MFSA MALTA FINANCIAL SERVICES AUTHORITY

Liquidity Stress Testing for Maltese Retail Investment Funds

by

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Abbreviations

AIF	Alternative Investment Fund
AIFMD	Alternative Investment Fund Managers Directive
ES	Expected Shortfall
ESMA	European Securities and Markets Authority
ESRB	European Systemic Risk Board
ETF	Exchange Traded Fund
GPD	Generalised Pareto Distribution
HQLA	High Quality Liquid Assets
MFSA	Malta Financial Services Authority
NAV	Net Asset Value
OLS	Ordinary Least Squares
STIFF	Stress Testing for Investment Funds Framework
STRESI	Stress Simulation for Investment Funds
UCITS	Undertakings for Collective Investment in Transferable Securities
VaR	Value-at-Risk
VAR	Vector Autoregressive

Executive Summary

The investment fund industry grew significantly over the last decade. Funds seem to have generally taken on more risks by investing into lower grade and less liquid securities to attain greater returns. Hence, the importance of testing the resilience of the investment funds and their financial stability implications in times of market stress has become more important and essential. Several recommendations have been put forward by the ESRB to mitigate systemic risks deriving from investment funds, particularly risks related to liquidity mismatches. ESMA has also issued guidelines on the different methodologies that can be adopted to perform liquidity stress testing relating to UCITS and AIFs (excluding closed-ended non-leveraged AIFs).

This report is a first attempt by the Financial Stability function within the Malta Financial Services Authority to develop a liquidity stress testing framework, both at micro and macro levels, for a sample of 64 Maltese retail investment funds. The micro-level stress test assesses the resilience of the individual investment funds to extreme but plausible weekly redemption shocks. On the other hand, the macro-level stress test is used to gauge a deeper insight on how the macro-economic environment can affect the liquidity profile of the Maltese fund industry, and to identify the types of funds which are most exposed to macro-economic shocks. Moreover, the macro-level stress test can be used as an effective tool to simulate liquidity shocks in those funds which do not have enough historical observations to be subject to a micro-level stress testing.

From our study, we find that under the micro-level stress test only one fund out of a sample of 64 Maltese retail funds failed the stress test under three different levels of redemption requests and under both the waterfall and slicing liquidation approaches. Another two funds failed under the 1% worst-case redemption request, with one of these funds failing only under the slicing approach. In terms of losses, most of the funds, which would need to liquidate the portfolio holdings to meet the extreme redemption requests, would suffer losses below 5% of their NAV. Moreover, the expected second-round effects appear to be generally limited both in terms of redemptions and the magnitude of liquidation costs.

The macro-level liquidity stress test shows that few macro-economic variables have a statistically significant effect on the investors' decisions when to subscribe or redeem their investments. We find that funds classified under the *other* and the mixed categories are the most exposed to shocks in the real economy. Indeed, these types of funds present the larger fluctuations in the expected net flows conditional on the different shock scenario taken into consideration. From our analysis it emerged that, based on historical data, the shocks which would statistically produce the worst expected net flows are a sharp decrease in the US interest rates, a tightening in the money supply in Malta and an increase in the unemployment rate in the Eurozone. Naturally, going forward, these factors need to be seen in conjunction with other macro-economic variables, investor mood and sentiment and other conditions that influence investor activity in investment funds.

Finally, in our analysis we did not take into consideration the use of borrowing facilities and leverage as well as the use of liquidity management tools such as gating, deferral of redemptions and redemption in kind due to this information not being available from the returns that were analysed.

Introduction

The investment fund industry experienced a significant growth since the end of the 2007-2008 financial crisis. Worldwide investment funds assets increased by 212% over the last ten years, from €16.9 trillion in December 2009 to €52.7 trillion in December 2019 (EFAMA, 2015, 2020). At European level, net assets reached €17.7 trillion in December 2019, an increase of 136% from 2009 (EFAMA, 2019, 2020). Net assets of the Maltese investment fund industry almost doubled, increasing from €7.9 billion in December 2009 to €15.5 billion ten years later.

The significant growth registered in the investment fund industry also increased the potential contribution to systemic risks, with the liquidity transformation activity undertaken by the investment fund managers being one of the main concerns. Particularly, in the retail funds, asset managers offer relatively high redemption frequencies, while their portfolios include investments in long term assets or assets which cannot be liquidated in short periods. From a financial stability point of view, the mismatch between the redemption right offered and the liquidity of the assets is particularly relevant since it could amplify and spread financial or economic shocks, creating contagion effects (Office of Financial Research, 2013).

The European Central Bank (ECB), through its Financial Stability Review (2019), recognised that investment funds are becoming riskier and less liquid by increasing their asset allocation to lower-rated and high-yield securities. In line with these concerns, studies found that the investment funds may not hold enough cash to mitigate the risks arising from their liquidity transformation activity (Chernenko & Sunderam, 2016). Moreover, Teo (2011) found that funds are becoming more exposed to liquidity risk to achieve greater returns.

Several stress testing frameworks have been developed in the last years as a tool that can be used to assess the resilience of investment funds under stressed market conditions. Among others Baranova et al (2017), Bouveret (2017), Fricke and Fricke (2017), the STRESI introduced by ESMA(2019), and Gourdel et al (2019) provide examples of different frameworks which can be applied to stress test the investment funds' liquidity profiles.

In this context, in April 2018, the European Systemic Risk Board (ESRB) published a set of recommendations on actions to address systemic risks related to *inter alia* liquidity mismatches and the use of leverage in investment funds (ESRB, 2018). Among other measures, the ESRB recommended that ESMA develops guidance on the methodology to be adopted by asset managers to perform liquidity stress tests in accordance with the AIFMD and UCITS Directive. It was also recommended that the guidance includes:

- the design of liquidity stress testing scenarios;
- the liquidity stress test policy, including internal use of liquidity stress test results;
- considerations for the asset and liability sides of investment fund balance sheets; and
- the timing and frequency for individual funds to conduct the liquidity stress tests.

In September 2019, ESMA published a set of guidelines on liquidity stress testing for UCITS and AIFs after issuing a public consultation paper in February 2019. The purpose of these guidelines is to establish consistent, efficient and effective supervisory practices within the European System of Financial Supervision and to ensure the common, uniform and consistent application of Union law. The final guidelines were published in July 2020 and they apply as from end September 2020.

In light of this growing focus on liquidity risk, the Financial Stability function of the Malta Financial Services Authority decided to develop its own stress testing framework, building up on the ESMA's STRESI, which takes the name of Stress Testing for Investment Funds Framework (STIFF). The STIFF follows a top-down approach and is applied both at micro and macro levels. At micro level, we test the resilience of the individual investment retail funds to extreme but plausible weekly redemption shocks to ensure that a fund does not have a liquidity mismatch between the portfolio of assets and any redemptions on the liabilities side. The weekly redemption shocks are estimated using Extreme Value Theory (in particular, by fitting a Generalized Pareto Distribution), and the liquidation impact is computed using the investment portfolios reported by the funds on a security-by-security basis. To calculate the different impacts attributable to various levels of severity, three different extreme thresholds are simulated. Moreover, an additional expected second-round effect is computed to analyse whether investment funds would continue to be resilient, in terms of liquidity profile, following a second round of outflows caused by the first-round redemptions. At a macro level, we analyse the effect of shocks in the macro-economic environment on the net flows of investment funds. The first step consists of regressing the net flows of the different retail funds' strategies on four macro-economic indicators. Then, the correlation structure of the macro-economic indicators is modelled through a vector autoregressive (VAR) model. Finally, the macro-level stress test estimates the impact of a macro-economic shock on both the expected and worst-case net flows for each type of fund. Both types of stress testing shed light on those funds or fund categories that would suffer the most and which are not well prepared for such scenarios should these materialise.

The STIFF enriches further the current fund stress testing literature in two different ways. Firstly, it uses a parametric approach to estimate the extreme redemptions, particularly relevant when considering funds which have a relatively short lifespan or funds with few data observations. Secondly, it applies a macro-economic scenario approach which is different from previous studies where the focus was on macro-financial variables.[1] Moreover, the STIFF's macro-level stress testing does not limit itself to the direct impacts of the macro-economic variables on the net flows, but it considers also the indirect impacts by modelling the correlation structure among these variables.

The report is structured as follows: the next section presents the framework adopted (STIFF) for both the micro and macro-level stress tests. Then we present the results obtained from the micro- and macro-level STIFF's application to a sample of Maltese domiciled retail investment funds. Finally, we present the limitations and assumptions of the STIFF.

Stress Testing for Investment Funds Framework (STIFF)

This chapter presents the two methodologies adopted in this report to stress test the liquidity of the Maltese retail investment fund sector, which together represent the two pillars of the STIFF, namely

1. the micro-level pure redemption shock, and
2. the macro-level scenario-based shock.

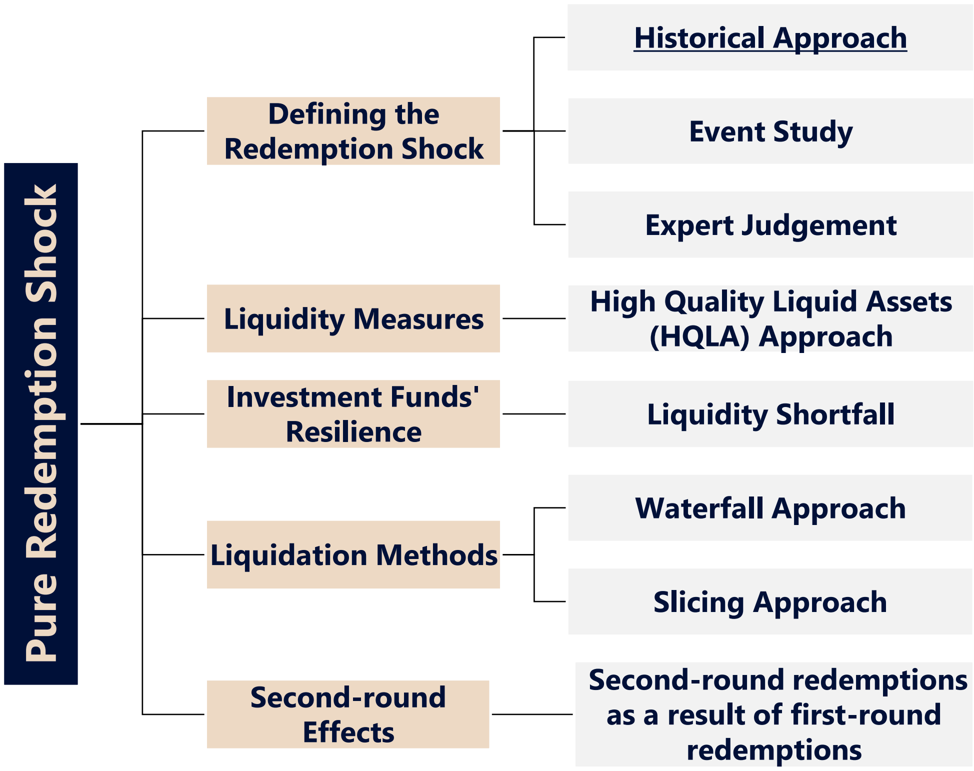
The Micro-Level Pure Redemption Shock

The first methodology focuses on the micro-level stress test and it consists mainly of four steps:

1. defining the redemption shock,
2. calculating the liquidity of the portfolio of the fund,
3. applying different liquidation approaches to simulate the managers' strategies to satisfy the investors' redemption requests, and
4. the incorporation of second round effects.

The methodology is presented in the following flow chart.

[1] Inter alia Bouveret (2017) and Babalos et al (2019).



Defining the Redemption Shock

The pure redemption shock can be calibrated in a variety of methods, namely through

(1) the **historical approach** where the shock is estimated on historical redemptions and calibrated by the distribution of net flows,

(2) an **event study approach** where the shock is calibrated using the net flows that occurred during a severe event, and

(3) an **expert judgement approach** which leaves full discretion in simulating the shock.

While the historical and event study approaches are a form of backward-looking stress testing, the expert judgement approach is a forward-looking type of stress testing. Backward-looking stress testing refers to the use of statistical techniques to derive quantitative parameters that describe a particular scenario based on historical data which ideally would include periods of distressed market conditions. Forward-looking stress testing refers to the construction of hypothetical scenarios that are based on extreme but plausible events which may arise due to various reasons such as a change in the behaviour of market participants or a change in regulation (IOSCO, 2018).

In this study we adopt the historical approach. Since most of the funds in our sample were only launched recently and they were not active during any major crises, the event study approach was not considered appropriate.

Given the limited number of redemption observations available for several funds within our sample, we use the Generalised Pareto Distribution (GPD) to estimate the shock. The GPD is a distribution commonly used in Extreme Value Theory because it is the only non-degenerate distribution that can be used to approximate the distribution of the exceedances over some threshold (Blakema & de Haan 1974; Pickands 1975). The probability density function of the GPD is given by

$$f_{(\mu,\sigma,\xi)}(x) = \frac{1}{\sigma}\left(1 + \frac{\xi(x-\mu)}{\sigma}\right)^{-\frac{1}{\xi}-1} \tag{1}$$

where μ represents the threshold used to define the exceedances, σ represents the scale parameter and ξ defines the shape of the distribution. To fit the extreme redemptions curve of the Maltese retail funds, the threshold μ is taken to be equal to the 90th percentile of the historical redemptions. The parameters σ and ξ are then estimated through Maximum Likelihood Estimation (MLE).

Once the GPD is estimated, three different extreme redemptions are simulated, namely the expected 10%, 5% and 1% worst case scenarios. The simulation is calibrated using an expected shortfall approach, which consists of computing the expected value of a redemption, conditional on such a redemption being higher than a defined threshold.[2]

The first extreme redemption is taken as the expected value of the GPD, and therefore, it represents the expected worst 10% redemption, denoted by ρ_{10}. This is estimated in two different ways: if ξ is statistically lower than one, then the expected value is calculated using the closed-form equation for the mean of the GPD, given by

$$\rho_{10} = \mu + \frac{\sigma}{1-\xi}. \tag{2}$$

Otherwise, the shock is estimated through the composite trapezoidal rule. This is a numerical technique to approximate the integral of a function. In this case, the shock is derived from the integral between μ and 100 (the maximum percentage redemption that a fund can incur) of the GPD.

$$\begin{aligned}\rho_{10} &= \frac{1}{\left(\mathrm{F}_{(\mu,\sigma,\xi)}(100)\right)} \cdot \int_{\mu}^{100} x \cdot f_{(\mu,\sigma,\xi)}(x)\ dx \\ &\approx \frac{1}{\left(\mathrm{F}_{(\mu,\sigma,\xi)}(100)\right)} \cdot \left(\frac{100-\mu}{\mathrm{n}}\right) \cdot \left(\frac{\mu \cdot \mathrm{f}(\mu)}{2} + \sum_{\mathrm{k}=1}^{\mathrm{n}-1}\left(\left(\mu + \mathrm{k}\frac{(100-\mu)}{\mathrm{n}}\right) \cdot \mathrm{f}\left(\mu + \mathrm{k}\frac{(100-\mu)}{\mathrm{n}}\right)\right) + \frac{100 \cdot \mathrm{f}(100)}{2}\right)\end{aligned} \tag{3}$$

Then, the second shock estimated is the expected worst 5% redemption, denoted by ρ_5. In order to estimate it, the first step is to compute the median of the GPD, through the closed-form equation:

$$\mathrm{m} = \mu + \frac{\sigma \cdot \left(2^{\xi} - 1\right)}{\xi}. \tag{4}$$

Once the median is obtained, ρ_5 becomes equal to the expected value of the GPD between the median and 100. This can be computed using the above-mentioned composite trapezoidal rule as:

$$\begin{aligned}\rho_5 &= \frac{1}{\left(\mathrm{F}_{(\mu,\sigma,\xi)}(100) - \mathrm{F}_{(\mu,\sigma,\xi)}(m)\right)} \cdot \int_{m}^{100} x \cdot f_{(\mu,\sigma,\xi)}(x)\ dx \\ &\approx \frac{1}{\left(\mathrm{F}_{(\mu,\sigma,\xi)}(100) - \mathrm{F}_{(\mu,\sigma,\xi)}(m)\right)} . \left(\frac{100-m}{n}\right) . \left(\frac{m \cdot f(m)}{2} + \right. \\ &\left. \sum_{k=1}^{n-1}\left(\left(m + k\frac{(100-m)}{n}\right) \cdot f\left(m + k\frac{(100-m)}{n}\right)\right) + \frac{100 \cdot f(100)}{2}\right)\end{aligned} \tag{5}$$

[2] In the risk management field, the expected shortfall is one of the two main approaches commonly used together with the Value-at-Risk (VaR). Differently from the expected shortfall, a VaR approach with a threshold probability level α would involve identifying the smallest redemption such that the probability of observing a larger outflow is at most $1-\alpha$. Despite being more complex from a computational perspective, the expected shortfall is considered a superior measure to VaR since, apart from being a coherent measure of risk, it accounts for the magnitude of extreme events. Also, the expected shortfall is a more conservative risk measure than the VaR, meaning that for any risk X and for the same probability level α, $\mathrm{ES}_{\alpha}(\mathrm{X}) \geq \mathrm{VaR}_{\alpha}(\mathrm{X})$.

Finally, the expected worst 1% redemption, denoted by ρ_1, is computed as the expected value of the GPD conditional on being in the 90th percentile of the distribution.[3] The 90th percentile, q^{90th}, of each redemption distribution is computed through the inverse GPD function, and then, ρ_1 is estimated through the composite trapezoidal rule as:

$$\begin{aligned}\rho_1 &= \frac{1}{\left(\mathrm{F}_{(\mu,\sigma,\xi)}(100) - \mathrm{F}_{(\mu,\sigma,\xi)}(q^{90th})\right)} \cdot \int_{q^{90th}}^{100} x \cdot f_{(\mu,\sigma,\xi)}(x)\ dx \\ &\approx \frac{1}{\left(\mathrm{F}_{(\mu,\sigma,\xi)}(100) - \mathrm{F}_{(\mu,\sigma,\xi)}(q^{90th})\right)} \cdot \left(\frac{100 - q^{90th}}{n}\right)\left(\frac{q^{90th} \cdot f\left(q^{90th}\right)}{2} + \right. \\ &\left. \sum_{k=1}^{n-1}\left(\left(q^{90th} + k\frac{\left(100 - q^{90th}\right)}{n}\right) \cdot f\left(q^{90th} + k\frac{\left(100 - q^{90th}\right)}{n}\right)\right) + \frac{100 \cdot f(100)}{2}\right)\end{aligned} \tag{6}$$

Liquidation Approaches and Impact

The next step is to analyse the liquidity of the investment portfolio of the investment funds[4]. Cash and deposits maturating within one year are considered highly liquid assets while the remaining investments of the funds are classified using an adjusted High-Quality Liquid Assets (HQLA) approach[5]. This involves assigning different liquidity weights to each asset type, based on different quality criteria as presented in the next table[6]:

Table 1: Liquidity weights based on an adjusted HQLA approach

	Credit Rating			
	CQS1 (AAA, AA+, AA, AA-)	**CQS2 (A+, A, A-)**	**CQS3 (BBB+, BBB, BBB-)**	**<CQS3 (BB+ and lower)**
Government bonds	(G1) 100	(G2) 85	(G3) 50	(G4) 0
Corporate bonds	(C1) 85	(C2) 50	(C3) 50	(C4) 0
Securitized	(O) 0	(O) 0	(O) 0	(O) 0

	Market Capitalisation / Total NAV		
	>1BIL	**1BIL > 500MIL**	**< 500 MIL**
Equities	(S1) 75	(S2) 50	(S3) 25
ETF	(E1) 75	(E2) 50	(E3) 25
Other Instruments	(O) 0	(O) 0	(O) 0

If a fund does not have sufficient cash to meet the extreme redemptions, the fund manager would start liquidating portions of the fund's portfolio. The liquidity weights in Table 1 are used to compute the haircuts suffered by a fund should assets belonging to that portion of the portfolio need to be liquidated. The assumption is that such an extreme redemption could occur during a distressed market scenario, which would impact the valuation of the assets and dry considerably the liquidity available in the markets. Namely, for each euro of assets belonging to G1 being sold, the manager would obtain one euro to cover the extreme redemption request. However, if the assets belong to G2, the manager will

[3] For only one fund, instead of the 90th percentile of the GPD the 99th percentile of the empirical redemption distribution was used. This is because the GPD turned out to not be a good fit to this fund's data, and the 90th percentile of the GPD resulted to be a redemption higher than 100% of the NAV. This was the only fund which did not pass the goodness of fit test at the 99% confidence level.

[4] The investment portfolios are taken as at December 2019.

[5] The HQLA approach is utilised by banks under BASEL III liquidity regulatory requirements.

[6] The information used for the classification of each asset was obtained from Refinitiv EIKON.

obtain only €0.85 for each euro sold, thus incurring a loss of €0.15, reflecting the higher liquidity costs and the higher risk of that category. Given that the liquidity weights are applied also to compute the haircuts suffered by the fund, it is assumed that the assets with a liquidity weight of zero will not be used to cover redemption requests.

The literature[7] identifies two main approaches which fund managers could follow when they need to liquidate their portfolio due to a liquidity shortfall, namely

1. the waterfall approach, and
2. the slicing approach.

Under the waterfall approach, the fund manager liquidates the most liquid assets first, subsequently moving to the less liquid assets in a descending order which reflects the liquidity weights of these assets as defined in Table 1. Under the slicing approach, the fund manager liquidates equally all the assets of the fund's portfolio to keep unchanged the asset composition of the fund. In our study, we assume that under the slicing approach the manager would liquidate the highly liquid assets first (that is cash and deposits up to one year)[8] and then liquidate proportionately the other remaining assets in the portfolio of the fund[9]. The losses suffered by each fund are then computed using the haircuts presented in Table 1 under both liquidation approaches. In this way, we estimate the drop in assets attributable to both the extreme redemptions and costs due to fire-sales. Finally, the new portfolio composition is computed based on the assets which were not liquidated to satisfy the redemptions.

Second-Round Effect

The first-round redemptions and losses incurred during the liquidation process by a fund may influence the other shareholders who in turn may choose to redeem their units from the fund. This section presents the methodology which is used to estimate the impact of second-round effects on funds.

The first step is to study the relationship between the redemptions and returns of a fund in $(t-1)$ and the redemptions at time t. More specifically, an OLS regression of the redemptions, Y_t, on lagged redemptions, Y_{t-1}, and lagged returns X_{t-1} is estimated for each fund:

$$Y_t = \alpha + \beta_1 Y_{t-1} + \beta_2 X_{t-1} + \epsilon_t$$

Then, the estimated first-round extreme redemptions and the respective liquidation losses are applied to the estimated model to forecast the expected redemptions during the following period. In this way, six different second-round effect redemptions are obtained for each sub-fund (applying the three different extreme redemption levels and the two different liquidation approaches). The waterfall and slicing approaches are then applied again to analyse how the manager would satisfy the second-round redemptions.

The Macro-Level Scenario-Based Shock

This section presents the methodology of the scenario-based approach which involves the modelling of the impact of the macro-economic shocks on investment funds. This approach examines directly how the investors' behaviour is influenced by the macro-economic environment. Under the scenario approach all funds are subject to the same macro-economic shocks which makes it simpler to aggregate

[7] (ESMA, 2019), (Bouveret, 2017), (Cetorelli, et al., 2016), (Baranova, et al., 2017)
[8] This approach is different from other previous studies we found in literature such as (ESMA, 2019). Our assumption is that while the manager still wants to keep the asset allocation unchanged, it would want to minimize the liquidity costs incurred.
[9] Within each asset category, the manager initially sells the most liquid assets, moving on to less liquid ones.

the results across the various fund strategies. The main steps involved in this approach are outlined in the below flow chart.

Scenario-based Shock

Macro-Economic Setting	• Identification of relevant macro-economic variables • Definition of correlation structure among macro-economic variables
Analysis of Investors' Behaviour Determinants	• Definition of how the selected macro-economic variables affect the fund investors' choices
Shock Simulation	• Application of a shock on a macro-economic variable • Correlation structure to estimate the effect on the other macro-economic variables
Conditional Net flow Estimation	• Direct effect of the variable shock on the investors' decisions • Indirect effect of the shock's impact on the other macro-economic variables

Modelling Approach

There are several approaches to model the impact of a macro-financial shock on investment funds. One possible approach is to first analyse the impact of a macro-financial shock on the returns of funds and then analyse the sensitivity between the returns of funds and net flows to understand how such a shock, in turn, impacts the funds' expected net flows (Morris et al. 2017; Fricke & Fricke 2017; Baranova et al. 2017; Van der Veer et al. 2017; Goldstein et al. 2017; Chevalier & Ellison 1997). An alternative approach is to study directly the relationship between the net flows of funds and the macro-financial variables, to examine the effect of the investors' behaviour in the financial markets (Bouveret 2017; Babalos et al. 2019). In this study, we use the latter approach.

Initially, we studied the relationship between net flows and various macro-financial variables such as equity, bond and volatility indices. However, the parameter estimates were statistically significant only for a few variables, with their sign not always being in line with the rational explanations and a poor goodness of fit. One possible explanation for this could be the lack of awareness of retail clients on the latest developments occurring in the financial markets, instead being influenced by the economic situation. Therefore, we try to model the expected net flows using macro-economic variables to provide with a better explanatory power.

Four macro-economic variables, namely industrial production, unemployment rate, money supply and 10-year government interest rates, are selected to study their relationship with net flows. The criteria used in the selection of these variables is their relevance in determining the savings and investment decisions taken by retail clients. We collect the selected macro-economic variables for two different regions, namely Malta and the Eurozone. Investors originating from these regions hold 80% of the net asset value of our sample of investment funds. Therefore, it is expected that the economic situation in these regions would substantially influence the shareholders' investment decisions.

Additionally, we select two other variables for the model, namely the US industrial production and the US 10-year government interest rates. Even though US investors have almost insignificant presence in the Maltese retail funds industry, these two indicators are also selected since they are considered as main drivers of the global economy.[10] These exogenous variables are separately modelled through a vector autoregressive (VAR) model in order to account for the interdependencies between these economies, partially following the approach adopted by Pesaran, Schuermann, Treutler and Weiner (2003)[11], which is going to be denoted here as PSTW. Therefore, a VAR model composed of ten variables (four macro-economic variables for the two different regions, plus the two US variables) is fitted using monthly observations starting from November 2001 until December 2019. However, the dynamics between the monthly net flows of the retail Maltese funds aggregated by strategy and the macro-economic variables is analysed using data from December 2014 to December 2019 since several funds started operating in the last few years. Therefore, it is likely that in the last few years there may have been structural changes in the net flow dynamics of the Maltese retail funds.

The relationships between the monthly net flows and the macro-economic variables are estimated through an OLS regression. Then the liquidity stress testing is carried out by observing the effect of a shock in a macro-economic variable on the expected and the worst-case conditional net flows. This is performed using the generalised impulse response function of the VAR model to integrate the indirect effect of such a shock on the other macro-economic variables.

Model Construction

For $\mathrm{i} = \{\mathrm{Malta},\ \mathrm{Eurozone}\}$, the domestic variable vector $\mathbf{x}_{\mathrm{i,t}}$ is defined as:

$$\mathbf{x}_{\mathrm{i,t}} = \begin{pmatrix} \mathrm{ip}_{\mathrm{i,t}} \\ \mathrm{ur}_{\mathrm{i,t}} \\ \mathrm{ms}_{\mathrm{i,t}} \\ \mathrm{ir}_{\mathrm{i,t}} \end{pmatrix}$$

where

$$\begin{aligned} \mathrm{ip}_{\mathrm{i,t}} &= \ln\left(\mathrm{IP}_{\mathrm{i,t}}/\mathrm{CPI}_{\mathrm{i,t}}\right) \\ \mathrm{ur}_{\mathrm{i,t}} &= \ln\left(1+\mathrm{UR}_{\mathrm{i,t}}/100\right) \\ \mathrm{ms}_{\mathrm{i,t}} &= \ln\left(\mathrm{M3}_{\mathrm{i,t}}/\mathrm{CPI}_{\mathrm{i,t}}\right) \\ \mathrm{ir}_{\mathrm{i,t}} &= \ln\left(1+\mathrm{Yield}_{\mathrm{i,t}}^{10\mathrm{Y}}/100\right) \end{aligned}$$

and $\mathrm{IP}_{\mathrm{i,t}}$ is the industrial production index, $\mathrm{CPI}_{\mathrm{i,t}}$ the consumer price index, $\mathrm{UR}_{\mathrm{i,t}}$ the unemployment rate, $\mathrm{M3}_{\mathrm{i,t}}$ represents the money supply, while $\mathrm{Yield}_{\mathrm{i,t}}^{10\mathrm{Y}}$ is the 10-year government bond yield.

Moreover, the vector $\mathbf{x}_{\mathrm{US,t}}$ is defined as:

$$\mathbf{x}_{\mathrm{US,t}} = \begin{pmatrix} \mathrm{ip}_{\mathrm{US,t}} \\ \mathrm{ir}_{\mathrm{US,t}} \end{pmatrix}.$$

The monthly net flows of the fund strategy *j* are then modelled through an OLS regression as:

$$\mathrm{NetFlow}_{\mathrm{j,t}} = \alpha_{\mathrm{j}} + \boldsymbol{\beta}'\boldsymbol{\Delta}\mathbf{x}_{\mathrm{t}} + \eta_{\mathrm{j,t}} \tag{7}$$

where

$\mathbf{x}_{\mathrm{t}} = \begin{pmatrix} \mathbf{x}_{\mathrm{Malta},t} \\ \mathbf{x}_{\mathrm{Eurozone},t} \\ \mathbf{x}_{\mathrm{US},t} \end{pmatrix}$ and $\eta_{\mathrm{jt}} \sim \mathrm{i.i.d.}\left(0, \omega_{\eta,j}^2\right)$.

[10] For parsimonious reasons, the US unemployment rate and money supply are excluded from our model due to the assumption that they would have a limited direct impact on Maltese retail funds investors' decisions.
[11] See also (Pesaran, et al., 2004).

The correlation structure among $\mathbf{x}_{\mathrm{t}}$ is further modelled through the VAR(1) model:

$$\boldsymbol{\Delta}\mathbf{x}_{\mathrm{t}} = \boldsymbol{a}_0 + \boldsymbol{\Phi}\boldsymbol{\Delta}\mathbf{x}_{\mathrm{t}-1} + \boldsymbol{\epsilon}_{\mathrm{t}} \tag{8}$$

with the assumptions that:

$$\mathrm{E}(\boldsymbol{\epsilon}_{\mathrm{t}}) = \mathbf{0}\,;\, \mathrm{E}(\boldsymbol{\epsilon}_{\mathrm{t}}\boldsymbol{\epsilon}_{\mathrm{s}}) = \begin{bmatrix} \boldsymbol{\Sigma} \text{ for } \mathrm{t} = \mathrm{s} \\ \mathbf{0} \text{ for } \mathrm{t} \neq \mathrm{s} \end{bmatrix}.$$

Then, to analyse how a shock in a macro-economic variable would affect the net flows of fund strategy *j*, the approach followed is a simplification of the model developed by PSTW. As a first step, the net flows of the fund strategy *j* at time $(t+1)$ is split between a forecastable conditional mean $\mu_{j,t}$ and a non-forecastable innovation component denoted by $\xi_{j,t+1}$:

$$\mathrm{NetFlow}_{\mathrm{j,t+1}} = \mu_{j,t} + \xi_{j,t+1}. \tag{9}$$

Combining (7) and (8), it is possible to see that the conditional mean component can be redefined as:

$$\mu_{j,t} = \alpha_j + \boldsymbol{\beta}'(\boldsymbol{a}_0 + \boldsymbol{\Phi}\boldsymbol{\Delta}\mathbf{x}_{\mathrm{t}}) \tag{10}$$

while the innovation term can be re-written as:

$$\xi_{j,t+1} = \eta_{j,t+1} + \boldsymbol{\beta}'\boldsymbol{\epsilon}_{\mathrm{t}+1}. \tag{11}$$

Moreover, under the assumption that the idiosyncratic shock of the strategy net flow $\eta_{j,t+1}$ and the macro-economic shock $\boldsymbol{\epsilon}_{\mathrm{t}+1}$ are distributed independently and with constant covariance matrix, the variance of the shock component $\xi_{j,t+1}$ can be written as:

$$\mathrm{var}(\xi_j) \equiv \omega^2_{\xi,j} = \omega^2_{\eta,j} + \boldsymbol{\beta}'\boldsymbol{\Sigma}\boldsymbol{\beta}. \tag{12}$$

Assuming now that the n^{th} macro-economic variable in $\mathbf{x}_{\mathrm{t}}$ is shocked between time t and time $(t+1)$ with a shock δ_n, and if the macro-economic innovation term $\boldsymbol{\epsilon}_{\mathrm{t}+1}$ follows a multivariate normal distribution, the expected effect on the other innovation terms can be computed as:

$$\mathrm{E}(\boldsymbol{\epsilon}_{t+1} \,|\, \epsilon_{n,t+1} = \delta_n) = \boldsymbol{\Sigma}\mathbf{e}_n\sigma^{-1}_{nn}\,\delta_n \tag{13}$$

where $\mathbf{e}_n$ is a selection vector of dimension (10×1), which takes the value of one only in the element which corresponds to the n^{th} macro-economic variable and zero elsewhere. If the shock is unexpected and, therefore, it does not alter the shape of the innovations' distribution, the unconditional variance can still be used. Then:

$$\xi_{j,t+1} \,|\, \epsilon_{n,t+1} = \delta_n \sim N(\boldsymbol{\beta}'\boldsymbol{\Sigma}\mathbf{e}_n\sigma^{-1}_{nn}\,\delta_n\,, \omega^2_{\xi,j}). \tag{14}$$

At this point, given the distribution of the innovation term, it is possible to generate different possible net flows which could occur if the chosen macro-economic variable suffers a shock equal to δ_n, drawing the outcomes from:

$$\begin{aligned} \mathrm{NetFlow}^n_{\mathrm{j,t+1}} &= \mu_{j,t} + \boldsymbol{\beta}'\boldsymbol{\Sigma}\mathbf{e}_{\boldsymbol{n}}\sigma^{-1}_{nn}\,\delta_n + \omega^2_{\xi,j} \cdot Z \\ &= \alpha_j + \boldsymbol{\beta}'(\boldsymbol{a}_0 + \boldsymbol{\Phi}\boldsymbol{\Delta}\mathbf{x}_{\mathrm{t}}) + \boldsymbol{\beta}'\boldsymbol{\Sigma}\mathbf{e}_n\sigma^{-1}_{nn}\,\delta_n + \omega^2_{\xi,j} \cdot Z \end{aligned} \tag{15}$$

with Z being randomly drawn from a standard normal distribution. In particular, fixing $Z = -2.33$ gives the 99% value-at-risk case, while with $Z = 0$, it represents the expected/average net-flow given a shock.

For completeness, should the shock be anticipated, the covariance matrix of the macro-economic innovation terms, conditional on the shock, would become equal to:

$$\mathrm{E}\left(\boldsymbol{\epsilon}_{t+1}\boldsymbol{\epsilon}_{t+1} \mid \epsilon_{n,t+1} = \delta_n\right) = \boldsymbol{\Sigma} - \boldsymbol{\Sigma}\mathbf{e}_n(\mathbf{e}'_n\boldsymbol{\Sigma}\mathbf{e}_n)^{-1}\mathbf{e}'_n\boldsymbol{\Sigma}. \tag{16}$$

STIFF's Application Results

Sample Construction

The sample consists of 64 retail investment funds[12] licensed in Malta covering a total net asset value of €3.1 billion or 88% of the total NAV of the Maltese retail funds as at end of 2019. The sample is selected on the following criteria:

1. Funds are systemically relevant to the Maltese financial sector.[13]
2. Funds have been active for at least two years.
3. The number of redemption observations was sufficient to be able to fit a distribution.

Of the 64 selected funds, six are licensed as AIFs targeting retail investors while the remaining 58 are UCITS funds. In terms of asset allocation, 23 are bond funds, 13 equity funds, 11 mixed[14] funds, 10 diversified[15] funds, and seven funds classified as other[16].

Table 2: NAV and number of funds under analysis

Category	**NAV of Selected Sample (€ bn)**	**No. of Funds for Selected Sample**	**% Retail NAV Analysed**
Bond	1.7	23	100
Diversified	0.4	10	57
Equity	0.3	13	86
Mixed	0.6	11	88
Other	0.1	7	94
Total	**3.1**	**64**	**88**

The redemptions of each fund are aggregated at a weekly level and the redemptions as a percentage of the beginning of the weekly NAVs are then computed. The number of weekly percentage redemptions varies significantly between the funds because of the different inception dates. The average number of weekly observations available for each fund is 365, ranging from a minimum of 103 to a maximum of 692. Therefore, for most of the funds, the data covers their whole life. Table A.1 presents various descriptive statistics for the funds under analysis. One observes that in most of the cases, the average net weekly flow is positive, and the maximum net inflow is much larger than the maximum net outflow.

[12] This includes AIFs targeting retail investors and UCITS funds.
[13] The methodology used to identify the systemically relevant funds is an internal methodology developed by the Financial Stability function to classify funds into domestic and locally based funds.
[14] Mixed funds are funds investing in bonds and equities.
[15] Diversified funds are funds investing in a broader set of assets.
[16] This is a residual category, which contains also real estate and money market funds since there was only one fund in each of these two categories.

The Micro-Level Pure Redemption Shock

Estimation of Extreme Redemptions

The first step is to compute the 90th percentile of each fund's redemption empirical distribution to find the exceedances on which to fit the GPD. Table A.2 in the appendix presents both the threshold μ and the GPD estimated parameters σ and ξ. As one can observe, only 14 funds (or 21.9% of the sample) have a 90th percentile equal to or higher than 1%, meaning that for most of the Maltese retail funds under analysis the fund managers can expect to suffer minimal weekly redemptions. For 26 funds (or 40.6% of the sample), the estimated shape parameter is not statistically different from one. This means that for those funds, the fitted GPD distribution does not have a finite first moment and the trapezoidal rule is used instead to compute all the expected extreme redemptions.

The estimated expected redemptions obtained for the worst 10%, 5% and 1% redemptions are presented in Table A.*3*. For both the worst 10% and 5% redemptions, most of the funds (57 funds and 54 funds respectively) have an expected redemption in the range of 0% to 5%. For the worst 1% redemption, 51 funds have expected redemptions in the range of 0% to 10% while the remaining 13 funds have higher expected redemptions, up to a maximum redemption of 44%.

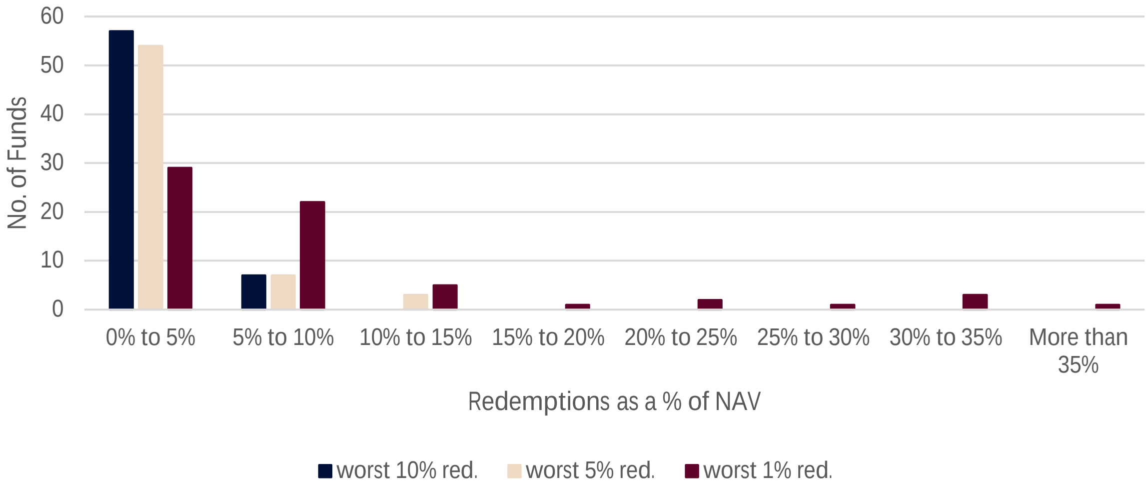


Figure 1: Redemption shock at different levels (10%, 5%, 1%) as a % of NAV

Looking at the worst 1% redemption aggregated at a fund strategy level, 60.9% of the bond funds and 60% of the diversified funds have expected redemptions in the range 0% to 5% while 92.3% of equity funds, 72.7% of mixed funds and all funds classified as *other* have expected redemptions in the range 0% to 10%. There are only three bond funds and one mixed fund with expected redemptions higher than 30%.

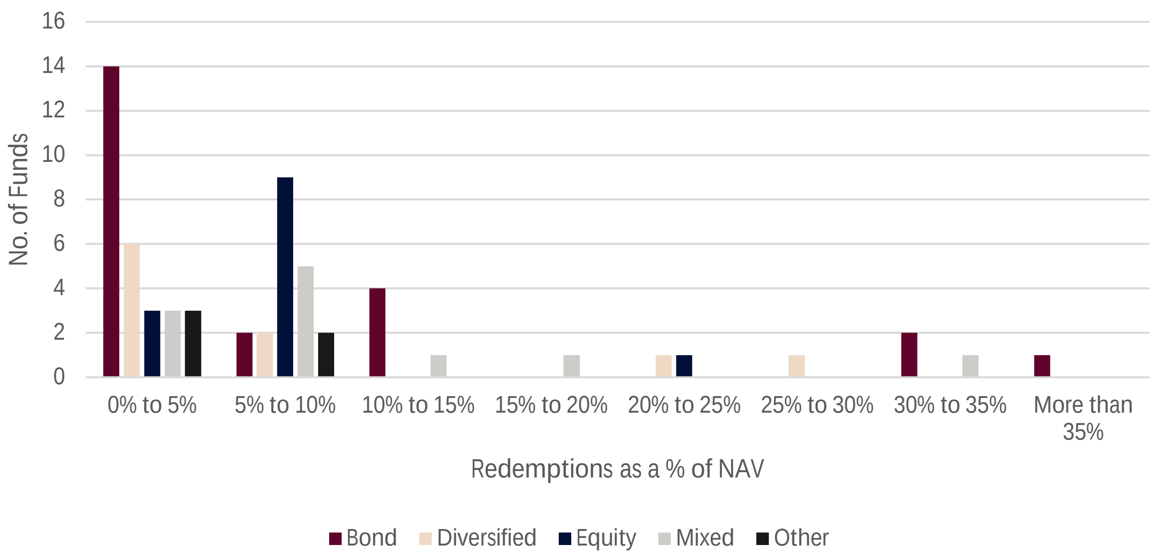


Figure 2: Redemption shock at 1% level by strategy

Liquidation of Assets

Prior to commencing with the estimation of the liquidation process, the amount of highly liquid assets for each fund is computed. The liquidity shortfall is then computed as:

$$\text{Liquidity shortfall} = \text{Expected Redemptions} - \text{Highly Liquid Assets}$$

for each level of expected redemptions. Thus, a manager would need to start liquidating the investment portfolio of the fund if the liquidity shortfall is positive.

These results are presented in Table A.3, with those funds experiencing a liquidity shortfall highlighted in red. The overall liquidity profile of the funds appears appropriate, since most of the funds would not need to liquidate any further assets in order to satisfy a worst-case redemption scenario. In the case of a 10% worst expected redemption, only four funds (or 6.3% of the sample) do not hold enough highly liquid assets. This number slightly increases for the worst 5% scenario to six funds (or 9.4%). Instead, for the 1% worst expected redemption, 20 funds (or 31.3%) do not hold enough highly liquid assets and are expected to liquidate further assets under such a scenario.

Except for the 1% worst case scenario, we find that the waterfall and slicing approaches present almost the same results in terms of losses and funds not meeting the worst expected redemption requests. This is mainly due to the low number of funds which experience a liquidity shortfall.

There is only one fund, namely Fund 54 classified as a diversified fund, which cannot meet the redemption requests under the three different levels of redemption scenarios. Another two funds, Fund 34 and Fund 29, cannot meet the redemption requests under the 1% worst-case scenario. However, while Fund 34 faces liquidity problems under both the waterfall and slicing approaches, Fund 29 falls short of liquidity only under the slicing approach. Fund 34 is a bond fund which has a substantial high simulated redemption as a percentage of NAV, and its portfolio is composed of a high percentage of instruments classified as illiquid under the adjusted HQLA approach (sub-investment grade bonds and other bonds). Fund 29 is another bond fund which failed the test because 55% of its NAV is invested in sub-investment grade bonds.

Even in terms of losses, the waterfall and the slicing approaches yield similar results. Most of the funds which would need to liquidate their portfolio holdings to meet the extreme redemption requests would suffer losses below 5% of their NAV. For Fund 54, the liquidation losses are not computed since its whole portfolio is classified as illiquid, and therefore it could not be sold under this liquidity stress testing framework. Only two bond funds and a diversified fund would incur losses higher than 5% of the NAV in the 1% worst redemption scenario under the waterfall approach (namely, Fund 29 with losses higher than 10%, while Fund 19 and Fund 34 would incur losses between 5% and 10%). Instead, under the slicing approach, an additional mixed fund would suffer losses higher than 5% (namely, Fund 44).

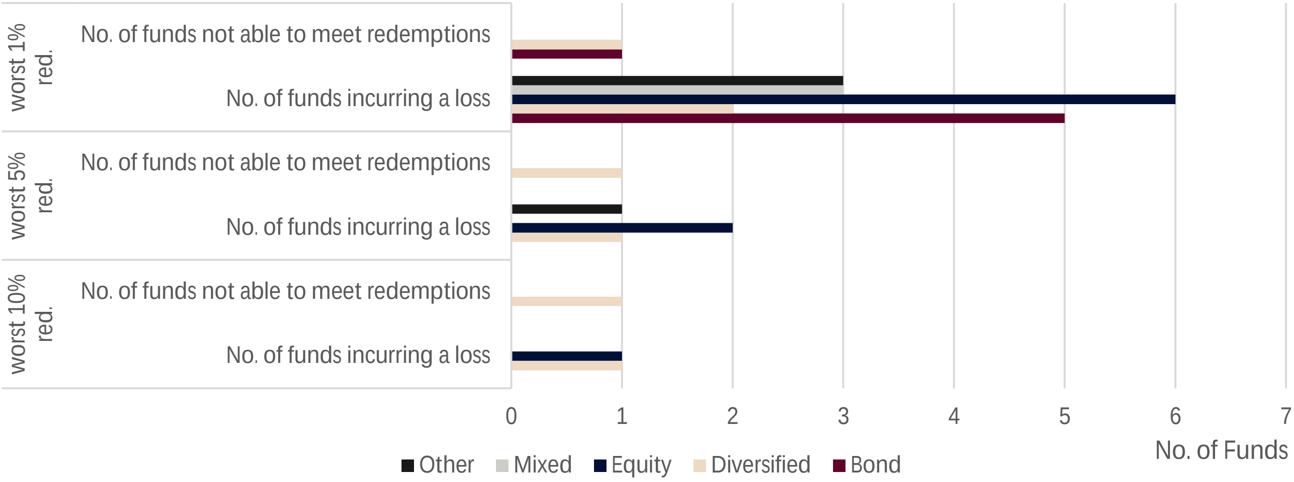


Figure 3: Liquidation under the waterfall approach

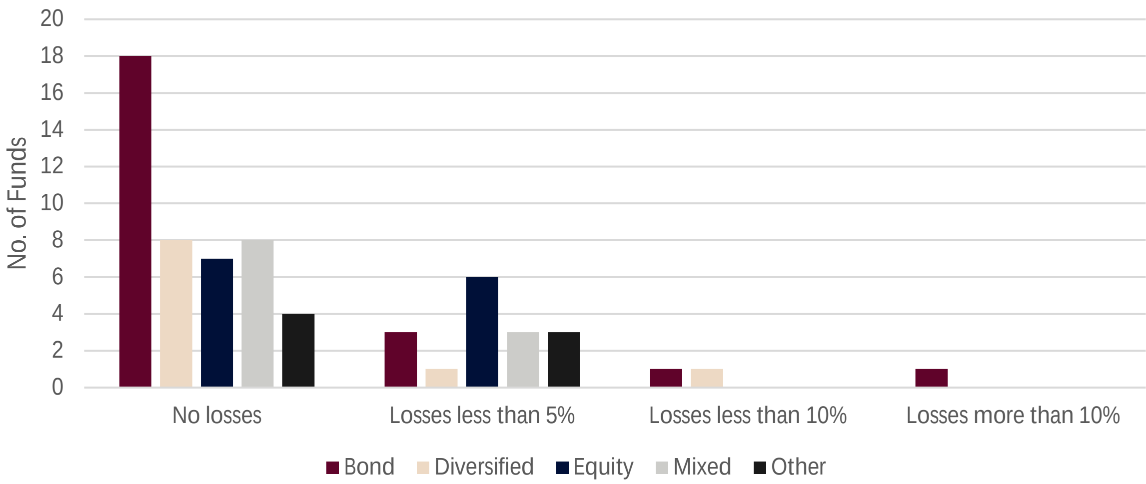


Figure 4: Losses incurred to meet the 1% worst redemption under the waterfall approach

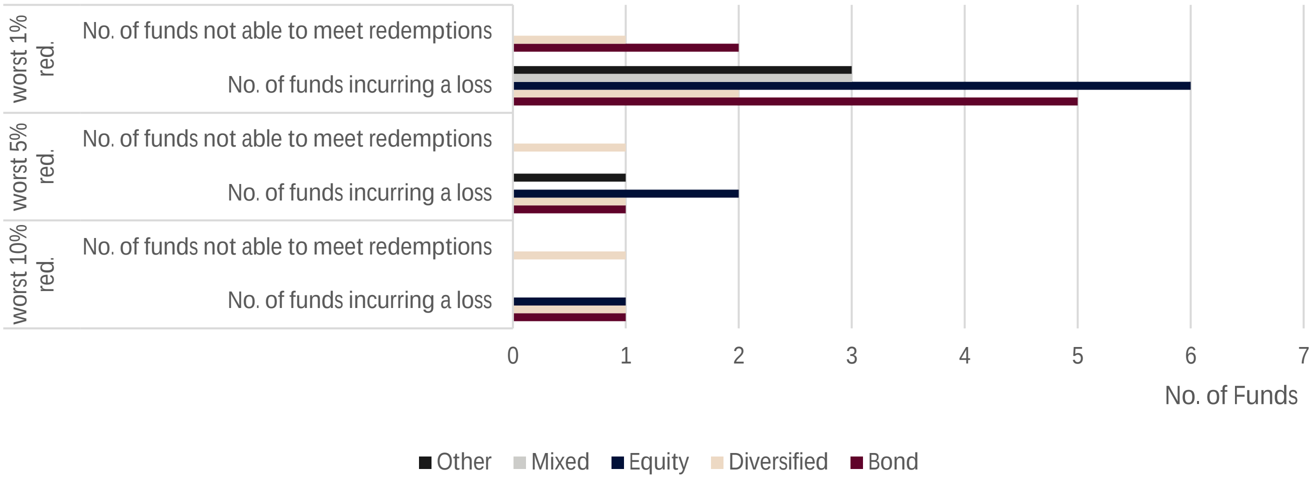


Figure 5: Liquidation under the slicing approach

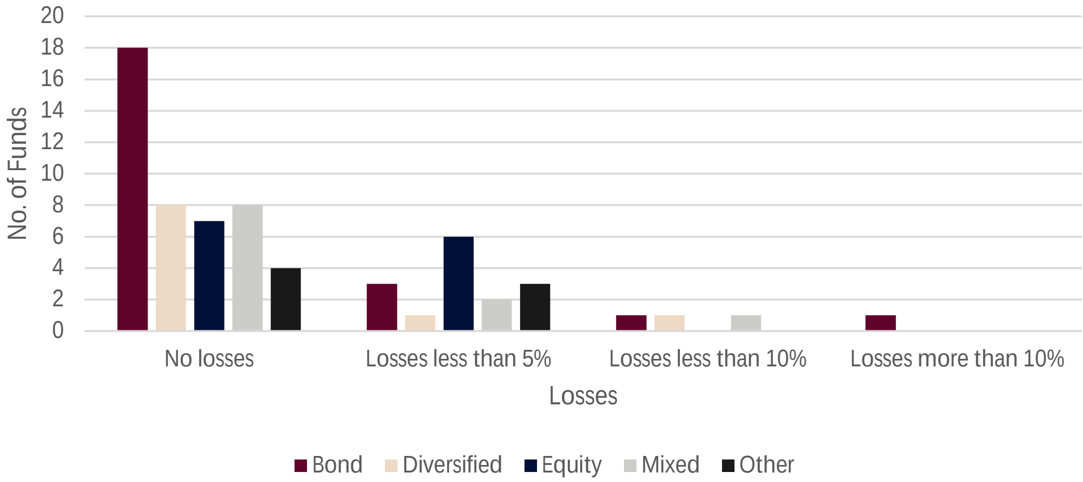


Figure 6: Losses incurred to meet the 1% worst redemption under the slicing approach

At a strategy level, equity funds suffer the most in the three worst redemption scenarios, both in terms of redemptions and losses due to liquidation of assets. Should the 1% worst case redemption occur simultaneously in all the equity funds, the total NAV of this category of funds would shrink by 8.5% with an additional 0.8% of NAV being lost due to liquidation costs.

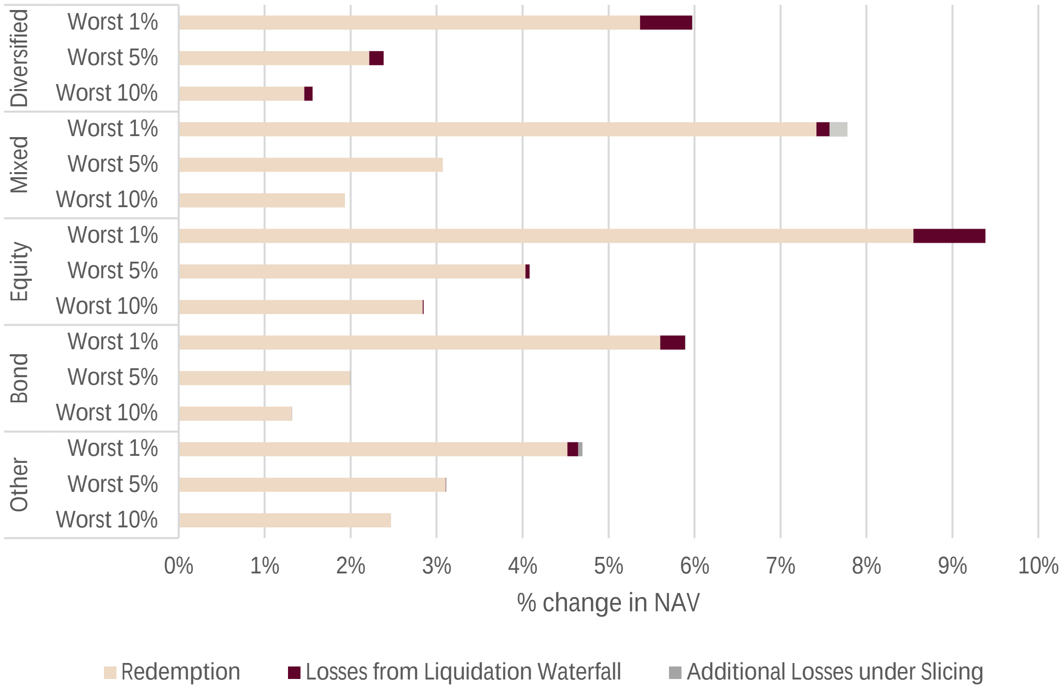


Figure 7: Effect of extreme redemptions on the aggregated NAV by strategy

Portfolio Redefinition and Second-Round Effects

The portfolio composition of each fund is re-calculated according to the liquidation approach performed by the fund manager to meet the extreme redemption scenarios. Therefore, six different re-defined portfolios are obtained for each fund (one for each scenario and for each liquidation approach). Then, we analyse the relationship between the redemptions at a certain point in time, t, the redemptions that occurred in $t-1$ and the performance of the fund in $t-1$. This is carried out to estimate the second-round redemptions which the funds would expect to experience as a result of the previous extreme redemptions.

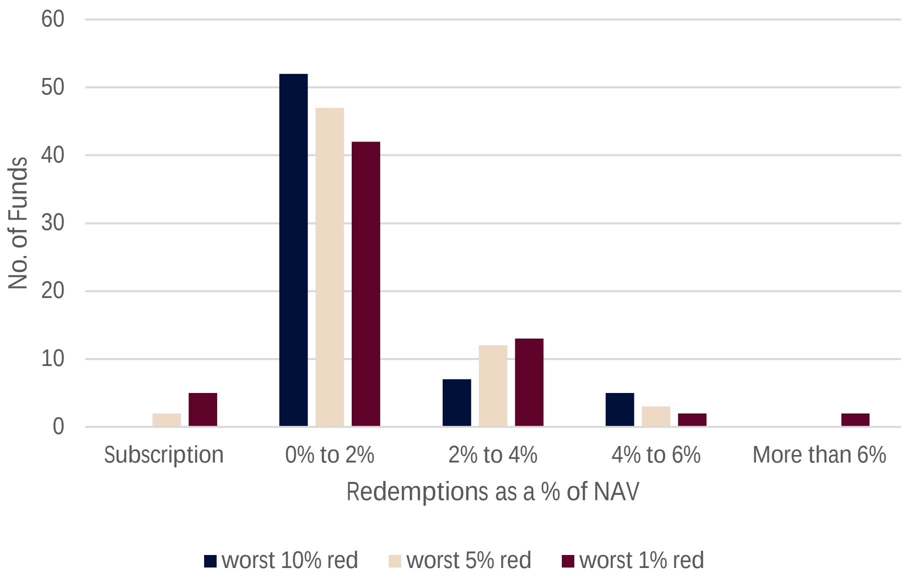


Figure 8: Second-round redemptions under the waterfall approach

From our analysis, we found that the second-round redemptions appear to be contained. In only a few cases, funds would expect net subscriptions as a result of a severe redemption or negative return in the previous period. This can be explained by the fact that some investors may seek new investment opportunities in such a scenario.

Most of the second-round redemptions would be below 2% in all the three scenarios. Since the simulated second-round redemptions are almost the same under both the waterfall and the slicing approaches, only the second-round redemptions under the waterfall approach are presented in Figure 8. Both the waterfall and the slicing approaches are then applied to analyse how the funds would further liquidate their portfolios to meet these additional redemptions. Under the waterfall approach, all the losses are very contained, lower than 2% of NAV. Only for two funds the second-round redemptions due to the 1% worst redemption would result in losses between 2% and 4%. Fund 29 becomes unable to meet the second-round redemptions after a 1% worst case even under the waterfall approach.

Differently from the first round, there is a higher number of funds which would incur losses due to the liquidation of their portfolio, both under the waterfall and slicing approaches. This is because several funds would have their cash buffers dried up after the first-round extreme redemption. However, the second-round losses are, on average, much smaller than the ones in the first-round.

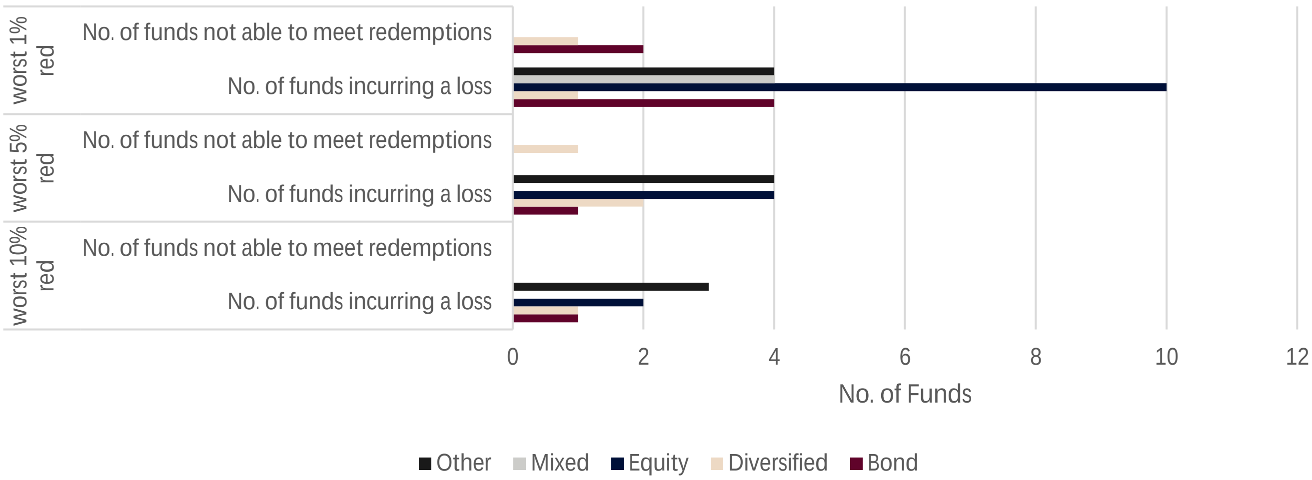


Figure 9: Second-round liquidation under the waterfall approach

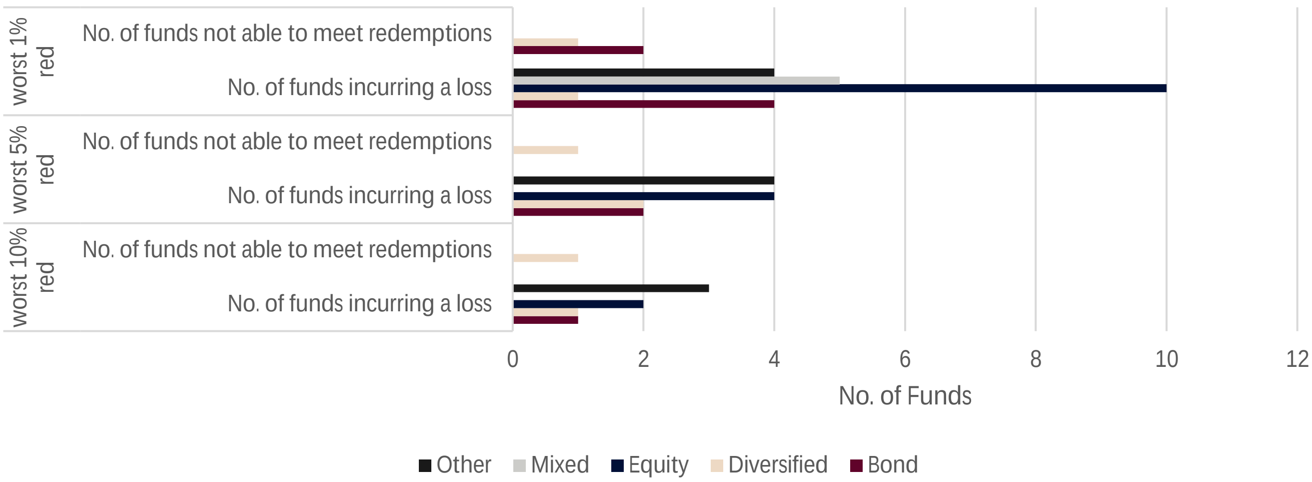


Figure 10: Second-round liquidation under the slicing approach

The aggregated second-round effect at a strategy level under both the waterfall and slicing approaches give almost the same results. Similar to the results obtained in the first-round, equity funds suffer the most out of all the fund categories although the losses are now less, at 2% of the NAV. From the aggregated figures it is possible to notice that except for mixed funds, all other fund categories experience losses due to liquidation for all the severity levels. This contrasts with the results obtained from the first round where losses were mainly observed only for the 1% worst redemption. One concludes that although the funds are generally ready to bear a first-round of extreme redemptions, they would not have enough cash to meet the expected second-round redemptions.

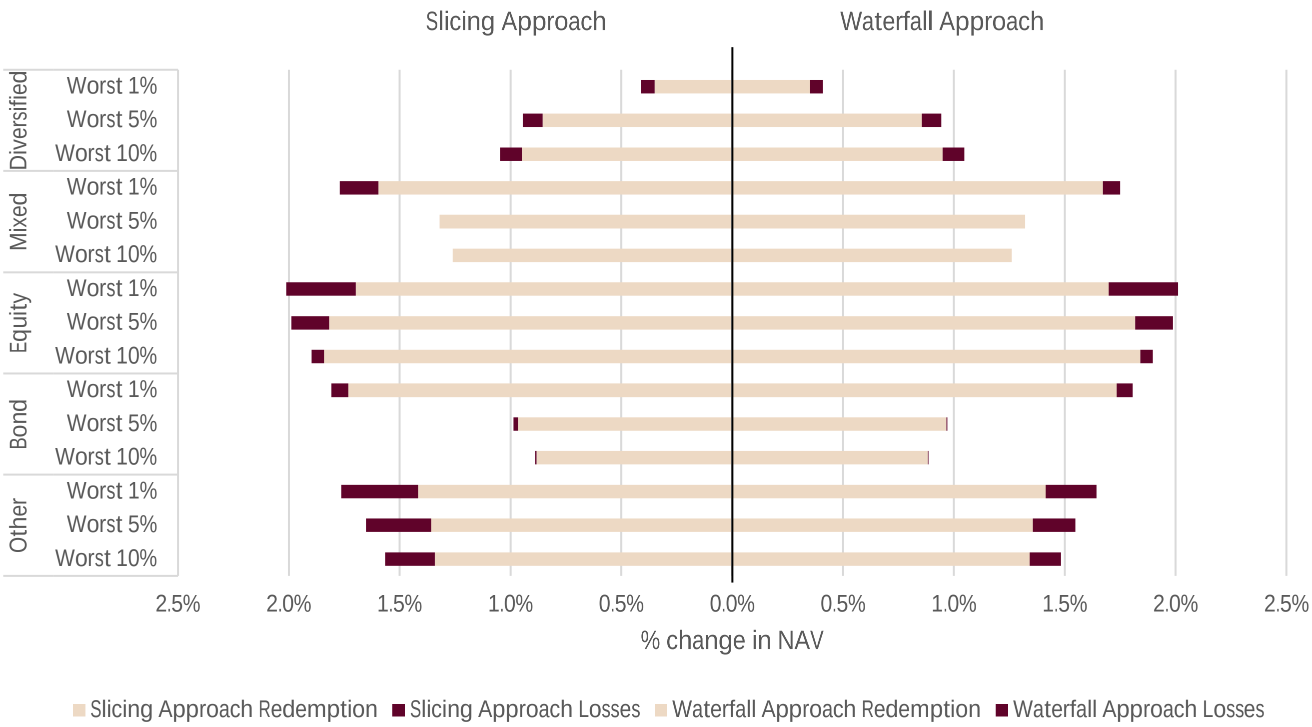


Figure 11: Second-round effect of extreme redemptions on the aggregated NAV by strategy

Macro-Level Scenario-based Shock

Effect of Macro-Economic Variables on Investors' Decisions

First, we fit an OLS regression to study the relationship between net flows and the ten selected macro-economic variables for the different types of funds (bond, equity, mixed, diversified and other). From our analysis, we find that there are few statistically significant relationships between net flows and the selected variables. The following table represents the parameter estimates of the model and their statistical significance at the 1%, 5% and 10% levels.

Table 3: Parameter estimates for the OLS regression

	Bond	Diversified	Equity	Mixed	Other
Constant	0.55*	0.53	0.60**	0	-0.8
ip - US	-0.22	0.09	0.65**	0.76	2.17**
ip – MT	0.05	-0.05	0.01	0	0.34***
ip - EA	-0.1	-0.53*	-0.22	0.04	-0.64
ur - MT	-2.01	-1.34	3.10**	6.06*	-2.19
ur - EA	-3.38	-3.58	-2.57	-5.33	-11.52
ms - MT	0.1	0.07	0.01	0.35***	0.19
ms - EA	-0.05	1.14	-0.68	1.08	-1.62
ir - US	2.35*	-1.63	0.18	6.70**	4.2
ir - MT	-3.08*	0.08	1.52	-7.66**	7.16
ir – EA	0.24	0.96	1.2	1.22	-5.35

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

As reported in Table *3*, the Maltese interest rate parameter *ir - MT* is significantly negative in the bond funds model. This is justified by the inverse relationship that there is between bond prices and interest rates. The coefficient of the US interest rates, *ir – US,* is significantly positive and this can be explained by the fact that since Maltese retail bond funds invest substantially in Maltese bonds, should the US bonds benefit from decreasing interest rates, the investors could decide to move to bond funds targeting that market.

The industrial production in the Eurozone, *ip – EA,* is negatively related to net flows in the diversified funds model. This relationship can be justified by the fact that when the real economy is weakening, investors move their money to diversified funds since these types of funds can provide with more uncorrelated and protected strategies.

A stronger economic situation looks beneficial for both equity funds and *other* funds. Indeed, they both show statistically significant coefficients with the US industrial production, with net flows of *other* funds being statistically related to industrial production in Malta as well.

For mixed funds, net flows are significantly positively related to money supply in Malta and the US interest rates while significantly negatively related with the Maltese interest rate. Similar to what was discussed for bond funds, one possible explanation for the latter relationship can be that should the US interest rates start decreasing, investors could decide to move their money to funds targeting US bonds.

The significant relationships of net flows with the other variables, such as unemployment rates in the equity funds and mixed funds models, appear contradictory.

After fitting the OLS regression, the dependency among the exogenous variables is modelled through a VAR model. The covariance matrix is extracted from the VAR model, providing with both the volatilities of and the interdependencies between the macro-economic variables' innovation term ξ.

Application of a Macro-Economic Shock to the Model

Following the OLS and VAR model estimations, each macro-economic variable is stressed by applying a 2.33-σ shock (corresponding to the 99th percentile) to its innovation term, ξ. The covariance matrix and the OLS coefficients are then used to compute the effect that such a shock would have on the other macro-economic variables and, in turn, on the expected net flows. The expected net flows, conditional on a shock in each macro-economic variable, are illustrated in Figure 12.

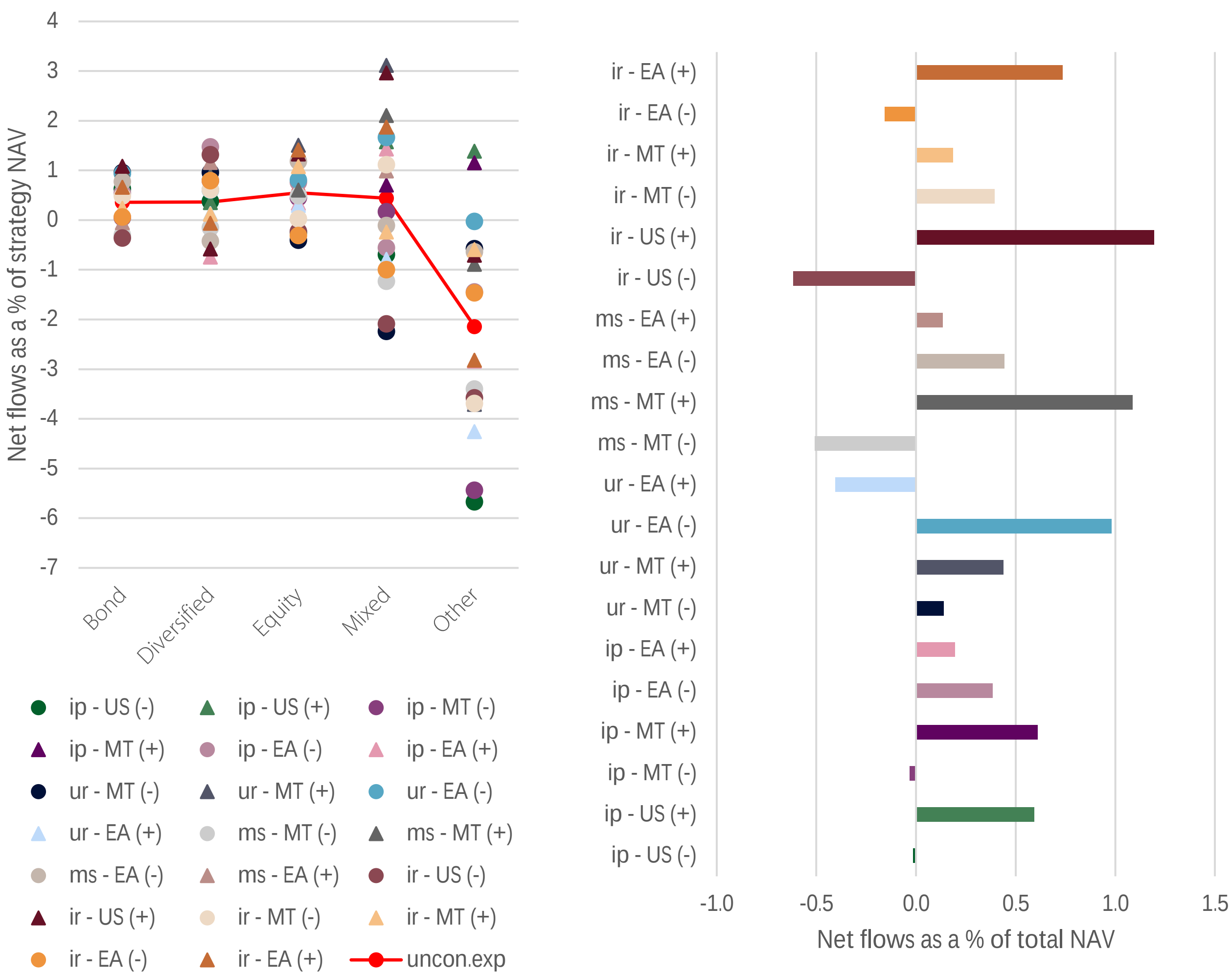


Figure 12: Expected net flows given a 2.33-σ unanticipated shock in a macro-economic variable

As shown in Figure 12, *other* and mixed funds appear to be the most sensitive strategies to changes in the macro-economic environment, with a dispersion in their expected net flows larger than in bond and equity funds.

The worst scenario for bond funds would be in the case of decreasing interest rates in the US as this could drive the bond investors to foreign bond funds which focus on such a market. In fact, under such a scenario, the expected net flow would be negative and equal to 0.4% of the strategy's total NAV. Also, a tightening in the money supply in Malta would negatively impact bond funds, with an expected outflow equal to 0.3%. Differently from bond funds, diversified funds would be substantially affected by an increase in the US interest rates, with an expected outflow under such a scenario equal to 0.6%. Like bond funds, diversified funds would suffer from a sharp tightening in the money supply in Malta, however, the worst effect would be under a tightening in the Eurozone's money supply, with an expected outflow of 0.4%.

A shock in the US industrial production would particularly impact *other*, mixed and equity funds, which would suffer expected outflows equal to 5.7%, 0.7% and 0.2% respectively. *Other* funds are also particularly exposed to the Maltese industrial production (expected outflow of 5.4% in case of a shock). Mixed funds, instead, seem more exposed to a deteriorating economic scenario in the Eurozone, with an expected outflow in case of a drop in the industrial production equal to 0.6% and an expected outflow in case of a spike in the unemployment rate equal to 0.8%. Overall, *other* funds seem to be the weaker category of funds, with a positive expected net flow only in the case of a positive shock in the US and

Maltese industrial production. The shocks that would mostly affect the Maltese retail funds are a sharp decrease in the US interest rates (expected net outflow equal to 0.6% of the total Maltese retail funds NAV), a sharp tightening in the money supply in Malta (-0.5% net flow) and a spike in the unemployment rate in the Eurozone (-0.4% net flow). Importantly, these scenarios show the "expected" net flow in the strategies, and therefore, they are the baseline net flow which could occur.

For this reason, an additional worst-case outflow is computed applying a negative 2.33-σ shock to the OLS innovation terms $\eta_{j,t}$. Therefore, this shock represents a 2.33-σ idiosyncratic negative shock to the strategy's net flows. The results indicate that the **net flows of equity and bond funds are more stable than for the remaining strategies.** In fact, under all the scenarios, they would suffer a lower worst-case outflow than the remaining strategies. The situation is instead particularly severe for the funds classified under *other* funds, since, even with a very positive macro-economic environment (given by a positive 2.33-σ shock in the Maltese or US industrial production) they would still suffer a net outflow higher than 8% of their assets.

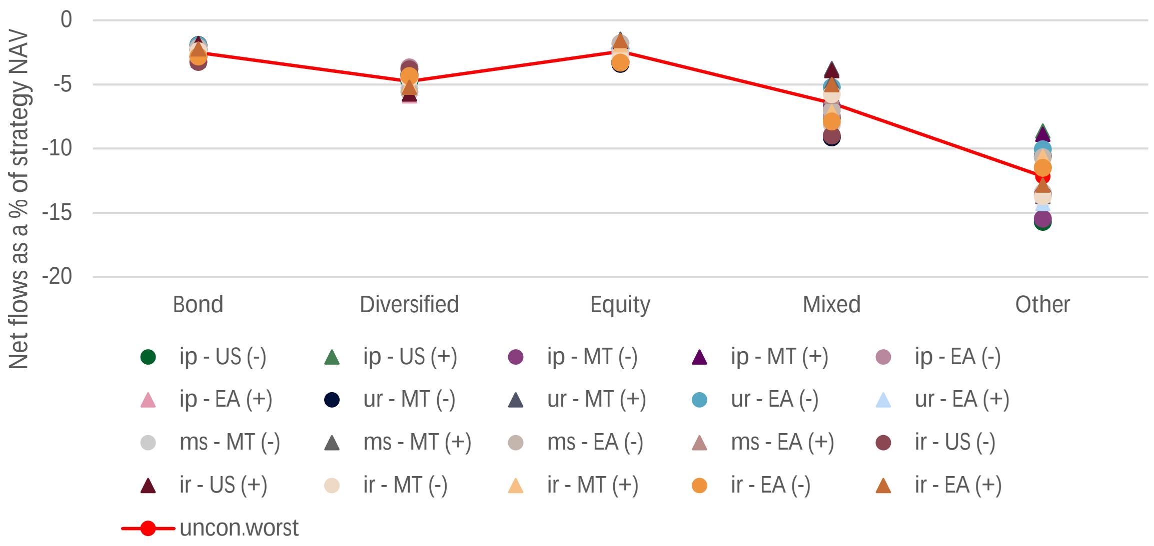


Figure 13: Worst 99% net flows given a 2.33-σ unanticipated shock in a macro-economic variable

Table 4: Strategy's Liquidity Profile

Strategy	Average Highly Liquid Assets	Highly Liquid Assets as a % of Strategy NAV
Bond	11.19%	10.43%
Diversified	9.57%	7.24%
Equity	6.79%	7.29%
Mixed	13.20%	9.30%
Other	20.40%	32.39%

In order to analyse the resilience of each fund strategy, we compared the different simulated scenarios to both the average highly liquid assets of the funds belonging to each strategy and the total highly liquid assets in each strategy as a percentage of its total NAV. The results show that the Maltese retail fund strategies hold enough liquidity to face shocks in the macro-economic environment. Most of the strategies hold a cash buffer well above the worst scenario generated.

This methodology could be useful to assess the resilience of funds belonging to a certain strategy, for which, however, there are not enough historical observations to fit a micro-level stress testing. The scenarios generated above could provide the fund manager with a peer-based proxy to stress test the liquidity profile of such funds.

Limitations and Assumptions

Like other stress testing frameworks, the STIFF also has various limitations and assumptions and all the analysis and results presented in this report should be interpreted within these constraints.

- The STIFF uses an adjusted HQLA approach, which is a modified version of the standard HQLA approach developed under Basel III.[17] The adjusted HQLA approach assigns different liquidity weights to asset types. However, some of these haircuts can be seen as excessive for certain asset classes. Moreover, some instruments are classified as illiquid, while they could instead be liquidated under normal circumstances.

- The methodology used for the estimation of the second-round effects is based on a regression model which most of the time would result in very poor explanatory power. Moreover, the results of the second-round effects estimate only an expected redemption scenario, conditional to the previous worst-case redemption and liquidation losses. Therefore, the results give no indication with regards to the loss magnitude caused by an additional worst-case redemption, should the distressed situation persist over time.

- This liquidity stress testing exercise is assuming no spill-over effects from the funds onto the financial markets when liquidating their holdings to satisfy the redemption requests. This assumption is supported by the relatively small size of the disposed holdings compared to the normally traded quantities in the financial markets. While this can be considered as a valid assumption when dealing with a large and very liquid stock exchange, it would not be the case if the assets liquidated are traded, for example, on the Malta Stock Exchange. This risk is partially mitigated by the fact that, due to the small market capitalisation of the Maltese public companies, most of the Maltese assets would be classified under the lowest liquidity classes by the adjusted-HQLA approach used, and therefore, the probability of such holdings being disposed is very low.

- In the macro-economic model, several variables were initially considered but rejected, as they resulted to give insignificant or counterintuitive relationships. For this reason, further research is required to establish which macro-economic variables are affecting the retail investors' decisions. Moreover, several funds started operating only recently, so it is likely that there are some structural changes in the fund categories' net flow series.

- The fund categories' series are obtained by aggregating the funds according to a classification which is based on the investment policies disclosed by the fund managers in the fund's Offering Supplement. However, these investment policies often include a wide range of instruments which the funds can invest in, while they would mainly target only one asset type. Therefore, this creates bias in the classification adopted. Further studies should consider other possible classification methods, so that the assigned categories reflect the actual investment strategy targeted by each fund.

[17] The main difference is that in the adjusted HQLA approach, the equity instruments are assigned with different liquidity weights based on the market capitalisation.

Conclusion

This study presents a new liquidity stress testing framework (STIFF) together with an application to the Maltese retail investment funds, representing a first attempt to assess the resilience of such funds to a severe but plausible weekly redemption shock. In the STIFF, the stress test is carried out both at micro and macro levels. The micro-level stress test assesses the resilience of the individual investment funds and is mainly addressed to the relevant supervisory functions to assist them in identifying the most vulnerable funds. The macro-level stress test provides a deeper insight on how the liquidity profile of funds is influenced by the macro-economic environment, and to identify the types of funds which are most exposed to macro-economic shocks. Moreover, it provides a peer-based proxy for those funds which have been recently launched, and for which there are not enough historical observations to fit an extreme curve.

The micro-level liquidity stress test shows that almost all Maltese retail funds selected for the sample hold enough highly liquid assets to stand three different levels of worst-case redemption requests, without incurring material liquidation losses. This assessment is computed using two different liquidation approaches, namely the waterfall and slicing approaches. Only one fund fails the stress test under the three different levels of shock and under both the liquidation approaches. Another two funds fail under the 1% worst-case redemption request and one of them only under the slicing liquidation approach. Moreover, the expected second-round effects appear to be generally limited both in terms of redemptions and the magnitude of liquidation costs.

The macro-level liquidity stress test shows that the *other* and the mixed fund categories are the most vulnerable to changes in the macro-economic environment.

Going forward, the Financial Stability function will perform both the micro and the macro-level liquidity stress test on a regular and ad-hoc basis. Furthermore, it is in the intention of the function to review regularly the STIFF to find alternative ways to improve it and to achieve more reliable and robust results.

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Appendix

Table A.1: Summary Statistics

Fund	No. of Weekly Obs.	Average Red.	Average Net Flow	Max Red.	Max Net Outflow	Max Net Inflow
Fund 1	164	0.21	2.38	3.30	-2.56	120.80
Fund 2	446	0.17	0.76	9.22	-1.06	16.99
Fund 3	448	0.16	0.63	11.73	-2.52	41.71
Fund 4	335	0.51	0.39	15.92	-5.98	16.82
Fund 5	126	0.32	1.04	13.45	-1.03	39.09
Fund 6	239	0.29	0.28	2.76	-2.24	6.07
Fund 7	153	0.20	2.49	12.07	-11.08	32.34
Fund 8	104	0.14	2.48	2.92	-0.75	18.44
Fund 9	234	0.29	0.02	8.37	-7.98	5.55
Fund 10	692	0.23	0.12	4.63	-4.60	53.02
Fund 11	687	0.29	-0.06	14.97	-14.64	11.23
Fund 12	691	0.20	0.12	4.50	-4.34	56.40
Fund 13	692	0.25	-0.13	3.93	-3.68	1.77
Fund 14	692	0.33	-0.20	5.61	-5.51	0.66
Fund 15	692	0.27	-0.11	5.27	-5.22	0.68
Fund 16	624	0.06	0.29	2.22	-1.54	7.69
Fund 17	203	0.23	1.22	8.93	-8.92	97.79
Fund 18	208	1.04	0.85	10.07	-10.07	23.50
Fund 19	208	1.36	-0.56	31.88	-31.62	6.54
Fund 20	208	1.11	0.57	23.80	-20.69	25.43
Fund 21	136	0.97	1.09	34.87	-11.06	29.99
Fund 22	402	0.36	0.26	21.89	-21.89	70.24
Fund 23	182	0.03	0.24	3.62	-3.62	33.33
Fund 24	157	0.06	0.75	1.43	-1.27	22.90
Fund 25	157	0.11	1.05	1.65	-1.34	18.65
Fund 26	216	0.05	0.32	3.41	-3.31	5.90
Fund 27	258	0.39	-0.09	16.27	-16.27	7.56
Fund 28	258	0.28	-0.06	23.84	-23.84	9.76
Fund 29	103	0.76	-0.28	21.83	-21.83	5.88
Fund 30	164	0.23	2.24	1.41	-1.16	99.62
Fund 31	164	0.27	1.63	1.91	-1.43	54.50
Fund 32	160	0.28	-0.15	11.19	-11.19	5.94
Fund 33	117	0.49	1.65	5.48	-4.28	39.74
Fund 34	429	1.24	1.61	66.86	-66.86	477.81
Fund 35	164	0.16	1.09	2.88	-2.67	31.77
Fund 36	280	0.12	0.85	2.30	-2.30	13.06
Fund 37	343	0.15	0.97	3.33	-2.25	13.32
Fund 38	432	0.32	0.18	18.00	-17.99	35.95
Fund 39	432	0.32	0.33	32.55	-29.50	35.91

Fund 40	399	0.38	0.84	12.33	-7.81	30.68
Fund 41	632	0.38	0.09	20.07	-20.04	68.59
Fund 42	635	0.19	0.16	5.75	-5.75	116.51
Fund 43	206	0.13	0.09	5.24	-5.24	5.17
Fund 44	234	0.30	0.82	18.54	-18.54	104.33
Fund 45	124	0.01	0.11	0.25	-0.24	0.70
Fund 46	402	0.05	0.33	1.95	-1.90	7.00
Fund 47	627	0.38	-0.09	14.63	-14.07	4.76
Fund 48	627	0.18	0.27	3.45	-3.43	2.84
Fund 49	556	1.58	-0.35	10.96	-10.73	8.86
Fund 50	556	0.24	0.14	3.09	-2.79	7.68
Fund 51	556	0.23	-0.09	10.27	-10.24	1.95
Fund 52	556	0.29	-0.09	6.35	-6.34	3.05
Fund 53	556	0.13	0.09	0.89	-0.80	3.03
Fund 54	356	0.22	0.15	6.78	-6.33	11.55
Fund 55	627	0.45	0.08	11.83	-10.88	35.88
Fund 56	316	0.24	0.68	2.61	-2.59	17.81
Fund 57	557	0.25	0.07	4.35	-4.07	2.40
Fund 58	557	0.25	0.20	2.03	-1.51	2.82
Fund 59	557	0.34	0.07	12.29	-11.78	23.34
Fund 60	556	0.28	-0.04	6.65	-6.51	11.88
Fund 61	168	0.07	0.40	2.32	-2.32	17.07
Fund 62	158	0.46	0.67	7.85	-7.46	39.53
Fund 63	240	0.21	0.56	9.15	-2.25	26.94
Fund 64	195	0.21	0.29	12.76	-7.86	10.79

Table A.2: GPD parameter estimates[18]

Fund	**μ**	**σ**	**ξ**	**Fund**	**μ**	**σ**	**ξ**
Fund 1	0.69	0.20	0.88	**Fund 33**	1.43	1.26	0.03
Fund 2	0.34	0.20	0.59	**Fund 34**	2.07	2.37	0.99
Fund 3	0.39	0.32	0.56	**Fund 35**	0.39	0.52	0.22
Fund 4	1.23	0.51	0.56	**Fund 36**	0.35	0.40	0.18
Fund 5	0.50	0.39	0.85	**Fund 37**	0.31	0.36	0.41
Fund 6	1.02	0.75	-0.28	**Fund 38**	0.76	1.07	0.40
Fund 7	0.00	0.00	5.27	**Fund 39**	0.68	0.80	0.53
Fund 8	0.38	0.36	0.30	**Fund 40**	1.06	1.41	0.25
Fund 9	0.56	1.30	0.10	**Fund 41**	0.97	0.72	0.64
Fund 10	0.55	0.24	0.55	**Fund 42**	0.43	0.45	0.58
Fund 11	0.65	0.96	0.42	**Fund 43**	0.09	0.64	0.51
Fund 12	0.40	0.33	0.74	**Fund 44**	0.00	0.49	1.52
Fund 13	0.50	0.18	0.38	**Fund 45**	0.02	0.02	0.80
Fund 14	0.70	0.29	0.51	**Fund 46**	0.14	0.06	0.80
Fund 15	0.51	0.24	0.66	**Fund 47**	0.83	0.46	0.57

[18] The red figures indicate that the estimated shape parameter is not statistically different from one.

Fund 16	0.15	0.06	0.90	**Fund 48**	0.33	0.27	0.28
Fund 17	0.31	1.34	0.27	**Fund 49**	3.26	2.75	-0.25
Fund 18	2.87	3.66	-0.40	**Fund 50**	0.45	0.28	0.30
Fund 19	2.54	0.97	0.92	**Fund 51**	0.36	0.21	0.92
Fund 20	3.27	1.89	0.55	**Fund 52**	0.55	0.16	0.59
Fund 21	2.33	3.41	0.38	**Fund 53**	0.28	0.15	-0.02
Fund 22	0.00	4.02	0.09	**Fund 54**	0.52	0.20	0.68
Fund 23	0.00	0.56	0.49	**Fund 55**	0.84	0.40	0.43
Fund 24	0.20	0.36	-0.03	**Fund 56**	0.47	0.20	0.25
Fund 25	0.30	0.25	0.25	**Fund 57**	0.45	0.16	0.82
Fund 26	0.09	0.13	0.58	**Fund 58**	0.46	0.20	0.33
Fund 27	1.13	0.77	0.47	**Fund 59**	0.59	0.26	0.93
Fund 28	0.51	0.32	0.91	**Fund 60**	0.45	0.37	0.82
Fund 29	1.24	0.89	1.19	**Fund 61**	0.00	3.87	-1.67
Fund 30	0.69	0.20	0.03	**Fund 62**	1.22	2.58	-0.17
Fund 31	1.02	0.48	-0.46	**Fund 63**	0.42	0.78	0.59
Fund 32	0.29	1.06	0.62	**Fund 64**	0.10	0.88	0.63

Table A.3: Simulated worst redemptions at the 10%, 5% and 1% levels[19]

Fund	**Worst 10% Red.**	**Worst 5% Red.**	**Worst 1% Red.**	**Liquid Assets**	**Shortfall Worst 10%**	**Shortfall Worst 5%**	**Shortfall Worst 1%**
Fund 1	1.56	2.32	6.64	2.39	-0.84	-0.08	4.25
Fund 2	0.81	1.19	2.99	4.00	-3.19	-2.81	-1.01
Fund 3	1.12	1.70	4.32	6.85	-5.73	-5.15	-2.53
Fund 4	2.39	3.28	7.36	8.18	-5.79	-4.90	-0.82
Fund 5	1.93	3.22	10.12	12.25	-10.33	-9.04	-2.14
Fund 6	1.61	1.97	2.59	4.92	-3.31	-2.94	-2.32
Fund 7	2.42	6.10	31.67	21.27	-18.85	-15.17	10.4
Fund 8	0.91	1.31	2.65	21.53	-20.62	-20.22	-18.87
Fund 9	2.00	3.03	5.71	6.38	-4.38	-3.35	-0.67
Fund 10	1.08	1.50	3.41	13.07	-11.99	-11.56	-9.66
Fund 11	2.31	3.62	8.60	11.61	-9.29	-7.99	-3.01
Fund 12	1.41	2.29	6.78	6.96	-5.55	-4.67	-0.18
Fund 13	0.79	1.04	1.90	4.69	-3.89	-3.65	-2.79
Fund 14	1.31	1.80	3.89	12.19	-10.88	-10.39	-8.30
Fund 15	1.21	1.72	4.43	8.52	-7.31	-6.80	-4.08
Fund 16	0.50	0.76	2.46	11.75	-11.25	-10.99	-9.29
Fund 17	2.16	3.56	8.04	15.63	-13.48	-12.08	-7.59
Fund 18	5.49	7.07	9.43	12.05	-6.56	-4.98	-2.62
Fund 19	5.77	8.76	23.82	1.66	4.12	7.10	22.17
Fund 20	6.99	10.09	22.57	11.31	-4.32	-1.22	11.26
Fund 21	7.87	11.79	26.19	49.10	-41.23	-37.31	-22.91

19 Red figures indicate a liquidity shortfall.

Fund 22	4.44	7.62	15.85	28.54	-24.10	-20.92	-12.69
Fund 23	1.07	1.96	5.57	9.56	-8.49	-7.60	-4.00
Fund 24	0.55	0.78	1.32	6.66	-6.11	-5.87	-5.34
Fund 25	0.64	0.89	1.68	6.08	-5.45	-5.19	-4.41
Fund 26	0.38	0.63	1.77	4.66	-4.28	-4.03	-2.90
Fund 27	2.60	3.75	8.46	6.06	-3.46	-2.31	2.40
Fund 28	1.83	3.03	9.70	12.58	-10.75	-9.55	-2.89
Fund 29	5.16	9.01	30.45	9.40	-4.24	-0.39	21.05
Fund 30	0.90	1.06	1.42	1.05	-0.14	0.02	0.38
Fund 31	1.35	1.54	1.82	1.57	-0.23	-0.03	0.24
Fund 32	2.73	4.81	13.99	34.08	-31.35	-29.27	-20.09
Fund 33	2.73	3.63	5.80	23.91	-21.19	-20.28	-18.11
Fund 34	8.54	14.77	43.95	26.89	-18.35	-12.12	17.06
Fund 35	1.05	1.55	3.05	8.38	-7.32	-6.83	-5.33
Fund 36	0.84	1.21	2.25	4.02	-3.17	-2.81	-1.76
Fund 37	0.93	1.42	3.27	6.28	-5.35	-4.86	-3.01
Fund 38	2.55	3.95	9.18	4.55	-1.99	-0.59	4.64
Fund 39	2.39	3.67	9.36	1.89	0.50	1.78	7.47
Fund 40	2.95	4.37	8.83	12.62	-9.67	-8.25	-3.79
Fund 41	2.72	4.23	11.09	9.55	-6.82	-5.32	1.54
Fund 42	1.50	2.30	6.15	4.43	-2.93	-2.12	1.73
Fund 43	1.35	2.39	6.69	10.78	-9.43	-8.39	-4.09
Fund 44	3.48	7.08	30.39	17.20	-13.72	-10.12	13.19
Fund 45	0.12	0.19	0.60	10.77	-10.65	-10.58	-10.17
Fund 46	0.42	0.63	1.87	11.11	-10.69	-10.48	-9.23
Fund 47	1.89	2.70	6.50	3.59	-1.70	-0.89	2.90
Fund 48	0.70	0.98	1.90	6.28	-5.58	-5.29	-4.38
Fund 49	5.45	6.84	9.27	100.04	-94.59	-93.20	-90.78
Fund 50	0.85	1.17	2.19	4.49	-3.64	-3.32	-2.30
Fund 51	1.29	2.13	6.96	3.64	-2.35	-1.51	3.32
Fund 52	0.94	1.27	2.75	0.80	0.15	0.47	1.95
Fund 53	0.42	0.52	0.75	2.16	-1.74	-1.64	-1.41
Fund 54	1.09	1.56	3.95	0.11	0.98	1.45	3.84
Fund 55	1.54	2.10	4.25	4.92	-3.38	-2.82	-0.67
Fund 56	0.73	0.94	1.55	2.20	-1.47	-1.26	-0.65
Fund 57	1.08	1.63	4.70	3.66	-2.57	-2.03	1.05
Fund 58	0.75	0.98	1.75	12.99	-12.24	-12.01	-11.24
Fund 59	1.75	2.80	8.79	2.72	-0.98	0.07	6.07
Fund 60	1.74	2.90	9.01	11.14	-9.40	-8.24	-2.12
Fund 61	1.45	2.02	2.28	13.91	-12.46	-11.89	-11.63
Fund 62	3.42	4.86	7.59	9.50	-6.08	-4.64	-1.90
Fund 63	2.16	3.64	10.11	15.78	-13.61	-12.14	-5.66
Fund 64	2.19	3.98	11.99	12.52	-10.33	-8.55	-0.53

Table A.4: Expected second-round redemptions

	2nd Round Redemptions - Waterfall Approach			2nd Round Redemptions - Slicing Approach		
Fund	**Worst 10% Red.**	**Worst 5% Red.**	**Worst 1% Red.**	**Worst 10% Red.**	**Worst 5% Red.**	**Worst 1% Red.**
Fund 1	0.89	0.90	0.91	0.89	0.90	0.90
Fund 2	0.80	0.78	0.71	0.80	0.78	0.71
Fund 3	0.62	0.55	0.24	0.62	0.55	0.24
Fund 4	2.53	2.56	2.70	2.53	2.56	2.70
Fund 5	0.57	0.29	-1.22	0.57	0.29	-1.22
Fund 6	1.33	1.37	1.44	1.33	1.37	1.44
Fund 7	2.01	4.32	20.76	2.01	4.32	20.78
Fund 8	0.61	0.65	0.79	0.61	0.65	0.79
Fund 9	1.29	1.20	0.97	1.29	1.20	0.97
Fund 10	0.49	0.49	0.50	0.49	0.49	0.50
Fund 11	2.30	2.49	3.23	2.30	2.49	3.23
Fund 12	0.81	0.98	1.83	0.81	0.98	1.83
Fund 13	0.65	0.62	0.53	0.65	0.62	0.53
Fund 14	1.10	1.36	2.43	1.10	1.36	2.43
Fund 15	0.83	0.90	1.29	0.83	0.90	1.29
Fund 16	0.48	0.47	0.42	0.48	0.47	0.42
Fund 17	1.10	1.07	0.96	1.10	1.07	0.96
Fund 18	4.01	3.73	3.31	4.01	3.73	3.31
Fund 19	4.11	2.56	-5.31	4.11	2.56	-5.31
Fund 20	4.23	4.04	1.70	4.23	4.04	1.70
Fund 21	4.01	3.60	2.12	4.01	3.60	2.12
Fund 22	4.29	4.28	4.26	4.29	4.28	4.26
Fund 23	0.06	-0.02	-0.36	0.06	-0.02	-0.36
Fund 24	0.27	0.31	0.39	0.27	0.31	0.39
Fund 25	0.50	0.53	0.63	0.50	0.53	0.63
Fund 26	0.19	0.22	0.33	0.19	0.22	0.33
Fund 27	1.62	2.01	3.67	1.62	2.01	3.67
Fund 28	1.20	1.72	4.61	1.20	1.72	4.61
Fund 29	2.92	2.13	32.56	2.92	2.13	32.30
Fund 30	0.98	1.03	1.14	0.98	1.03	1.15
Fund 31	1.26	1.36	1.48	1.26	1.36	1.47
Fund 32	0.86	0.58	-0.67	0.86	0.58	-0.67
Fund 33	2.44	2.62	3.03	2.44	2.62	3.03
Fund 34	1.73	2.03	1.05	1.73	2.03	1.05
Fund 35	0.86	0.98	1.36	0.86	0.98	1.36
Fund 36	0.63	0.65	0.73	0.63	0.65	0.73
Fund 37	0.63	0.64	0.70	0.63	0.64	0.70
Fund 38	1.70	2.15	3.39	1.70	2.15	3.36
Fund 39	1.72	1.56	0.84	1.72	1.56	0.84
Fund 40	0.93	0.85	0.59	0.93	0.85	0.59

Fund 41	1.00	0.94	0.57	1.00	0.94	0.57
Fund 42	0.45	0.42	0.24	0.45	0.42	0.24
Fund 43	0.66	0.79	1.32	0.66	0.79	1.32
Fund 44	2.11	2.57	2.28	2.11	2.57	0.25
Fund 45	0.00	-0.01	-0.09	0.00	-0.01	-0.09
Fund 46	0.45	0.52	0.92	0.45	0.52	0.92
Fund 47	1.41	1.54	2.03	1.41	1.54	2.03
Fund 48	0.65	0.73	0.97	0.65	0.73	0.97
Fund 49	1.55	1.45	1.28	1.55	1.45	1.28
Fund 50	1.14	1.21	1.47	1.14	1.21	1.47
Fund 51	0.92	0.86	0.41	0.92	0.86	-0.07
Fund 52	1.83	1.85	1.97	1.83	1.86	1.99
Fund 53	0.43	0.43	0.44	0.43	0.43	0.44
Fund 54	1.39	1.38	1.30	1.39	1.38	1.30
Fund 55	1.00	1.11	1.53	1.00	1.11	1.53
Fund 56	1.42	1.44	1.49	1.42	1.44	1.49
Fund 57	1.23	1.21	1.08	1.23	1.21	1.08
Fund 58	0.81	0.98	1.54	0.81	0.98	1.54
Fund 59	1.65	1.86	2.96	1.65	1.86	2.96
Fund 60	0.81	0.82	0.89	0.81	0.82	0.89
Fund 61	0.53	0.63	0.67	0.53	0.63	0.67
Fund 62	2.08	2.23	2.52	2.08	2.23	2.52
Fund 63	1.36	1.80	3.70	1.36	1.80	3.70
Fund 64	0.69	0.61	0.26	0.69	0.61	0.26

Table A.5: Parameter Estimates for OLS Regression

Category	constant	ip - US	ip – MT	ip - EA	ur - MT	ur - EA	ms - MT	ms - EA	ir - US	ir - MT	ir – EA
Bond	0.55*	-0.22	0.05	-0.10	-2.01	-3.38	0.10	-0.05	2.35*	-3.08*	0.24
Diversified	0.53	0.09	-0.05	-0.53*	-1.34	-3.58	0.07	1.14	-1.63	0.08	0.96
Equity	0.60**	0.65**	0.01	-0.22	3.10**	-2.57	0.01	-0.68	0.18	1.52	1.20
Mixed	0.00	0.76	0.00	0.04	6.06*	-5.33	0.35***	1.08	6.70**	-7.66**	1.22
Other	-0.80	2.17**	0.34***	-0.64	-2.19	-11.52	0.19	-1.62	4.20	7.16	-5.35

*Significant at 10% level, **Significant at 5% level, ***Significant at 1% level

Table A.6: Expected Net flows conditional on a 2.33-σ shock[20]

Category	ip - US		ip - MT		ip - EA		ur - MT		ur - EA		ms - MT		ms - EA		ir - US		ir - MT		ir - EA	
	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+
Bond	0.6	0.1	0.0	0.7	0.5	0.2	1.0	0.2	0.9	0.2	0.3	1.0	0.8	0.1	0.4	1.1	0.5	0.2	0.1	0.7
Diversified	0.4	0.4	0.8	0.1	1.5	0.7	1.0	0.2	0.6	0.1	0.2	0.9	0.4	1.2	1.3	0.6	0.6	0.1	0.8	0.1
Equity	0.2	1.3	0.5	0.6	0.8	0.3	0.4	1.5	0.8	0.3	0.5	0.6	1.2	0.1	0.2	1.3	0.0	1.1	0.3	1.4
Mixed	0.7	1.6	0.2	0.7	0.6	1.4	2.2	3.1	1.7	0.8	1.2	2.1	0.1	1.0	2.1	3.0	1.1	0.2	1.0	1.9
Other	5.7	1.4	5.4	1.2	1.4	2.8	0.6	3.7	0.0	4.3	3.4	0.9	0.6	3.6	3.6	0.7	3.7	0.6	1.5	2.8

Table A.7: 99% worst net flows conditional on a 2.33-σ shock[20]

Category	ip - US		ip - MT		ip - EA		ur - MT		ur - EA		ms - MT		ms - EA		ir - US		ir - MT		ir - EA	
	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+	-	+
Bond	2.3	2.8	2.8	2.2	2.3	2.7	1.9	3.1	1.9	3.1	3.2	1.9	2.1	2.9	3.2	1.8	2.4	2.6	2.8	2.2
Diversified	4.8	4.8	4.3	5.2	3.7	5.9	4.2	5.4	4.5	5.0	5.3	4.2	5.6	4.0	3.8	5.7	4.5	5.0	4.3	5.2
Equity	3.2	1.6	2.5	2.3	2.2	2.6	3.4	1.5	2.2	2.7	2.5	2.4	1.8	3.1	3.2	1.6	3.0	1.9	3.3	1.6
Mixed	7.6	5.3	6.7	6.2	7.4	5.4	9.1	3.8	5.2	7.7	8.1	4.8	7.0	5.9	9.0	3.9	5.8	7.1	7.9	5.0
Other	15.7	8.6	15.5	8.9	11.5	12.9	10.6	13.7	10.0	14.3	13.4	10.9	10.6	13.7	13.6	10.7	13.7	10.6	11.5	12.8

[20] All the figures in the table are expressed as a percentage of the fund strategies' total NAV. The + and – indicate an increase and decrease in the macro-economic variables, respectively. Red figures indicate that the fund strategy would experience an outflow.

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