., holding of funds A, B and C by the whole German investment fund sector), we aggregate VM at country-sector level.

2.1 VM payments from EMIR data

EMIR data are transaction-by-transaction data on derivatives collected through trade repositories. They have been reported by entities resident in the EU since February 2014 and include the details of each individual derivative transaction conducted by these counterparties. For each derivative transaction more than 120 data fields are available. The collected information includes the type of derivative, the underlying security, the price, the amount outstanding, the execution and clearing venues of the contract, the valuation, the collateral (margin) and life-cycle events. Owing to their volume, high frequency and variety, the EMIR data can be classified as *big data*.

In this paper, we work with EMIR data that are accessible to the ECB, focusing on a sub-sample that is restricted to the trades reported by counterparties located in the euro area. We enrich the reported data with the sector of the reporting entity applying the classification algorithm of Lenoci and Letizia (2021), which combines information from four official lists (ECB's lists of monetary financial institutions and investment funds, EIOPA's list of insurance undertakings and ESMA's list of CCPs) and four other data sources (ECB's RIAD, Orbis, Refinitiv Lipper and Bank Focus). Since EMIR data are highly granular and complex, we also extensively manipulate and clean them. In particular, the data are initially reported by both counterparties to a trade and, therefore, we pair the two legs of the trade (where possible and applicable). Furthermore, we run various quality checks and remove outliers.[2]

While EMIR data are reported at transaction level, VM is reported at portfolio level. This implies that for all trades belonging to the same collateral portfolio, the reporting counterparty is required to provide one value for VM *received* and one value for VM *posted* (i.e., one value for each of the two VM variables, where one of these typically equals 0). These two variables are required to be reported in *stocks*, reflecting the cumulative margin payments since the starting date of the contract. For paired trades, when one counterparty receives (posts) VM, the other counterparty sharing the same portfolio will post (receive) the same amount (see an illustrative example in Table 1).

Table 1
Illustrative example of VM stock reporting in EMIR data after pairing of the two legs of a trade for a given portfolio.

LEI 1	LEI 2	Trade ID	Portfolio code	Notional value	VM stock received 1	VM stock posted 1	VM stock received 2	VM stock posted 2
ABC	DEF	111	ABCDEF00	100	200	0	0	200
ABC	DEF	222	ABCDEF00	500	200	0	0	200

Notes: The representative portfolio (identified by the collateral portfolio code ABCDEF000) consists of two contracts (identified by trade IDs 111 and 222 with notional values of 100 and 500 respectively) between two counterparties (identified by their LEIs ABC and DEF respectively). While the two contracts have different trade IDs and notional values, they belong to the same collateral portfolio and thus share the same values for VM *stock received* by ABC from DEF and VM *stock posted* by DEF to ABC (200). By the same token, VM *stock posted* by ABC to DEF has the same value as VM *stock received* by DEF from ABC (0). The total notional value of this portfolio equals 600.

[2]Despite this processing, the final data are still subject to some data quality limitations such as missing values, residual unpaired transactions or possible under-reporting.

To compute margin from transaction-level data, we first define a reliable and unique collateral portfolio code for each pair of counterparties sharing a portfolio of derivatives by concatenating the legal entity identifiers (LEIs) of the two counterparties with the reported collateral portfolio codes. If one of the latter does not exist, then it is replaced by the reported VM value. To filter out potential outliers with suspiciously high VM values, we drop portfolios for which the value of either VM *stock posted* or VM *stock received* exceeds 80% of the total notional value of the portfolio (computed as the sum of the notional values of all contracts in the portfolio). We make two considerations for the choice of this threshold. First, since the stock of VM reflects the market value of a portfolio, it should not exceed the total notional value of all contracts in a portfolio. Second, as VM is set to 0 at the beginning of the contract and it is rather unlikely that it approaches 100% of the total notional value, we opt in our cleaning procedure for a more conservative threshold than 100% and choose a threshold of 80%. The difference between the use of the two thresholds is rather minor: the choice of the 80% threshold drops less than 0.1% of notional value as compared to the use of the 100% threshold.

Having cleaned the reported VM data, we compute *net* VM *stock posted* (V_t) as the difference between the reported VM *stock posted* (V_t^P) and VM *stock received* (V_t^R) on each day and for each collateral portfolio ($V_t = V_t^P - V_t^R$). The value of the $flow$ of margin payments exchanged on a given day t, call it $flow_t$, can then be derived by taking the difference between the value of *net* VM *stock posted* on day t and on day $t-1$, i.e. $flow_t = V_t - V_{t-1}$. $flow_t$ can take both positive and negative values, indicating respectively a liquidity outflow (margin call) or liquidity inflow. We isolate the positive part, signalling a net outflow of cash, by defining it as the value of $flow_t$ if it is positive and zero otherwise, and denote it as VM *flow posted*. Similarly, we define the negative part, signalling a net inflow of cash, as the absolute value of $flow_t$ if $flow_t$ is negative and zero otherwise, and denote it as VM *flow received*. As a result, the positive and negative parts are always non-negative (see Table 2).

Having isolated the positive and negative parts of $flow_t$, we aggregate each of them (separately) from individual counterparty to country-sector level. Such aggregation leads to a significant information loss but it is the only feasible way for us to build our panel data as SHSS data are only available at sector level (see Section 2.3). At the same time, the separation of positive and negative values of VM flows mitigates this information loss somewhat. If the aggregation to country-sector level were done before the separation, the positive and negative values of margin flows by different entities within a sector would often offset each other, so that more variability in the data would be lost.

Table 2
Definition of *net VM flow posted* and the separation of its positive and negative parts using two types of portfolios: with an increasing and decreasing *net VM stock posted* (Case 1 and 2 respectively).

Time	Net VM stock posted	Portfolio	Flow	Sign	VM flow posted Value	VM flow posted Sign	VM flow received Value	VM flow received Sign
$t-1$	$V_{t-1} = V_{t-1}^P - V_{t-1}^R$	Case 1:						
t	$V_t = V_t^P - V_t^R$	$V_t > V_{t-1}$	$flow_t = V_t - V_{t-1}$	+	$flow_t$	+	0	None
$t-1$	$V_{t-1} = V_{t-1}^P - V_{t-1}^R$	Case 2:						
t	$V_t = V_t^P - V_t^R$	$V_t < V_{t-1}$	$flow_t = V_t - V_{t-1}$	-	0	None	$-flow_t$	+

Notes: V_t^P and V_t^R stand respectively for *VM stock posted* and *VM stock received* at time t. The *net VM stock posted* at time t, denoted as V_t, is computed as the difference between V_t^P and V_t^R. The margin flow at time t, denoted as $flow_t$, is the difference between V_t and V_{t-1}.

To each portfolio, we also assign a currency for the VM posted/received to filter out only portfolios where margins are posted/received in EUR. Since, in principle, it is possible to receive or post margins in multiple currencies for contracts belonging to the same portfolio, we use values converted to EUR and define that a portfolio receives (posts) margin in a given currency if the outstanding notional of the contracts receiving (posting) margin in that currency exceeds an 80% threshold of the total outstanding notional of the portfolio. Overall, around 60% of the VM flows over the three-months period is in EUR.

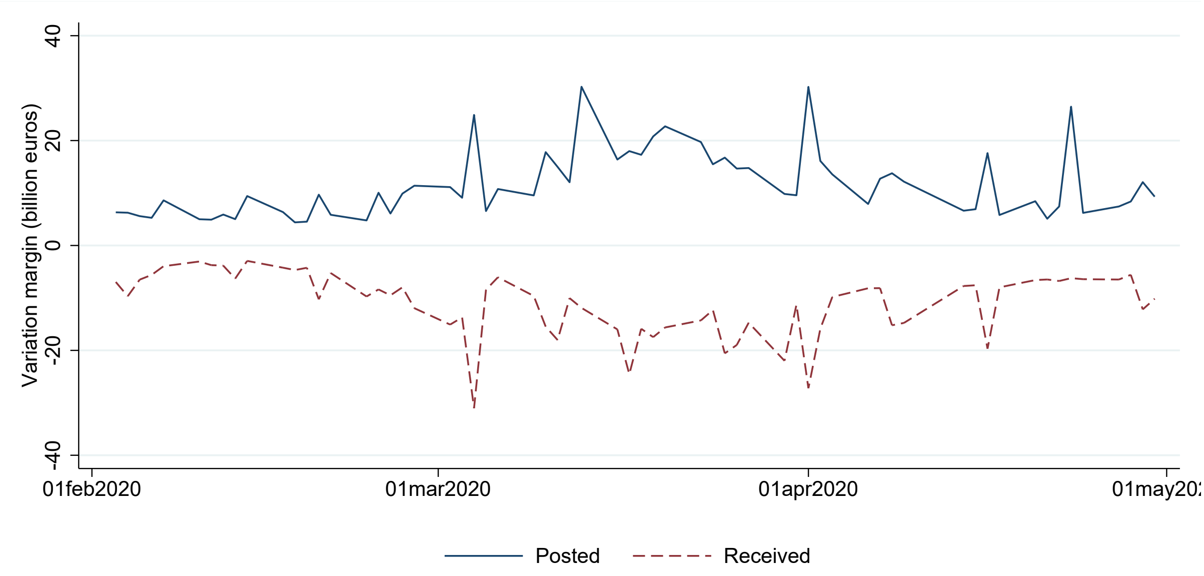
Figure 2 shows that during the March 2020 market turmoil, the daily VM payment flows of euro area non-bank entities increased more than fivefold, from around €5 bn in the first half of February 2020 to more than €20 bn in March 2020, with peaks of over €30 bn.[3] We exclude from the chart VM of CCPs and banks, since CCPs positions are fully balanced (VM received equals VM paid) and banks/large dealers usually pay VM not only for their own trading purposes but also on behalf of their clients, which complicates the analysis. Banks are also not large holders of MMFs (see Section 2.3).

2.2 MMF flows from Refinitiv Lipper data

According to Lipper data from Refinitiv, the euro area MMF sector holds assets with a total value of around €1.2 trillion in early 2020. MMFs domiciled in Ireland, Luxembourg and France represent the lion's share of the sector in the euro area. The sector is highly diverse. Funds are available in different currencies (EUR, GBP or USD) and are of three types: public debt CNAV, LVNAV and short-term variable net asset value (VNAV). Each category has different regulatory requirements in terms of pricing, shares of public debt and shares of weekly liquid assets, among others.[4]

[3]See also Fache Rousová et al. (2020) for similar evidence on VM faced by investment funds.
[4]For more information on the requirements, see Capotă et al. (2022).

Figure 2
VM flows of euro area non-bank entities.



Notes: The figures are obtained by aggregating VM flows posted and received where the flows are derived from the reported VM stocks (see also Table 2).
Sources: EMIR data and authors' calculations.

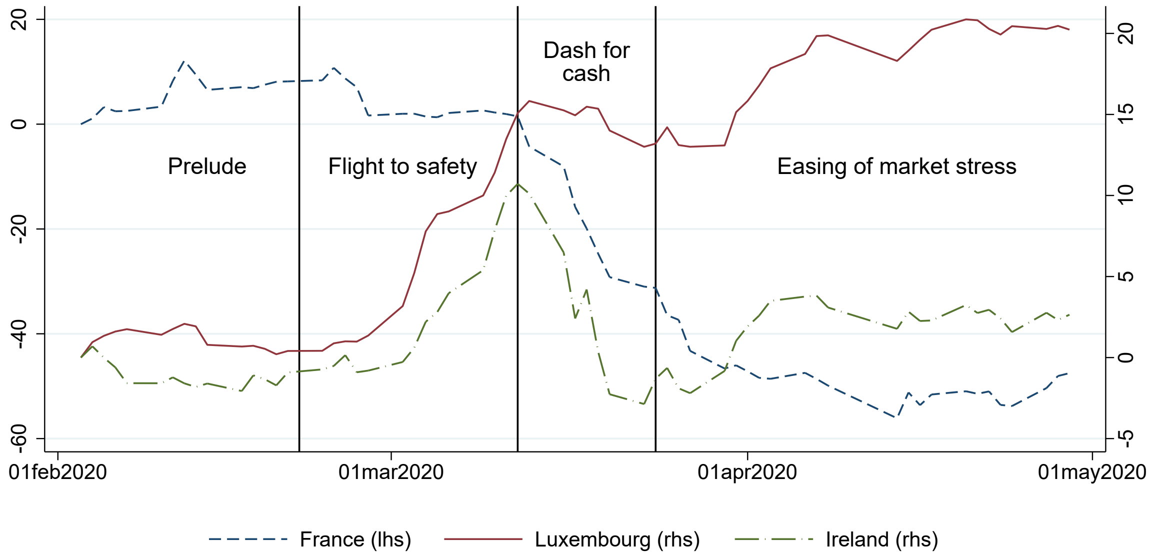
Since the majority of VM payments by euro area investors are done in EUR, we focus on MMFs denominated in EUR. These represent around 46% of the euro area MMF total net assets (TNAs) with respective TNAs of MMFs in France, Luxembourg and Ireland being equal to €335 bn, €99 bn and €118 bn respectively. Overall, French MMFs thus make up almost two thirds of the EUR-denominated MMF assets.

We use Refinitiv Lipper daily data on MMFs' TNAs to compute daily flows at fund level by taking the difference between the TNAs on two consecutive days. We do not take into account funds' performance as MMFs are supposed to have a very stable net asset value. For instance, according to Capotă et al. (2022), for the majority of the USD-denominated LVNAV funds, the deviation in net asset value was typically less than 10 basis points (i.e. less than 0.1%) during the February-April 2020 market turmoil. As for the EUR-denominated LVNAVs that constitute the majority of MMFs in Ireland and Luxembourg, "no LVNAV breached the 20 bps collar in March, a few funds were close to the threshold, with one fund having an 18 bps deviation" (ESMA, 2021). We consider these valuation effects to be small in comparison with the effect from flows on TNAs (almost 8% outflows for euro area MMFs).

Figure 3 shows cumulative flows into EUR-denominated MMFs domiciled in France, Ireland and Luxembourg over our period of interest, i.e. from February to April 2020. Despite some differences, the flows across the three types of MMFs, particularly across Irish and Luxembourgish

MMFs, reflect the four different stages of market developments over February to April 2020 as classified by FSB (2020).

Figure 3
Cumulative flows into EUR-denominated MMFs



Notes: Values in EUR bn. To derive cumulative flows, we compute daily changes in TNAs (daily flows) for each fund and accumulate them over time starting from 1 February 2022. The cumulative flows are aggregated across all funds in a given domicile. Value at each specific date shows how much flows entered/left funds domiciled in a country since 1 February 2022. The vertical lines are drawn on 22 February, 12 March and 24 March 2020 and refer to the ends/beginnings of the four distinct periods (prelude, flight to safety, dash for cash and easing of market stress) defined in FSB (2020).
Sources: Refinitiv Lipper and authors' calculations.

First, during the 'prelude', markets were relatively calm, which was reflected by fairly flat MMF flows. After the first lockdowns in Italy on 21 February 2020, markets reacted by 'flying to safety', with Irish and Luxembourgish MMFs experiencing strong inflows. On 11 March, World Health Organization declared Covid-19 a pandemic, which triggered the highly-volatile 'dash for cash' period, during which investors scrambled for cash and redeemed shares from all three types of MMFs. After significant interventions by central banks around the globe, the market stress eased towards the end of March and during April. In line with these overall market developments, inflows in Irish and Luxembourgish MMFs resumed, while the outflows from French MMFs decreased and came to halt around mid-April 2020. The dynamics for French MMF towards the end of March 2020 differs somewhat from that of Irish and Luxembourgish MMFs as it reflects not only the pandemic-related market dynamics but also significant redemption flows at the end of each quarter. This is because (French non-financial) companies regularly withdraw cash from French MMFs at the end of each quarter to settle expenses and structure their balance sheets (AMF, 2020, Figure 80).

2.3 Investors' holdings of MMF shares from SHSS

To link the VM data to the MMF data, we use information on euro area sector holdings of MMFs from the Securities Holdings Statistics by Sector (SHSS). SHSS data provide quarterly information on investor holdings of individual funds, where investors are aggregated at country-sector level. Since there are 19 euro area countries and 10 sectors, the sector-country combinations provide us with 190 different investor groups.[5]

Since not all MMFs are held by euro area investors, merging MMF flows data with SHSS data somewhat reduces our sample of EUR-denominated MMF funds. The final sample of MMFs still remains representative for Luxembourg and France, where it represents more than 90% of TNAs of all EUR-denominated MMFs domiciled in these countries, €327 bn and €89 bn respectively. Irish funds in our final sample make up around 30% (€35 bn) of TNAs of all EUR-denominated MMFs domiciled in Ireland. The share of non-euro area investors investing in Irish MMFs is particularly high as there is a strong link between Irish MMFs and British financial institutions.[6]

3 Empirical model

Compiling all the data together, we obtain a daily fund-level panel over the three months period from February to April 2020. In our model, the dependent variable is the daily flows in individual MMFs and the explanatory variables of interest are VM flows of sectors in different euro area countries, which hold the individual MMFs. Since we expect that VM flows posted (received) drive MMF outflows (inflows), we run separate regressions for MMF outflows and inflows.

Specifically, we estimate the following empirical specifications:

$$Outflows_{i,t} = \sum_g \beta_g * VM\ flows\ posted_{g,t} * MMF\ held_{g,i,q(t)-1} + I_i + T_t + \epsilon_{i,t} \quad (1)$$

$$Inflows_{i,t} = \sum_g \beta_g * VM\ flows\ received_{g,t} * MMF\ held_{g,i,q(t)-1} + I_i + T_t + \epsilon_{i,t} \quad (2)$$

where i denotes the MMF, g the investor group at sector-country level, t the date and $q(t)$ the corresponding quarter of date t. $VM\ flows\ posted_{g,t}$ refers to VM flows posted by investor

[5] The countries include Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovenia, Slovakia and Spain. The sectors are banks, national central banks (NCBs), central clearing houses (CCPs), non-financial corporations (NFCs), government, insurance corporations (ICs), pension funds (PFs), investment funds (IFs), other financial institutions (OFIs) and others.

[6] For statistics on holdings of MMFs by the largest investor sectors (investor groups), see Section 3.1. In that section, we also provide information on VM flows experienced by these largest MMF investor groups.

group g at date t belonging to quarter q, while $VM\ flows\ received_{g,t}$ is VM flows received.[7] $MMF\ held_{g,i,q(t)-1}$ is a dummy equal to one if the investor group g holds MMF i at the end of the previous quarter $q-1$ (i.e., for dates in February and March 2020, the end of the previous quarter is the end of December 2019, while for dates in April 2020, it is the end of March 2020).[8] To control for any MMF-specific characteristics such as fund age and type, we also include fund fixed effects (FEs), denoted as I_i. Similarly, to control for market volatility over time, we include daily time fixed effects and denote them as T_t. The variable $Outflows_{i,t}$ equals to MMF outflows when they are positive and to zero when they are negative (that is, when there are inflows). The same applies to the variable $Inflows_{i,t}$. β_g are the coefficients of interest that capture the effect of VM flows on MMF in-/outflows, while $\epsilon_{i,t}$ is the error term.

Since it could be plausible to assume that the individual fund effects and VM payments faced by investors into these MMFs are uncorrelated, we don't estimate only FE models but run also random effect (RE) models. We report the results of the Hausman tests, which indicate the more preferable model specification (i.e., RE or FE model). To further check the robustness of the results, we also estimate a model in which we include the lagged dependent variable (i.e., lagged MMF in-/outflows) as an explanatory variable to control for potential autocorrelation in MMF flows. In this specification, we however exclude fund FEs to avoid biased estimates (Wooldridge, 2010).

In addition to the simultaneous effects of VM payments on MMF flows, we also run regressions with lead (forward) and lagged values of VM flows to capture the potential dynamics over time. If margin is called today, it is to be posted today, tomorrow or the day after tomorrow, so we expect margin posted today or in the next few days to have an impact on MMF outflows today.[9] Therefore, we add two leads (forwards) of VM flows posted to regression 1. For margin received, we expect a different timing: investors receiving margins may deposit the funds to MMFs not only on the same day but also later on, so we add one and two lags of VM flows received to regression 2.

Positive and significant coefficients for contemporaneous/lead margin flows posted and contemporaneous/lagged margin flows received would confirm our hypothesis that investors use

[7] More specifically, $VM\ flows\ posted_{g,t}$ is the positive part of the net margin flows posted and $VM\ flows\ received_{g,t}$ is the negative part, as described in Section 2.1.

[8] Put differently, we filter the explanatory variables to include only those investor groups, which held MMF i at the end of the previous quarter.

[9] The exact timing when margin is to be posted depends on whether the portfolio is cleared or uncleared by a CCP. Furthermore, the EMIR reporting may also not allow for the exact identification of the date when margin are posted/received.

MMFs for liquidity purposes to pay margin calls. When investors receive margins, they would buy MMF shares, while when they have to pay margins, they would redeem MMF shares.

We run all the regressions separately for each MMF domicile. We have two reasons for that. First, it helps us further control for the potential differences in the type of MMFs including the underlying regulatory framework. In particular, most EUR-denominated MMFs domiciled in Ireland and Luxembourg are LVNAV funds, while French MMFs are typically VNAV funds (ESMA, 2021). Second and more importantly, the largest investor groups for each domicile are different.

3.1 Reducing the high data dimension in the model

As mentioned in Section 2.3, we classify investors into groups that reflect all possible combinations of 10 sectors in 19 countries, i.e., 190 investor groups. But to reduce the high dimension of the data, in the regressions we focus on the investor groups with the largest holdings of MMFs in each domicile and among them on those that are subject to large VM payments.[10] We consider the combination of these two aspects (i.e., investment into a MMF and the size of VM payments) in selecting the sectors because the two aspects are not necessarily related to each other. In particular, the size of VM payments does not depend only on the size of the sector but also on the extent the sector uses derivatives and the volatility in the market value of these derivatives.

Specifically, for each MMF domicile, we rank investor groups according to the share of MMFs' TNAs that they hold and restrict them to the top ten investor groups (Table 3). Given that we are interested in the effect of VM flows on MMFs' flows, we then select the five sectors with the largest VM flows among the top ten investor groups for each domicile. Since some sectors with large VM payments belong to the top ten investor groups for more than one domicile, we end up with nine investor sectors of interest. These nine investor groups are listed in Table 4, which provides statistics on daily VM flows faced by them.

Looking across domiciles, three investor groups stand out as potential candidates for being particularly strong drivers of MMF flows: Luxembourgish IFs, Dutch PFs and German IFs. This is because they are among the largest holders of MMFs in at least two domiciles and also

[10]We have also considered the opposite approach, in which we first select the sectors with the largest VM payments and among them those with large investment into MMFs. This alternative approach, however, results in the selection of several banking sectors whose holdings of MMFs are almost negligible. Moreover, banks tend to have many more options to obtain liquidity than non-banks and, therefore, we do not expect them to rely on MMFs for their own liquidity management. In particular, in the March 2020 market turmoil, banks often sourced liquidity from central banks, which introduced various measures to provide banks with immediate liquidity support. See Daskalova and Weißler (2020) for more information on the ECB's liquidity support to euro area banks.

Table 3
Top ten holders of EUR-denominated MMFs

Luxembourgish MMFs Asset-shares: 270, TNA: EUR 89 bn	**French MMFs** Asset-shares: 265, TNA: EUR 327 bn	**Irish MMFs** Asset-shares: 56, TNA: EUR 35 bn
1. IT IC	1. FR IC	**1. LU IF**
2. LU IF	**2. FR IF**	**2. IE IF**
3. IE IC	3. FR NFC	3. IE IC
4. NL IF	**4. LU IF**	**4. NL PF**
5. DE IF	**5. DE IF**	5. IT IC
6. NL PF	6. IT IC	**6. IT IF**
7. DE IC	7. LU IC	7. NL IF
8. FR IC	**8. FR Bank**	**8. DE IF**
9. LU IC	9. NL NFC	9. ES NFC
10. ES IF	10. **ES IF**	10. IE PF

Notes: The ranking is based on investor groups' holdings of MMFs as of end of December 2019. TNA (total net assets) are computed as an average of daily values over February 2020. Number of asset-shares is computed over the period February-April 2020. Data is for the sample of MMFs, for which holdings data from SHSS are available. The top five groups in terms of the largest VM payments among the top ten largest investor groups are in bold.
Sources: SHSS, Refinitiv Lipper and authors' calculations.

have large VM flows (Table 4). More specifically, Luxembourgish IFs are among the top five investors into MMFs in all three domiciles, while they also experienced large VM flows with both mean and median exceeding €1 bn. VM flows faced by Dutch PFs were even greater (with mean and median over €1.5 bn) and Dutch PFs also belong to the top ten investor groups into both Luxembourgish and Irish MMFs. German IFs belong to the top ten investors into MMFs in all three domiciles, while they also experienced substantial VM flows with mean over €800 mn. Other sectors seem less suitable candidates. For instance, French banks experienced exceptionally large VM flows but their holding of MMFs are very limited. On the other hand, French insurers represent by far the top holder sector of French MMFs but their VM flows are fairly small.

Most MMFs in our sample (262, and 270 asset-shares) are domiciled in Luxembourg, representing €89 bn in total net assets. While the number of French MMFs in our sample (250 funds, and 265 asset-shares) is slightly lower than that of Luxembourgish MMFs, French MMFs stand out for their large TNAs (almost €327 bn). Finally, Irish MMFs in our sample are small in terms of both the number of funds (50, and 56 asset-shares) and their TNA (€35 bn).

Table 4
Variation margin flow statistics by selected investor group

Daily VM flow posted (EUR mn)					
	5th percentile	Median	95th percentile	Mean	Std. dev.
1. FR Bank	5,170	10,712	27,361	13,351	7,189
2. NL PF	424	1,626	4,134	1,852	1,206
3. LU IF	491	1,073	2,337	1,175	582
4. DE IF	206	722	2,636	900	729
5. FR IF	198	366	1,350	468	328
6. IE IF	84	241	708	310	224
7. ES IF	20	123	742	222	342
8. IT IF	43	97	497	151	146
9. FR IC	26	70	300	118	93
Daily VM flow received (EUR mn)					
	5th percentile	Median	95th percentile	Mean	Std. dev.
1. FR Bank	3,862	10,099	29,125	13,376	8,611
2. NL PF	366	1,783	3,831	1,862	1,171
3. LU IF	427	1,150	1,928	1,140	485
4. DE IF	122	621	1,957	805	688
5. FR IF	156	364	1,017	446	305
6. IE IF	100	219	751	310	201
7. ES IF	16	97	1,119	215	396
8. IT IF	28	98	461	145	139
9. FR IC	12	114	321	137	108

Notes: Based on VM flows from the beginning of February to the end of April 2020. Sorted by mean of VM flow posted and received.
Sources: EMIR data and authors' calculations.

4 Empirical results

We estimate equations 1 and 2 using panel regressions with standard errors clustered at the fund level. We start with estimating the contemporary effects of VM flows on MMF flows over February to April 2020 and report the results in Tables 5 and 6, respectively. Across all three model specifications (i.e., FE, RE and lagged dependent variable models) and the three MMF domiciles as well as for both MMF outflows and inflows, we estimate positive and significant effects of VM payments faced by some sectors on MMF flows. The signs of the coefficients are as expected: we estimate that investors withdraw funds from MMFs to post VMs (see Table 5), while VM flows received increase MMF inflows (see Table 6).

Table 5
Regression results for MMF outflows and VM flows posted

Dependent variable: MMF outflows											
Luxembourgish MMFs				French MMFs				Irish MMFs			
*Independent variables: VM flows posted * MMF held*											
	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)
LU IF	**0.002***	**0.002***	0.001	FR IF	-0.004	-0.003	-0.005	LU IF	0.000	0.001	-0.000
	[0.054]	[0.066]	[0.163]		[0.513]	[0.593]	[0.307]		[0.900]	[0.843]	[0.950]
DE IF	0.002	0.002	**0.003***	LU IF	**0.011*****	**0.011*****	**0.007*****	IE IF	-0.003	-0.003	-0.007
	[0.303]	[0.423]	[0.082]		[0.000]	[0.000]	[0.000]		[0.620]	[0.704]	[0.129]
NL PF	**0.009****	**0.008****	**0.011****	DE IF	**0.024****	**0.020****	**0.037*****	NL PF	**0.011*****	**0.011*****	**0.010*****
	[0.023]	[0.030]	[0.010]		[0.011]	[0.026]	[0.003]		[0.004]	[0.009]	[0.001]
FR IC	0.002	0.001	0.003	FR Bank	0.000	0.000	0.000	IT IF	-0.013	-0.012	-0.004
	[0.809]	[0.905]	[0.694]		[0.143]	[0.117]	[0.638]		[0.210]	[0.227]	[0.674]
ES IF	0.005	0.005	0.005	ES IF	-0.010	-0.009	-0.011	DE IF	-0.001	-0.002	0.001
	[0.332]	[0.332]	[0.314]		[0.217]	[0.233]	[0.279]		[0.729]	[0.724]	[0.819]
Fund effects	RE	FE	No	Fund effects	RE	FE	No	Fund effects	RE	FE	No
Lagged dep.	No	No	Yes	Lagged dep.	No	No	Yes	Lagged dep.	No	No	Yes
Date FE	Yes	Yes	Yes	Date FE	Yes	Yes	Yes	Date FE	Yes	Yes	Yes
Observations	15,803	15,803	15,535	Observations	15,218	15,218	14,953	Observations	3,055	3,055	2,986
R-squared	0.069	0.221	0.129	R-squared	0.079	0.301	0.162	R-squared	0.065	0.263	0.153
Hausman test	p-value: 0.08			Hausman test	p-value: 0.00			Hausman test	p-value: 0.67		

Notes: The table shows regression results of MMFs' outflows against the interaction between VM flows posted by investor groups and a dummy equal to one when the investor groups hold the MMF. Investor groups included in the regressions are the five groups with the largest VMs among the top ten largest investor groups. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6

Regression results for MMF inflows and VM flows received

Dependent variable: MMF inflows											
Luxembourgish MMFs				French MMFs				Irish MMFs			
*Independent variables: VM flows received * MMF held*											
	(1)	(2)	(3)		(4)	(5)	(6)		(7)	(8)	(9)
LU IF	**0.002***	**0.002***	0.001	FR IF	0.002	0.002	0.001	LU IF	0.002	0.003	-0.001
	[0.003]	[0.004]	[0.272]		[0.336]	[0.456]	[0.811]		[0.492]	[0.398]	[0.768]
DE IF	0.002	0.001	**0.004***	LU IF	**0.004*****	0.000	**0.006*****	IE IF	-0.002	-0.001	-0.009
	[0.179]	[0.463]	[0.024]		[0.006]	[0.968]	[0.002]		[0.770]	[0.901]	[0.153]
NL PF	**0.013***	0.011	**0.14***	DE IF	0.002	-0.007	**0.025*****	NL PF	0.005	0.005	**0.010*****
	[0.091]	[0.136]	[0.025]		[0.725]	[0.412]	[0.000]		[0.117]	[0.193]	[0.000]
FR IC	0.012	0.011	0.016	FR Bank	0.000	0.000	-0.000	IT IF	0.002	0.003	-0.002
	[0.229]	[0.248]	[0.240]		[0.627]	[0.608]	[0.696]		[0.678]	[0.480]	[0.839]
ES IF	0.001	0.001	0.004	ES IF	**0.009***	**0.010***	0.005	DE IF	0.003	0.003	0.003
	[0.753]	[0.848]	[0.171]		[0.069]	[0.058]	[0.371]		[0.524]	[0.522]	[0.531]
Fund effects	RE	FE	No	Fund effects	RE	FE	No	Fund effects	RE	FE	No
Lagged dep.	No	No	Yes	Lagged dep.	No	No	Yes	Lagged dep.	No	No	Yes
Date FE	Yes	Yes	Yes	Date FE	Yes	Yes	Yes	Date FE	Yes	Yes	Yes
Observations	15,803	15,803	15,535	Observations	15,218	15,218	14,953	Observations	3,055	3,055	2,986
R-squared	0.085	0.293	0.221	R-squared	0.015	0.162	0.043	R-squared	0.036	0.241	0.080
Hausman test	p-value: 0.00			Hausman test	p-value: 0.00			Hausman test	p-value: 0.81		

Notes: The table shows regression results of MMFs' inflows against the interaction between VM flows received by investor groups and a dummy equal to one when the investor groups hold the MMF. Investor groups included in the regressions are the five groups with the largest VM flows among the top ten largest investor groups. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Overall, the estimated coefficients are found to be fairly stable across the three model specifications both in terms of size and significance, suggesting that our results are by and large robust to the choice of the model.[11] The results of the Hausman test differ by domicile: they indicate that Irish MMF flows can be estimated using the RE model, while the FE model is preferable for modelling Luxembourgish and French MMF flows.

As expected, investors with larger holdings of MMFs and larger exposures to derivatives (as measured by VM flows) tend to have a significant effect on MMF outflows. In particular, the regressions confirm that an important role for MMF outflows is played by the top three non-bank sectors in terms of the largest derivative exposures, i.e., by Dutch PFs, Luxembourgish IFs and German IFs (see also the ranking in Table 4 and related discussion). In addition, we find that these sectors typically use MMFs for both purposes: as a source of liquidity to meet VM payments and as a storage of liquidity when VM is received.

More specifically, VM flows of all these three sectors are found to have significant effects on Luxembourgish MMF flows (both in- and outflows). In addition to their large derivative exposures, these sectors also belong to the top six sectors in terms of holdings of Luxembourgish MMFs (see ranking in Table 3). VM flows of Luxembourgish and German IFs are also found to have significant effects on French MMF flows (again both in- and outflows). The two sectors belong to the top five holders of French MMFs.[12] Finally, it is Dutch PFs whose VM payments are found to have a significant effect on both Irish MMF inflows and outflows. Dutch PFs rank fourth in terms of Irish MMF holdings and first in terms of the size of non-bank VM payments.

The estimated effects are not only statistically but also economically significant. The significant coefficients range between 0.002 and 0.037, which implies that if a sector faced VM flows of the size of €1 bn, a MMF held by this sector is estimated to have experienced flows from around €2 mn to €37 mn. For instance, for Irish MMFs, the estimated coefficients for VM paid by Dutch PFs are found to be around 0.010, which means that if Dutch PFs need to post €1 bn in VM on a given day, an Irish MMF held by the Dutch PFs is estimated to have suffered outflows of around €10 mn on that day.

These individual MMF effects might look small, but there are several reasons why they can be interpreted as a lower bound for the actual effects during the acute phase of the March 2020

[11] We have also estimated dynamic panel models such as the Arellano-Bond model. For Luxembourgish and French MMFs, this estimator yielded qualitatively similar results as those obtained by the model with lagged dependent variable. For Irish MMFs, standard errors could not be estimated due to a low number of observations.

[12] There is some tentative evidence that VM received flows by Spanish IFs increase French MMF inflows as the RE and FE models suggest so. But this result is not further confirmed by the lagged dependent variable model and the VM posted by this sector is also not found significant in the regressions for French MMF outflows.

market turmoil. First, they are estimated using the whole period from February to April 2020 and as such represent averages over this period, whereby it could be expected that the effects for outflows were larger in the most acute phase of the market stress such as during the 'dash for cash' period. When shortening the period to March 2020 only, the estimated coefficients in the outflows regressions indeed tend to increase, although some are also less significant, most likely owing to a smaller sample size (see Tables B1, B2 and B3 in Annex B1). Furthermore, the fact that we can use in the regressions only country-sector level data on VM flows (instead of VM flows for each individual investor) means that our estimates likely suffer from measurement error downwards bias, because the individual firm-level variability in the data is dampened by the aggregation.

Moreover, aggregating the estimates of these individual MMF effects across the full sample of MMFs in the three domiciles and across all holder sectors in the regressions, we calculate that our models explain between 37% and 63% of the actual MMF outflows from February to April 2020, depending on the particular model and/or method of aggregation (see upper panel in Table 7). To compute these percentages, we first predict the daily outflows for each MMF using the estimated β coefficients from Table 5 and sum them across all MMFs and time. Second, we calculate the ratio of these predicted total outflows to the actual total outflows and multiply it by 100%. We tend to obtain slightly lower percentages when we use only the significant coefficients (lines (2) and (4)) rather than all estimated coefficients (lines (1) and (3)) from Table 5. By construction, the figures are lower when in the denominator we aggregate the actual outflows across all MMFs in our sample (lines (1) and (2)) rather than when considering only MMFs held by the investors included in the regressions (lines (3) and (4)). For instance, when interested in aggregate outflows experienced by *all* MMFs in our sample regardless of their holders, the best performing model predicts almost half of these aggregate outflows (RE model, 48%).

Overall, the models for inflows perform somewhat worse than the models for outflows (see lower panel in Table 7), explaining between 7% to 50% of the actual aggregate MMF inflows. In particular, they explain up to 37% of aggregate inflows into all MMFs as compared to 48% in the case of the models for outflows. These results suggest that investors might be reluctant to store the liquidity received from VMs in MMFs during market stress or they might postpone such decision by a few days after the VMs are received in view of the high uncertainty (see also Subsection 4.1).

Table 7
Share of aggregate MMF outflows and inflows explained by our model

	Random Effects	Fixed Effects	Lagged Dep. Var.
	MMF Outflows		
(1) All MMF outflows	48%	47%	37%
(2) Predict using significant coefs.	47%	45%	39%
(3) Only MMFs held by investors	63%	62%	49%
(4) Cases (2) and (3) combined	62%	60%	52%
	MMF Inflows		
(1) All MMF inflows	27%	14%	37%
(2) Predict using significant coefs.	19%	7%	32%
(3) Only MMFs held by investors	37%	19%	50%
(4) Cases (2) and (3) combined	26%	9%	43%

Notes: This table shows the share of the total February-April 2020 MMF outflows and inflows that can be explained by our models. To compute the percentages in lines (1), we first predict the daily outflows (inflows) for each MMF using the estimated β coefficients from regression equation 1 (2). We then sum the predicted and actual outflows (inflows) across MMFs and time, and divide the former over the latter (the result is multiplied by 100% to obtain percentages). In lines (2), we predict MMF outflows (inflows) in the numerator using only the significant β coefficients. In lines (3), we use all estimated coefficients as in lines (1) but use a smaller denominator: we only consider the actual outflows (inflows) of the MMFs held by at least one of the investor groups included in the regression. Calculations in lines (4) implement restrictions from lines (2) and (3) simultaneously. The calculations include all EUR MMFs domiciled in Ireland, France, and Luxembourg.

4.1 Regressions with leads and lags of VM flows

We now turn to estimating the model with leads (forward values) of VM flows posted and lags of VM flows received. To limit the number of the coefficients in the model, we keep in the regressions only those sectors whose estimates of the simultaneous VM payments are found significant and positive. We report the results of the lagged dependent variable model in Tables 5 and 6 as this model is likely to account the best for potential autocorrelation in error terms and thus might be the most suitable for estimating the lead/lagged effects of VM flows. At the same time, we show in Tables A1 – A4 in Appendix A1 that these results are by and large consistent to the results from other model specifications (i.e. FE and RE models).

When investors learn about the need to post VM, the actual VM payment can occur today or tomorrow (typically in case of centrally cleared trades) or the day after tomorrow (in case of non-centrally cleared trades). Therefore, we also expect the investors to withdraw liquidity from MMFs within this timeframe. The results in Table 8 are in line with this expectation, even if we detect only one sector, German IFs, whose forward values of VM flows posted have a significant impact on (French) MMF outflows.

Table 8
Regression results for MMF outflows and VM flows posted - including leads (model specification with lagged dependent variable)

	Dependent variable: MMF outflows					
	Luxembourgish MMFs		French MMFs		Irish MMFs	
*Independent variables: VM posted flows * MMF held*						
LU IF (t)	**0.002****	**0.002****	**0.008****	**0.009*****		
	[0.014]	[0.013]	[0.016]	[0.009]		
LU IF (t+1)	-0.001	-0.001	-0.002	0.000		
	[0.492]	[0.633]	[0.547]	[0.979]		
LU IF (t+2)		-0.001		-0.003		
		[0.493]		[0.490]		
DE IF (t)	0.003	0.003	**0.024****	**0.020***		
	[0.247]	[0.295]	[0.024]	[0.081]		
DE IF (t+1)	0.001	0.000	**0.015*****	0.002		
	[0.417]	[0.715]	[0.004]	[0.787]		
DE IF (t+2)		0.001		**0.021***		
		[0.718]		[0.089]		
NL PF (t)	**0.010****	**0.011****			**0.009****	**0.009*****
	[0.018]	[0.022]			[0.014]	[0.009]
NL PF (t+1)	0.001	0.000			0.002	-0.000
	[0.614]	[0.974]			[0.542]	[0.978]
NL PF (t+2)		0.001				0.002
		[0.337]				[0.365]
Lagged dep. var.	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,997	14,459	14,423	13,893	2,861	2,736
R-squared	0.129	0.130	0.164	0.169	0.138	0.150

Notes: The table shows regression results of MMFs' outflows against the interactions between simultaneous and future VM flows posted by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9
Regression results for MMF inflows and VM flows received - including lags (model specification with lagged dependent variable)

	Dependent variable: MMF inflows					
	Luxembourgish MMFs		French MMFs		Irish MMFs	
*Independent variables: VM flows received * MMF held*						
LU IF (t)	0.001	0.002	-0.000	-0.001		
	[0.279]	[0.130]	[0.890]	[0.805]		
LU IF (t-1)	-0.000	0.001	**0.005****	0.005		
	[0.887]	[0.537]	[0.037]	[0.237]		
LU IF (t-2)		-0.002		0.001		
		[0.156]		[0.762]		
DE IF (t)	0.002	0.001	0.011	0.010		
	[0.377]	[0.456]	[0.105]	[0.130]		
DE IF (t-1)	**0.005****	**0.004***	**0.020****	**0.017***		
	[0.048]	[0.067]	[0.039]	[0.096]		
DE IF (t-2)		0.001		0.005		
		[0.424]		[0.163]		
NL PF (t)	**0.007****	**0.007***			**0.007****	**0.006****
	[0.026]	[0.058]			[0.031]	[0.036]
NL PF (t-1)	**0.010***	0.008			0.002	0.000
	[0.055]	[0.208]			[0.538]	[0.905]
NL PF (t-2)		0.002				0.003
		[0.541]				[0.505]
ES IF (t)			0.004	0.006		
			[0.413]	[0.243]		
ES IF (t-1)			-0.002	0.001		
			[0.594]	[0.729]		
ES IF (t-2)				-0.009		
				[0.125]		
Lagged dep. var.	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,527	15,254	14,938	14,665	2,980	2,905
R-squared	0.226	0.225	0.049	0.048	0.091	0.100

Notes: The table shows regression results of MMFs' inflows against the interactions between simultaneous and past VM flows received by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Regarding VM flows received and MMF inflows, we find that German and Luxembourgish IFs deposit the funds received from VM payments into (Luxembourgish and French) MMFs with one day delay (see Table 9). This suggest that investors may not immediately reinvest the VM flows received into MMFs. Apart from potential operational issues (e.g. a late arrival of margin payments during the day), one reason could be that investors expect a market reversal amid stressed markets. In addition, investors may invest the VM flows received into MMFs only partially as they may aim to diversify the storing of liquidity across different asset types.

The results for leads and lags are also economically significant. The significant coefficients range from 0.004 to 0.021, which suggest that VM payments of around €1 bn can trigger a flow into or from an MMF between €4 mn and €21 mn. For instance, for French MMFs, the estimated coefficient for a 2-day forward value of VM flow posted by German IFs (t+2) equals 0.021 and comes in addition to the significant estimate of the contemporary effect of similar size. Hence, German IFs are estimated to withdraw around €20 mn from each French MMF that they hold in order to post€1 bn of VM today (contemporaneous effect) and another €21 mn to post €1 bn of VM in two days (a 2-day forward estimate). The contemporaneous effects are likely detected owing to the need to pay VM on centrally cleared trades, while the 2-day forward estimate could reflect the need to pay VM on non-centrally cleared trades, for which VM payments can be less timely. Regarding inflows, German IFs are estimated to invest around €17 mn to €20 mn to each French MMF held by them one day after they received VM flow of €1 bn. On the same day, they are also estimated to invest around €4 mn to €5 mn into each Luxembourgish MMF held by them. Overall, the models with leads and lags tend to explain a slightly higher share of the actual aggregate MMF outflows and inflows (see Table A5 in Appendix A1).

5 Conclusions

In this paper we investigate whether the significant volatility in MMF flows during the March 2020 market turmoil was driven by investors' liquidity needs related to derivative margin payments. We combine three highly granular unique data sets to construct a daily fund-level panel data spanning from February to April 2020 and estimate the effects of VM flows posted and received by the largest holders of EUR-denominated MMFs on flows of these MMFs.

Overall, the results support the hypothesis that investors into MMFs used MMFs to manage liquidity related to VM calls in the March 2020 market turmoil. In particular, we estimate that VM payments faced by euro area non-bank financial sectors—in particular investment funds and pension funds—could have driven almost half of the aggregate outflows from EUR-denominated MMFs domiciled in euro area. At the same time, we find that investors might be more reluctant to store the liquidity received from VMs in MMFs during market stress or they might postpone such decision by a few days after the VMs are received in view of the high uncertainty.

Our results are by and large robust for all EUR-denominated MMFs domiciled in the euro area as they apply across all three countries in which such MMFs are domiciled (i.e., France, Ireland and Luxembourg). The results are also robust to different model specifications. Moreover, we find these results despite the fact that the unavailability of the data does not allow us to conduct the analysis at firm-to-MMF level but only at the less accurate country-sector-to-MMF level.

The findings suggest several policy implications. First of all, in the context of liquidity management of non-bank financial intermediaries, they highlight the risks of reliance on the cash-like properties of MMF shares as a reliable source of liquidity under stress. Although no MMF had to suspend redemptions in the March 2020 market turmoil, non-banks' liquidity management should account for the fact that the value of MMFs can sometimes decline and MMFs can suspend redemptions in exceptional circumstances. As emphasized in ECB (2021), MMFs should also be made more resilient to significant outflows and the structure of their investor base should also be taken into account.

Second, the results underline the importance of unearthing and monitoring interconnectedness across markets, including from relatively small but volatile links, and across borders. This is particularly relevant in view of the recent regulatory reform in the derivatives market, which has introduced the daily exchange of margin for the vast majority of derivative exposures. While the exchange of margin in the form of high-quality collateral reduces counterparty credit risk, our results suggest that it can also increase liquidity risk in the financial system and create spillovers across different markets.

In particular, our paper highlights that during the March 2020 market turmoil some non-bank financial intermediaries passed on their liquidity squeeze from margin calls to MMFs, which in turn largely stopped providing funding to banks and NFCs. By the same token, our paper points at a new channel of the ECB's unprecedented policy actions enacted during the March 2020 market turmoil, including the announcement of the pandemic emergency purchase programme (PEPP) and further measures on 18th March 2020. Following the announcement, the market volatility and thus also VM payments (which move mechanically with market volatility) significantly declined. The unearthed link between VM payments and MMF flows in our paper suggests that the announcement also helped stabilise the outflows faced by MMFs.

Finally, we could investigate those links only thanks to the availability of various granular datasets, including trade repository data that started to be collected as a part of the global derivatives market reform. Overall, this suggests that granular (regulatory) data collections are key for analysing interconnectedness.

While our paper is the first—to our knowledge—to empirically and systematically assess the role of derivative margin for MMF flows, it also opens the door and calls for further research in the area of interconnectedness between the derivatives market and other markets. In particular, BCBS, CPMI, IOSCO (2022) suggests that to meet margin payments, non-bank financial intermediaries used not only MMFs but also bank deposits, the repo market and credit or liquidity lines, while some even liquidated assets (e.g., bonds). Furthermore, non-banks are subject not only to VM payments but can face also other liquidity needs during periods of market stress, notably initial margin payments and redemptions (the latter in the case of investments funds). We leave both these areas for further research.

References

Aldasoro, I., F. Balke, A. Barth, and E. Eren (2020). Spillovers of funding dry-ups. *Journal of International Economics 137.*

AMF (2020, July). 2020 Markets and risks outlook. Autorité des Marchés Financiers (AMF).

Avalos, F. and D. Xia (2021). Investor size, liquidity and prime money market fund stress. BIS Quarterly Review (March).

Bank of England (2020, August). Financial Stability Report – August 2020.

Bank of England (2022, December). Financial Stability Report – December 2022.

Bardoscia, M., G. Bianconi, and G. Ferrara (2019). Multiplex network analysis of the UK over-the-counter derivatives market. *International Journal of Finance and Economics 24*(4), 1520–1544.

Bardoscia, M., G. Ferrara, N. Vause, and M. Yoganayagam (2021). Simulating liquidity stress in the derivatives market. *Journal of Economic Dynamics and Control 133*, 104215.

BCBS, CPMI, IOSCO (2022, September). Review of margining practices.

Biais, B., F. Heider, and M. Hoerova (2020). Variation margins, fire sales, and information-constrained optimum. *Review of Economic Studies*.

BlackRock (2020, July). Lessons from COVID-19: The experience of European MMFs in short-term markets. BlackRock.

Boucinha, M., L. Capotă, K. Cera, E. Faïk, J. Galléty, M. Giuzio, M. Grodzicki, I. Kerner, S. Kördel, L. Molestina Vivar, G. Nicoletti, E. Ryan, and C. Weistroffer (2020, May). Recent stress in money market funds has exposed potential risks for the wider financial system. Financial Stability Review - Box, ECB.

Bouveret, A., A. Martin, and P. E. McCabe (2022). Money market fund vulnerabilities: A global perspective. *Finance and Economics Discussion Series 12.*

Capotă, L.-D., M. Grill, L. Molestina Vivar, N. Schmitz, and C. Weistroffer (2022, October). Is the EU money market fund regulation fit for purpose? Lessons from the COVID-19 turmoil. Working Paper Series 2737, ECB.

Chen, R. and E. Kemp (2023, September). Putting out the NBFire: lessons from the uk's liability-driven investment (ldi) crisis. IMF Working Paper WP/23/210, International Monetary Fund.

Chernenko, S. and A. Sunderam (2014). Frictions in shadow banking: Evidence from the lending behavior of money market mutual funds. *The Review of Financial Studies 27*, 1717–1750.

Cipriani, M. and G. La Spada (2021). Sophisticated and unsophisticated runs. *Federal Reserve*

Bank of New York Staff Reports (956).

Czech, R., S. Huang, D. Lou, and T. Wang (2021, December). An unintended consequence of holding dollar assets. Staff Working Paper 953, Bank of England.

Darpeix, P. (2021, July). Econometric analysis of the determinants of redemption flows of french money market funds during the 2020 crisis. amf-france.org.

Daskalova, S. and M. Weißler (2020). Liquidity conditions and monetary policy operations in the period from 29 January to 5 May 2020. Economic Bulletin 4/2020 - Box, ECB.

de Guindos, L. and I. Schnabel (2020, April). The ECB's commercial paper purchases: A targeted response to the economic disturbances caused by COVID-19. The ECB Blog.

de Jong, A., A. Draghiciu, L. Fache Rousová, A. Fontana, and E. Letizia (2019). Impact of variation margining on EU insurers' liquidity: An analysis of interest rate swaps positions. Financial Stability Report - Thematic Article 16, European Insurance and Occupational Pensions Authority (EIOPA).

ECB (2016, December). Looking back at otc derivative reforms: Objectives, progress and gaps. ECB Economic Bulletin.

ECB (2020, June). Survey on credit terms and conditions in euro-denominated securities financing and otc derivatives markets (sesfod). European Central Bank.

ECB (2021). Eurosystem contribution to the European Securities and Markets Authority (ESMA) consultation on the framework for EU money market funds. European Central Bank.

Epstein, L. and L. Li (2022). Investor Base and Prime Money Market Fund Behavior. FEDS Notes 2022-04-19, Board of Governors of the Federal Reserve System (U.S.).

ESMA (2021, March). ESMA report on trends, risks and vulnerabilities. European Securities and Markets Authority.

Fache Rousová, L., M. Ghio, S. Kördel, and D. Salakhova (2020, November). Interconnectedness of derivatives markets and money market funds through insurance corporations and pension funds. Financial Stability Review - Box, ECB.

Fache Rousová, L., M. Gravanis, A. Jukonis, and E. Letizia (2020). Derivatives-related liquidity risk facing investment funds. Financial Stability Review - Special Feature, ECB.

FSB (2020, November). Holistic review of the March market turmoil. Financial Stability Board.

FSB (2021). Policy proposals to enhance money market fund resilience.

Garcia Pascual, A., R. Singh, and J. Surti (2021, September). Investment funds and financial stability: Policy considerations. Departmental Paper No 2021/018.

Glasserman, P. and Q. Wu (2018, December). Persistence and procyclicality in margin requirements. *Management Science 64*(12), 5705–5724.

Jensen, J. R. and S. D. Achord (2019, November). Pension companies will have large liquidity needs if interest rates rise. Analysis 23, Danmarks Nationalbank.

Jukonis, A., E. Letizia, and L. Rousová (2022, December). The impact of derivatives collateralisation on liquidity risk: evidence from the investment fund sector. Working Paper Series 2756, ECB.

Kacperczyk, M. and P. Schnabl (2010). When safe proved risky: Commercial paper during the financial crisis of 2007-2009. *Journal of Economic Perspectives 24*, 29–50.

Lenoci, F. D. and E. Letizia (2021). Classifying counterparty sector in EMIR data. In *Data Science for Economics and Finance*, pp. 117–143. Springer, Cham.

Li, L., Y. Li, M. Macchiavelli, and X. Zhou (2021). Liquidity restriction, runs, and central bank interventions: Evidence from money market funds. *Review of Financial Studies* (34), 5402–5437.

McCabe, P. (2010). The cross section of money market fund risks and financial crises. *FEDS Working Paper 51*.

McDonald, R. and A. Paulson (2015). AIG in hindsight. *Journal of Economic Perspectives 29*.

Paddrik, M., S. Rajan, and H. Peyton Young (2020, August). Contagion in derivatives markets. *Management Science 66*(8), 3603–3616.

PWG (2020, December). Report of the president's working group on financial markets: Overview of recent events and potential reform options for money market funds.

Strahan, P. E. and B. Tanyeri (2015). Once burned, twice shy: Money market fund responses to a systemic liquidity shock. *The Journal of Financial and Quantitative Analysis 50*, 119–144.

Szczepanski, M. (2016, October). Money market funds: Measures to improve stability and liquidity.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). MIT Press.

A1 Robustness of regression results with leads and lags of VM flows

Table A1
Regression results for MMF outflows and VM flows posted - including leads (FE specification)

	Dependent variable: MMF outflows					
	Luxembourgish MMFs		French MMFs		Irish MMFs	
*Independent variables: VM flows posted * MMF held*						
LU IF (t)	**0.002****	**0.003****	**0.011*****	**0.012*****		
	[0.021]	[0.030]	[0.001]	[0.001]		
LU IF (t+1)	-0.000	-0.000	-0.000	0.001		
	[0.697]	[0.896]	[0.994]	[0.780]		
LU IF (t+2)		-0.001		-0.004		
		[0.407]		[0.404]		
DE IF (t)	0.002	0.002	**0.016***	0.017		
	[0.470]	[0.461]	[0.089]	[0.132]		
DE IF (t+1)	0.000	-0.000	**0.010***	0.003		
	[0.787]	[0.908]	[0.071]	[0.649]		
DE IF (t+2)		0.000		0.014		
		[0.810]		[0.229]		
NL PF (t)	**0.009****	**0.010****			**0.010****	**0.011****
	[0.031]	[0.034]			[0.021]	[0.020]
NL PF (t+1)	-0.001	-0.001			0.004	0.002
	[0.812]	[0.687]			[0.301]	[0.653]
NL PF (t+2)		-0.000				0.003
		[0.796]				[0.286]
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,265	14,727	14,688	14,158	2,930	2,805
R-squared	0.223	0.227	0.302	0.305	0.256	0.245

Notes: The table shows regression results of MMFs' outflows against the interactions between simultaneous and future VM flows posted by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A2
Regression results for MMF outflows and VM flows posted flows - including leads (RE specification)

	Dependent variable: MMF outflows					
	Luxembourgish MMFs		French MMFs		Irish MMFs	
*Independent variables: VM flows posted * MMF held*						
LU IF (t)	**0.002****	**0.003****	**0.011*****	**0.012*****		
	[0.013]	[0.024]	[0.001]	[0.001]		
LU IF (t+1)	-0.000	-0.000	-0.000	0.001		
	[0.659]	[0.893]	[0.889]	[0.789]		
LU IF (t+2)		-0.001		-0.004		
		[0.409]		[0.399]		
DE IF (t)	0.002	0.002	**0.018***	0.018		
	[0.397]	[0.407]	[0.057]	[0.104]		
DE IF (t+1)	0.001	0.000	**0.012****	0.004		
	[0.516]	[0.947]	[0.018]	[0.470]		
DE IF (t+2)		0.001		0.016		
		[0.649]		[0.165]		
NL PF (t)	**0.010****	**0.010****			**0.010****	**0.011****
	[0.027]	[0.031]			[0.013]	[0.013]
NL PF (t+1)	0.000	-0.000			0.004	0.002
	[0.825]	[0.902]			[0.286]	[0.660]
NL PF (t+2)		0.000				0.003
		[0.723]				[0.313]
Fund RE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,265	14,727	14,688	14,158	2,930	2,805
R-squared	0.069	0.07	0.086	0.095	0.071	0.077

Notes: The table shows regression results of MMFs' outflows against the interactions between simultaneous and future VM flows posted by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A3
Regression results for MMF inflows and VM flows received - including lags (FE specification)

	Dependent variable: MMF inflows					
	Luxembourgish MMFs		French MMFs		Irish MMFs	
*Independent variables: VM flows received * MMF held*						
LU IF (t)	**0.002****	**0.002***	-0.003	-0.004		
	[0.047]	[0.078]	[0.197]	[0.146]		
LU IF (t-1)	0.001	0.002	**0.004***	0.006		
	[0.579]	[0.223]	[0.091]	[0.204]		
LU IF (t-2)		-0.002		0.000		
		[0.238]		[0.976]		
DE IF (t)	0.000	0.000	-0.007	-0.005		
	[0.874]	[0.972]	[0.419]	[0.514]		
DE IF (t-1)	**0.003***	**0.003***	0.002	0.003		
	[0.089]	[0.090]	[0.804]	[0.684]		
DE IF (t-2)		0.001		-0.010*		
		[0.560]		[0.084]		
NL PF (t)	0.006	0.006			0.005	0.005
	[0.171]	[0.167]			[0.123]	[0.131]
NL PF (t-1)	0.013	0.010			0.001	0.001
	[0.136]	[0.213]			[0.816]	[0.899]
NL PF (t-2)		**0.007*****				0.001
		[0.000]				[0.700]
ES IF (t)			**0.008***	**0.008***		
			[0.088]	[0.094]		
ES IF (t-1)			0.005	**0.006***		
			[0.126]	[0.096]		
ES IF (t-2)				-0.004		
				[0.416]		
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,530	15,257	14,945	14,672	2,980	2,905
R-squared	0.304	0.304	0.162	0.159	0.249	0.243

Notes: The table shows regression results of MMFs' inflows against the interactions between simultaneous and past VM flows received by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A4
Regression results for MMF inflows and VM flows received - including lags (RE specification)

	Dependent variable: MMF inflows					
	Luxembourgish MMFs		French MMFs		Irish MMFs	
*Independent variables: VM flows received * MMF held*						
LU IF (t)	**0.002****	**0.002***	-0.002	-0.002		
	[0.037]	[0.058]	[0.509]	[0.379]		
LU IF (t-1)	0.001	0.002	**0.005****	0.006		
	[0.598]	[0.249]	[0.027]	[0.180]		
LU IF (t-2)		-0.002		0.001		
		[0.231]		[0.723]		
DE IF (t)	0.001	0.000	-0.001	0.001		
	[0.627]	[0.757]	[0.919]	[0.939]		
DE IF (t-1)	**0.004***	**0.003***	0.008	0.009		
	[0.055]	[0.060]	[0.276]	[0.303]		
DE IF (t-2)		0.001		-0.003		
		[0.404]		[0.355]		
NL PF (t)	0.007	0.006			**0.005***	**0.005***
	[0.104]	[0.114]			[0.088]	[0.099]
NL PF (t-1)	0.014	0.011			0.001	0.001
	[0.105]	[0.192]			[0.742]	[0.850]
NL PF (t-2)		**0.007*****				0.002
		[0.000]				[0.632]
ES IF (t)			0.007	0.008		
			[0.108]	[0.103]		
ES IF (t-1)			0.003	0.005		
			[0.199]	[0.135]		
ES IF (t-2)				-0.006		
				[0.290]		
Fund RE	Yes	Yes	Yes	Yes	Yes	Yes
Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,530	15,257	14,945	14,672	2,980	2,905
R-squared	0.103	0.105	0.024	0.023	0.037	0.047

Notes: The table shows regression results of MMFs' inflows against the interactions between simultaneous and past VM flows received by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A5
Share of aggregate MMF outflows and inflows explained by our model (regressions including leads / lags of the independent variables)

	Random Effects	Fixed Effects	Lagged Dep. Var.	Random Effects	Fixed Effects	Lagged Dep. Var.
	MMF Outflows					
	One lead			Two leads		
(1) All MMF outflows	49%	47%	41%	47%	44%	40%
(2) Predict using significant coefs.	49%	46%	44%	42%	42%	47%
(3) Only MMFs held by investors	65%	62%	54%	62%	58%	53%
(4) Cases (2) and (3) combined	65%	61%	59%	56%	56%	62%
	MMF Inflows					
	One lag			Two lags		
(1) All MMF inflows	28%	14%	37%	29%	15%	37%
(2) Predict using significant coefs.	21%	17%	29%	9%	10%	12%
(3) Only MMFs held by investors	38%	19%	50%	39%	20%	50%
(4) Cases (2) and (3) combined	29%	23%	40%	13%	13%	16%

Notes: This table shows the share of the total February-April 2020 MMF outflows and inflows that can be explained by our models. To compute the percentages in lines (1), we first predict the daily outflows (inflows) for each MMF using the estimated β coefficients from regression equation 1 (2). We utilize the regression specifications that include leads (lags) of the dependent variables, and whose results are reported in Tables 8, A1, and A2 (9, A3, and A4). We then sum the predicted and actual outflows (inflows) across MMFs and time, and divide the former over the latter (the result is multiplied by 100% to obtain percentages). In lines (2), we predict MMF outflows (inflows) in the numerator using only the significant β coefficients. In lines (3), we use all estimated coefficients as in lines (1) but use a smaller denominator: we only consider the actual outflows (inflows) of the MMFs held by at least one of the investor groups included in the regression. Calculations in lines (4) implement restrictions from lines (2) and (3) simultaneously. The calculations include all EUR MMFs domiciled in Ireland, France, and Luxembourg.

B1 Outflow results for March 2020

Table B1

Regression results for MMF outflows and VM flows posted - Luxembourgish MMFs - comparing subperiods

	Dependent variable: MMF outflows					
	Random Effects Model		Fixed Effects Model		Lagged Dependent Model	
*Independent variables: VM posted flows * MMF held*						
FR IF	**0.002***	**0.003***	**0.002***	**0.004****	0.001	0.001
	[0.054]	[0.055]	[0.066]	[0.045]	[0.163]	[0.227]
LU IF	0.002	0.003	0.002	0.003	**0.003***	**0.003**
	[0.303]	[0.237]	[0.423]	[0.331]	[0.082]	[0.147]
DE IF	**0.009****	**0.015**	**0.008****	**0.013**	**0.011*****	**0.012***
	[0.023]	[0.127]	[0.030]	[0.203]	[0.010]	[0.068]
FR BANK	0.002	0.004	0.001	0.004	0.003	0.003
	[0.809]	[0.728]	[0.905]	[0.781]	[0.694]	[0.719]
ES IF	0.005	0.004	0.005	0.003	0.005	0.004
	[0.332]	[0.443]	[0.332]	[0.460]	[0.314]	[0.378]
Observations	15,803	5,502	15,803	5,502	15,535	5,502
R-squared			0.221	0.292	0.129	0.170
Period	**Feb-Apr**	**March**	**Feb-Apr**	**March**	**Feb-Apr**	**March**

Notes: The table shows regression results of MMFs' outflows against the interactions between simultaneous and future VM flows posted by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B2
Regression results for MMF outflows and VM flows posted - French MMFs - comparing subperiods

	Dependent variable: MMF outflows					
	Random Effects Model		Fixed Effects Model		Lagged Dependent Model	
*Independent variables: VM posted flows * MMF held*						
FR IF	-0.004	-0.002	-0.003	0.002	-0.005	-0.005
	[0.513]	[0.734]	[0.593]	[0.783]	[0.307]	[0.280]
LU IF	**0.011*** **	**0.013*** **	**0.011*** **	**0.012*** **	**0.007*** **	**0.008*** **
	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]
DE IF	**0.024** **	**0.024** **	**0.020** **	**0.013**	**0.037*** **	**0.033*** **
	[0.011]	[0.017]	[0.026]	[0.184]	[0.003]	[0.002]
FR BANK	0.000	0.000	0.000	0.001	0.000	0.000
	[0.143]	[0.132]	[0.117]	[0.259]	[0.638]	[0.554]
ES IF	-0.010	-0.009	-0.009	-0.008	-0.011	-0.009
	[0.217]	[0.242]	[0.233]	[0.310]	[0.279]	[0.351]
Observations	15,218	5,250	15,218	5,250	14,953	5,248
R-squared			0.301	0.364	0.162	0.217
Period	**Feb-Apr**	**March**	**Feb-Apr**	**March**	**Feb-Apr**	**March**

Notes: The table shows regression results of MMFs' outflows against the interactions between simultaneous and future VM flows posted by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B3

Regression results for MMF outflows and VM flows posted - Irish MMFs - comparing subperiods

	Dependent variable: MMF outflows					
	Random Effects Model		Fixed Effects Model		Lagged Dependent Model	
*Independent variables: VM posted flows * MMF held*						
LU IF	0.000	-0.000	0.001	-0.002	-0.000	-0.000
	[0.900]	[0.874]	[0.843]	[0.617]	[0.950]	[0.988]
IE IF	-0.003	-0.007*	-0.003	-0.008	-0.007	-0.007
	[0.620]	[0.072]	[0.704]	[0.213]	[0.129]	[0.155]
NL PF	**0.011*** **	**0.018** **	**0.011*** **	**0.017* **	**0.010*** **	**0.014** **
	[0.004]	[0.011]	[0.009]	[0.052]	[0.001]	[0.015]
IT IF	-0.013	-0.009	-0.012	-0.013	-0.004	-0.004
	[0.210]	[0.399]	[0.227]	[0.263]	[0.674]	[0.712]
DE IF	-0.001	-0.001	-0.002	-0.003	0.001	0.000
	[0.729]	[0.780]	[0.724]	[0.600]	[0.819]	[0.989]
Observations	3,055	1,035	3,055	1,035	2,986	1,022
R-squared			0.263	0.241	0.153	0.167
Period	**Feb-Apr**	**March**	**Feb-Apr**	**March**	**Feb-Apr**	**March**

Notes: The table shows regression results of MMFs' outflows against the interactions between simultaneous and future VM flows posted by investor groups and a dummy equal to one when the investor groups hold the MMF. The time period used is from the beginning of February to the end of April 2020. Standard errors are clustered at fund level. P-values are in brackets.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

PUBLICATIONS

Derivative Margin Calls: A New Driver of MMF Flows

Working Paper No. WP/2023/061