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## When margins call: liquidity preparedness of non-bank financial institutions

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**Abstract**

We propose a novel framework to assess systemic risk stemming from the inadequate liquidity preparedness of non-bank financial institutions (NBFIs) to derivative margin calls. Unlike banks, NBFIs may struggle to source liquidity and meet margin calls during periods of significant asset price fluctuations, potentially triggering asset fire sales and amplifying market volatility. We develop a set of indicators and statistical methods to assess liquidity preparedness and examine risk transmission through common asset holdings and counterparty exposures. Applying our framework to euro area NBFIs during the Covid-19 turmoil and the 2022–2023 monetary tightening, we observe an increase in distressed entities, which, in turn, seem to exhibit more liquidity-driven selling behaviours than their non-distressed peers. Network analysis suggests that certain counterparties of distressed entities appear particularly vulnerable to margin call-induced liquidity shocks. Our framework offers policymakers valuable tools to enhance the monitoring and resilience of the NBFI sector.

**JEL codes:** C02, E52, G01, G11, G23

**Keywords:** Non-bank Financial Institutions, Derivative margin calls, Liquidity risk, Financial stability, Network analysis

## Non-technical summary

Recent financial market disruptions, such as the turmoil in March 2020, the collapse of Archegos in 2021, and the volatility in commodities and UK pension funds in 2022, have highlighted a critical challenge for financial stability: the ability of non-bank financial institutions (NBFIs) to meet liquidity demands during periods of market stress. This paper proposes a novel framework to monitor the risks associated with margin calls in the derivatives market, focusing on NBFIs, and to assess their broader implications for financial stability.

Margin calls require financial institutions to provide cash or eligible assets to cover potential losses on derivative positions. These requirements were strengthened after the global financial crisis to reduce counterparty credit risk. At the same time, they have also introduced a potential pro-cyclical source of vulnerability, particularly for NBFIs, which often do not have the same liquidity buffers as banks during market distress. When market volatility increases sharply, margin calls rise, creating sudden and significant liquidity needs. If NBFIs struggle to meet these calls, they may be forced to sell assets quickly, potentially worsening market instability. Also, if they fail to meet their margin obligations, this stress can spillover to banks and other financial entities that act as clearing members or trading counterparties. Institutions like the Financial Stability Board (FSB), the European Central Bank (ECB), and the Bank of England (BoE) have emphasised the need for improved liquidity preparedness.

First, we develop a set of entity-level indicators and analytical techniques to identify NBFIs facing liquidity stress due to large margin calls relative to their liquid asset holdings. Once distressed entities are identified, we assess the broader systemic implications of liquidity shortfalls using two complementary approaches. The first examines portfolio overlap between distressed and non-distressed NBFIs to determine which asset classes are most susceptible to margin call-driven fire sales. The second employs network analysis to estimate the spillover effects of these fire sales on banks and other counterparties.

In this context, we developed a new analytical framework for assessing the liquidity preparedness of NBFIs, mapping the transmission channels, and identifying vulnerable entities. First, we develop a set of entity-level indicators and statistical methods to identify NBFIs facing liquidity stress due to large margin calls relative to their liquid asset holdings. Once distressed entities are identified, we assess the broader systemic implications of liquidity shortfalls using two complementary approaches. The first examines portfolio overlap between distressed and non-distressed NBFIs to identify which asset classes are most likely to be liquidated in margin call-driven fire sales. The second employs network analysis to estimate the spillover effects of NBFI fire sales on banks and other counterparties.

We apply our tools to two case studies using data from the euro area during the Covid-19 market turmoil in 2020 and the monetary policy tightening in 2022-2023. Our findings indicate that liquidity stress among NBFIs spiked significantly in both periods, and that the selling strategies of distressed NBFIs were less proportional to their portfolio composition than those of other, non-distressed entities. During the Covid-19 turmoil, both distressed and non-distressed funds primarily sold equities, although they differed in terms of issuer country and industry sector. In contrast, during the monetary policy tightening period, government bonds were more frequently among the top five asset classes sold by liquidity distressed funds. Furthermore, while most counterparties had limited exposure to distressed NBFIs, a few exhibited higher vulnerability, raising concerns about potential liquidity shortages and systemic risks.

Our study contributes to the growing research on monitoring liquidity risk in NBFIs. While traditional stress-testing frameworks have expanded beyond banks to include investment funds and insurance firms, they still lack comprehensive integration of NBFIs. As NBFIs have significantly increased their role in financing the real economy, incorporating their liquidity risks into stress-testing methodologies is crucial. Our framework provides a practical tool to identify liquidity stress transmission channels and assess potential contagion effects, complementing existing supervisory approaches such as system-wide stress tests conducted by prudential authorities.

Building on recent research on liquidity preparedness in NBFIs, our study employs network analysis to examine how liquidity stress spreads in the derivatives market, particularly from investment funds to other financial institutions. Given the interconnectedness of NBFIs within the broader financial system, understanding these transmission mechanisms is essential for designing effective macroprudential policies. Our framework can also be used to evaluate policy measures aimed at enhancing NBFI resilience, such as mandating higher liquidity buffers and diversifying funding sources. By systematically analysing these policy tools, our findings offer valuable insights for regulators seeking to mitigate systemic risks associated with NBFI liquidity shocks.

# 1 Introduction

In recent years, several episodes of liquidity stress in financial markets – such as the March 2020 market turmoil, the Archegos failure in March 2021, the commodities markets turmoil in 2022, and the September 2022 issues experienced by many pooled liability-driven investment funds in the UK – have highlighted the need to monitor the liquidity preparedness of non-bank financial institutions (NBFIs) to meet margin calls in the derivatives market [1, 2, 3, 4]. During these episodes, financial market volatility sharply increased, triggering large spikes in margin calls on derivative exposures and imposing significant liquidity pressures on market participants that have to exchange daily variation and initial margins related to their derivatives positions.

The requirement to exchange margins in the form of cash or eligible assets on a daily basis was implemented as part of the over-the-counter (OTC) derivative reform following the global financial crisis, aiming to mitigate counterparty credit risk. However, it has also increased market participants' vulnerability to liquidity stress, due to the pro-cyclical nature of margins in response to sharp price fluctuations. In [5], the authors show that, while margin requirements are designed to reduce risk, they can increase market volatility, make margin constrained investors better off, and lead to greater return reversals. While both banks and non-bank financial institutions can face liquidity shortfalls under stress - bank runs and fire sales being classic examples in the banking sector [6] - the measures available to them to manage such stress differ. Banks have more stable access to central bank liquidity facilities and regulatory liquidity buffers, which can help them absorb temporary funding shocks. By contrast, NBFIs lack comparable backstops and face greater difficulty in securing cash or high-quality liquid assets (HQLA) in times of market turmoil. This has important financial stability implications. A "dash for cash"[1] driven by widespread margin calls can lead to asset fire sales or a rapid unwinding of derivative exposures, which might further fuel already high price volatility and lead to disorderly market functioning. In the event of extraordinarily large market movements, the failure of NBFIs to meet margin obligations can spread to other market participants, such as banks acting as clearing members of central counterparties or dealers in the bilaterally cleared OTC space, potentially transforming liquidity stress at the individual entity level into a system-wide issue. It can also increase step-in risk,

[1]The term "dash for cash" refers to a sudden widespread demand by financial institutions and investors of liquid assets, typically cash or cash-equivalents, in response to severe market stress that increases liquidity needs, e.g., during the Covid-19 market turmoil.

transferring the pressure on the banking sector[2] and spreading contagion through the financial system, given the interconnectedness between banks and NBFIs [7].

For this reason, strengthening the NBFI sector's resilience to liquidity shocks by enhancing and monitoring NBFI liquidity preparedness is a key priority of the international NBFI policy agenda [8]. According to the Financial Stability Board (FSB) [9], one of the "key amplifiers" of financial contagion is the "unexpectedly large margin calls for derivatives and securities trades." In the Financial Stability Review (May 2025) [10] the ECB states that "an adequate policy response should focus on addressing key structural vulnerabilities in the NBFI sector, including monitoring and tackling risks arising from non-bank leverage, enhancing the liquidity preparedness of non-bank market participants to meet margin and collateral calls, and mitigating liquidity mismatch in the investment fund sector." Also, the Bank of England (BoE) in its Financial Stability Review [11, 12] argued that vulnerabilities related to margin calls are among the key vulnerabilities in market-based finance.

This paper introduces a novel analytical framework to assess systemic risk stemming from the inadequate liquidity preparedness[3] of NBFIs to derivative margin calls. We first propose a set of entity-level indicators and statistical methods to identify NBFIs experiencing liquidity stress due to unexpected or large margin calls relative to their liquid asset holdings. To evaluate the broader systemic implications of such liquidity shortfalls, we then introduce two additional statistical methods that capture potential contagion through common asset holdings and counterparties' exposures. The first tool examines portfolio overlap between distressed and non-distressed NBFIs to identify which asset classes are most likely to be liquidated in margin call-driven fire sales and whether selling strategies are proportional to portfolio composition. The second employs network analysis to estimate counterparties' exposure to distressed NBFIs, to consider the potential risks of contagion and financial instability. Together, these components provide a comprehensive liquidity risk framework, detecting distressed NBFIs, analysing asset-selling behaviour by distinguishing between distressed and non-distressed entities, and identifying

[2]This risk transfer can happen if banks acting, e.g., as clearing members step-in proving liquidity to non-bank clients.

[3]In this paper, the expression *adequate liquidity preparedness* refers to the ability of NBFIs to respond to sudden margin and collateral calls under conditions of financial stress, and does not relate to the notion of efficiency in risk-return optimisation, short-term profitability, or optimal resource allocation during periods of market stress. The term *preparedness* is intentionally used to align with the terminology and framework adopted by the FSB's working group on liquidity preparedness for margin and collateral calls (see final report [8]).

counterparties most exposed to potential contagion arising from NBFIs.

We apply our liquidity framework to two case studies, using euro area data: the Covid-19 market turmoil and the 2022-2023 monetary policy tightening. The Covid-19 crisis serves as an example of how an exogenous market shock can trigger extreme spikes in margin calls, straining NBFI liquidity. In contrast, the monetary policy tightening driven by Central Banks' rate hikes to curb inflationary pressures illustrates how a more gradual and, to some extent, anticipated shift in financing conditions can influence NBFI liquidity needs through their derivative exposures.

Our findings show that the fraction of funds experiencing liquidity stress significantly increased from late February to late March 2020, at the height of the Covid-19 market turmoil, and declined sharply only after the ECB's Pandemic Emergency Purchase Programme (PEPP) announcement. During the 2022-2023 monetary policy tightening, we measure statistically significant increases in liquidity stress around certain key announcements and effective dates of rate hikes. In addition, during the Covid-19 turmoil, both distressed and non-distressed funds primarily sold equities, although they differed in terms of issuer country and industry sector. In contrast, during the monetary policy tightening period, government bonds were more frequently among the top five asset classes sold by liquidity distressed funds. In both periods, we observe that the selling strategies of distressed NBFIs were less proportional to their portfolio composition than those of non-distressed entities. Finally, we find that counterparties of distressed NBFIs generally maintain a low exposure to them in terms of margin calls to be received. However, a few counterparties appear more vulnerable to market shocks, posing potential risks of liquidity shortages or broader financial instability.

This study contributes to the growing literature on monitoring indicators for liquidity risk by proposing a novel framework to assess NBFI vulnerabilities to unexpected derivative margin calls. Our liquidity framework complements existing supervisory tools, such as system-wide stress tests regularly conducted by prudential authorities. While traditional stress-testing frameworks have expanded beyond banks [13] to include investment funds [14, 15, 16] and insurance firms, a comprehensive integration of NBFIs remains limited. Given that NBFIs have significantly increased their role in financing the real economy in the euro area—e.g., investment funds' assets more than doubled between 2009 and 2019, reaching €14 trillion by the end of the period [14]—incorporating their liquidity risks into stress-testing methodologies is crucial. Our indicators provide a practical tool to identify liquidity stress transmission channels and assess potential contagion effects [15].

Methodologically, our study builds on recent research highlighting the importance of liquidity preparedness in NBFIs, particularly concerning margin calls, leverage, and hedging strategies. For instance, Alfaro et al. [17] introduce the concept of Liquidity After Solvency Hedging (LASH) risk, showing how NBFI hedging activities can generate substantial liquidity demands in response to interest rate fluctuations. Similarly, Bouveret et al. [18] develop a framework to assess the vulnerabilities of leveraged investment funds under market stress, while Ianiro et al. [19] propose a duration-based approach to measuring synthetic leverage in interest rate swaps. Analysing Dutch regulatory data, Jansen et al. [20] find that liquidity risk is more pronounced for pension funds with lower funding ratios, as they hold larger swap positions and lower cash holdings, exposing them to the risk of substantial margin calls when interest rates rise. Expanding on this literature [21, 22, 23, 24, 25], our study employs network analysis to examine how liquidity contagion spreads in the derivative market, particularly from investment funds to other market participants such as banks. Given the high interconnectedness of NBFIs within the broader financial system, understanding these transmission mechanisms is crucial for designing effective macroprudential policies.

This work contributes to the debate around policy measures aimed at enhancing NBFI resilience to liquidity shocks, particularly in the context of international regulatory discussions [8]. Our methodological framework can be used to assess the effectiveness of new policy tools, such as mandating adequate levels of liquid assets and diversifying liquidity and funding sources. Furthermore, it allows authorities to test the sufficiency of NBFI liquidity buffers under adverse scenarios and evaluate the potential impact of policy interventions, including higher cash buffers and broader holdings of high-quality liquid assets. By providing a systematic approach to analysing these policy tools, our findings offer valuable insights for regulators designing macroprudential measures to mitigate systemic risk in the sector.

The paper is organized as follows: Section 2 describes the data, Section 3 introduces the liquidity indicators and methodological framework, Section 4 presents the case studies and main findings, and Section 5 provides the final remarks and conclusions. The appendix reports supplementary plots and tables, as well as a list of acronyms used in the paper.

## 2 Data

This section presents the data required to build and apply our framework for assessing the liquidity preparedness of NBFIs for derivative margin calls. For the sake of simplicity, in the following, NBFIs will be referred to as funds.[4] The framework combines information on daily derivative margin calls, collected under the European Market Infrastructure Regulation (EMIR), with data on funds' holdings provided by LSEG Lipper IM Data. The securities held by funds are classified as HQLA using the European System of Central Banks' (ESCB) Centralised Securities Database (CSDB). This classification reflects the standards established for banks under the Basel Liquidity Coverage Ratio requirements [26] and follows the methodology proposed in [27]. EMIR and Lipper data offer fund-level granularity, and are merged using the Legal Entity Identifier (LEI) code of each fund [27]. CSDB data, instead, provides granularity at the security level, where each security is identified by its International Securities Identification Number (ISIN).

### 2.1 EMIR derivatives data

EMIR dataset contains information on derivative contracts collected under the European Market Infrastructure Regulation (EMIR)[5] which came into force in 2012. EMIR is a European Union (EU) regulation aimed at improving the transparency of OTC derivatives markets, mitigating credit risk, and reducing operational risk. To achieve this, EMIR requires that OTC derivatives meeting certain requirements[5] are subject to the clearing obligation, and for all OTC derivatives that are not centrally cleared, that risk mitigation techniques apply. In addition, all derivatives transactions conducted by counterparties resident in the EU must be reported to Trade Repositories (TRs). The regulation applies to both financial intermediaries and non-financial companies, provided their positions exceed the specified thresholds set by the regulation[5]. It operates on a dual-reporting system, imposing reporting obligations on both counterparties. The European Central Bank (ECB) has access to transaction data when at least one of the following conditions holds: at least one counterparty is located in the euro area (EA), the reference entity of the derivative contract is in the EA, or the reference obligation is sovereign debt from a EA country. The EMIR data are pre-processed using the ECB's data cleaning procedure [28] and the sector

[4] NBFIs comprise a range of entities, including but not limited to, investment funds, insurance companies, and pension funds.

[5] Regulation (EU) No 648/2012 of the European Parliament and of the Council of 4 July 2012 on OTC derivatives, central counterparties and trade repositories. OTC derivatives are subject to the clearing obligation when they meet specific criteria, including certain thresholds for notional amounts and types of derivatives.

classification enrichment [29]. In addition, data deduplication is performed during pre-processing to address issues of double reporting at the counterparty level.

EMIR data are reported at trade level and include information on the counterparties involved, the type of derivative instruments, the underlying assets, and whether the transactions are centrally cleared or not. In the centrally cleared markets, transactions are processed through a central clearing counterparty (CCP), which serves as an intermediary between the parties of the contract, ensuring the integrity and stability of trades. The CCP mitigates counterparty risk by requiring collateral (margin) from both parties to cover potential losses. Usually, it relies on clearing members, typically banks, that are responsible for managing their clients' margin requirements and ensuring compliance with the CCP's risk management standards. This framework is designed to enhance system resilience and reduce systemic risk. Conversely, in the non centrally cleared case, transactions are cleared bilaterally, directly between the counterparties.

Entities must post margins to open and maintain a derivative position. These margins are collected in cash and eligible assets and ensure counterparties are covered against potential losses to mitigate default risk. Under EMIR regulation, margin information is reported at the portfolio level rather than the trade level. In this context, a portfolio refers to a set of trades between two counterparties that share the same portfolio code. This implies that the margin, even when reported in each trade of the portfolio, applies once to all of them.[6] Moreover, margins must be reported as stocks, reflecting the cumulative margin payments since the starting date of the contract. There are two types of margins: *initial* and *variation* margins.

*Initial margin* (IM), as stated in [30], "is collected to cover potential changes in the value of each participant's position – the potential future exposure – over an appropriate closeout period, in the event that a participant holding the position defaults." It is divided into a "core" component, which addresses market risk, and "add-ons" intended to mitigate other risks, such as liquidity or concentration risk. Typically, initial margins can be posted in cash and non-cash collateral, with non-cash collateral comprising highly liquid assets.

*Variation margin* (VM), instead, "represents funds that are collected to extinguish current exposures resulting from changes in market prices" [30]. In derivatives markets, VM exchanges commonly involve only cash payments. VM is computed by the change in market value of the derivative position. This entails establishing a fair market price for each position, evaluating

[6] For example, assuming a portfolio has three trades and each trade reports a margin of 10, the margin of the whole portfolio is 10.

whether a position incurred a loss or gained a profit, and subsequently posting or receiving VM amounts to or from the counterparty. While VM payments typically occur at least once daily, more frequent intra-day settlements are also possible.

**Net margin flow**

To assess the liquidity preparedness of non-bank financial institutions, we compute the daily net margin flow that entities must post in cash or eligible assets. Given that margins are reported as stock, we first determine the daily net stock between posted and received margins. We assume that an entity can net the daily posted and received variation margins at the counterparty level, but not the initial margin calls, since VMs are posted in cash. The daily net stock from counterparty $i$ to $j$ is given by:

$$\text{netstock}_{ij}(t) = \text{IMpstd}_{ij}(t) + \text{VMnetstock}_{ij}(t) \tag{1}$$

where $\text{IMpstd}_{ij}(t)$ is the stock of posted initial margin and $\text{VMnetstock}_{ij}(t) = \text{VMpstd}_{ij}(t) - \text{VMrcvd}_{ij}(t)$ is the net variation margin stock, i.e. the difference between the posted and received variation margin stocks from entity $i$ to $j$ at the day $t$.

To obtain the margin that an entity $i$ has to post each day to $j$, if any, we compute the daily net flow[7], i.e., the difference between the net stock position of two consecutive business days.

$$\text{netflow}_{ij}(t) = \text{netstock}_{ij}(t) - \text{netstock}_{ij}(t-1) \tag{2}$$

Then, the total flow that entity $i$ has to post during day $t$ is given by:

$$\text{Flow}_{i}(t) = \sum_{j} \text{netflow}_{ij}(t) \tag{3}$$

Furthermore, we can categorise portfolios based on their underlying asset type $\alpha \in$ [INTR, EQUI, CURR, CRDT, COMM, MIXT], i.e. interest rate, equity, currency, credit, commodity, and mixed assets, and whether they are centrally cleared, $\gamma \in [CC, NCC]$. i.e., centrally cleared portfolio or not. Our focus is on pure portfolios, which are composed exclusively of derivative

[7]Net margin flows may, by design, experience distortions around contract closure, when the stock of related variation margin posted is reset to zero, without a corresponding exchange of cash or HQLA. [31]

trades on the same asset type $\alpha$. We thus have:

$$\begin{aligned}
\text{netstock}_{ij}^{\alpha,\gamma}(t) &= \text{IMpstd}_{ij}^{\alpha,\gamma}(t) + \text{VMnetstock}_{ij}^{\alpha,\gamma}(t) \\
\text{netflow}_{ij}^{\alpha,\gamma}(t) &= \text{netstock}_{ij}^{\alpha,\gamma}(t) - \text{netstock}_{ij}^{\alpha,\gamma}(t-1) \\
\text{Flow}_{i}^{\alpha,\gamma}(t) &= \sum_j \text{netflow}_{ij}^{\alpha,\gamma}(t)
\end{aligned} \tag{4}$$

When we do not distinguish between cleared, not cleared portfolios, we refer to net stock and flow margins as follows: $\text{netstock}_{ij}^{\alpha}(t) = \sum_\gamma \text{netstock}_{ij}^{\alpha,\gamma}(t)$, $\text{netflow}_{ij}^{\alpha}(t) = \sum_\gamma \text{netflow}_{ij}^{\alpha,\gamma}(t)$ and $\text{Flow}_{i}^{\alpha}(t) = \sum_\gamma \text{Flow}_{i}^{\alpha,\gamma}(t)$.

## 2.2 NBFIs portfolio holdings

We obtain the funds' portfolio holdings data from LSEG Lipper IM.[8] This is a commercial data provider that aggregates data from different sources, including fund companies, regulatory filings, and financial data providers. It also allows fund management firms to disclose data to ensure that their holdings and performance are fully covered. Holdings are available for individual LEIs associated with primary funds at the ISIN level and with a monthly frequency. Relevant variables include the market value of holdings, the security type, funds' attributes, such as the domicile country ($c$), the asset universe ($au$), and asset type ($at$).[9]

We merge holdings' data with securities characteristics using the ESCB Centralised Securities Database. This source includes information on individual securities, such as debt securities, equities and mutual fund shares, that are either issued by EU residents, or held and transacted by EU residents, or denominated in euros, irrespective of location of the issuer or the holder. CSDB uses commercial data providers and other existing sources to select the most reliable value for each attribute and enhance data quality, addressing possible data gaps.

We use CSDB to classify securities as HQLA.[10] HQLA holdings are classified in three levels: $Level^1$ assets include qualifying government bonds; $Level^{2A}$ and $Level^{2B}$ include less liquid assets such as qualifying covered bonds, corporate bonds, asset-backed securities, and stocks.

[8] https://www.lseg.com/en/data-analytics/financial-data/fund-data/lipper-fund-data

[9] Please note that $\alpha$ indicates the portfolio asset type reported in EMIR, while $at$ the funds' asset type reported in LSEG Lipper IM.

[10] Less than 1% of the securities (ISINs) in the portfolios of our funds during the Covid-19 period could not be classified as HQLA because the necessary data were only partially available in the CSDB.

| Code | 10 | 15 | 20 | 25 | 30 | 35 |
|---|---|---|---|---|---|---|
| Sector Name | Energy | Materials | Industrials | Consumer Discretionary | Consumer Staples | Health Care |
| **Code** | 40 | 45 | 50 | 55 | 60 | |
| **Sector Name** | Financials | Information Technology | Communication Services | Utilities | Real Estate | |

Table 1: GICS sector codes and names. Source: MSCI and Standard & Poor's (S&P).

This classification relies on security-level information such as the issuer's country of residence, the issuer's statistical classification of economic activity (NACE), instrument type, maturity, and asset securitisation type. In our analysis, we use the Global Industry Classification Standard (GICS) for industry classification, mapping NACE codes to GICS codes based on the tables in [32]. We choose this classification for its relevance to stock market categorisation, market index construction, and portfolio management. GICS, developed by Morgan Stanley Capital International and Standard & Poor's, classifies publicly traded companies by primary business activities through a four-level hierarchy that consists of 11 sectors, 25 industry groups, 74 industries, and 163 sub-industries. Table 1 provides the names and codes of the 11 GICS sectors.

The stock of HQLA owned by the fund $i$ is computed following the method and classification proposed in [27, 33]:

$$HQLA_i = cash_i + Level_i^1 + 0.85Level_i^{2A} + 0.6Level_i^{2B}. \tag{5}$$

No haircut is applied to the market value of the most liquid assets ($cash$ and $Level^1$), while haircuts of 15% and 40% are applied to $Level^{2A}$ and $Level^{2B}$ assets, respectively.

# 3 Methods

This section introduces a set of liquidity indicators and a methodological framework for identifying distressed funds, defined as those experiencing liquidity stress triggered by high and unexpected derivative margin calls. The proposed indicators quantify margin call exposures relative to HQLA and cash buffers. Our framework identifies distressed funds, analyses when the occurrence of such funds is statistically significant, and examines potential differences in HQLA selling behaviour between distressed and non-distressed funds. Finally, the framework evaluates the potential transmission of liquidity risk from distressed funds to their counterparties, primarily banks.

### 3.1 Liquidity Indicators

We propose a set of liquidity indicators. The first one ($Liq_i$) is defined as the ratio between the fund $i$ daily net flow and its liquidity buffer, defined as its $HQLA$ holdings:

$$Liq_i^{\alpha}(t) = \frac{\text{Flow}_i^{\alpha}(t)}{HQLA_i(t)} \tag{6}$$

where $\alpha$ denotes a portfolio's asset class. The numerator has a daily frequency, while the denominator has a monthly one. Therefore, the ratio is computed by comparing the daily margin flows within a given month to the $HQLA$ at the end of the preceding month.

As variation margins can only be posted in cash, the first indicator $Liq_i^{\alpha}(t)$ assumes that high-quality liquid assets can be converted to cash, accounting for possible haircuts but not for other liquidation costs. But what if the liquidation is too costly? Is the cash buffer adequate? We thus focus on variation margin calls and propose a second indicator, computed as the ratio between daily net variation margin flows and cash buffer, similarly to what was done in [31]:

$$\text{VMLiq}_i^{\alpha}(t) = \frac{\text{VMFlow}_i^{\alpha}(t)}{cash_i(t)} \tag{7}$$

where $\text{VMFlow}_i(t) = \sum_j \text{VMnetflow}_{ij}(t) = \sum_j \text{VMnetstock}_{ij}(t) - \text{VMnetstock}_{ij}(t-1)$.

### 3.2 Detection of funds subject to liquidity stress

From the perspective of a fund's liquidity risk, it is crucial not only to assess whether the daily margin to be posted is high relative to the liquidity buffer provided by its high-quality liquid assets or cash holdings, but also to determine whether these margins to be posted are unexpected. A fund $i$ is considered to have an outflow on a given day $t$ if it is required to post some margin, i.e., when the daily net flow is positive. We then restrict our analysis to such outflows by defining $\text{Flow}_i^{\alpha}(t)^+ = max(\text{Flow}_i^{\alpha}(t), 0)$, and introduce the corresponding liquidity indicator as $\text{Liq}_i^{\alpha}(t)^+ = \frac{\text{Flow}_i^{\alpha}(t)^+}{HQLA_i(t)}$.

We consider a fund $i$ on a certain day $t$ to be subject to liquidity stress (and refer to such a fund as distressed) if it experiences an extraordinary margin call compared to its past distribution over the previous month. Within our framework, distressed funds are those that are unprepared for the derivative margin calls they face. The z-score[11] $z(X) = \frac{X - mean(X)}{std(X)}$ is a useful metric for outlier detection because it standardizes the data, making it easier to identify values that deviate significantly from past data. This metric extends our framework for assessing liquidity preparedness beyond the "raw" ratios of equations (6) and (7), which capture the realised liquidity pressure on a given day. By standardising these ratios relative to their past distributions, the resulting z-scores enable the identification of extreme values or stress episodes in a manner that is inherently expectation-based and forward-looking. We consider the fund $i$ to be distressed at time $t$ when the z-score exceeds two; $z(Liq_i^{\alpha}(t)^+) > 2$. We also investigate the z-score of $VMLiq_i^{\alpha}(t)^+$ to detect unexpected variation margin calls concerning cash reserves. To account for potential deviations from the Gaussian distribution, we apply the bootstrap method to resample the time series of the proposed indicators while removing temporal dependencies. This approach generates a benchmark distribution for the fraction of funds experiencing liquidity stress, against which the observed fraction can be compared to assess the statistical significance of deviations.

We then investigate the distribution of distressed funds across asset classes and countries to statistically identify the most affected by extreme margin calls. Specifically, we use the hypergeometric test to assess whether the observed number of funds in a specific category, such as a particular asset class or country, significantly deviates from what would be expected by chance, given the overall sample distribution. This approach helps to account for sample heterogeneity by comparing observed and expected frequencies, ensuring that any identified patterns are not simply the result of an unbalanced sample. As we test multiple hypotheses, one for each country and asset class, we apply a false discovery rate (FDR) correction. This ensures the reliability of the results by accounting for the increased risk of false positives arising from testing many hypotheses simultaneously.

### 3.3 Top Sold HQLA-country-sector group

Once distressed funds are identified, we analyse potential differences in HQLA selling behaviour compared to non-distressed funds. We first group HQLA by their level ($Level^1$, $Level^{2A}$, $Level^{2B}$), their issuer's country group, and their GICS industry sector for equities. GICS sectors

[11] We compute the z-score using the mean and standard deviation calculated at the fund level over a time window of the previous month. Using the mean and standard deviation of past data ensures that the z-score is not influenced by the outlier itself, provides a clear baseline for comparison, and enables real-time, consistent, and unbiased anomaly detection.

are reported in Table 1 while country groups are in Table 2. To clarify the HQLA-country-sector group notation, we provide two examples: "2B-NAM-35" refers to $Level^{2B}$ HQLA, whose issuer is in North America and industry sector is Health Care, while "1-EAC" refers to $Level^{1}$ HQLA, whose issuer is in the Euro Area Core.[12] We aggregate HQLA-country-sector group holdings at

| Euro Area Core | Euro Area Periphery | Europe Not Euro Area | International Entities | Africa | Asia | North America | Oceania | South America |
|---|---|---|---|---|---|---|---|---|
| EAC | EAP | NEA | XX | AFR | ASI | NAM | OCE | SAM |

Table 2: Country group names and their acronyms based on geographic locations. See the Table A2 in the Appendix for more details on the relative country codes.

the fund level obtaining $\text{mktvalue}_g^i(t)$ and $\text{shares}_g^i(t)$, i.e. market values and number of shares of HQLA-country-sector group $g$, held by the fund $i$ during the considered month $t$.

Our goal is to analyse the top sold HQLA-country-sector groups to detect potential concentrations in entities' selling behaviours, which could trigger fire sales and exacerbate liquidity issues. Since the portfolio holdings data are reported monthly, we consider funds classified as distressed at the monthly level. Starting with funds labelled as distressed on a given day $t$, we then aggregate the data to the monthly level. Specifically, we consider a fund $i$ to be distressed in a given month $m$ if it is labelled as distressed on more than 10 business days within that month.[13] Accordingly, for a given month $m$, a fund $i$ can be classified as distressed $dis(i,m) = 1$ or not $dis(i,m) = 0$. We then analysed distressed funds separately from those that are not distressed to determine whether the selling behaviour of funds under liquidity stress differs from that of other funds.

First, we select the HQLA-country-sector groups $g$ with a negative variation in the number of shares, i.e. $\Delta s_g^d(m) < 0$,

$$\Delta s_g^d(m) = \left[ \sum_{i|dis(i,m)=d} \text{shares}_g^i(m) - \text{shares}_g^i(m-1) \right] \tag{8}$$

where $d = 1$ ($d = 0$) indicates funds classified as distressed (not). We then compute the monthly variation in the market value holdings $\Delta mktv_g^d(m)$ in the HQLA-country-sector group $g$ at month

[12]The Euro Area core (EAC) includes Germany, France, the Netherlands, Belgium, Luxembourg, Austria, and Finland, while the Euro Area periphery (EAP) consists of Spain, Italy, Ireland, Slovenia, Slovakia, Greece, Portugal, Cyprus, Malta, Estonia, Latvia, Lithuania, and Croatia (as of 2023).

[13]An exception is made for the first month in the time series of each considered case study. Due to the rolling window, there are fewer data points, so the threshold is adjusted to more than 3 business days.

$m$, but only if the variation of the number of shares is negative. Finally, we sort the values in ascending order to identify the top sold HQLA-country-sector groups.

We define the fraction of market value holdings in the HQLA-country-sector group $g$ that is held at the end of month $m-1$ by funds in the state $d$ (distressed or not) at month $m$, similarly to the portfolio weight, as follows:

$$M_g^d(m-1) = \frac{\sum_{i|dis(i,m)=d} \mathrm{mktv}_g^i(m-1)}{\sum_g \sum_{i|dis(i,m)=d} \mathrm{mktv}_g^i(m-1)} \tag{9}$$

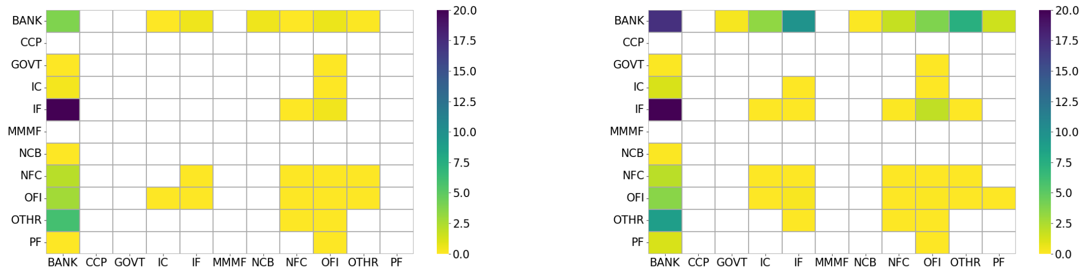
### 3.4 Propagation of liquidity risk to banks and other counterparties

The derivative market can be modelled as a complex network where the nodes represent various entities, such as banks, CCPs, and NBFIs, involved in trading derivatives, and the links denote their connections within the market. Specifically, we can represent the daily net flow $\mathrm{netflow}_{ij}^{\alpha,\gamma}(t)$ as a network, where the links between nodes correspond to the net posted margin flows from one entity to another. To obtain a broader understanding of the daily net flow structure, we group entities by sector and calculate the average across the daily values. As a representative case, we illustrate here only the Covid-19 period. We distinguish between initial and variation margins, as well as between centrally cleared markets and bilaterally cleared ones. The results in Figure 1 show that Investment Funds (IFs) primarily trade with banks.[14] Limited trading activity among IFs is observed, with the few connections that exist being negligible in terms of volume compared to their interactions with other sectors, and these connections are only observed in non-centrally cleared variation margins. All funds that report both in EMIR and LSEG Lipper IM data are classified as IFs [29].

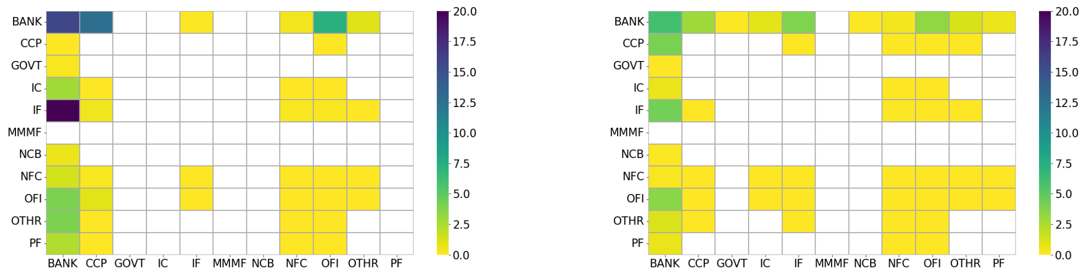
In network terminology, a network is bipartite when the entities (or nodes) can be divided into two distinct groups, and connections only exist between nodes in different groups, not within the same group. So, from the IFs' perspective, if we divide the entities into two groups, IFs and all other sectors, we can say that the IFs' network is approximately bipartite, with most of their interactions occurring with entities in the other group, and few connections among IFs themselves.

Using the methodology described above, a fund $i$ is classified as distressed on day $t$ if it experiences an unexpected outflow. If unprepared, the fund may face liquidity shortages, posing

[14]The coefficient of variation of the daily posted margin for equity pure portfolios is in Figure A1 of the Appendix.




(a) $IMpstd^{EQUI,NCC}$ (b) $VMpstd^{EQUI,NCC}$




(c) $IMpstd^{EQUI,CC}$ (d) $VMpstd^{EQUI,CC}$

Figure 1: Average daily posted margin (stock, mln €) for equity pure portfolios from January to April 2020. Source: EMIR data; ECB and own calculations.

significant risks to its counterparties, primarily banks, as will be discussed in Section 4. The potential inadequacy of distressed funds' liquidity buffer could propagate liquidity stress to counterparties, thereby triggering a systemic crisis across the financial system. An entity $j$ is subject to an outflow to its counterparty $i$, when the posted margin is higher than the received margin so $netflow_{ji}^{\alpha}(t)^{+} = max(netflow_{ji}^{\alpha}(t), 0)$. From the perspective of the counterparty $i$, inflows from distressed funds ($j \in \mathcal{D}$) pose a risk, as funds have to post cash or HQLA to it. To assess the exposure of bank $i$ to distressed funds, we compute the ratio:

$$Exp_i^{\alpha}(t) = \frac{\sum_{j \in \mathcal{D}} netflow_{ji}^{\alpha}(t)^{+}}{\sum_j netflow_{ji}^{\alpha}(t)^{+}}. \tag{10}$$

The higher the exposure, the greater the associated liquidity risk for the counterparties.

## 4 Results

In the final report [8], the FSB recommends "the scenario design for margin and collateral calls during normal market conditions, as well as in extreme but plausible stressed market conditions."

We therefore apply our liquidity framework to two case studies: the Covid-19 pandemic and the monetary policy tightening in 2022–2023. The Covid-19 pandemic serves as a recent example of an extreme yet plausible spike in margin calls, whereas the monetary policy tightening conditions, prompted by central bank rate hikes in response to inflationary pressures, represent a more gradual and expected shift in market conditions driven by monetary policy adjustments.

In the Covid-19 case, we focus on equity pure portfolios, as the most significant margin calls in the entire derivatives market are observed within these portfolios, as we will also show in this section. In the other case study, we consider derivatives covering all the assets, including interest rates, equities, currencies, credits, and commodities.

## 4.1 Covid-19 Pandemic

The Covid-19 market turmoil significantly impacted the derivatives market, as the increased volatility in financial markets led to a sharp increase in margin calls. During the week ending on 28 February 2020, equity markets in many countries recorded the greatest single-week decline since the Global Financial Crisis [30]. The global economic uncertainty caused severe fluctuations in asset prices, which in turn led to increased margin calls. Consequently, investors experienced strong liquidity pressure to provide additional collateral to cover potential losses.

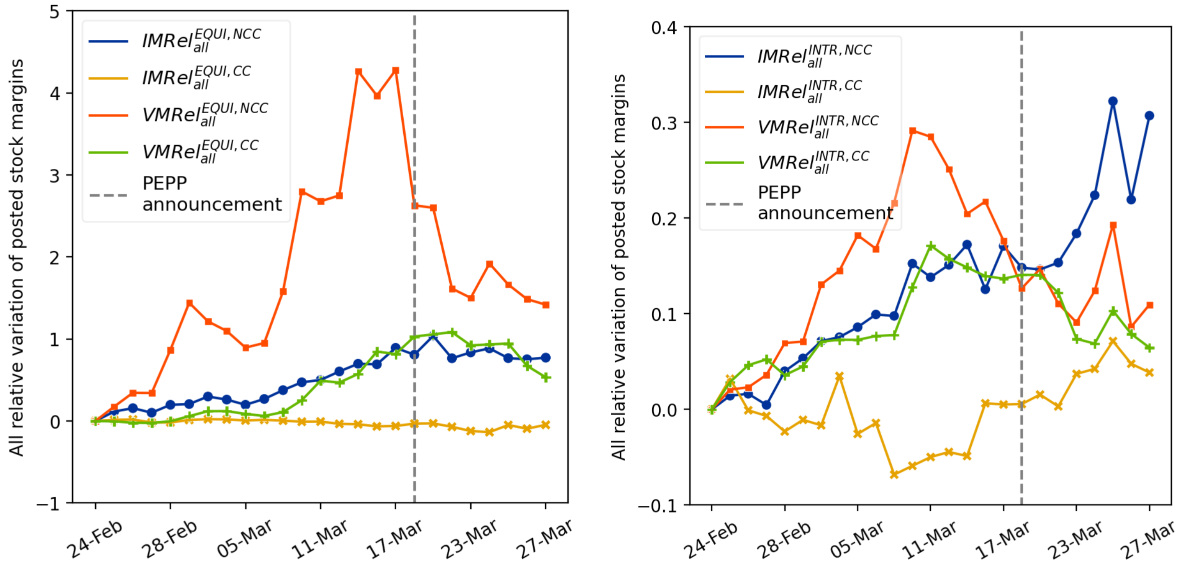
As a starting point, we focus on the pivotal five weeks of the COVID-19 pandemic (24 Feb - 27 Mar 2020). Figure 2 illustrates the relative variation of posted stock margins, defined as follows:

$$\mathrm{IMRel}_{all}^{\alpha,\gamma}(t) = \frac{\sum_{i,j}\left(\mathrm{IMpstd}_{ij}^{\alpha,\gamma}(t) - \mathrm{IMpstd}_{ij}^{\alpha,\gamma}(t_0)\right)}{\sum_{i,j}\mathrm{IMpstd}_{ij}^{\alpha,\gamma}(t_0)} \tag{11}$$

$$\mathrm{VMRel}_{all}^{\alpha,\gamma}(t) = \frac{\sum_{i,j}\left(\mathrm{VMpstd}_{ij}^{\alpha,\gamma}(t) - \mathrm{VMpstd}_{ij}^{\alpha,\gamma}(t_0)\right)}{\sum_{i,j}\mathrm{VMpstd}_{ij}^{\alpha,\gamma}(t_0)} \tag{12}$$

where $t_0$ is February 24th.

We report only the cases of equity and interest rate pure portfolios, as these asset classes were the most impacted by spikes in margin calls during the considered period. The largest spikes of the relative change are observed in the case of variation margin calls in the non-centrally cleared markets. In the case of equity pure portfolios, the stock of posted margins increased by roughly 4 times on March 17. The subsequent drop follows the ECB announcement of the € 750 billion




(a) Equity pure portfolios

(b) Interest rate pure portfolios

Figure 2: Relative change of posted margin stock in the case of equity (panel a) and interest rate (panel b) pure portfolios. The colours represent different types of margins, initial or variation, and whether they are centrally cleared. (24 Feb - 27 Mar 2020). The sample is composed of 20455 entities in the equity case, and of 10552 in the interest one. Source: EMIR data; ECB and own calculations.

Pandemic Emergency Purchase Programme on March 18.[15] Since PEPP was announced late in the evening, it was incorporated into market prices only on 19 March 2020. This unconventional measure aimed at stabilising financial markets and supporting the economy by purchasing various securities. For interest rate pure portfolios, we observe an increase in the relative variation of posted stock margins, though it is less pronounced, staying below 0.3 for both centrally cleared and non-centrally cleared trades. Finally, for interest rate pure portfolios, we observe a decreasing trend in variation margin and an increasing trend in initial margin for non-centrally cleared trades following the PEPP announcement.

### 4.1.1 Liquidity dynamics

When merging the information on liquid assets from LSEG Lipper IM to the derivatives data in EMIR, we consider only funds with non-zero daily net flows for over 10 business days from January to April 2020. We collect their monthly (end-of-month) holdings from December to March 2020, and we filter out monthly observations where the cash buffer is smaller than 1000€ to

[15] https://www.ecb.europa.eu/mopo/implement/pepp/html/index.en.html

avoid missing data and reporting errors. Also, we consider only those LEIs whose cash and HQLA holdings data are available for all the months under consideration to ensure a balanced sample across the months. We then proceed to detect and remove outliers by computing the relative variation of HQLA holdings between two consecutive months and filtering out those whose values are under 0.5 and above 99.5 percentile. This choice also ensures that LEIs' monthly relative variation of HQLA cannot be higher than four times, in absolute value.

The sample, denoted by $\mathcal{IF}$, consists of 839 funds. Table 3 reports the number of funds for each euro-area country and shows that most of them are domiciled in Luxembourg, Ireland, France, and Germany. Mutual Funds and Exchange Traded Funds (ETFs) make up the vast majority of the sample, as shown in Table 4, while the asset type $at$ consists mainly of equity, bond, and mixed assets (see Table 5). The classification of funds' asset types $at$, as reported in Lipper, is based on the primary securities they invest in, helping to categorise funds according to their investment strategy.

| | AT | BE | DE | FI | FR | IE | IT | LU | NL | PT | Total |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Covid-19 | 4 | 5 | 51 | 0 | 104 | 288 | 15 | 353 | 3 | 16 | 839 |
| 2022-2023 | 15 | 1 | 76 | 7 | 21 | 297 | 59 | 890 | 22 | 0 | 1388 |

Table 3: Funds' country $c$. Source: LSEG Lipper IM

| | Exchange Traded Funds | Hedge Funds | Mutual Funds | Total |
|---|---|---|---|---|
| Covid-19 | 275 | 1 | 563 | 839 |
| 2022-2023 | 228 | 3 | 1157 | 1388 |

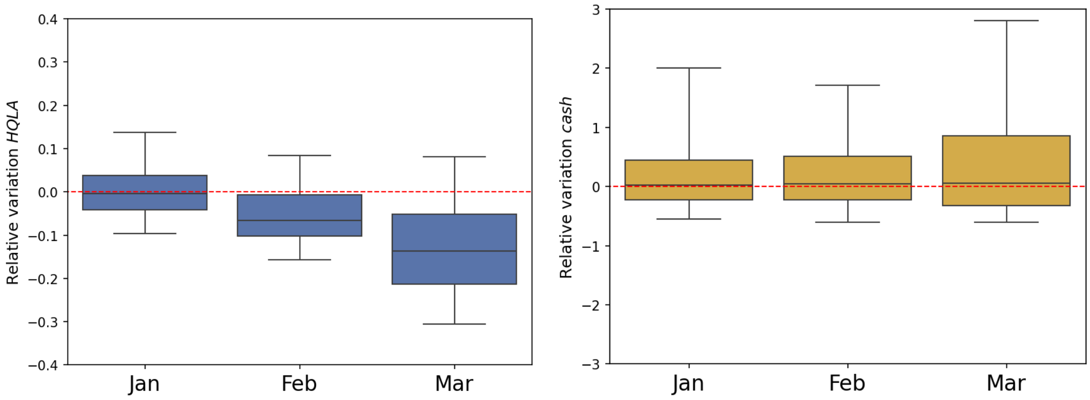
Table 4: Funds' asset universe $au$. Source: LSEG Lipper IM

| | Alternatives | Bond | Commodity | Equity | Mixed Assets | Money Market | Other | Total |
|---|---|---|---|---|---|---|---|---|
| Covid-19 | 56 | 68 | 0 | 548 | 167 | 0 | 0 | 839 |
| 2022-2023 | 56 | 518 | 8 | 575 | 228 | 2 | 1 | 1388 |

Table 5: Funds' asset type $at$. Source: LSEG Lipper IM

Figure 3 reports the boxplot of the distribution of the relative monthly variation of $HQLA$ and $cash$ in the considered period (end-of Dec 2019-Mar 2020). The relative variation of $HQLA$, in Figure 3a, shows a decreasing trend and increased heterogeneity across funds.[16] At the end

[16]The aggregate distribution of $HQLA$ and $cash$ is reported in the Appendix, see Figure A2.




(a) Relative variation of $HQLA$ (b) Relative variation of $cash$

Figure 3: Distribution of $HQLA$ and $cash$ relative variation for entities involved in equity pure derivatives portfolios, end-of-month data from December 2019 to March 2020. Whiskers represent the 10th and 90th percentiles. The number of funds is 839. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

of January, half of the funds in the sample showed a decrease in $HQLA$ compared to the end of December, while by the end of March, this proportion had increased to three-quarters. This result indicates that a large fraction of funds experienced a severe decline in the amount of available HQLA, possibly in response to margin requirements. A different trend is observed in the case of the relative variation of $cash$, see Figure 3b. The median remains close to zero, but an increasing trend and heterogeneity across funds are also observed.

Figure 4 reports the daily cumulative stock $CumNetStock^{EQUI}(t) = \sum_{i\in\mathcal{IF}} \sum_j netstock_{ij}^{EQUI}(t)$ (in blue) and the fraction of the daily cumulative stock due to variation margins, given by $VMPortNetStock(t) = \frac{\sum_{i\in IF} \sum_j VMnetstock_{ij}^{EQUI}(t)}{CumNetStock^{EQUI}(t)}$, (in yellow). For comparison, the orange line shows the Euro STOXX 50 Volatility Index (VSTOXX50).[17] We observe a sharp increase in the daily cumulative stock trend beginning in mid-February, followed by a week of fluctuation after the PEPP announcement on March 18, and then a sharp decline. The daily cumulative stock volumes return to their January levels only by the end of April. Similarly, the fraction of daily net stock represented by variation margins (in yellow) follows this trend, increasing from 5-10% before the pandemic to almost 40% at the peak. The main difference with the daily cumulative stock volume is during the period from March 12 to 17, when the cumulative stock continues to grow or remains stable despite a decrease in the portion attributed to variation

[17]VSTOXX50 represents the implied volatility of options on the Euro STOXX 50 Index, which includes 50 major Eurozone stocks. It reflects market expectations of near-term volatility: higher VSTOXX50 values indicate greater market uncertainty, while lower values suggest stability.

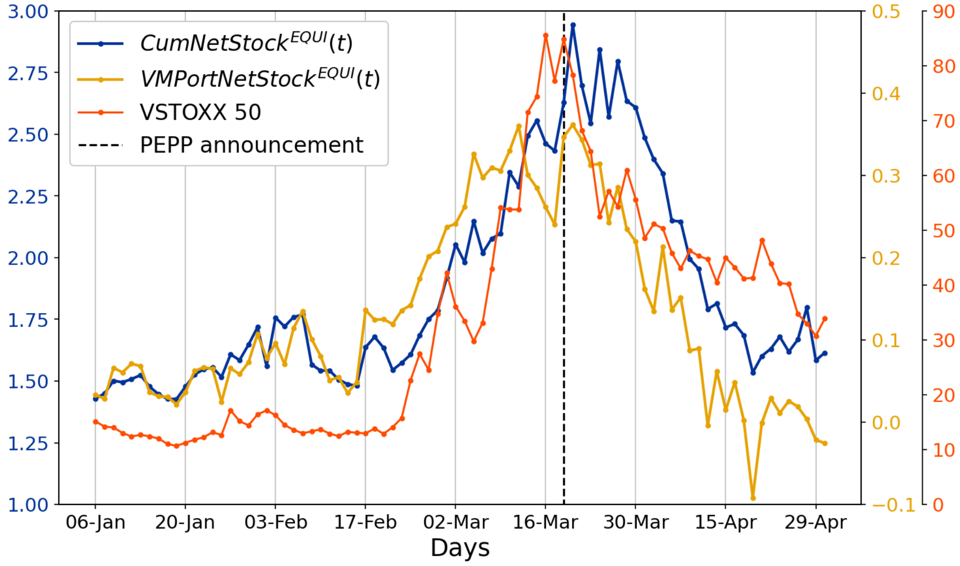



Figure 4: Daily cumulative stock (bln €), the fraction of daily cumulative stock given by variation margins, Euro STOXX 50 Volatility Index. Equity pure portfolios of the considered sample of funds, Jan-Apr 2020. Source: LSEG Lipper IM, EMIR, and own calculations.

margins. This can be explained by the fact that variation margins react quickly to high volatility, leading to a sharp initial increase as market fluctuations intensified in early March. However, as volatility remained elevated, initial margins were also adjusted upward to account for sustained risk, causing total margin requirements to rise. As a result, while cumulative stock continued to grow, the relative contribution of variation margins declined, reflecting the shift toward higher initial margins during this period. The VSTOXX50 shows a similar overall pattern, anticipating by a short lag the cumulative stock and the fraction due to VM. This is in line with the idea that higher volatility requires funds to post more collateral and therefore higher margins. However, the relationship between daily cumulative stock and volatility is not uniform over time, as there are periods where margins continue to rise even without a corresponding increase in volatility, such as in early March, or where margins remain stable despite decreasing volatility, as observed after the PEPP announcement.

From a liquidity perspective, these results indicate that funds not only had to cope with sharp increases in margin calls, but also that most of these calls needed to be covered in cash, as they were variation margins. If buffers were inadequate, funds had to liquidate assets, contributing to a downward spiral of asset price depreciation and rising haircuts. Recent results in [31] highlight the risk that investment funds may lack sufficient cash to cover margin calls. This underscores the importance of funds having diverse and reliable sources of liquidity and collateral.

### 4.1.2 Detection of funds subject to liquidity stress

We now apply the methodology outlined in Section 3.2, which relies on the liquidity metrics from Eq. (6) and (7), to identify funds that experienced liquidity stress. Figure 5 reports the fraction of funds classified as distressed according to the two metrics. Specifically, the blue line in the top panel is the fraction of distressed funds according to the ratio between outflows and HQLA, i.e. $z(Liq_i^{EQUI}(t)^+) > 2$. We notice that almost a quarter of the funds were subject to liquidity stress. Before March 17th, the trend of the fraction mirrors the VSTOXX50 index. After, additional peaks appear in the curve of the fraction of distressed funds that are not seen in the cumulative flow. This occurs because, despite the decreasing volatility, some funds still face high and unexpected margin calls relative to their typical values. The bottom panel shows in yellow the fraction of distressed funds according to the ratio between variation margin outflows and the cash buffer, i.e., $z(VMLiq_i^{EQUI}(t)^+) > 2$. We observe an even higher magnitude of peaks, up to 40% of funds are distressed, and a larger number of peaks. The differences between the curves in Figure 5 highlight the importance of HQLA and its orderly conversion to cash.

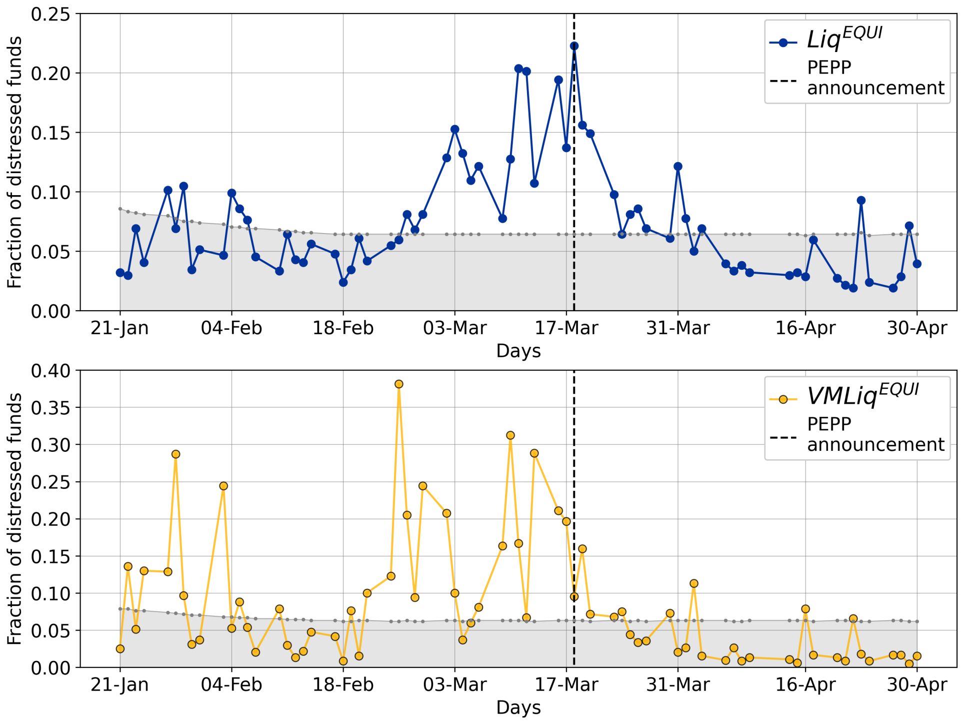


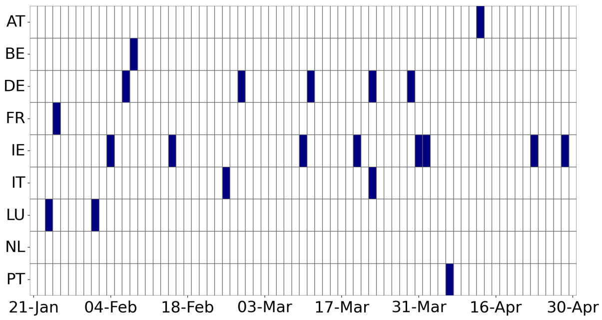

Figure 5: Fraction of distressed funds ($z > 2$): liquidity indicator shown in blue and VM-liquidity indicators in yellow. Equity Pure Portfolio, Jan-Apr 2020. The grey area represents the threshold determined by the bootstrap method, serving as a benchmark to assess statistically significant deviations. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

We now study which funds are more likely to be distressed, both according to their country $c$ and to the asset type $at$. Since the sample is unbalanced for these two characteristics (see Tables 3 and 5), we perform the hypergeometric test[18], which is particularly useful when the sample is not evenly distributed across categories. This test evaluates the probability of observing a specific number of distressed funds in a particular category (such as a given country or asset type) while accounting for the fact that all categories are not equally represented in the sample. In our case, the test compares the observed number of distressed funds in a category with the expected number, based on the overall proportion of funds from that category in the entire set of funds under investigation. Using this test, we can determine whether the number of distressed funds in a given category is significantly higher or lower than it would be expected by chance, given the unbalanced distribution of funds across different countries and asset types. This allows us to make more robust inferences about which categories are more likely to have distressed funds, despite the uneven sample composition. Figure 6 presents the test results. The test helps to detect that Luxembourg, the most represented country in the sample, is robust from a liquidity perspective, as it is not over-represented among the distressed funds during the Covid-related period. In contrast, Ireland, the second most represented country in the sample, shows a notable over-representation among the distressed funds. We also note an over-representation of funds whose asset type $at$ is Equity. This is expected, as we are considering only equity pure portfolios, and the margins related to these portfolios exhibit the largest relative variation during the Covid-19 period, as shown in Figure 2.

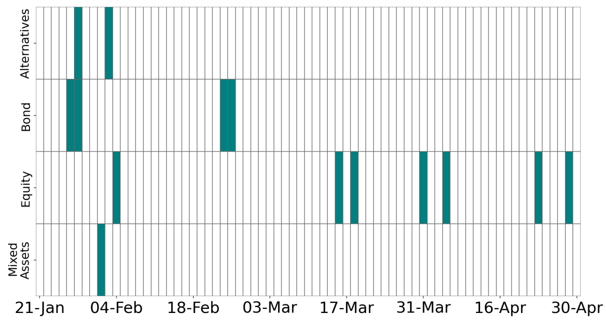
#### 4.1.3 Top Sold HQLA-country-sector groups

After classifying funds as distressed or non-distressed, we investigate which HQLA-country-sector groups experienced the most intense selling activity. We focus only on HQLA-country-sector groups that experienced negative monthly variations in both the number of shares and the market value $\Delta s^d_g(m) < 0$, $\Delta mktv^d_g(m) < 0$ in each month $m$. We analyse distressed and non-distressed funds separately as two groups to determine whether their strategies are proportional to each group's portfolio composition and whether these selling strategies differ. To assess the former, we compute the standard deviation of the ratio of the HQLA-country-sector group $g$'s fraction of market value in month $m$ to its fraction at the end of month $m-1$. This ratio indicates

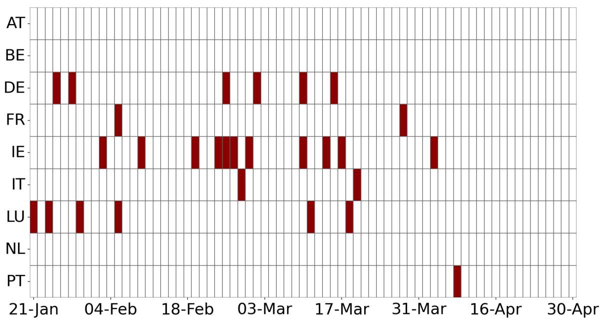
[18] We do not test features represented in the sample by fewer than three funds to prevent the risk of indirect identification and ensure compliance with confidentiality.



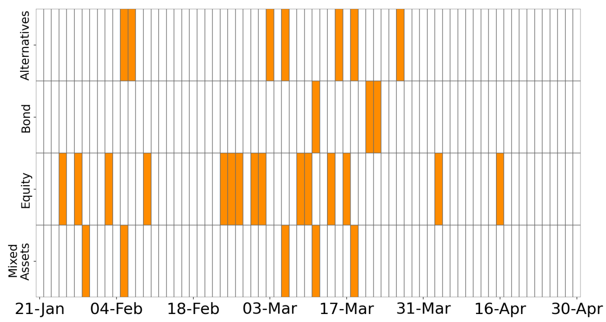

(a) Country $c$, $z(Liq_i^{EQUI}(t)^+) > 2$




(b) Asset type $at$, $z(Liq_i^{EQUI}(t)^+) > 2$




(c) Country $c$, $z(VMLiq_i^{EQUI}(t)^+) > 2$




(d) Asset type $at$, $z(VMLiq_i^{EQUI}(t)^+) > 2$

Figure 6: Hypergeometric test on country $c$ and asset type $at$ representation of distressed funds, equity pure portfolios, Jan-Apr 2020. A coloured rectangle indicates that a certain group on a specific day is overrepresented, confidence interval of 95%. Additionally, the false discovery rate (Benjamini-Hochberg procedure [34]) is applied to correct for multiple testing to ensure the robustness of our findings. Source: LSEG Lipper IM, CSDB, EMIR and own calculations.

the relative variation in the fraction of the market value of a particular HQLA-country-sector group from one month to the previous. If selling strategies are proportional to the portfolio composition, the ratio of the fraction of market value should be the same for all the asset groups $g$, thus its standard deviation should be zero. In contrast, a high standard deviation indicates that the selling strategy deviates from the proportional liquidation hypothesis, suggesting a selective choice of sold assets. Figure 7 reports the standard deviation of the ratio of the fraction of market value of the HQLA-country-sector group for distressed and non-distressed funds' groups separately. We observe that, in all months, the standard deviations are higher for the distressed funds' group, indicating that its selling strategies are less proportional to its portfolio composition compared to the non-distressed funds' group. We now continue our analysis by exploring which HQLA-country-sector groups are sold the most and whether these differ between distressed and non-distressed funds. Figure 8 shows the five top most sold HQLA-country-sector groups $\forall m$, $d = 0, 1$, obtained by sorting them in descending order based on $\Delta mktv_g^d(m)$, i.e.

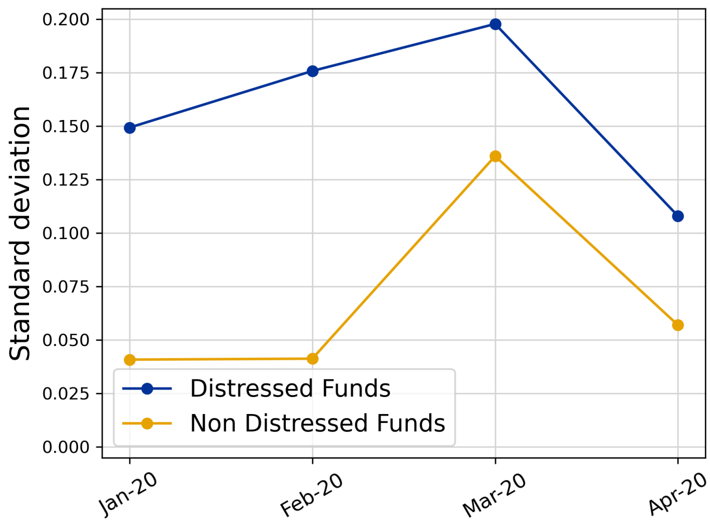



Figure 7: The standard deviation of the ratio of the HQLA-country-sector group $g$'s fraction of market value in month $m$ to its fraction at the end of month $m-1$, restricted to groups that exhibit negative monthly changes in both the number of shares and market value i.e., $\Delta s_g^d(m) < 0$, $\Delta mktv_g^d(m) < 0$ in each month $m$. Distressed funds are in blue, and non-distressed funds are in yellow. Jan-Apr 2020. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

the monthly variation in market value. The top panel represents the distressed funds' group, while the bottom panel represents the non-distressed funds' group. Each column corresponds to a different month $m$, and the colours indicate the relative fraction of market value at the end of the previous month, i.e. the fraction of market value rescaled by its maximum value across asset groups $M_g^d(m-1)/max_g\left(M_g^d(m-1)\right)$. Thus, the value 1 indicates that the corresponding asset group was the most present in the portfolio. We examine whether there are any differences between the top sold HQLA-country-sector groups by distressed and non-distressed funds. In general, both distressed and non-distressed funds primarily sold $Level^{2B}$ assets, i.e. equities, but the selling patterns of the two groups differ in terms of country and sectors. January is the only exception, as the largest negative variation in market values for distressed funds involves $Level^{2A}$ followed by $Level^{2B}$ HQLA, whereas for non-distressed funds, it involves only $Level^{2B}$ HQLA. Colours in Figure 8 help determine whether the top sold HQLA-country-sector groups are also the most represented at the beginning of each month, giving further insights on whether selling strategies are proportional to fund groups' portfolio composition. For distressed funds, February stands out as the only month where the most liquidated HQLA-country-sector group also holds the highest relative market value in the portfolio. In contrast, January and March show a different pattern, where the most represented asset groups were not the most sold in terms of

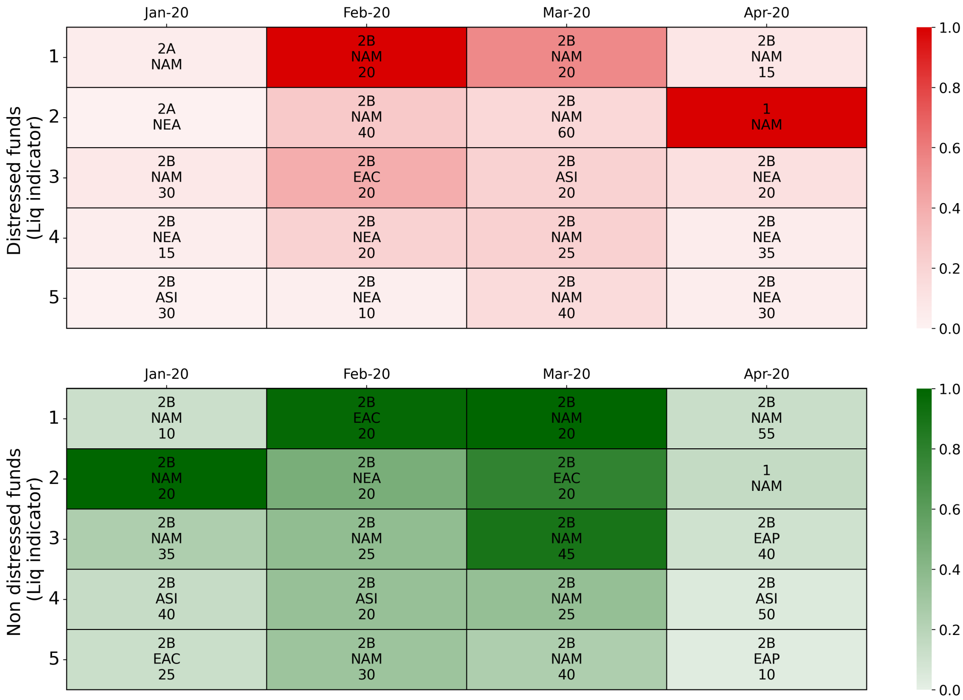
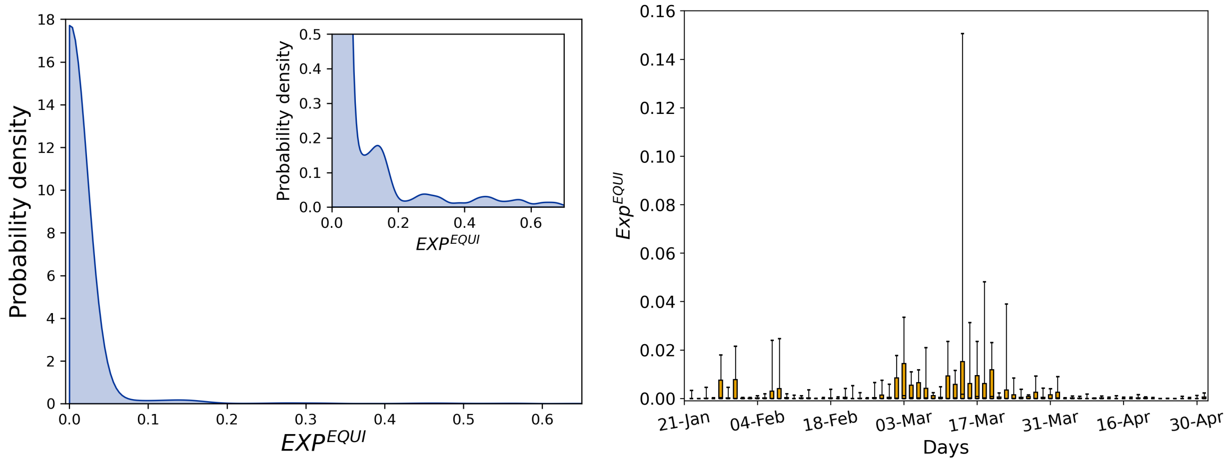



Figure 8: Top 5 most sold HQLA-country-sector groups with the largest decrease in the market value holdings $\Delta mktv_g^d(m)$ in a given month $m$. The top table corresponds to distressed funds, while the bottom table corresponds to non-distressed funds, based on the liquidity indicator $Liq$. Colours represent the relative fraction of market value holdings in the HQLA-country-sector group $g$ held at the end of the previous month $m-1$ by funds in state $d$ (distressed or non distressed) at month $m$. Jan-Apr 2020. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

market value. In April, the second most sold asset group had the highest portfolio representation, while the top liquidated asset group had a comparatively smaller presence. For non-distressed funds, asset sales from January to March closely aligned with portfolio composition, as the most sold assets also had a high relative market value. However, this trend shifted in April, when the five most sold asset groups had a lower presence in the portfolio. This pattern hints, on an aggregate level, at a more reactive or liquidity-driven selling behaviour of distressed funds, offloading assets in a way that does not always align with their portfolio composition. Their sales might be influenced by immediate liquidity needs rather than portfolio representation. In contrast, non-distressed funds seem to demonstrate more stable selling patterns, with liquidations more closely reflecting portfolio weights. This divergence suggests that distress influences selling priorities at an aggregate level, potentially amplifying market dislocations and liquidity stress during periods of turbulence.




(a) Kernel Density Estimation

(b) Boxplot at the daily level

Figure 9: Entities' exposure to distressed funds ($Exp_i^{EQUI}$) during the considered period (Jan–Apr 2020). In the boxplot, for confidentiality reasons, the percentiles of the distribution are calculated by averaging values across three entities, and the whiskers represent the 10th and 90th percentiles. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

#### 4.1.4 Propagation of liquidity risk to banks and other counterparties

We now identify the banks and other institutions that were more exposed to margin calls as being counterparties of distressed funds. This analysis sheds light on possible systemic risk propagation mechanisms. We consider the funds classified as distressed by using the indicator $Liq$ at least one day during the period from January to April 2020. In total, there are 48 counterparties, of which 44 are classified as banks [29]. The set of Euro Area counterparties $\mathcal{C}$ consists of 24 entities: 21 banks and 3 NBFIs. With two exceptions, these banks are either clearing members of CCPs or are part of a banking group whose parent is a CCP clearing member. In Figure 9, we report the kernel density estimation (KDE) and the boxplot of the counterparties' exposure to distressed funds $Exp_i^{EQUI}(t)$, as in Eq. 10. From the KDE plot, we can see that most of the exposure values are below 0.1, but a few observations show higher values. At the counterparty level, the exposure indicator does not show relevant exposure, except for four entities whose 75th and 90th percentiles are below 0.02 and 0.15, respectively, and one entity whose 75th percentile is close to zero but exhibits high values on a few days. The variability in exposure across days, as indicated by the large whiskers and non-negligible interquartile ranges, suggests that certain counterparties may be more vulnerable to market shocks and could experience liquidity shortages or other liquidity stresses, which could have broader implications for financial stability.

## 4.2 Monetary policy tightening 2022-2023

The 2022-2023 period of monetary policy tightening, characterised by significant interest rate increases by central banks to manage inflation, influenced global financial markets, including derivatives. These adjustments contributed to greater volatility in interest rate derivatives and currency swaps. This period was chosen as a second case study for its contrast with the Covid-19 pandemic: while the pandemic was an unforeseen shock, monetary tightening was a more predictable response to rising inflation. Both cases underscore distinct liquidity stress scenarios relevant to NBFI preparedness.

We focus on the period between July 2022 and September 2023 (Q3 2022 – Q3 2023). On July 21, 2022, the ECB raised its key interest rates for the first time in 11 years, increasing the deposit facility rate to 0% in response to rising inflation. The ECB continued tightening monetary policy until September 14, 2023, when the deposit facility rate reached its peak at 4%.

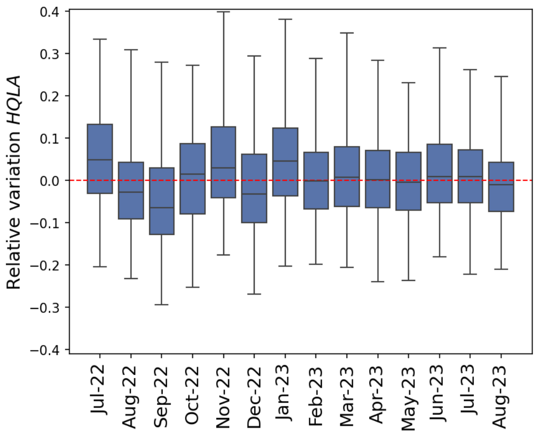
### 4.2.1 Liquidity dynamics

We first identify euro-area funds that report both in EMIR and LSEG Lipper IM data between July 2022 and September 2023, and clean the data as explained in Section 4.1.1. We keep only those entities whose cash and HQLA holdings data are available for all the considered months, and we end up with 1388 funds.[19] Figure 10 shows the distribution of the relative monthly variation of $HQLA$ and $cash$, which remained stable over the period July 2022 - Sept 2023 (See Figure A3 in Appendix).

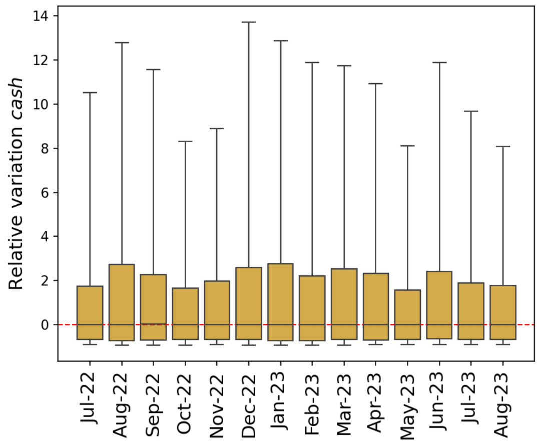
The relative variation of $HQLA$ in Figure 10a exhibits a decreasing trend in Q3 2022 and a relatively stable trend in 2023 across funds. A different trend is observed for the relative variation of $cash$; while the median remains close to zero, a strong heterogeneity across funds is observed. Table 3 reports the number of funds for each euro-area country in the monetary policy tightening 2022-2023. Most of them are domiciled in Luxembourg, Ireland, Germany, and Italy, and are Mutual or Exchange Traded Funds (Table 4). Also, the asset type $at$ consists mainly of equity, bond, and mixed assets (Table 5).

The cumulative net daily stock, variation stock, and portfolios' notional reported by investment funds are shown, respectively, in the top, centre, and bottom panels of Figure 11. Different colours correspond to distinct derivatives' asset type portfolios, with purple representing the

[19] We fill in missing monthly data only if the previous data point is available and no more than two months old.




(a) Relative variation of $HQLA$



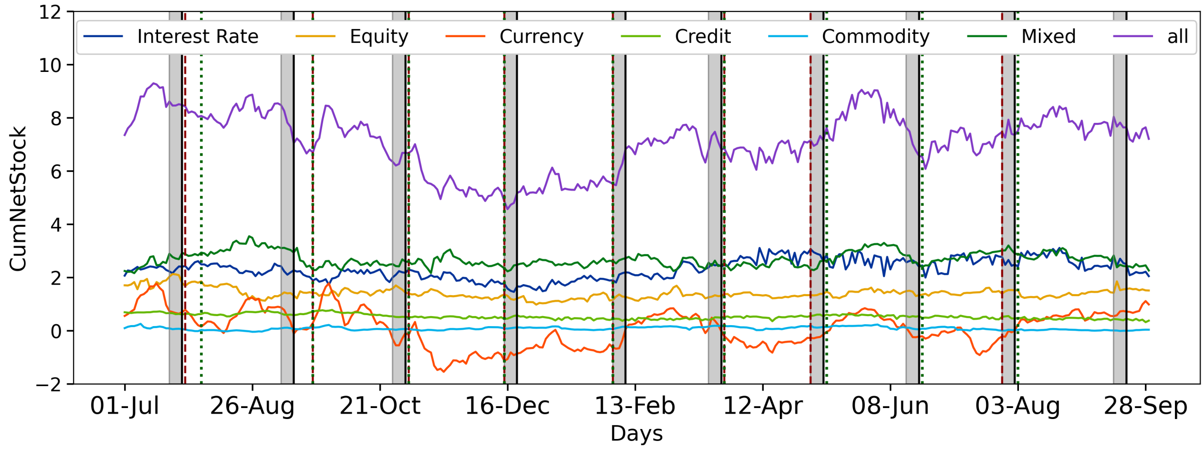

(b) Relative variation of $cash$

Figure 10: Distribution of $HQLA$ and $cash$ relative variation for entities involved in all derivatives portfolios, end-of-month data from June 2022 to August 2023. Whiskers represent the 10th and 90th percentiles. The number of funds is 1388. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

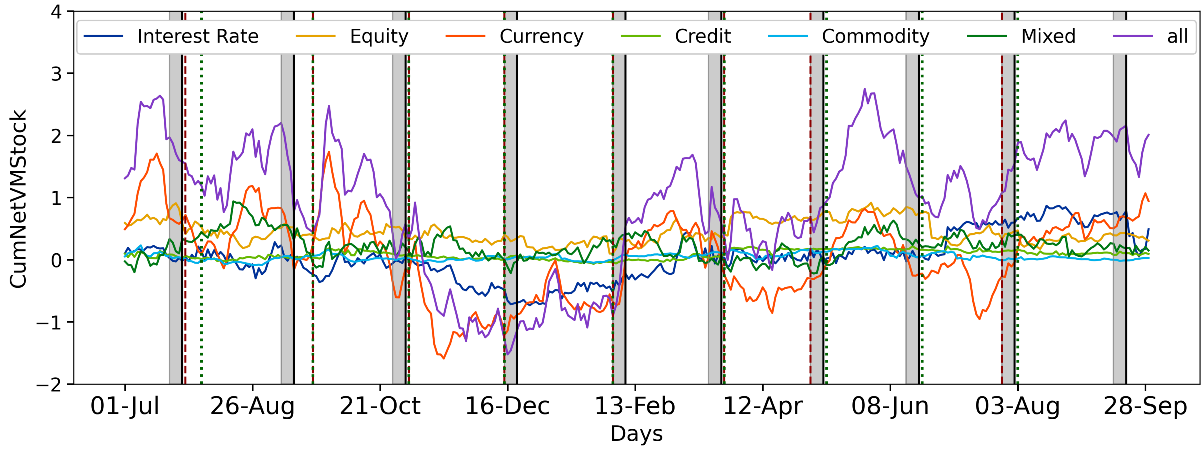
aggregate. Currency and interest rate portfolios exhibit the highest volatility in terms of margin, particularly in the variation margin case, while the notional remains relatively stable. The volatility of the currency market is influenced by fluctuations in key exchange rates between the euro and other currencies.

#### 4.2.2 Detection of funds subject to liquidity stress

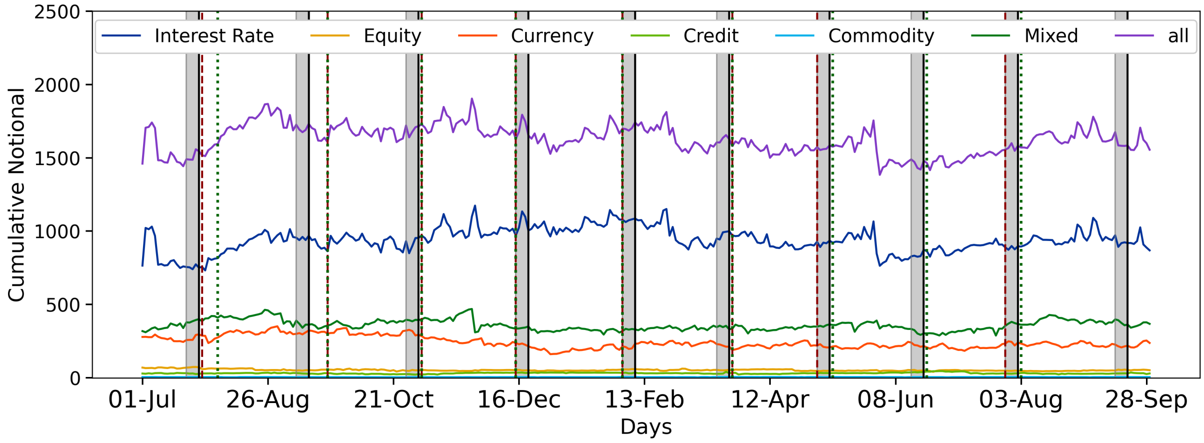
Figure 12 shows the fraction of funds classified as distressed, considering all derivative portfolios. The blue and yellow lines represent the fraction of distressed funds based on the liquidity indicators $Liq$ and $VMLiq$, defined as $z(Liq_i^{all}(t)^+) > 2$ and $z(VMLiq_i^{all}(t)^+) > 2$, respectively. Focusing on periods when the fraction of distressed funds in blue exceeds the threshold in grey, we observe different patterns across the time windows defined by the announcement and effective dates. In September 2022, there is both anticipation and delay, as well as an absence during the interest change time window. However, until December 2022, the patterns are mostly synchronised with the interest change time windows. A different pattern emerges when considering the fraction of distressed funds in yellow, which appears in significant numbers not only during the interest change time windows but also in the periods between them. We repeat the analysis focusing on interest rate pure portfolios, as they are more affected by changes in monetary policy. The fraction of funds classified as distressed in this case is shown in Figure 13. Comparing the




(a) Cumulative net daily stock $CumNetStock^{\alpha} = \sum_{i \in \mathcal{IF}} \sum_{j} \text{netstock}_{ij}^{\alpha}$




(b) Cumulative net daily variation margins stock $CumNetVMStock^{\alpha} = \sum_{i \in \mathcal{IF}} \sum_{j} \text{VMnetstock}_{ij}^{\alpha}$




(c) Cumulative notional (both initial and variation margins)

Figure 11: Aggregated stock margins (bln €), $\mathcal{IF}$ sample, Q3 2022 - Q3 2023. Different colours correspond to distinct derivatives' asset type $\alpha$ pure portfolios, with purple representing the case of all asset types. Black, green, and red vertical lines indicate the effective dates of interest rate changes by the ECB, the Federal Reserve (Fed), and the BoE, respectively. Grey areas represent the time window between the announcement and effective dates of ECB interest rate changes. Source: LSEG Lipper IM, EMIR, and own calculations.

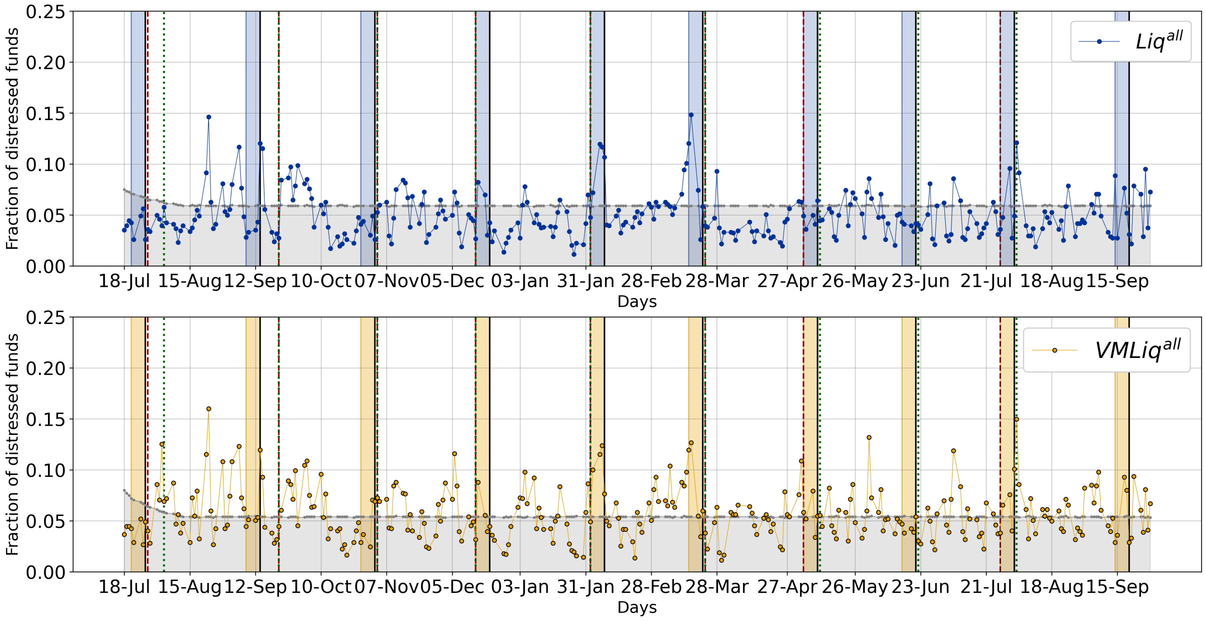



Figure 12: Fraction of distressed funds ($z > 2$): liquidity indicator shown in blue and VM-liquidity indicators in yellow. All Portfolios, July 2022 - Sept 2023. Black, green, and red vertical lines indicate the effective dates of interest rate changes by the ECB, Fed, and BoE, respectively. The light blue and yellow areas represent the time window between the announcement and effective dates of ECB interest rate changes. The grey area denotes the threshold determined by the bootstrap method, serving as a benchmark for assessing statistically significant deviations. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

blue lines in Figs. 12 and 13, we observe similar trends but higher peaks for interest rate pure portfolios. A different pattern emerges for the yellow lines, where the trends slightly deviate, yet higher peaks are also observed for interest rate pure portfolios.

We now aim to analyse how distressed funds are distributed based on funds' country $c$ and the asset type $at$, when derivatives of any asset type are considered. The sample is unbalanced for these two characteristics, as shown in Tables 3 and 5. To address and mitigate the impact of this imbalance in the data, we perform the hypergeometric test, as in the previous case study. The results are presented in Figure 14, where the observed over-representation in distressed funds is roughly the same for both the $Liq$ and $VMLiq$ indicators. The most over-represented country is Ireland, followed by Luxembourg, particularly in the case of the $VMLiq$ indicator. Concerning asset type, the over-representation is evenly distributed across Bond, Equity, and Mixed Assets categories.

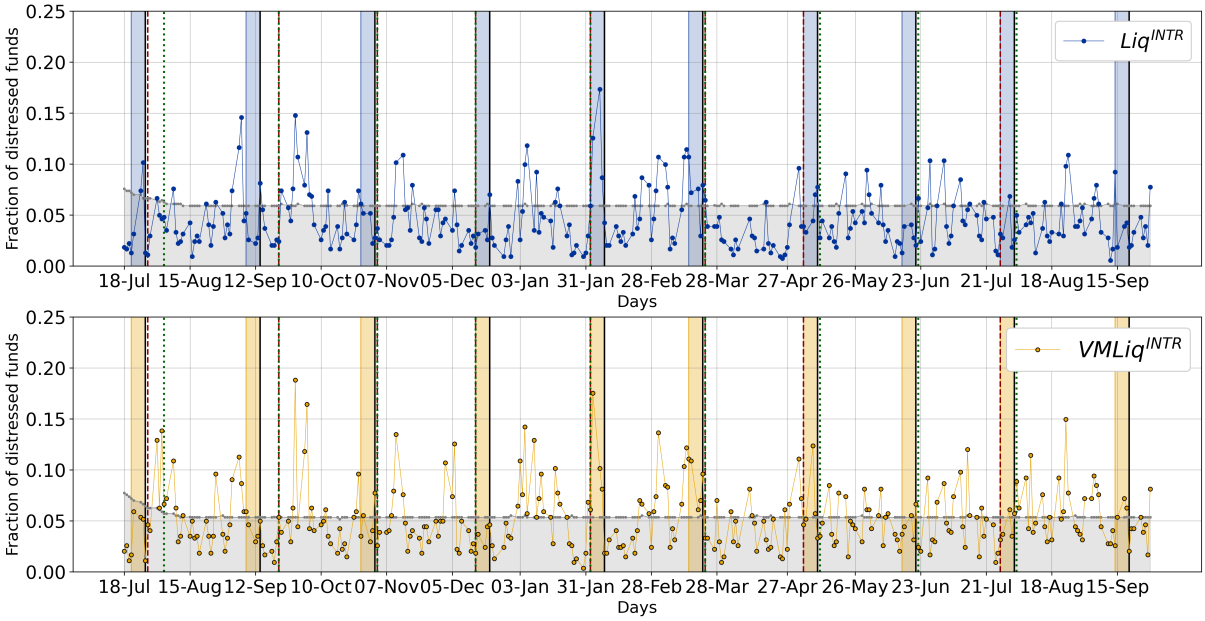


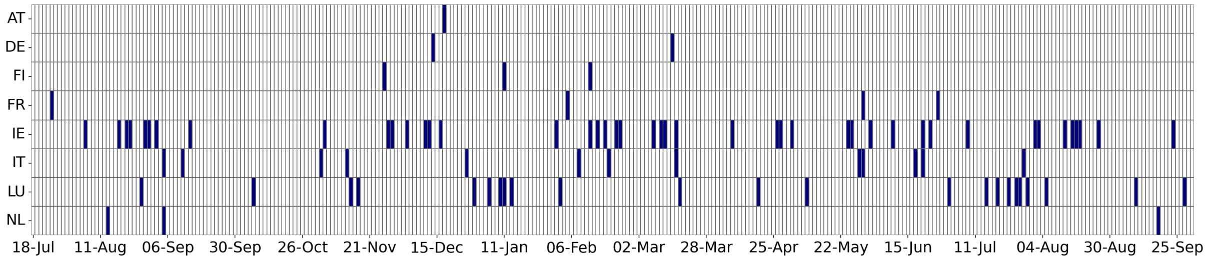

Figure 13: Fraction of distressed funds ($z > 2$): liquidity indicator shown in blue and VM-liquidity indicators in yellow. Interest Rate pure Portfolios, July 2022 - Sept 2023. Black, green, and red vertical lines indicate the effective dates of interest rate changes by the ECB, Fed, and BoE, respectively. The light blue and yellow areas represent the time window between the announcement and effective dates of ECB interest rate changes. The grey area denotes the threshold determined by the bootstrap method, serving as a benchmark for assessing statistically significant deviations. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

#### 4.2.3 Top Sold HQLA-country-sector groups

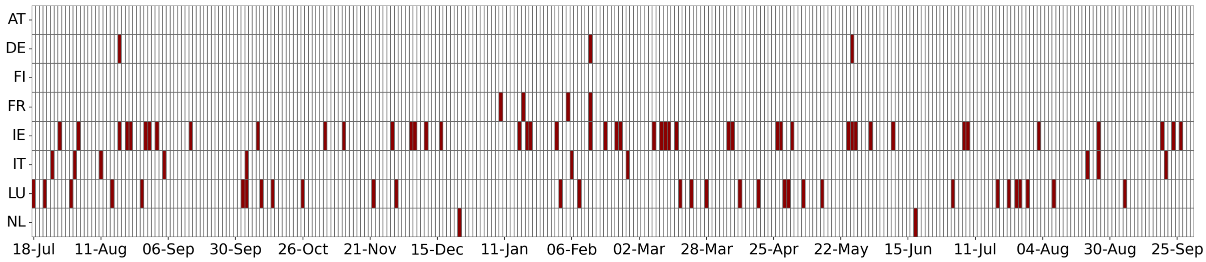
We use the same methodology as in Section 4.1.3, focusing on HQLA-country-sector group that experienced negative relative variations in both the number of shares and the market value, i.e., $\Delta s_g^d(m) < 0$ and $\Delta mktv_g^d(m) < 0$. Figure 15 reports the standard deviation of the ratio of the HQLA-country-sector group $g$'s fraction of market value in month $m$ to its fraction at the end of month $m-1$, separately for distressed and non-distressed funds' groups. As for the Covid case study, in all months, we observe that the standard deviations are higher for distressed funds, indicating that their selling strategies are less proportional to portfolio composition compared to non-distressed funds. To investigate the selling strategies in more detail, we then analyse which HQLA-country-sector groups are sold the most. The top-sold groups are shown in Figure 16, where colours indicate the relative fraction of market value at the end of the previous month, i.e. the fraction of market value rescaled by its maximum value across groups $M_g^d(m-1)/max_g\left(M_g^d(m-1)\right)$. We examine whether the selling behaviour of funds subject to liquidity stress is similar to that of others and find differences in the top-five sold HQLA categories between funds under liquidity stress and those not subject to it. We observe that $Level^1$ HQLA, primarily consisting of government bonds, is more frequently represented in the top-five sold HQLA categories for funds subject to liquidity stress compared to those not under stress. The colours in Figure 8 help determine whether selling strategies are proportional to portfolio composition. For distressed funds, in September, October, and December 2022, as well as February and March 2023, the most sold HQLA-country-sector group corresponds to a high relative fraction of market value. In contrast, during the other months, all five top-sold groups had a relatively lower presence in the portfolio. For non-distressed funds, the top-sold HQLA-country-sector groups generally had a high relative fraction of market value over the entire period.

#### 4.2.4 Propagation of liquidity risk to banks and other counterparties

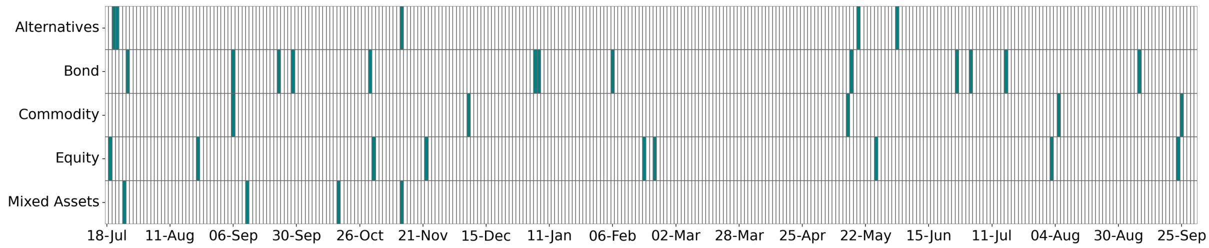
We identify counterparties of the funds classified as distressed by using the indicator $Liq$ at least one day during the period from July 2022 and September 2023. In total, there are 102 entities, of which 89 are classified banks [29]. The set of Euro Area counterparties $\mathcal{C}$, consists of 51 entities: 44 banks and 7 NBFIs. With three exceptions, these banks are either clearing members of CCPs or are part of a banking group whose parent is a CCP clearing member. The KDE plot and the boxplot of the counterparties' exposure to distressed funds $Exp_i^{all}(t)$ for the indicator $Liq$ in Figure 17 shows that most entities have low exposures to distressed funds, with a few exceptions that are important from a systemic perspective. The KDE plot reveals that most exposure values are below 0.1, with only a few observations exhibiting higher values, and just 19 observations exceeding 0.4. At the counterparty level, the exposure indicator does not show significant exposure, except for four entities whose 75th and 90th percentiles are below 0.01 and 0.05, respectively; one entity whose 75th percentile is near zero but displays high values on certain days; and one entity whose 75th and 90th percentiles are below 0.05 and 0.2. The variability in exposure across days, reflected by the large whiskers and notable interquartile ranges on certain days, suggests that some counterparties may be more vulnerable to liquidity shocks driven by distressed funds.



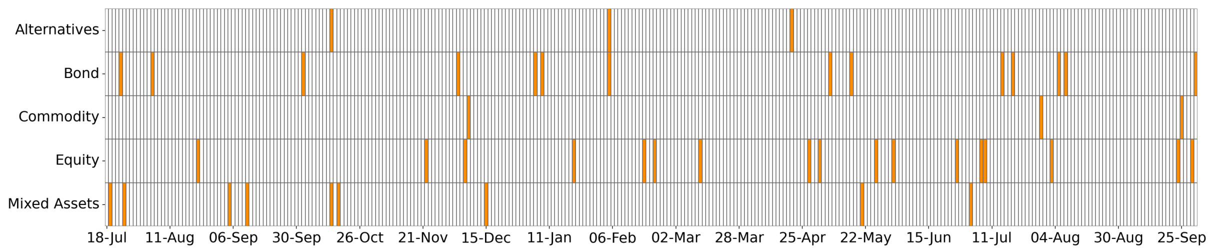

(a) Country $c$, $z(Liq_i(t)^+) > 2$




(b) Country $c$, $z(VMLiq_i(t)^+) > 2$




(c) Asset type $at$, $z(Liq_i(t)^+) > 2$




(d) Asset type $at$, $z(VMLiq_i(t)^+) > 2$

Figure 14: Hypergeometric test on country $c$ and asset type $at$ representation of distressed funds, portfolios of any asset type, July 2022 - September 2023. A coloured square indicates that a certain group on a specific day is overrepresented, confidence interval of 95%. Additionally, the false discovery rate (Benjamini-Hochberg procedure [34]) is applied to correct for multiple testing to ensure the robustness of our findings. Source: LSEG Lipper IM, CSDB, EMIR and own calculations.

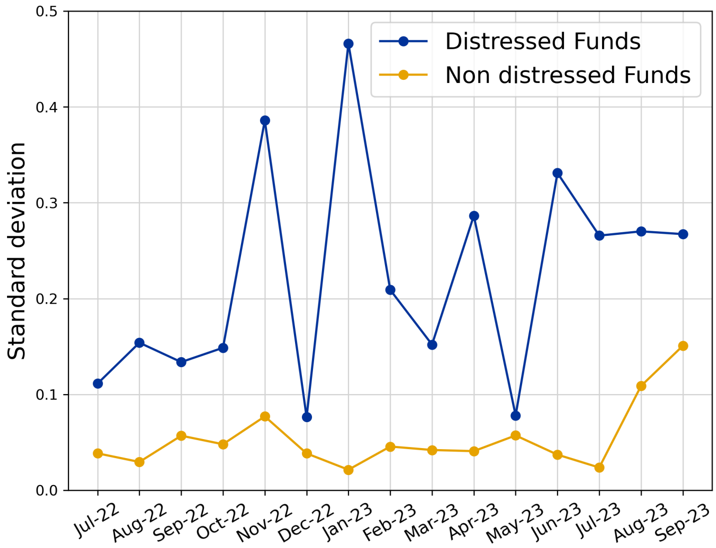



Figure 15: The standard deviation of the ratio of the HQLA-country-sector group $g$'s fraction of market value in month $m$ to its fraction at the end of month $m-1$, restricted to groups that exhibit negative monthly changes in both the number of shares and market value i.e., $\Delta s_g^d(m) < 0$, $\Delta mktv_g^d(m) < 0$ in each month $m$. Distressed funds are in blue, and non-distressed funds are in yellow. Jul 2022-Sep 2023. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

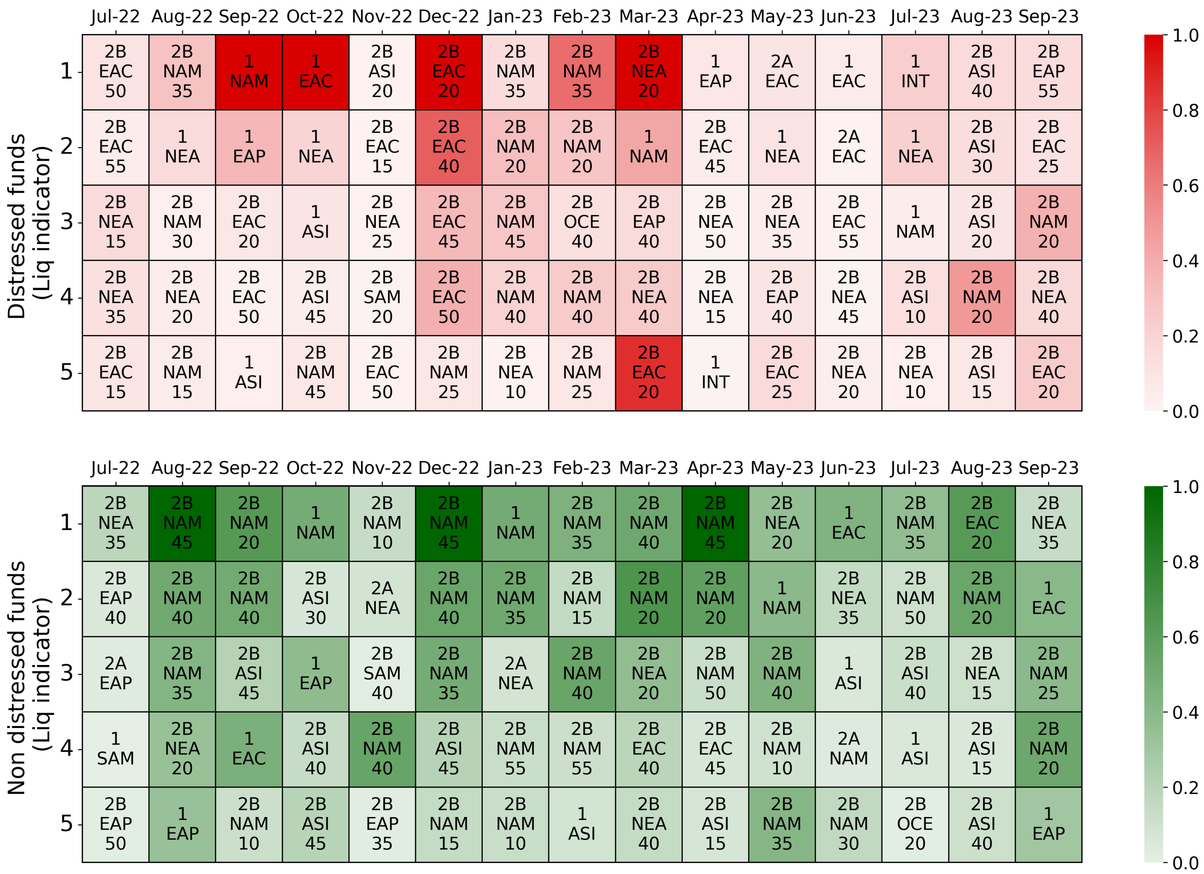
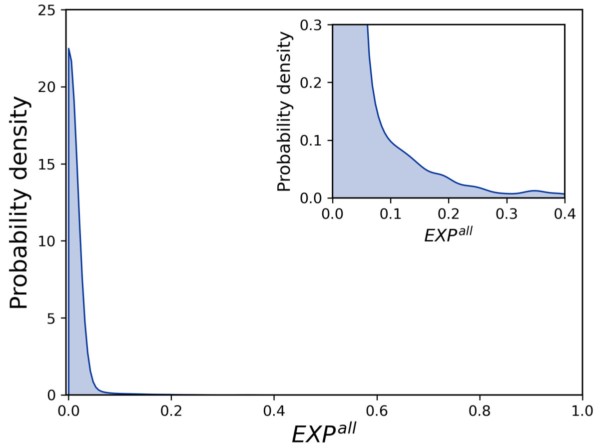
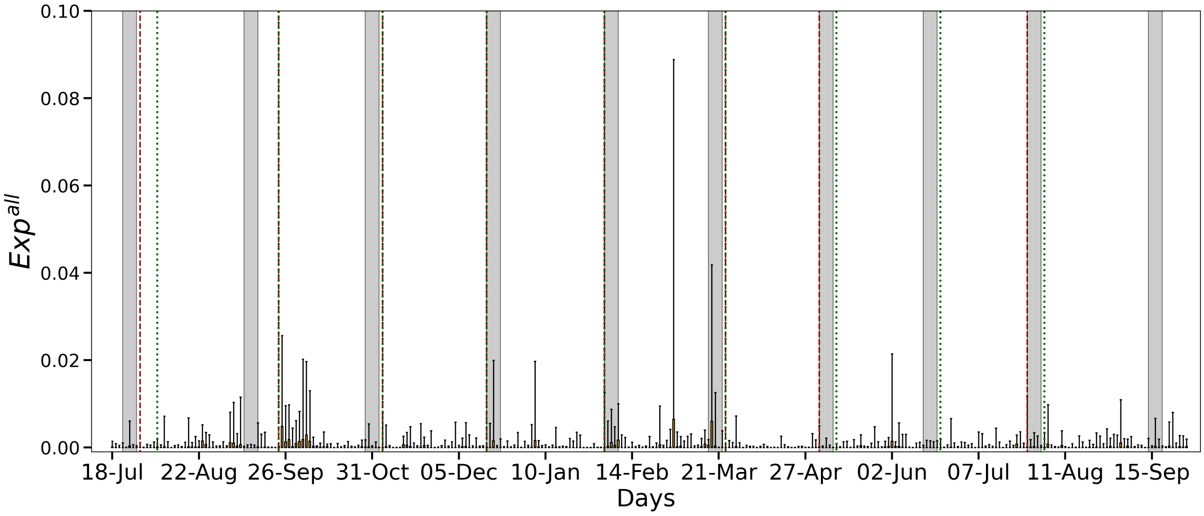



Figure 16: Top 5 most sold HQLA country-sector groups with the largest decrease in the market value holdings $\Delta mktv_g^d(m)$ in a given month $m$. The top table corresponds to distressed funds, while the bottom table corresponds to non-distressed funds, based on the liquidity indicator $Liq$. Colours represent the relative fraction of market value holdings in the HQLA-country-sector group $g$ held at the end of the previous month $m-1$ by funds in state $d$ (distressed or non-distressed) at month $m$. Jul 2022-Sep 2023. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.




(a) Kernel Density Estimation




(b) Boxplot at the daily level

Figure 17: Entities' exposure to distressed funds ($Exp_i^{all}(t)$) during the considered period (Jul 2022 – Sep 2023), all asset portfolios. The inset of subfigure (a) displays only exposure values below 0.4, excluding 19 observations that exceed this threshold. In the boxplot, for confidentiality reasons, the percentiles of the distribution are calculated by averaging values across three entities, and the whiskers represent the 10th and 90th percentiles. Black, green, and red vertical lines indicate the effective dates of interest rate changes by the ECB, Fed, and BoE, respectively. Grey areas represent the time window between the announcement and effective dates of ECB interest rate changes. Source: LSEG Lipper IM, CSDB, EMIR, and own calculations.

# 5 Conclusions and policy implications

This paper introduces a novel set of liquidity indicators along with a methodological framework designed to assess the ability of NBFIs to meet derivative margin calls and to promptly identify entities facing liquidity stress. Large margin calls can give rise to asset fire sales by market participants scrambling for liquidity and can transmit stress to other parts of the financial system. Our methodological framework can be integrated into micro- and macro-prudential policy toolkits supporting various applications: monitoring NBFIs' liquidity preparedness for margin calls, conducting liquidity stress tests and scenario analyses, and calibrating adequate entity-specific liquidity levels, depending on the granularity and frequency of available data.

We apply our methodology to two case studies: the Covid-19 Pandemic and the 2022-2023 monetary policy tightening. Our analysis shows that the extreme spikes in margin calls in equity derivatives during the Covid-19 turmoil placed significant liquidity pressures on NBFIs, leading to widespread asset sales. In contrast, the effects of margin calls on interest rate derivatives during the monetary policy tightening were more gradual, yet still revealed notable liquidity stress among certain funds. We identify distressed funds and compare the composition of their liquid assets sold with their peers in the two periods. Distressed funds primarily sold equities (Level 2B HQLA) during the Covid-19 crisis, while government bonds (Level 1 HQLA) dominated the asset sales during monetary policy tightening. To assess the implications for systemic risk, we further examine the potential spillover effects on NBFI counterparties, particularly banks. Our findings indicate that while most counterparties had limited exposure to distressed funds, a subset of them exhibited vulnerabilities to NBFI liquidity shocks. This concentration suggests that while systemic contagion risk from margin calls is generally contained, certain market participants remain exposed to sudden liquidity strains.

Our findings reinforce the importance of adequate liquidity preparedness, which can contribute to ensuring financial stability. Margin and collateral calls serve as crucial safeguards against counterparty risk, but if they arise unexpectedly and affect a large portion of market participants, they can significantly amplify liquidity demand and lead to fire sales, as recent episodes of market stress have shown. This underscores the need for financial institutions to proactively manage liquidity risks and for authorities to better monitor NBFI liquidity preparedness, particularly in times of market stress, and run stress tests and scenario analyses.

Our indicators and methodology provide an easy to use framework that aligns with the recent international policy recommendations from the Financial Stability Board, which emphasises the integration of margin requirements into broader liquidity risk frameworks [8]. Future research could further expand our approach by incorporating collateral margin calls, offering a more comprehensive perspective on NBFI liquidity resilience.

In this context, a crucial aspect for the effectiveness of these indicators as early-warning tools is the availability of granular, frequent, and high-quality data. While daily, entity-level data on margin calls is available under EMIR reporting, obtaining high-frequency, high-quality data on NBFIs' broader liquidity positions remains a challenge. Asset holdings and balance-sheet data are often accessible only to regulators and supervisors, limiting the ability to fully assess systemic liquidity risks across jurisdictions. Improved data-sharing mechanisms among authorities, potentially under an internationally coordinated framework, would enable a more comprehensive view of liquidity vulnerabilities in the NBFI sector. Addressing these data gaps would significantly enhance the ability of regulators to monitor and mitigate liquidity risks effectively.

Overall, this study contributes to the ongoing policy debate on non-bank financial intermediation by proposing a framework that enhances the monitoring of liquidity preparedness. Strengthening the resilience of NBFIs is essential to mitigating systemic risks and ensuring the stability of the financial system.

## References

[1] European Systemic Risk Board. Liquidity risks arising from margin calls. Technical report, European Systemic Risk Board, 2020. https://www.esrb.europa.eu/pub/pdf/reports/esrb.report200608_on_Liquidity_risks_arising_from_margin_calls_3~08542993cf.en.pdf.

[2] Audrius Jukonis, Elisa Letizia, and Linda Rousová. The impact of derivatives collateralisation on liquidity risk: evidence from the investment fund sector. ECB Working Paper Series No. 2756, European Central Bank, 2022.

[3] Maddalena Ghio, Linda Rousová, Dilyara Salakhova, and German Villegas Bauer. Derivative margin calls: a new driver of MMF flows. Working Paper Series No. 2800, European Central Bank, 2023.

[4] Thomas Carraro, Linda Fache Rousová, Oana Furtuna, Maddalena Ghio, Kristina Kallage, Charles O'Donnell, Francesco Vacirca, and Sebastiano Michele Zema. Lessons learned from initial margin calls during the march 2020 market turmoil. Box 9, European Central Bank, 2021. Financial Stability Review, November 2021.

[5] Yajun Wang. Why can margin requirements increase volatility and benefit margin constrained investors? *Review of Finance*, 20(4):1449–1485, 2016.

[6] Robin Greenwood, Augustin Landier, and David Thesmar. Vulnerable banks. *Journal of Financial Economics*, 115(3):471–485, 2015.

[7] Emanuele Franceschi, Maciej Grodzicki, Benedikt Kagerer, Christoph Kaufmann, Francesca Lenoci, Luca Mingarelli, Cosimo Pancaro, and Richard Senner. Key linkages between banks and the non-bank financial sector. Special Feature B, European Central Bank, 2023. Financial Stability Review, November 2023.

[8] Financial Stability Board. Liquidity preparedness for margin and collateral calls: Final report. *https://www.fsb.org/uploads/P101224-1.pdf*, 2024.

[9] Financial Stability Board. Enhancing the resilience of non-bank financial intermediation: Progress report, April 2024. https://www.fsb.org/2024/04/liquidity-preparedness-for-margin-and-collateral-calls-consultation-report/.

[10] European Central Bank. Financial stability review. May 2025. https://www.ecb.europa.eu/pub/financial-stability/fsr/html/index.en.html.

[11] Bank of England. Financial stability review. June 2024. https://www.bankofengland.co.uk/financial-stability-report/2024/financial-stability-report-june-2024.pdf.

[12] Bank of England. Financial stability review. Nov 2024. https://www.bankofengland.co.uk/-/media/boe/files/financial-stability-report/2024/financial-stability-report-november-2024.pdf.

[13] Piergiorgio Alessandri, Prasanna Gai, Sujit Kapadia, Nada Mora, and Claus Puhr. A framework for quantifying systemic stability. *International Journal of Central Banking*, 5(3):47–81, 2009.

[14] Matthias Sydow, Aurore Schilte, Giovanni Covi, Marija Deipenbrock, Leonardo Del Vecchio, Pawel Fiedor, Gábor Fukker, Max Gehrend, Régis Gourdel, Alberto Grassi, Björn Hilberg, Michiel Kaijser, Georgios Kaoudis, Luca Mingarelli, Mattia Montagna, Thibaut Piquard, Dilyara Salakhova, and Natalia Tente. Shock amplification in an interconnected financial system of banks and investment funds. *Journal of Financial Stability*, 71:101234, 2024.

[15] Katarzyna Barbara Budnik, Aurea Ponte Marques, Carla Giglio, Alberto Grassi, Agha Durrani, Juan Manuel Figueres, Paul Konietschke, Catherine Le Grand, Julian Metzler, Francisco Javier Población García, et al. Advancements in stress-testing methodologies for financial stability applications. *ECB Occasional Paper Series*, 348, 2024.

[16] Matthias Sydow, Gábor Fukker, Tomasz Dubiel-Teleszynski, Fabio Franch, Sébastien Gallet, Helmut Gründl, Stelios Kotronis, Debora Miccio, Michela Pellegrino, Sebastian Schlütter, and Matteo Sottocornola. Banks and non-banks stressed: liquidity shocks and the mitigating role of insurance companies. Ecb working paper series no. 3000, European Central Bank, 2024.

[17] Laura Alfaro, Saleem A Bahaj, Robert Czech, Jonathon Hazell, and Ioana Neamtu. Lash risk and interest rates. Technical Report Staff Working Paper No. 1073, Bank of England, 2025.

[18] Antoine Bouveret, Massimo Ferrari, Michael Grill, Luis Molestina Vivar, Daniel Jonas Schmidt, and Christian Weistroffer. Leveraged investment funds: A framework for assessing risks and designing policies. *ECB Macroprudential Bulletin*, 26, 2025.

[19] Annalaura Ianiro, Agnese Leonello, and Dario Ruzzi. Measuring synthetic leverage in interest rate swaps. *ECB Macroprudential Bulletin*, 26, 2025.

[20] Kristy A.E. Jansen, Sven Klingler, Angelo Ranaldo, and Patty Duijm. Pension liquidity risk. DNB Working Paper 801, De Nederlandsche Bank, February 2024.

[21] Sebastiano Michele Zema. Uncovering the network structure of non-centrally cleared derivative markets: evidence from large regulatory data. *Empirical Economics*, 65(4):1799–1822, 2023.

[22] Argyris Kahros, Alessandro Pioli, Thomas Carraro, Marios Gravanis, and Francesco Vacirca. A descriptive analysis of the client clearing network in the european derivatives landscape. *Journal of Financial Market Infrastructures*, 9(1), 2021.

[23] Marco Bardoscia, Gerardo Ferrara, Nicholas Vause, and Michael Yoganayagam. Simulating liquidity stress in the derivatives market. *Journal of Economic Dynamics and Control*, 133:104215, 2021.

[24] Pawel Fiedor, Sarah Lapschies, and Lucia Országhová. Networks of counterparties in the centrally cleared eu-wide interest rate derivatives market. Technical Report Working Paper Series No. 54, European Systemic Risk Board (ESRB), September 2017. ESRB Working Paper Series.

[25] Claudio Barbieri, Maciej Grodzicki, Grzegorz Hałaj, and Riccardo Pizzeghello. System-wide implications of counterparty credit risk. *ECB Macroprudential Bulletin*, 26, 2025.

[26] Bank for International Settlements (BIS). Basel framework. *LCR - Liquidity Coverage Ratio*, LCR30 - High-quality liquid assets, 2023. `https://www.bis.org/basel_framework/chapter/LCR/30.htm`.

[27] Pierce Daly, Elisa Telesca, and Christian Weistroffer. Assessing liquidity vulnerabilities in open-ended bond funds: A fund-level redemption coverage ratio approach. Box 6, European Central Bank, 2023. Financial Stability Review, November 2023.

[28] Gemma Agostoni, Annalaura Ianiro, Audrius Jukonis, Francesca D Lenoci, Elisa Letizia, and Grzegorz Skrzypczynski. Using trade-level derivatives data for macroprudential analysis. Ips 224, evolving statistics in support of central bank policies, European Central Bank, 2023.

[29] Francesca D Lenoci and Elisa Letizia. Classifying counterparty sector in emir data. In *Data Science for Economics and Finance: Methodologies and Applications*, pages 117–143. Springer International Publishing Cham, 2021.

[30] Basel Committee on Banking Supervision (BCBS), Bank for International Settlements' Committee on Payments and Market Infrastructures (CPMI), and International Organization of Securities Commissions (IOSCO). Review of margining practices. *BIS publications*, September 2022.

[31] Margherita Giuzio, Annalaura Ianiro, Fabrizio Lillo, Valentina Macchiati, Elisa Telesca, and Andrzej Sowiński. Assessing the liquidity preparedness of investment funds to meet margin calls in derivatives markets. Box 5, European Central Bank, 2024. Financial Stability Review, May 2024.

[32] European Commission. Sustainable finance: Teg benchmark handbook, 2020. Publications Office of the European Union.

[33] Margherita Giuzio, Francesca Lenoci, and Christian Weistroffer. Portfolio rebalancing by euro area investment funds following outflows. Box 7, European Central Bank, 2019. Financial Stability Review, November 2019.

[34] Yoav Benjamini and Yosef Hochberg. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)*, 57(1):289–300, 1995.

# A Appendix

## A.1 List of Abbreviations

| Abbreviation | Meaning |
|---|---|
| NBFI | Non Bank Financial Institutions |
| ECB | European Central Bank |
| FSB | Financial Stability Board |
| Fed | Federal Reserve |
| BoE | Bank of England |
| EU | European Union |
| EA | Euro Area |
| UK | United Kingdom |
| OTC | Over-The-Counter |
| PEPP | Pandemic Emergency Purchase Programme |
| LASH | Liquidity After Solvency Hedging |
| HQLA | High-Quality Liquid Asset |
| EMIR | European Market Infrastructure Regulation |
| ESCB | European System of Central Banks |
| CSDB | Centralised Securities Database |
| LEI | Legal Entity Identifier |
| ISIN | International Securities Identification Number |
| TR | Trade Repository |
| CCP | Central Counterparty |
| IM | Initial Margin |
| VM | Variation Margin |
| INTR | Interest Rate |
| EQUI | Equity |
| CURR | Currency |
| CRDT | Credit |
| COMM | Commodity |
| MIXT | Mixed Assets |
| CC | Centrally Cleared |
| NCC | Not Centrally Cleared |
| NACE | Statistical Classification of Economic Activities |
| GICS | Global Industry Classification Standard |
| FDR | False Discovery Rate |
| IF | Investment Funds |
| BANK | Banks |
| GOVT | Government |
| IC | Insurance Companies |
| MMMF | Money Market Mutual Funds |
| NCB | National Central Banks |
| NFC | Non Financial Corporations |
| OFI | Other Financial Institutions |
| OTHR | Others |
| PF | Pension Funds |
| ETF | Exchange Traded Funds |
| VSTOXX50 | Euro STOXX 50 Volatility Index |
| KDE | Kernel Density Estimation |

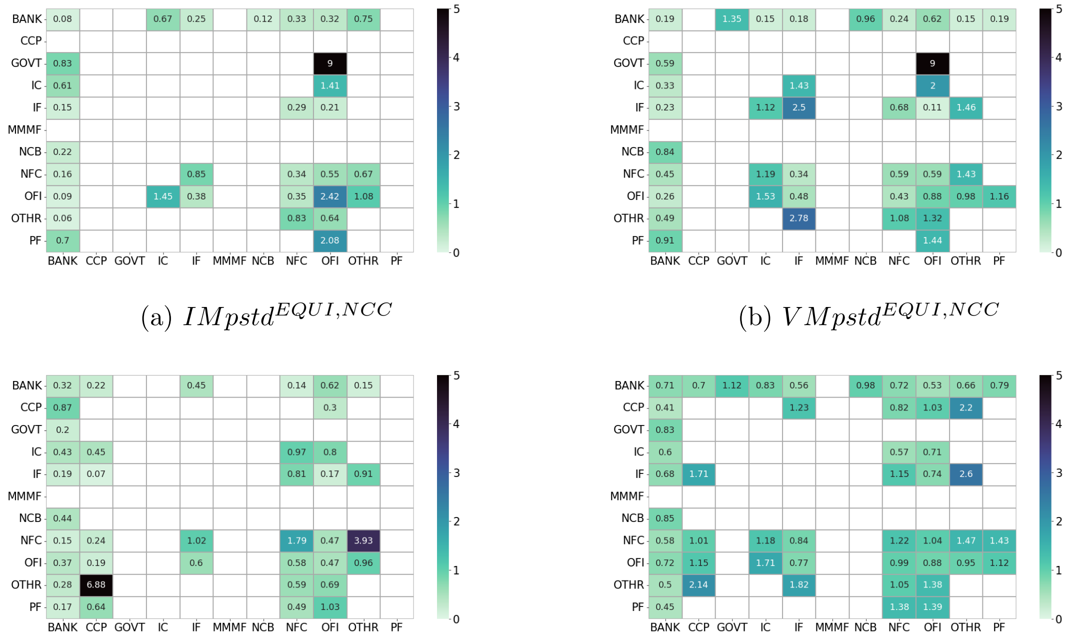
Table A1: List of Abbreviations.

## A.2 Country group definition

| **Country Group Names** | **Acronyms** | **Country Codes** |
|---|---|---|
| Euro Area Core | EAC | DE, FR, NL, BE, LU, AT, FI |
| Euro Area Periphery | EAP | ES, IT, IE, SI, SK, GR, PT, CY, MT, EE, LV, LT, HR(from 2023) |
| Non-Euro Area | NEA | AL, AD, BA, BG, CZ, DK, FO, GB, HU, IS, LI, MD, MK, ME, NO, PL, RO, RS, SE, UA, CH, HK, GG, GI, IM, JE, HR(until 2023) |
| International Entities | INT | XX (international entities) |
| Africa | AFR | DZ, AO, BJ, BW, BF, BI, CM, CV, CF, TD, KM, CD, CG, DJ, EG, GQ, ER, SZ, ET, GA, GM, GH, GN, GW, KE, LS, LR, LY, MG, MW, ML, MR, MU, MA, MZ, NA, NE, NG, RW, ST, SN, SC, SD, TZ, TG, TN, UG, ZM, ZW, ZA |
| Asia | ASI | AF, AM, AZ, BH, BD, BT, BN, KH, CN, CY, GE, IN, ID, IR, IQ, IL, JP, JO, KZ, KP, KR, KW, KG, LA, LB, MV, MN, MM, MY, NP, OM, PK, PH, QA, SA, SG, LK, SY, TJ, TH, TM, AE, UZ, VN, YE, TW, RU |
| North America | NAM | US, CA, MX, BM, BS, BB, HT, JM, KY, PR, AG, AI, AW, CU, DM, DO, GD, GP, HT, HN, MQ, MS, NI, SR, SX, TT, TC, VC, VG, VI |
| Oceania | OCE | AS, AU, CK, FJ, FM, GU, KI, MH, NC, NZ, PG, PW, WS, SB, TV, VU |
| South America | SAM | AR, BO, BR, CL, CO, EC, GY, PY, PE, SR, UY, VE, CW, PA |

Table A2: Description of country groups in terms of country codes.

## A.3 Derivative Market Structure by Sector



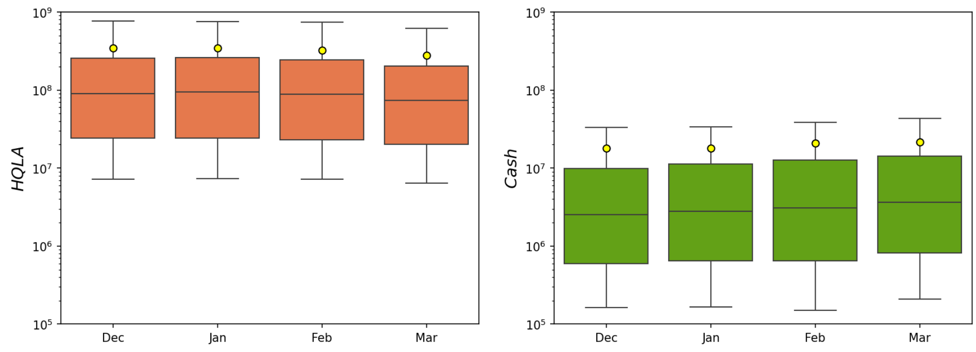
(a) $IMpstd^{EQUI,NCC}$ (b) $VMpstd^{EQUI,NCC}$

(c) $IMpstd^{EQUI,CC}$ (d) $VMpstd^{EQUI,CC}$

Figure A1: Coefficient of variation (ratio between mean and standard deviation) of the daily posted margin for equity pure portfolios from January to April 2020. Source: EMIR; ECB and own calculations.

## A.4 Distribution of HQLA and cash holdings

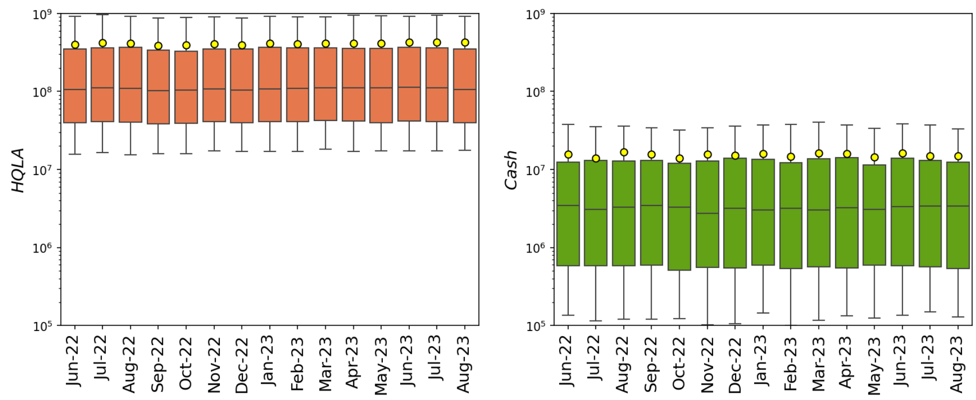
### A.4.1 Covid-19 Pandemic




(a) Distribution of $HQLA$ (b) Distribution of $cash$

Figure A2: Distribution of $HQLA$ and $cash$ of entities that are involved in equity pure derivatives portfolios, end-of-month data from December 2019 to March 2020. Whiskers and yellow scatter represent the 10th and 90th percentiles and the mean, respectively. The number of funds is 839. Source: LSEG Lipper IM, CSDB, EMIR; ECB and own calculations.

### A.4.2 Monetary policy tightening 2022-2023




(a) Distribution of $HQLA$ (b) Distribution of $cash$

Figure A3: Distribution of $HQLA$ and $cash$ of entities that are involved in derivatives portfolios, end-of-month data from June 2022 to August 2023. Whiskers and yellow scatter represent the 10th and 90th percentiles and the mean, respectively. The number of funds is 1388. Source: LSEG Lipper IM, EMIR, CSDB; ECB and own calculations.

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