Beyond the Surface: Open-Ended Funds' Investor Base and their Portfolio Allocation

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Abstract

This paper examines an exogenous liquidity shock that affected a subset of European mutual funds, triggered by redemptions from long-term investors – specifically Italian insurance companies – following the surge in Italian government bond yields in May 2018. Despite limited portfolio exposure to Italian assets, these funds experienced divestment driven by capital considerations of Italian insurance companies. We investigate how funds adjusted to this performance-unrelated shock, revealing that the composition of their investor base played a crucial role in shaping both their portfolio allocation decisions and their ability to attract new net flows. Funds with stable, long-term investors managed to avoid significant net outflows by attracting new long-term investors and de-risked, while funds with more short-term investors (e.g. other funds) were able to attract only other short-term investors, faced net outflows, and increased risk-taking. The findings suggest a sorting mechanism driven by long-term investors preference for funds with fewer short-term investors, likely to reduce expected outflow costs that could materialize during adverse market conditions. This dynamic has important implications for fund resilience and the relationship between fund flows and performance.

Keywords: Fund liquidity risk, Investor composition, Insurance companies, Capital regulation.

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1. Introduction[1]

Since the global financial crisis, the assets of the non-bank financial intermediary (NBFI) sector have risen significantly, alongside increased interconnections within the sector and across the global financial system. Within the broad NBFI category, open-end funds (OEFs) have become increasingly important, both in terms of their size and their impact on the functioning of financial markets. The literature has highlighted the role of their short-term liabilities in explaining their prominent influence on propagating shocks across asset classes (Manconi et al., 2012), acting pro-cyclically (Timmer, 2018; Fricke and Wilke, 2023), inducing market fragility (Jiang et al., 2022), and amplifying fire-sale spillovers (Chernenko and Sunderam, 2020; Falato et al., 2021).

Similar to bank deposits, the fragility of OEFs stems from the nature of their liabilities, which are contractually redeemable on demand. On the one hand, this feature provides liquidity services to clients; on the other hand, it creates first-mover advantages and run risks in the mutual fund because trading costs, potentially sizable in case of large outflows, are borne by the remaining fund investors (Jin et al., 2022).

This fragility may crucially depend on the characteristics of their investor base, particularly on how responsive different investors are to fund performance and asset shocks. Recent studies have suggested that the composition of the investor base significantly affects the sensitivity of fund flows to past performance, known as the flow-performance relationship (Allaire et al., 2023; DellaCorte and Santioni, 2023; Fricke et al., 2022). During periods of stress or after poor performance, funds with a greater share of long-term (LT) investors – such as households and insurance companies and pensions funds (ICPFs), which are generally less 'run-prone' – experience substantially lower outflows compared to funds dominated by short-term (ST) investors, such as other mutual funds.[2]

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[2]ICs have long-term liabilities and the empirical literature has found that they often act as market stabilizers or "safe hands", able to weather market fluctuations and serve as 'asset insulators' in the corporate bond market (Apicella et al., 2022; Chodorow-Reich et al., 2021; Coppola, 2022).

The literature has mainly focused on how the composition of a fund's investor base – particularly the proportion of ST versus LT investors – affects fund outflows and performance *after* shocks to investment returns. However, there is limited empirical evidence on whether these *ex-post* differences in investor sensitivity to shocks might impact investors' *ex-ante* demand. Specifically, it is unclear if investors show distinct preferences for funds with similar asset compositions but different investor base structures, a factor that ultimately shapes the equilibrium matching between investors and funds and influences the distribution of liquidity risk across funds. Additionally, previous research has not explored how potential complementarities among investors affect fund managers' portfolio adjustments when facing sudden redemptions. Our study addresses these gaps, offering insights into how investor-fund sorting affects fund resilience and risk-taking behavior.

Our results provide evidence of a sorting mechanism between bond funds and investors, which may contribute to a concentration of risk. Specifically, we find that the larger the share of ST investors in a fund, the less likely LT investors are willing to provide additional funds to offset liquidity shocks. This aligns with the expectation that LT investors anticipate higher trading costs in case of poor future performance, as a larger base of performance-sensitive ST investors exacerbates the first-mover advantage problem for the remaining LT investors (Fricke et al., 2022). Moreover, when LT investors reduce their holdings, we find that fund managers with a more run-prone investor base adopt riskier strategies. These strategies likely aim to boost expected returns and attract new inflows from ST investors to partially offset outflows. The interplay between an investor base skewed toward run-prone, performance-sensitive investors and a shift toward riskier, less liquid portfolios raises the potential for risk concentration within certain bond funds.

We address the endogeneity challenges associated with the matching between investors and funds by exploiting a liquidity shock affecting a subset of funds, which occurred for reasons exogenous to their performance. This approach allows us to isolate the impact of investor composition on fund responses without the confounding influence of endogenous performance-driven factors. Specifically, we leverage an exogenous shift in the investor base of a sample of European mutual funds, triggered by the political shock in Italy in May 2018. This shock, stemming from the formation of an unexpected coalition government after a general election, led to a sharp rise in Italian sovereign bond yields, which significantly impacted the capital ratios of domestic life insurance companies (ICs), major holders of European mutual funds' shares.[3]

In line with the literature on the 'shock-absorbing' role of ICs, we find that Italian ICs did not liquidate distressed domestic government securities in the quarters following the exogenous increase in sovereign bond yields. Instead, after the decline in their capital ratios, they divested from mutual fund shares – amounting to approximately 15 percent of their exposure across funds on average – that carried higher capital charges (referred to as "$Riskier$" funds in our analysis). Notably, these sales occurred only within their non-unit-linked (or with-profits) portfolio, which is capital-intensive since the investment risk is borne by the insurer. In other words, ICs actively "de-risked" their asset holdings to push up their Solvency Capital Requirement (SCR) ratios. This shift in IC behavior, driven by prudential capital considerations rather than performance-based investment decisions, provides a unique opportunity to exploit a shock to the capital supply curve for funds i) to uncover characteristics of the demand for fund shares of other investors, and ii) to explore how the shock prompts fund managers to adjust their asset allocation strategies to attract funds from other investors. For this analysis, we concentrate on bond funds, which are more prone to liquidity risk and first-mover advantages, and offer a broad range of investment options across the risk and liquidity spectrum.

Among the bond funds most impacted by the portfolio reallocation of Italian ICs,[4] those with a less stable investor base – i.e., with LT investors (households and euro area

[3]Italian ICs possessed two important characteristics that are key to our empirical analysis. First, a significant portion of their non unit-linked portfolio was invested in mutual fund shares with limited exposure to Italian securities. Second, the portfolio associated with non-unit-linked policies, where ICs borne the investment risk, was heavily invested in domestic sovereign bonds and other Italian securities. As a result, the market value of the assets in their non-unit-linked portfolios dropped by over 5 percent following the fall in domestic government bond prices in May 2018, leading to a notable shock to their capital ratios (on average about 35 percentage points).

[4]We only include funds with low direct holdings of Italian securities on the asset side and measure their ex-ante liability-side exposure to the sovereign shock by calculating, for each fund, the proportion of its shares held by Italian ICs in their non-unit linked portfolios. This proportion is further weighted by each IC's exposure to domestic securities within the same portfolio. Funds in the top quartile of the distribution of this variable are considered to be more (indirectly) exposed (i.e., through their liabilities) to the shock.

ICPFs) in the bottom three quartiles – were unable to offset redemptions from Italian ICs with inflows from other LT investors. Following the shock, they attracted new inflows primarily from ST investors, yet still experienced notable net outflows. This sorting among ST investors likely derives from the disutility that LT investors derive when purchasing fund shares predominantly held by ST investors. Simultaneously, these funds increased their portfolio risk, likely to appeal to ST investors prioritizing high returns, by raising their exposure to the high-yield segment, while reducing their holdings of less risky assets. This suggests that a less stable, performance-sensitive investor base can deter new inflows from LT investors post-shock, presumably leading funds to adopt riskier portfolio strategies as a partial response to attract new inflows from ST investors.

Conversely, funds with a higher share of LT investors were able to avoid significant net outflows by attracting new investments from other LT investors. This replacement was accompanied by a de-risking of their portfolios through increased allocations to cash-like assets, in line with the findings of Cutura et al. (2023), reflecting a strategy focused on prioritizing stability over higher returns.

Our findings uncover an additional ex-ante channel through which run-like incentives, created by strategic complementarities, can introduce significant vulnerabilities in open-end funds. From a policy perspective, this supports previous research (Allaire et al., 2023; Fricke et al., 2022; Fricke and Wilke, 2023) suggesting that assessing the resilience of the mutual fund sector requires more than examining portfolio exposures alone; it must also consider the fund's investor base. While there are substantial differences between types of intermediaries, this approach aligns with the Net Stable Funding Ratio (NSFR) used for banks, which assesses funding stability based on counterparty characteristics (e.g., households, firms, and financial institutions).

For financial stability, it is particularly concerning that the sorting mechanism identified in this paper may contribute to concentrate asset-side risks in funds with a more flighty, run-prone investor base. This concentration heightens susceptibility to runs and thus calls for policies that mitigate the first-mover advantage, not only to reduce shock propagation and fire sales from an ex-post perspective but also to address risk concentration ex-ante in these vulnerable funds.[5] Lastly, our evidence highlights how a financial shock can propagate through the system via LT investors, emphasizing the importance of tracking interconnections among financial intermediaries.

Our paper contributes to several stands of literature. First, it is related to works on funds' liquidity risk management. Building on the classic flow-performance relationship (Sirri and Tufano, 1998; Chevalier and Ellison, 1997), recent literature finds large heterogeneity across investors' responsiveness (Fricke et al., 2022; Jin et al., 2022; Fricke and Wilke, 2023; Allaire et al., 2023). By focusing on the effects of an exogenous shock to a subset of traditionally long-term investors, our results suggest that the investor base significantly affect funds' capacity to offset liquidity shocks and investment risk-taking incentives. Specifically, we find evidence that the investment strategy consistent with the concave flow-performance relationship for bond funds (Goldstein et al., 2017) – i.e. negative net flows lead funds' managers to sell riskier bonds and purchase safe and liquid assets in order to be ready to meet further redemptions – holds when the investor base includes a large share of LT investors, less sensitive to performance. In contrast, when the flow-performance relationship is steeper (Fricke and Wilke, 2023), i.e. there is a prevalence of more performance-oriented investors, also bond funds tend to take more risk to enhance their attractiveness for this type of investors.

Second, our paper is related to the literature on the investment strategies of insurance companies (Apicella et al., 2022; Chodorow-Reich et al., 2021; Coppola, 2022) and in particular to works on the effects of ICs' capital considerations (Ellul et al., 2015; Becker and Ivashina, 2015; Becker et al., 2022; Merrill et al., 2021). Consistent with these works, which mainly focus on the corporate bond market, our evidence shows that ICs did not amplify shocks in the sovereign bond market but capital considerations may drive spillover effects to other asset classes initially unaffected by the shock but with higher capital charges. To

[5]In this respect, funds with a high share of ST investors could greatly benefit from enhanced tools designed to curb the first-mover advantage, such as liquidity management tools (LMTs). Previous studies (Jin et al., 2022) suggest that these measures can reduce run-like incentives, lowering the risk of fire sales and spillovers during market shocks. We argue that a further benefit could be a reduction in expected outflow costs for LT investors in funds heavily held by run-prone investors. This may ultimately diminish LT investors' need to consider the composition of a fund's investor base in their investment decisions.

assess these effects, we show that it is key to distinguish between non-unit and unit portfolios, a dimension often neglected in empirical analyses.

Finally, we contribute to the literature on the shock transmission across financial intermediaries. This large literature, mainly on the banking sector, explored theoretically direct linkages (Allen and Gale, 2000; Freixas et al., 2000) and fire sales dynamics (Acemoglu et al., 2021; Caballero and Simsek, 2013; Greenwood et al., 2015), while empirical works mainly focused on measuring interconnectedness (Billio et al., 2012; Girardi et al., 2021; Duarte and Eisenbach, 2021; Ellul et al., 2022; Cetorelli et al., 2023). We provide direct micro-level evidence illustrating how the subsequent portfolio adjustment of ICs, driven by capital considerations, transmit the shock to other (unaffected) NBFIs.

The remainder of this paper is organized as follows. Section 2 describes data characteristics. Section 3 focuses on the Italian insurance companies' response to the shock. Section 4 presents evidence on the effect of the shock for funds. Section 5 provides a discussion of our results and the resulting policy implications. Finally, Section 6 concludes.

2. Data

The dataset used for our analysis combines multiple data sources on Italian insurance companies' assets and on those of the mutual funds they hold. This section provides a detailed description of each source. Our sample period goes from 2017-Q2 to 2019-Q2, centered around the political shock occurred in 2018-Q2 that we consider for our analysis.

2.1. Supervisory data on ICs' holdings

The primary data source is supervisory information on ICs' holdings provided by IVASS, the Italian supervisory authority for insurance companies. This confidential dataset is collected for supervisory purposes under the Solvency II regulation. It contains security-by-security holdings for each Italian insurance company, reported at market value at the end of each quarter. Crucially, the dataset specifies the liability type for each asset: life unit-linked, life non-unit-linked (or with-profit), and other liabilities. A security may be reported multiple times in a quarter if held in different portfolios. Our analysis focuses on traded securities – corporate and government debt, listed equity, and shares of open-end mutual funds – while we exclude shares of closed-end funds and unlisted equity.

The dataset also includes accounting variables at the insurer level, such as quarterly Solvency Capital Requirement (SCR) ratio, premium income and losses for each portfolio, yearly total assets, and return on equity.

The original dataset covers 103 ICs over our sample period. However, we are only interested in insurers that offer life insurance policies. Dropping ICs that do not operate in the life insurance sector leaves us with 52 ICs, of which six are only active in the with-profits segment. Table A.1 reports the main summary statistics for our sample of ICs.

2.2. Data on mutual fund characteristics and holdings

The second data source is Morningstar Inc., one of the largest providers of investment research to the asset management industry. For each fund share held by ICs, we gather key characteristics of the fund: size, domicile, quarterly net flows, investment category (assigned by Morningstar based on the fund's investment universe), net returns and rating score (ranging from 1 to 5, based on performance relative to peers).[6] For each fund, we also collect portfolio-level data on the asset composition (e.g. stocks, bonds, cash, etc.) at the security level, when available.

Table 1 displays the number of mutual funds' ISINs held by Italian ICs, those that are covered by the Morningstar dataset, as well as the associated assets under management. We are able to match approximately 90 percent of mutual funds' ISINs in unit-linked portfolios and around 70 percent in non-unit-linked portfolios with Morningstar data on fund characteristics (about 80 and 65 in terms of market value of the shares held by Italian ICs). The percentage is smaller, while remaining large, when we narrow down to mutual funds for which we are able to cover at least 70 percent of their portfolio holdings at the security level, to about 73 percent of the total for funds in the unit-linked portfolios and to 45 percent for the funds in the non-unit linked portfolios. Table A.2 reports the main summary statistics for our sample of funds held by Italian ICs.

[6] We assign a zero value to unrated funds.

Table 1: **Sample of funds included in the life portfolios of Italian ICs**

	N. of fund-isin			Tot. investment (€bn)		
	Tot.	MS sample	MS holdings	Tot.	MS sample	MS holdings
non-unit	1,250	873	568	67.4	43.5	22.3
unit	6,389	5,764	4,683	130.0	105.7	88.3
total	7,202	6,206	4,959	197.4	149.2	110.7

Notes: authors' calculations based on data from Morningstar and supervisory data from IVASS. Only assets related to life-insurance policies are considered. The first column (*Tot*) shows the number of funds included in the life portfolios. The second column (*MS sample*) presents the number of those matched in the Morningstar dataset. The third column (*MS holdings*) displays the number of funds matched in the Morningstar dataset and for which we also have information on at least 70 percent of their portfolio holdings. The other columns show total investment for the respective subsample.

2.3. Security-level information

We enhance data on securities held by ICs and mutual funds with security-level information from the Centralized Securities Database (CSDB), maintained by the European System of Central Banks (ESCB). This database covers all securities issued or held by euro area residents. For each security, we collect data on market price at the end of each quarter, outstanding issuance, issuer details (country and industry), financial duration, and credit ratings.[7]

Market prices from the CSDB allow us to compute the quantity of each security held by ICs over the sample period. This quantity forms the basis for calculating one of our dependent variables in Section 3.

$$q_{s,i,p,t} = \frac{SolvencyAmount_{i,p,s,t}}{P_{s,t}} \tag{1}$$

where $SolvencyAmount_{i,p,s,t}$ is the market value of security s, held by insurance company i in portfolio p (unit-linked or not) at time t, and $P_{s,t}$ is the security price at time t, from the CSDB. This method helps isolate changes in holdings due to trading activity

[7]Ratings are sourced from the four major rating agencies (Standard & Poor's, Fitch, Moody's, and DBRS). For securities with multiple ratings, the highest rating across agencies is used.

from changes driven by price fluctuations.[8]

2.4. *Other investors' holdings*

We supplement fund characteristics with information on the types of investors holding the same funds in the Italian ICs' portfolio, to distinguish between LT and ST investors. This data comes from the Eurosystem's Securities Holding Statistics - Sector (SHS-S), a confidential dataset providing granular quarterly data on the holdings of financial instruments by euro area residents, broken down by institutional sector and country of residency. From this dataset, we extract the market value of mutual fund shares held by other investors, aggregated at the fund level when multiple shares (with different ISINs) are issued by a fund.

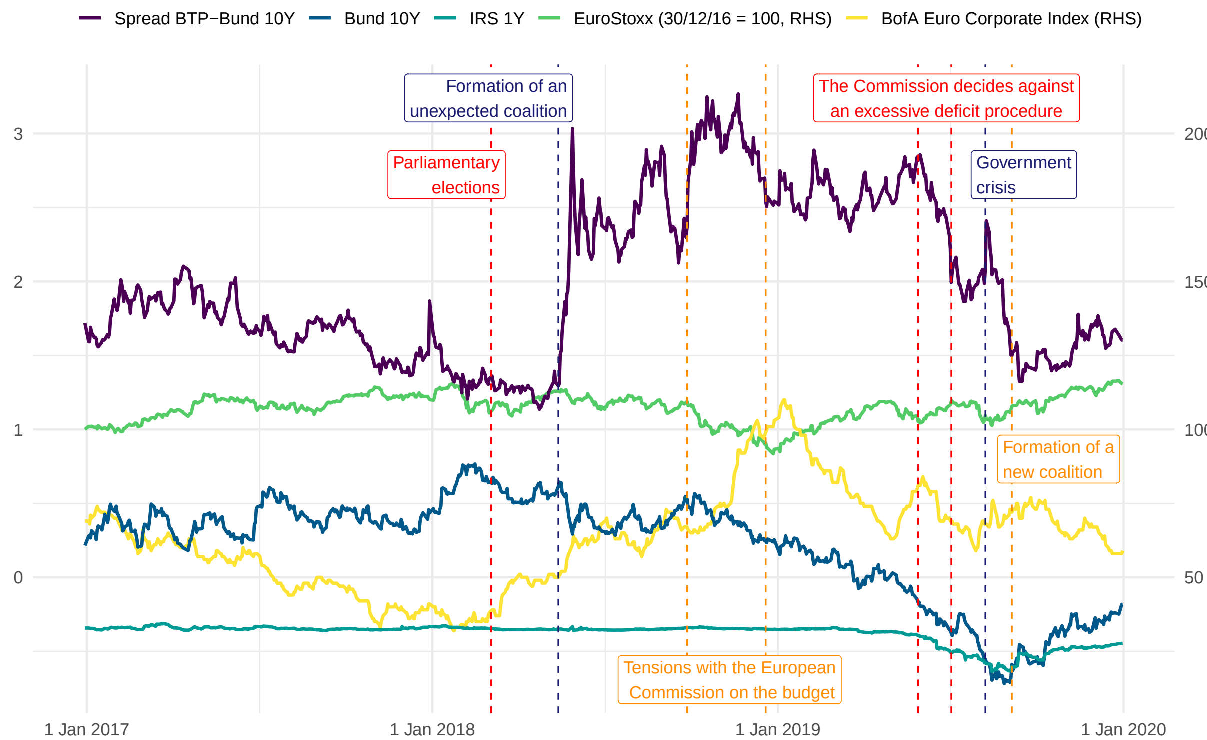
For euro area investors, we categorize holders into: households, insurance companies and pension funds (ICPFs), other financial intermediaries (mostly mutual funds), and a residual category. Non-euro area investors are aggregated due to the lack of sectoral breakdown.

3. Sovereign shock and insurance companies' de-risking of mutual fund holdings

3.1. *Origins of the shock*

At the end of May 2018, the Italian government bond market faced significant turmoil following the formation of an unexpected coalition government, which created heightened uncertainty regarding the new stance on the EU and fiscal policy. This political shock triggered a rapid increase in yields, as foreign investors sold off Italian assets in substantial amounts. Investor concerns over the government's potential economic policies put upward pressure on Italian government bond yields: the spread between Italian and German ten-year government bonds – a widely used indicator of tension in the Italian sovereign bond market – peaked at 330 basis points in mid-November.

Figure 1: **The 2018's idiosyncratic shock on Italian assets**



Notes: IRS 1Y refers to a one-year interest rate swap linked to the EONIA and the BofA Euro Corporate Index to the market value-weighted average option-adjusted swap spread of the index constituents in basis points. Sources: Bloomberg, ICE and MTS.

The shock also affected broader Italian financial markets, including corporate bonds and equities, but its impact was mostly confined to Italy. From early 2019, tensions began to ease due to several factors: an agreement between the Italian government and the European Commission on Italy's budget policies, more accommodative monetary conditions in the euro area, and improvements in global financial markets. Figure 1 shows the 10-year BTP-Bund spread alongside key events during this period of uncertainty. Notably, the elevated spread persisted for some time, only returning to pre-shock levels in the second half of the following year.

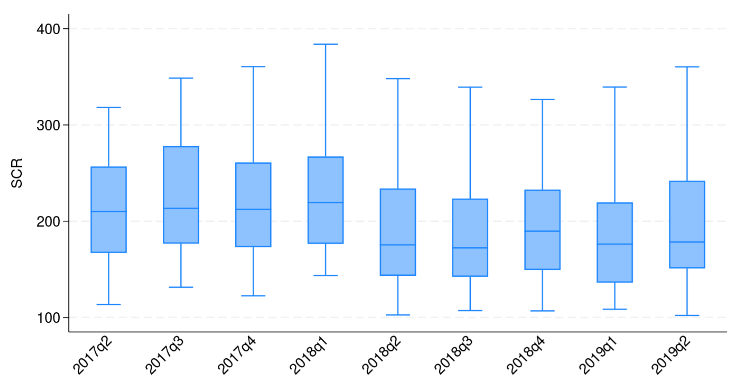
[8]CSDB prices may occasionally contain errors or outliers, especially for small issuers or infrequently traded securities. We flag a security price as potentially erroneous if it changes fifty-fold over the sample period. In some cases, we manually correct these errors when a straightforward solution exists. For example, prices may jump from 1 to 100 (or vice versa) due to a change in reporting basis rather than market value fluctuations. Securities with unresolved errors are omitted, but their total value is minimal, amounting to only 0.01 percent of the total holdings on average.

3.2. *Hypotheses on ICs investment response to sovereign shock*

Italian ICs' held a significant direct exposure to domestic sovereign bonds, which represented the large majority of assets, and Italian securities more broadly, while their 'indirect' exposure to Italian securities via fund shares was limited (see Appendix B for a description of ICs portfolios).

The sharp and unexpected rise in yields had significant and lasting effects on the valuation of ICs' assets. Importantly, the depreciation in asset values had a direct impact on the Solvency Capital Requirement (SCR) ratios, i.e the ratio between own funds (the difference between the market value of assets and liabilities) and the SCR requirement,[9] because, according to prudential regulations, asset values must be marked to market for capital requirement calculations. Figure 2 shows the distribution of SCR ratios across ICs over time. The SCR ratio dropped significantly between the first and second quarters of 2018, on average by about 35 percentage points.

Figure 2: **Box-plot of the Solvency ratios across insurance companies**



Notes: authors' calculations based on IVASS data. Solvency ratios are calculated as the ratio of own funds held for coverage to the solvency capital requirement established under Solvency II multiplied by 100.

Previous research (Ellul et al., 2011, 2015) pointed out that capital considerations play a key role in ICs' investment decisions. Specifically, unexpected capital losses resulting from shocks might trigger a de-risking strategy, as long as such portfolio adjustments help cushion the shock's impact on ICs' capital ratios. However, the shock and any subsequent de-risking strategy have markedly different effects on ICs' unit-linked and non-

[9] Appendix C presents a short introduction to Solvency II capital requirements.

unit-linked portfolios.

In unit-linked portfolios, the asset values are directly tied to the corresponding liabilities, meaning the shock is passed to policyholders without affecting ICs' capital. For the same reason, a de-risking strategy in these portfolios would not benefit capital ratios, as the capital absorption for market risk is effectively zero. In contrast, for more the non-unit-linked investment portfolio - backing the issuance of traditional life insurance policies - the rise in the Italian sovereign spread reduces the value of Italian securities investments, while the value of liabilities remains unchanged as it is sensitive to risk-free rates, not to the spread in sovereign interest rates. This results in a reduction in available capital. In this case, a de-risking strategy would help lower the risk-weighted minimum capital requirements related to market risk, thereby improving the SCR ratio.

This leads to our first hypothesis to be tested.

Hypothesis 1 (H1). *After the sovereign shock, ICs responded by selling fund shares with higher capital charges in their non-unit (i.e. capital intensive) portfolios. No similar adjustments were made in their unit-linked portfolios.*

Notably, our hypothesis focuses on ICs reducing their exposure to riskier funds solely due to capital considerations, not because these funds are directly affected by specific shocks. In our empirical setup, we argue that the sovereign shock serves as an exogenous liquidity shock for a subset of funds, namely those held by Italian ICs more affected by the shock. At the same time, this subset of funds had limited, if any, exposure to Italian securities.

We also expect that the shock had a heterogeneous impact on Italian ICs, leading to differentiated investment responses post-shock. Specifically, capital losses for ICs should depend on the proportion of Italian securities held in their non-unit portfolios, as these were the most directly affected by the sovereign shock. Consequently, the larger the capital loss an insurance company experienced, the stronger its incentive to de-risk its portfolio by selling riskier funds in the non-unit portfolio (the one predominantly driving capital requirements). Thus, the second hypothesis to be tested is:

Hypothesis 2 (H2). *After the sovereign shock, ICs with a higher pre-shock exposure to Italian securities engaged in a more aggressive de-risking strategy by selling relatively more fund shares with higher capital charges in their non-unit portfolios. No such adjustment should occur in their unit-linked portfolios.*

Another potential source of heterogeneity in ICs' de-risking response could arise from their initial capital levels. On the one hand, for a given capital loss, being closer to minimum prudential capital requirements may prompt a stronger response to avoid breaching them. However, we hypothesize that this effect may not be significant in our case for two reasons. First, nearly all ICs in the sample had capital levels well above the prudential minimum both before and immediately after the shock. Second, IC managers might have strong incentives to restore their initial capital positions, regardless of how high their pre-shock levels were, to minimize conflicts with other stakeholders. Since a clear theoretical prediction is not possible, this remains an empirical question. While we do not formulate a specific hypothesis, we still test for this additional source of heterogeneity, as it may influence our choice of the fund-level exposure variable.

3.3. Empirical tests

To test H1, we categorize funds held by Italian ICs into two groups based on their capital charges (i.e their riskiness), consistent with the Solvency II regulation. This distinction is made using either Morningstar fund categories or portfolio holdings data. Specifically, we define a $Riskier$ category that includes all equity and non-government fixed-income funds. Additionally, mixed and miscellaneous funds are included in this category if their fund-level capital absorption (estimated by applying Solvency II risk weights to the securities held by each fund) falls in the top quartile of the distribution (i.e., capital charge above 21%). Overall, about 70% of funds in the ICs' portfolio are classified as $Riskier$, and we create a dummy variable, *Riskier*, which takes a value of 1 if a fund belongs to this category.

We then estimate for each fund share s held by IC i in portfolio $p \in \{N, U\}$ (N for non-unit, U for unit portfolio) at time t the following panel regression model (Equation 2) between 2017-Q3 and 2019-Q2:

$$\begin{aligned}\ln(q_{s,i,p,t}) = & \sum_{t=17q3}^{T=19q2} \beta_{1,t} Riskier_s + \beta_{2,t} Riskier_s * NonUnit_p \\ + & \boldsymbol{\gamma}_{p,t} \mathbf{X}_{s,t} + \theta_{s,i,p} + \mu_{i,p,t} + \epsilon_{s,i,p,t}\end{aligned} \tag{2}$$

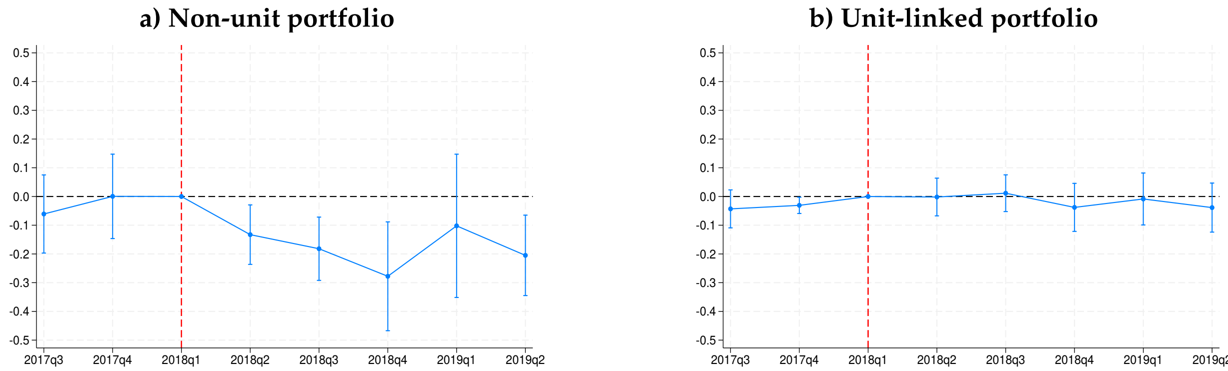
where $ln(q)$ is the log-quantity (where quantity is defined as in Equation 1 of Section 2.3) of fund s held by insurer i in portfolio p in quarter t. $Riskier_s$ is equal to 1 if fund s is in the riskier category and $NonUnit_p$ is equal to 1 if $p = N$. $\mathbf{X}_{s,p,t}$ includes time-varying fund level controls on exposure to IT securities, net flows and Morningstar five-star rating (i.e. a fund performance measure). We include fixed effects at the security-insurance-portfolio level ($\theta_{s,i,p}$) to take into account the average holding of each security in each IC portfolio and insurance-portfolio-time fixed effects ($\mu_{i,p,t}$) to control for time-varying changes at the insurance-portfolio level. We cluster standard errors at the insurance and fund levels.

For each quarter we estimate time-varying coefficients that capture the differential effect of $Riskier$ funds (relative to safer ones) in the unit-linked portfolios, denoted as $\beta_{1,t}$, and, for the non-unit portfolio, the additional interaction term, $\beta_{2,t}$.

In Figure 3, we plot the effects for each quarter in our sample for the two portfolios. The results support our first hypothesis. While there is no significant differential effect for $Riskier$ funds in either portfolio before the shock, we observe a substantial and persistent reduction in holdings of $Riskier$ funds immediately following the shock, but only in the non-unit portfolio, which has a greater impact on ICs' capital requirements.

The timing of these sales, along with the distinct behavior between the two portfolios, provides initial evidence that the decision to sell $Riskier$ funds is driven by capital considerations for Italian ICs. For funds these sales represent a shock on the investor side and are not motivated by a worsening in fund performance, i.e. by developments on the asset side.

Figure 3: **Change in Italian ICs' holdings of $Riskier$ funds between portfolios**



Notes: panels (a) and (b) depict the results of Equation 2 for riskier funds included in the non-unit portfolio and in the unit-linked one, respectively. The dashed vertical line indicates the last pre-shock period. Standard errors are clustered at the insurance and fund levels.

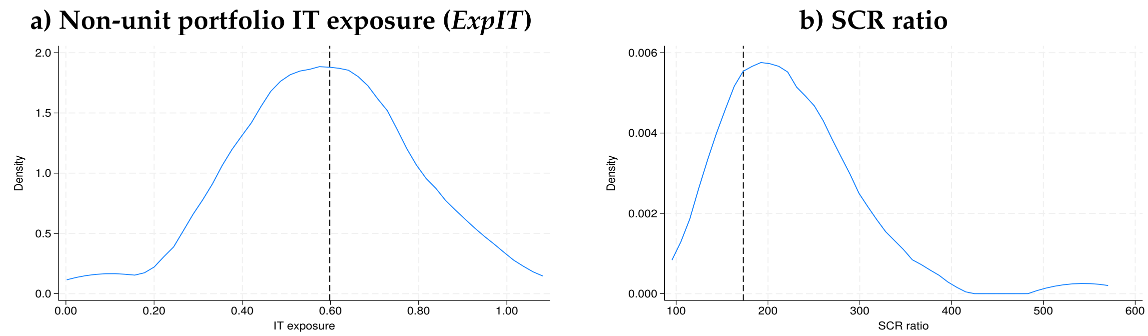
To test the second hypothesis regarding the cross-sectional heterogeneity of the de-risking strategy, we categorize ICs based on their exposure to Italian securities within the non-unit portfolio (Figure 4, panel a). Specifically, we divide insurance companies into two groups: those with pre-shock (Q1-2018) exposure to Italian securities in their non-unit portfolio below the median value (*LowExpIT*, below approximately 60 percent) and those with exposure above the median (*HighExpIT*).[10] For the additional test examining the role of initial capital levels, we further divide ICs based on whether their SCR ratio falls below ($LowSCR$) or above ($HighSCR$) the 25th percentile (around 180 percent, Figure 4, panel b).[11] This yields four distinct groups for our analysis. We report their number and share of investments in the unit and non-unit market segments in Table A.3.

We consider whether a higher exposure to the sovereign shock translated in a more intense de-risking strategy in the non-unit portfolio, as stated in Hypothesis 2. For this purpose we enrich the specification in Equation 2 with interaction terms among $Post$ (a dummy equal to 1 after May 2018), $Riskier_s$, $NonUnit_f$ and $HighExpIT_i$. Specifically, we

[10] As a preliminary check, in Appendix C we show that ICs in the $HighExpIT$ group – those with greater exposure to Italian securities – suffered a larger capital loss in the immediate aftermath of the sovereign shock (on average 30 percentage larger than the $LowExpIT$ group).

[11] We use the bottom quartile instead of the median as a conservative measure. The distribution of SCR ratios is highly concentrated at the upper end (above 200), making the bottom quartile the group most likely to experience effects related to low capital levels.

Figure 4: **Insurance companies distribution for Italian exposure and SCR ratio**



estimate the following regression model:

$$
\begin{aligned}
\ln(q_{s,i,p,t}) = \; & \beta_1 Riskier_s * Post_t + \beta_2 Riskier_s * Post_t * NonUnit_p \\
+ \; & \beta_3 Riskier_s * Post_t * HighExpIT_i \\
+ \; & \beta_4 Riskier_s * Post_t * NonUnit_p * HighExpIT_i \\
+ \; & \boldsymbol{\gamma}_{p,t} \mathbf{X}_{s,t} + \theta_{s,i,p} + \mu_{i,p,t} + \epsilon_{s,i,p,t}
\end{aligned} \tag{3}
$$

We estimate this model using time-varying coefficients for a set of fund-level variables $\mathbf{X}_{s,t}$ (exposure to IT securities, net flows, and Morningstar's five-star rating). In more comprehensive specifications, we also include fund category-time fixed effects and, as a robustness test, we saturate the regression with security-time fixed effects, restricting the sample to securities held by at least two IC-portfolio combinations at any given time t. Standard errors are clustered at the insurer-portfolio-time level.

Table 2 presents the results. The first three columns display estimates for the baseline specification from Equation 2, while columns (4)-(6) report the results for Equation 3. In column (1), the interaction term $Riskier * Post * NonUnit$ suggests a significant 15 percent reduction in holdings of riskier funds in non-unit portfolios, while no statistically significant change is observed for riskier funds in unit portfolios (coefficient $Riskier * Post$). In column (2), the latter term is absorbed by the inclusion of time-varying fund category controls, resulting in an estimated 10 percent reduction in holdings of $Riskier$ funds in non-unit portfolios. Column (3), which incorporates security-time fixed effects, shows an even larger reduction. In column (4), the baseline specification from column (1) is expanded to include the interaction with $HighExpIT$. This interaction indicates that the negative effect is concentrated in ICs more exposed to Italian securities: the term $Riskier * Post * NonUnit * HighExpIT$ reflects a reduction of more than 30 percent in the non-unit portfolios of more exposed ICs, with no significant change observed in unit portfolios. The results remain largely consistent in the more saturated specification with fund category-time fixed effects in column (5). When we restrict the sample by including security-time fixed effects the coefficient for more exposed ICs remain negative but it is not statistically significant for the adopted levels.

Table 2: **Exposure to IT securities and subsequent de-risking**

	(1) lnq	(2) lnq	(3) lnq	(4) lnq	(5) lnq	(6) lnq
Riskier x Post	0.0091 (0.7088)			-0.0103 (0.7085)		
Riskier x Post x NonUnit	-0.1540*** (0.0053)	-0.1024* (0.0741)	-0.4837*** (0.0001)	-0.0072 (0.9083)	0.0601 (0.3577)	-0.4003** (0.0338)
Riskier x Post x HighExpIT				0.0476 (0.3277)	0.0633 (0.1887)	0.2169*** (0.0017)
Riskier x Post x NonUnit x HighExpIT				-0.3504*** (0.0018)	-0.3854*** (0.0010)	-0.1844 (0.3848)
IC-Time-Port. FE	Yes	Yes	Yes	Yes	Yes	Yes
IC-Sec.-Port. FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund contr.*Time	Yes	Yes	No	Yes	Yes	No
IF category-Time FE	No	Yes	No	No	Yes	No
Sec.-Time FE	No	No	Yes	No	No	Yes
Adj. R-squared	0.9262	0.9266	0.9283	0.9262	0.9266	0.9283
Observations	89108	88975	65921	89108	88975	65921

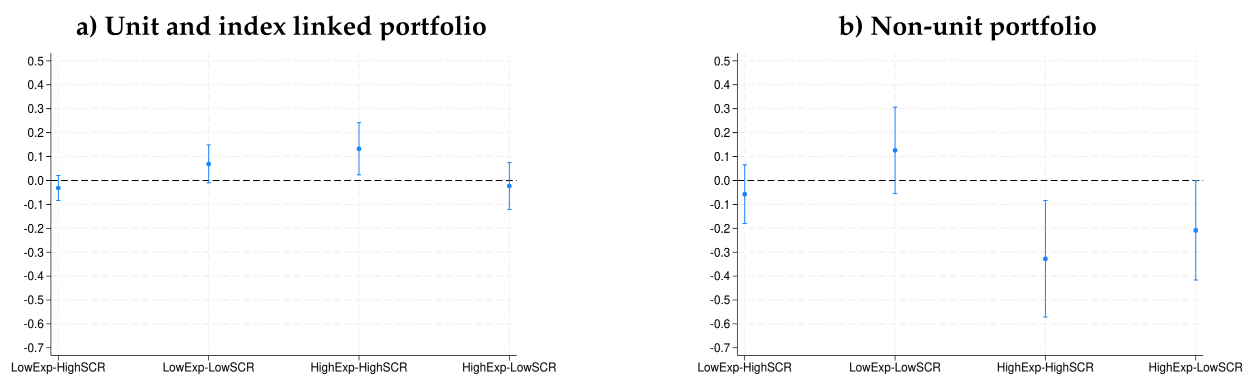
Notes: columns (1)-(3) display estimates of Equation 2. Columns (4)-(6) report the results of Equation 3. The dependent variable in all columns is lnq, which is the log-quantity of fund s held by insurer i in portfolio p in quarter t. Standard errors are clustered at the insurer-portfolio-time level. p-values in parentheses; *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Lastly, we test whether the previous effect also depends on ICs' initial capital levels by augmenting the specification in Equation 3 with additional interaction terms with *LowSCR*, which is a dummy that identifies ICs with pre-shock capital levels in the bottom quartile. In Figure 5, we present the marginal effects and confidence intervals for changes in holdings of *Riskier* funds (relative to safer ones) across the four categories of ICs outlined in Table A.3. These categories are created by interacting the dummies for ICs' exposure to Italian securities (*HighExpIT*) with their pre-shock capital levels (*LowSCR*).

As expected, the unit-linked portfolios show little to no significant variation in ICs' holdings of riskier funds relative to safer ones (panel a). However, in the non-unit portfolios (panel b), ICs with higher exposure to Italian securities exhibit a statistically significant and substantial reduction in their holdings of riskier funds. Importantly, there are no statistically significant differences in this de-risking behavior between ICs with higher exposure to Italian securities based on their pre-shock capital position. This suggests that ICs pursued de-risking strategies primarily in response to capital losses caused by the sovereign spread, regardless of their initial capital levels.

The absence of a stronger effect among ICs with weaker pre-shock capital positions may be explained by the fact that, even for this group, capital levels were comfortably above the minimum regulatory requirements. Moreover, IC managers might have incentives to restore their initial capital positions, regardless of their pre-shock levels.

Figure 5: **Marginal effect for $Riskier$ funds across ICs' categories**



Notes: panels (a) and (b) depict the results of Equation 3 estimated by including interactions with $LowSCR$ in order to identify the four groups of ICs outlined in Table A.3. Standard errors are clustered at the insurance-portfolio-time level.

Overall, this evidence suggests that the initial exposure to Italian securities in the non-unit portfolio was the primary factor driving the reduction in holdings of $Riskier$ funds – specifically those with higher capital charges – within that same portfolio. On the other hand, the initial capital level did not appear to significantly influence the cross-sectional variation in ICs' responses to the sovereign shock. In contrast, fund holdings in the unit-linked and index-linked portfolios showed no significant change in response to the shock, regardless of fund risk levels or ICs' exposure to Italian securities.

4. Response of funds indirectly exposed to the shock via insurance

4.1. Hypotheses

In this section, we outline testable hypotheses on how the liquidity shock experienced by funds with high initial exposure to Italian ICs affected funds differently based on the pre-shock prevalence of LT or ST investors among fund shareholders. Following prior research (Fricke et al., 2022; Allaire et al., 2023), we categorize insurance companies and households as LT investors, while mutual funds and non-residents are classified as ST investors. Although all impacted funds had substantial liability-side exposure to Italian ICs, the composition of their remaining investor base varied considerably, even among funds with similar portfolios.

To develop our testable hypotheses, we build on several findings from the previous literature. First, it is well recognized that mutual fund managers have a strong incentive to maximize assets under management (AUM), which directly influences their compensation schemes (Chevalier and Ellison, 1997). We expect this incentive to significantly guide their choices (Cutura et al., 2023) when responding to unexpected outflows.

Second, the redeemable-at-demand structure of fund liabilities, coupled with the timing and incidence of trading costs, creates positive strategic complementarities and a first-mover advantage for investors. When large outflows occur, the remaining fund investors bear the trading costs, which are especially substantial for illiquid assets (Chen et al., 2010). This dynamic is pronounced in bond funds, which tend to exhibit a concave flow-performance relationship due to illiquid secondary markets that drive up trading costs when funds quickly liquidate large bond positions (Goldstein et al., 2017).[12]

Third, recent work by Allaire et al. (2023), Fricke et al. (2022) and Fricke and Wilke (2023) highlights that investor behavior varies by investment horizon: ST investors, such as other mutual funds, frequently reshuffle their fund investments and exhibit a steeper flow-performance relationship compared to LT investors like insurance companies and households, who trade less frequently. As a result, LT investors tend to be net receivers

[12] Equity mutual funds, holding securities traded in much more liquid secondary markets, are less subject to the first-mover advantage, leading to a convex flow-performance relationship (Chevalier and Ellison, 1997; Sirri and Tufano, 1998).

of the negative outflow externalities that are often driven by more active ST investors in the same fund.

Our first hypothesis addresses the impact of the liquidity shock on the composition of the investor base in the most affected funds. Redemptions by Italian ICs drive net outflows which, without offsetting new investments, mechanically reduce the share of LT investors. A shift toward a higher proportion of ST investors amplifies strategic complementarities underlying the first-mover advantage and increases run-prone behavior (Chen et al., 2010), particularly in funds that had a low share of LT investors prior to the shock. For these funds this tilting of the investor base may cause potential investors to expect substantially higher future costs from outflow externalities in the event of negative fund performance shocks. As these costs are largely borne by LT investors (Fricke et al., 2022), they are likely to become more hesitant to invest in funds with a high proportion of run-prone ST investors. This rationale leads us to the following hypothesis.

Hypothesis 3 (H3). *After exogenous sales from Italian ICs, funds with more ST investors faced greater difficulty in replacing them with other LT investors.*

In a second step, we focus on the impact on the funds' portfolio allocation. Bond funds generally exhibit a concave flow-performance relationship as investors' flows are highly sensitive to bad performance (Goldstein et al., 2017). According to past literature, in case of outflows fund managers should sell riskier bonds and purchase safe and liquid assets in order to be ready to meet further redemptions (Cutura et al., 2023).[13] However, since the flow-performance relationship is steeper for funds with more ST investors (Fricke and Wilke, 2023), the reaction of bond funds in this group may be different: they may take more risk to enhance their attractiveness for ST investors. Funds with an ex ante prevalence of LT investors may instead aim to prevent further outflows by reducing potential negative externalities (concave flow-performance relationship), focusing on stability over higher returns. In other words, the concave relationship of bond funds may hold only when the investor base includes a large share of long-term investors, less sensitive to

[13]In contrast, equity funds tend to increase risk levels to improve their returns relative to their peers in order to attract inflows, engaging in a tournament behaviour (Brown et al., 1996).

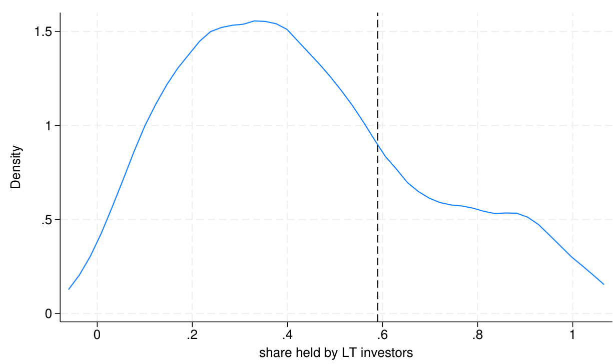
performance. Therefore, we test the following hypothesis:

Hypothesis 4 (H4). *After exogenous sales from Italian ICs, funds with more ST investors took more risk, whereas funds with more LT investors de-risked.*

4.2. Fund-level classifications of exposure to sovereign shock and LT

In the subsequent analysis exploring the effect of the investor base we differentiate funds in the non-unit portfolio of Italian ICs based on the share of LT investors they had in Q1-2018. In particular, we introduce a dummy variable $HighShareLTInv$, which is equal to 1 for funds in the top quartile of the distribution of the share of LT investors (i.e. above 59 percent). Those below this threshold are categorized as having a low share of LT investors (Figure 6).

Figure 6: **Distribution of the share of the fund held by long-term investors at the end of 2018-Q1**



Building on the results of Section 3, we derive a fund-level measure of indirect exposure to the Italian sovereign shock through the fund share holdings of Italian ICs. To better isolate the effects stemming solely from the investor-side, first, we focus exclusively on funds within the non-unit portfolio that have low direct holdings of Italian securities; therefore, we exclude funds in the top decile of the distribution, i.e. those with more than about 20 percent of assets invested in Italian securities at Q1-2018.[14] This restriction narrows our sample to 550 out of the 609 available funds included in the non-unit portfolio

[14]The results hold also when we exclude funds in the top quartile of the distribution, i.e. those with more than about 10 percent of assets invested in Italian securities.

of Italian ICs. This approach ensures that any observed investment behavior of funds is driven by investor actions (i.e., de-risking of Italian ICs) rather than direct exposure of funds to the Italian securities, allowing for a cleaner test of our hypotheses.

Then we estimate $FundExp_f$, which is a measure of the liability-side exposure to Italian securities for each fund f at Q1-2018. We calculate a weighted average, where the weight is the share of the fund f held by each Italian insurance company i. This is combined with the exposure $ExpIT_i$ of each insurer's non-unit portfolio to Italian securities. Formally, it is defined as:[15]

$$FundExp_f = \sum_i \frac{MktValueHoldings_{i,f}}{TotNetAssets_f} \cdot ExpIT_i \tag{4}$$

The median value of $FundExp_f$ is 3.8 percent in Q1-2018, but the distribution is skewed, with the 75th percentile at 17 percent. Consequently, we construct $HighExpFund_f$, which is a dummy variable equal to 1 for funds in the top quartile of the $FundExp_f$ distribution.

In the following, we concentrate on bond funds, as they are more susceptible to liquidity risk and to the inefficiencies deriving from run-prone incentives.

4.3. Empirical results

4.3.1. Change in the investor base and net flows (H3)

After the sovereign shock (described in Section 3), redemptions of shares in $Riskier$ $HighExpFund$ funds by Italian ICs likely impacted both the composition of funds' investor base, their net flows and performance. To analyze these dynamics, in a first step, we consider for each fund f and quarter t in our sample: (i) the share held by Italian ICs in their non-unit portfolio (*ShareItIC*); (ii) the share held by other long-term investors (*OthShareLongTerm*), comprising Italian ICs' unit-linked portfolios, other euro area ICs, and households; and (iii) the share held by short-term investors (*ShareShortTerm*), predominantly mutual funds and foreign holders. Then, we focus on the impact on quarterly

[15] Since we do not observe any statistically significant differences across insurance companies based on their capital levels, we do not consider the SCR ratio as a weighting factor in Equation 4.

net flows (*NetFlows*) and returns (*Returns*).[16] Our sample comprises 248 bond funds.

We estimate the following regression model to evaluate differential impacts of the liquidity shock on investor composition and net flows across funds with varying initial exposures to Italian ICs and investor bases.

$$\begin{aligned} Y_{f,t} =& \beta_0 Post * HighExpFund_f + \beta_1 Post * HighExpFund_f * HighShareLTInv_f \\ &+ \beta_2 Post * HighShareLTInv_f + \gamma_t X_{f,t} + \mu_f + \theta_{cat(f),t} + \epsilon_{f,t} \end{aligned} \tag{5}$$

where $Y_{f,t}$ is alternatively equal to *ShareItIC*, *ShareOthLongTerm*, *ShareShortTerm*, *NetFlows*, or *Returns*. For each $Y_{f,t}$, our primary coefficients of interest are those that capture the post-shock change for funds with higher exposure to Italian ICs' non-unit portfolios (*HighExpFund*), segmented by their investor composition. Specifically: β_0 represents the post-shock change for highly exposed funds predominantly held by ST investors, while β_1 is the differential effect (on top of β_0) for highly exposed funds with a larger share of LT investors ($HighShareLTInv_f$). As the baseline category consists of funds with low exposure to Italian ICs and a high share of ST investors, the coefficient β_2 is the differential effect for funds with lower exposure to Italian ICs and a higher share of LT investors.

We include a set of controls, $X_{f,t}$, that interact fund-level variables with time dummies. These controls include Morningstar's five-star rating and the fund's legal domicile for all dependent variables. To account for unobserved heterogeneity, we incorporate time-invariant fund fixed effects (μ_f) and fund category-time fixed effects ($\theta_{cat(f),t}$), which control for time-varying shocks at the fund-category level, as defined by Morningstar's Global Category. Table A.5 in Appendix A provides a summary of bond funds in our sample, organized by the six Morningstar Global Categories present in our sample, and shows the number of funds with high and low shares of LT investors prior to the shock.

As shown in Table 3, column (1), and consistent with our prior insurance-level findings, $HighExpFund$ funds experienced a significant decline in the share held by Italian

[16] Investor base information is derived from the SHS-S dataset and supervisory data for Italian ICs, segmented by portfolio. Non-euro area investors cannot be classified by sector and are therefore excluded from the long-term investor category. Net flow and returns data are retrieved from Morningstar.

Table 3: **Exposure to IT securities and subsequent de-risking**

	(1) ShareItIC	(2) ShareOthLongTerm	(3) ShareShortTerm	(4) NetFlows	(5) Returns
Post x HighExpFund	-0.1235***	-0.0128	0.1225***	-0.0652***	0.0073**
	(0.0000)	(0.4430)	(0.0001)	(0.0002)	(0.0271)
Post x HighShareLTInv	0.0098	0.0162	-0.0053	-0.0141	0.0043**
	(0.4459)	(0.2346)	(0.6518)	(0.3784)	(0.0323)
Post x HighExpFund x HighShareLTInv	0.0737***	0.0355*	-0.1303***	0.0911***	-0.0071*
	(0.0002)	(0.0987)	(0.0000)	(0.0001)	(0.0768)
Fund contr.*Time	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
IF category-Time FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.9818	0.9653	0.9593	0.3336	0.5329
Observations	1588	1585	1566	1862	1851

Notes: columns (1)-(5) display estimates of Equation 5. Standard errors are clustered at the fund level. p-values in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

ICs in their non-unit portfolios relative to other (riskier) funds. This reduction was especially pronounced for $HighExpFund$ funds with a higher share of ST investors (-12 percentage points relative to non-exposed funds with a high share of ST investors), while funds with a greater share of LT investors showed a comparatively smaller decrease (-4 percentage points, also relative to the reference group). Notably, funds with low exposure to Italian ICs and a high share of LT investors did not record any significant change in their IC share relative to the base category.

The post-shock share of other LT investors does not show a statistically significant change for $HighExpFund$ funds with a high share of ST investors (Table 3, column 2), although the coefficient is negative. For $HighExpFund$ funds with a higher ex ante share of LT investors, however, the increase is statistically significant, rising by 3.9 percentage points. This nearly offsets the decline in the share held by Italian ICs (column 1).

The share of ST investors rose substantially for $HighExpFund$ funds with a low pre-shock share of LT investors (about 12 percentage points relative to the baseline category; Table 3, column 3). In contrast, the share of ST investors did not significantly change across other fund types, including $HighExpFund$ funds with a high share of LT investors.

These shifts in investor composition were accompanied by significant post-shock negative net flows only for $HighExpFund$ funds with a low share of LT investors, which declined by 6.5 percentage points relative to the baseline category (Table 3; column 4). Together with the results in columns (1)-(3), the overall evidence indicates that sales from

Italian ICs were only partially offset by additional investments from ST investors, while other LT investors, if anything, reduced their post-shock exposure to these funds. In contrast, $HighExpFund$ funds with a high share of LT investors maintained relatively stable net flows, showing a slight positive change (1.2 percent) relative to the baseline, with Italian ICs' sales fully offset by new flows from other LT investors.

In terms of performance (Table 3; column 5), we observe that $HighExpFund$ funds with a low share of LT investors showed a performance improvement of about 1 percentage point relative to the baseline category. In contrast, returns for exposed funds with a high share of LT investors rose at the same rate as non-exposed funds with a high share of LT investors. These performance results align with the portfolio adjustments hypothesized in H4 and discussed in Section 4.3.2.

In summary, our findings support H3, showing that, following the shock, funds with a less stable investor base (i.e. those with fewer LT investors) struggled more to offset redemptions by Italian ICs with new inflows from other LT investors.[17]

4.3.2. Change in the fund portfolio allocation (H4)

In this section, we assess the impact of ICs' sales on funds' portfolio reallocation across funds that experienced a liquidity shock from Italian ICs but differed in their prior share of LT investors (H4).

For each fund, we estimate the share of the portfolio invested in six asset categories. These categories are: *BondHY* (bonds rated lower than BBB-), *Bond A-BBB* (non-Italian bonds with rating from A+ to BBB-), *CorpBond AAA-AA* (corporate bonds rated AA- or higher), and *SafeAsset* (cash and sovereign bonds rated AA- or higher), *Equity* (non-Italian stocks) and *FundShares* (shares of other funds). Italian securities, which are directly affected by the shock, are categorized separately as *IT*.[18] In our sample of bond funds, the

[17] Figures A.1, A.2, A.3, A.4, and A.5 in Appendix A present the marginal effects for $HighExpFund$ funds with high and low shares of LT investors, based on a model specification with time-varying coefficients. The results reinforce the finding that the post-shock changes in the share of each type of investor for $HighExpFund$ funds followed distinct patterns, depending on the initial composition of the investor base.

[18] Figure A.6 in Appendix A presents the portfolio reallocation results using an alternative asset classification. This classification replaces the original non-Italian bond categories – *BondHY*,*Bond A-BBB* and *CorpBondAAA-AA* – with two broader categories: *BondCorp* (non-Italian corporate bonds) and *BondSovOther* (sovereign bonds rated A+ or below), distinguishing assets only by issuer type.

categories *Equity* and *FundShares* are marginal, so the classification – primarily based on bond credit ratings – effectively provides a ranking of these securities also in terms of liquidity (Table A.6). We omit funds for which over 30 percent of the portfolio data is unavailable (for instance due to derivatives and other securities lacking sufficient information such as unlisted securities). Our final sample for this analysis consists of 216 funds.

Equation 6 describes our baseline model.

$$\begin{aligned} AssetShare_{f,j,t} = &\beta_{1,j} Post_t * HighExpFund_f * HighShareLTInv_f \\ &+ \gamma_t X_{f,t} + \zeta_{f,j} + \theta_{cat(f),j,t} + \epsilon_{f,j,t} \end{aligned} \tag{6}$$

The dependent variable ($AssetShare_{f,j,t}$) represents the proportion of fund f's portfolio allocated to asset category j in quarter t. Our primary variable of interest is the effect of the sovereign shock on highly exposed funds within each group across asset categories, specifically $Post*HighExpFund*HighShareLTinv$ for each category j. This setup allows us to analyze the varying impacts on each fund group across asset classes. Additionally, we include a set of fund-level controls interacted with time dummies (vector $X_{f,t}$) and incorporate fixed effects for fund-asset category ($\zeta_{f,j}$) and Morningstar fund category-asset category-time ($\theta_{cat(f),j,t}$) to account for the evolving preferences of each fund category toward specific asset classes.

The results, shown in Figure 7, show that funds' investment behavior is indeed heterogeneous across the two groups of funds. Specifically, funds with a high share of LT investors prior to the shock de-risked their portfolios, increasing their allocation to cash and low-risk assets by approximately 5 percentage points (panel a). This result is inline with the recent evidence by Cutura et al. (2023) on bond funds. From Section 4.3.1, this de-risking appears to be correlated with net inflows from long-term investors, suggesting that a more conservative investment strategy is attractive to this investor group.[19]

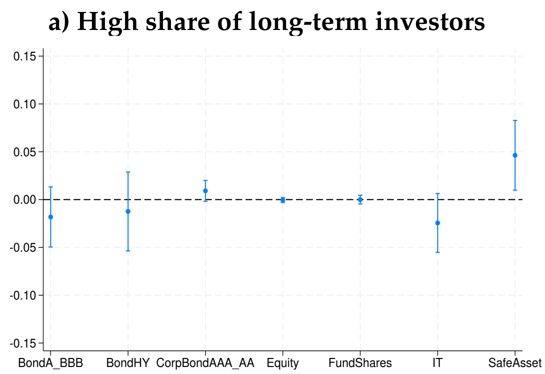
In contrast, funds with a lower share of LT investors before the shock increased the overall risk profile of their portfolios (Figure 7, panel b). These funds notably raised their

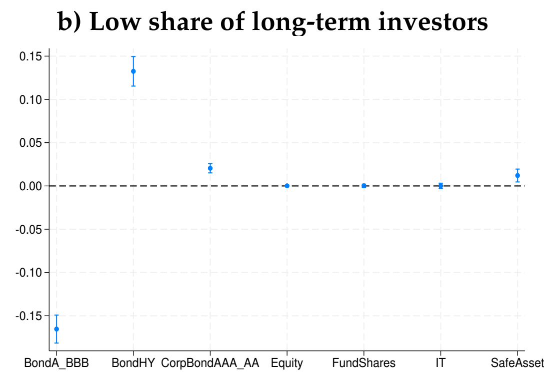
[19]The results of tests presented in this section are qualitatively similar also by including mixed funds.

exposure to corporate bonds, especially in the high-yield segment, while reducing their holdings of less riskier bonds (excluding cash-like assets). This shift reflects more aggressive risk-taking behavior, likely aimed at attracting performance-sensitive investors such as other investment funds. This strategic increase in risk aligns with the observation that, after the shock, these funds improved their quarterly performance and drew in more of this investor type (as discussed in Section 4.3.1), despite experiencing net outflows overall.

Crucially, this increased risk exposure did not stem from selling more liquid assets to meet redemptions, as the share invested in safe assets remained stable or even slightly increased in some cases. This pattern supports the hypothesis that these funds intentionally raised their risk levels to appeal to a specific investor segment and partially offset the outflows from Italian ICs.

Figure 7: **Marginal effect of $HighExpFund$ across the main categories of assets for $Riskier$ bond funds, broken down by investor base**





Notes: panels (a) and (b) shows the results of Equation 6. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the distribution; panel (b) shows results for funds with a lower share of long-term investors. The sample includes only riskier bond funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities. Standard errors are clustered at the fund level.

To further analyze portfolio adjustments over time, we replace $Post$ with a series of time dummies in Equation 6. Focusing on the three main asset categories (*Bond A-BBB*, *BondHY*, and *SafeAsset*), Figure A.7 shows that both funds with high and low shares of LT investors began adjusting their portfolios immediately following the shock. This timing of portfolio adjustments closely aligns with the shifts observed across different investor shares (Figures A.1, A.2 and A.3).

Overall, consistent with H4, these results suggest that the investor base significantly affect funds' investment behaviour. After net outflows, the investment behavior of bond funds with less LT investors is not consistent with a concave flow-performance relationship as they took more risk, likely to enhance their attractiveness for their ex-ante investor base.

5. Discussion and policy implications

The academic literature and policy debate have largely focused on how run-like incentives among fund investors – stemming from the first-mover advantage due to strategic complementarities in redemption decisions – can lead funds to propagate asset-side shocks across the financial system (Falato et al., 2021). This often results in fire sales (Manconi et al., 2012) and pro-cyclical investment strategies (Timmer, 2018). Recent research has begun to explore how these inefficiencies depend on the composition of a fund's investor base, highlighting the role of differing liability structures among investors (Allaire et al., 2023; Fricke et al., 2022; Fricke and Wilke, 2023). All in all, a robust body of evidence now shows that financial frictions related to fund design, particularly run-like incentives during negative performance periods, distort asset prices and capital allocation due to spillovers across investors and asset classes *after* a shock.

However, it remains an open empirical question whether these *ex-post* distortions influence investors *ex-ante* in their decision to invest across funds. Specifically, it has not been explored how investors, especially those who typically bear the majority of outflow costs, account for potential future costs from asset-side shocks in their fund investment choices. Our results contribute to this discussion by demonstrating that the demand from specific investor types also depends on the composition of other investors within the same fund, suggesting that ex-post inefficiencies also impact the *ex-ante* accumulation of risks on the liability *and* asset sides of funds *before* a shock occurs.

Vulnerabilities linked to strategic complementarities also bear significant implications for financial stability, as the sorting mechanism between funds and investors discussed in this paper may lead to a concentration of risks. Specifically, we observe that the greater the share of ST investors in a fund, the less likely LT investors are to purchase shares in the event of an exogenous fund liquidity shock. This pattern suggests that LT investors anticipate higher trading costs in the event of poor future performance, as a large base of performance-sensitive ST investors would likely lead to substantial redemptions. This reduced demand from LT investors incentivizes fund managers to adopt riskier strategies aimed at boosting expected returns, ultimately with the goal of attracting additional investments from performance-sensitive ST investors. In contrast, when a fund has a higher proportion of LT investors, the risk of future runs and potential trading costs for remaining investors are lower. In this context, fund managers of such funds are more inclined to de-risk, consistent with Cutura et al. (2023), aiming to appeal to LT investors who prioritize stability over higher returns.

Consequently, funds with a flightier investor base tend to attract even more run-prone investors, further destabilizing their investor composition and increasing their vulnerability to runs if a future asset-side shock occurs. Additionally, these funds tend to shift towards riskier, less liquid assets to maintain appeal for ST investors. These dynamics ultimately lead to a concentration of liability-side liquidity risk in funds holding riskier and less liquid assets, amplifying systemic risk.

From a policy perspective, our findings highlight an additional *ex-ante* channel through which run-like incentives, driven by strategic complementarities, may introduce significant vulnerabilities in open-end funds. In particular, funds with a lower share of LT investors would particularly benefit from the broader adoption of tools and measures designed to reduce the first-mover advantage (e.g., liquidity management tools, LMTs). As previous literature suggests (Jin et al., 2022), such measures can help curb run-like incentives, thereby reducing the likelihood of fire sales and spillovers during market shocks. We argue that these measures could also lower the expected outflow costs for LT investors in funds with high exposure to run-prone investors, helping to reduce the concentration of risk that we have identified.

More generally, our results suggest a rationale for monitoring fund liquidity risks by taking into account their investor base composition. In this respect, even taking into account the significant differences across intermediaries, this would parallel the structure of the Net Stable Funding Ratio (NSFR) for banks, which considers the funding stability associated with different counterparties (e.g., households, firms, and other financial intermediaries).

These concerns become more relevant as recently investments by funds in other funds' shares have substantially increased (Fricke and Wilke, 2023), interconnections within the open-end fund sector have intensified, potentially prompting more funds to adopt riskier strategies to meet the demand of performance-sensitive investors. From a financial stability perspective, this dynamic concentrates asset-side risks specifically in intermediaries that are most susceptible to runs. In this context, measures aimed at mitigating the vulnerabilities of this particular cohort of funds become especially critical.

6. Conclusions

This paper investigates an exogenous liquidity shock to a subset of euro-area mutual funds, prompted by redemptions from traditionally long-term investors, insurance companies. We examine how funds with different initial investor compositions navigated the shock, focusing on their ability to attract new investments, the origins of these inflows, and the adjustments made to their portfolios to support this rebalancing.

Our analysis exploits an exogenous spike in Italian government bond yields following the May 2018 general election, which caused a capital shock for Italian insurance companies. In response, these companies reduced their holdings of riskier mutual funds in their non-unit-linked portfolios, resulting in a liquidity shock for funds significantly held by Italian insurance companies. A key contribution of this paper is demonstrating how portfolio adjustments by long-term investors, such as insurance companies, can propagate shocks to non-bank intermediaries previously unaffected by market conditions.

The impact of this shock varied depending on the funds' initial investor base composition. We focus on bond funds, the segment most vulnerable to liquidity risk, and find that funds with a higher proportion of long-term investors, such as households and other EU insurance companies, managed to avoid significant net outflows by attracting new flows from long-term investors. Accompanying this investor replacement, these funds de-risked their portfolios by increasing their share of safe assets – a strategy valued by investors with longer horizons. Conversely, funds with less stable investor bases, particularly those dominated by ST investors, were unable to replace Italian IC redemptions with new flows from LT investors. Consequently, they faced net outflows and took on greater portfolio risk, likely to appeal to ST investors who prioritize high expected returns.

Our findings underscore how the composition of a fund's investor base can influence its response to liability-side shocks and ultimately it may affect its flow-performance relationship. Broadly, these results reveal a sorting mechanism between investors and funds: this is driven by long-term investors preference for funds with fewer performance-sensitive, short-term investors, in an attempt to minimize expected outflow costs in the event of adverse fund performance shocks.

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A. Additional tables and figures

Table A.1: **ICs main variables**

Variable	N	Mean	10^{th} P.	25^{th} P.	Median	75^{th} P.	90^{th} P.	St.Dev
Assets (Eur Bn)	438	14.92	0.38	2.34	7.07	16.8	33.06	23.25
Share unit-linked assets	438	0.19	0	0.05	0.12	0.21	0.53	0.22
Exposure to IT	432	0.59	0.37	0.43	0.59	0.72	0.85	0.19
ROE	438	0.06	-0.02	0.03	0.07	0.11	0.18	0.11
SCR	438	2.13	1.33	1.55	1.97	2.53	3.12	0.78

Notes: the table reports, for each variable, the mean, standard deviation, median and 10^{th}, 25^{th}, 75^{th}, 90^{th} percentile and number of unique insurance-time observations. *Assets* is the total market value of tradeable securities in the life-insurance portfolios. *Share unit-linked assets* is the share of market value of the investment for the unit-linked segment of the overall portfolio. *Exposure to IT* is the share of Italian assets in the with-profits portfolio of the insurance over time.

Table A.2: **Open-end funds held by ICs - main variables**

Variable	N	Mean	Median	10^{th} P.	25^{th} P.	75^{th} P.	90^{th} P.	St.Dev
*Panel A: mutual funds held by ICs (**non-unit-linked portfolio**)*								
Portfolio share								
Bond HY	4889	0.18	0.02	0	0	0.32	0.65	0.27
Bond A-BBB	4889	0.15	0.03	0	0	0.23	0.51	0.22
Bond corp. AAA-AA	4889	0.02	0	0	0	0.01	0.06	0.07
Safe assets	4889	0.08	0.01	0	0	0.07	0.26	0.17
Foreign equity	4889	0.34	0	0	0	0.88	0.97	0.42
Italian securities	4889	0.09	0.02	0	0	0.08	0.25	0.17
Bond other sovereign	4889	0.08	0	0	0	0.05	0.23	0.18
Fund shares	4889	0.04	0	0	0	0.03	0.09	0.14
Bond corp.	4889	0.28	0.04	0	0	0.63	0.89	0.37
n.a.$>30\%$	7044	0.29	0	0	0	1	1	0.46
Investors' share								
ICs (with-profits)	6198	0.08	0.01	0	0	0.07	0.2	0.18
Long term (IT+EA)	6618	0.42	0.38	0.11	0.22	0.59	0.82	0.26
Oth. Fin. Interm. (IT+EA)	6757	0.19	0.14	0	0.04	0.29	0.43	0.18
Non-EA	6758	0.11	0.05	0	0.01	0.14	0.31	0.15
Fund characteristics								
Fund size (Eur mln)	6782	1810	676	73	197	1964	4632	3636
Flows (%)	5998	0.66	-0.05	-10.91	-4.89	5.4	15.37	7.91
Net return (%)	6781	0.69	0.41	-4.08	-1.03	2.42	5.65	3.63
MS rating	7044	2.13	3	0	0	4	5	1.88
Risky fund dummy	6162	0.83	1	0	1	1	1	0.38
Shock exp.	5658	0.05	0.01	0	0	0.04	0.13	0.11
*Panel B: mutual funds held by ICs (**unit-linked portfolio**)*								
Portfolio share								
Bond HY	27386	0.12	0	0	0	0.12	0.47	0.22
Bond A-BBB	27386	0.12	0	0	0	0.18	0.44	0.2
Bond corp. AAA-AA	27386	0.02	0	0	0	0.01	0.08	0.07
Safe assets	27386	0.09	0.01	0	0	0.08	0.3	0.18
Foreign equity	27386	0.42	0.12	0	0	0.94	0.98	0.45
Italian securities	27386	0.08	0	0	0	0.06	0.22	0.17
Bond other sovereign	27386	0.07	0	0	0	0.03	0.2	0.17
Fund shares	27386	0.07	0	0	0	0.03	0.09	0.21
Bond corp.	27997	0.19	0	0	0	0.29	0.82	0.32
n.a. $>30\%$	33164	0.21	0	0	0	0	1	0.41
Fund characteristics								
Fund size (Eur mln)	32604	923	332	45	116	877	2129	2210
Flows (%)	28850	0.44	-0.72	-10.94	-5.64	5.53	15.67	8.23
Net return (%)	32418	0.97	0.61	-4.38	-1.01	3.1	6.77	4.17
MS rating	33164	2.21	3	0	0	4	4	1.8
Risky fund dummy	30901	0.82	1	0	1	1	1	0.38

Notes: the table reports, for each variable, the mean, standard deviation, median and 10^{th}, 25^{th}, 75^{th}, 90^{th} percentile and number of unique mutual fund-time-observations. *Portfolio share* are the shares of fund assets invested in a specific category (as defined in Section 4.3.2). *Inv. share* are the share of the fund held by a specific category of investors (as defined in Section 4.3.1).

Table A.3: **Insurance companies classification for Italian exposure and SCR ratio**

	N. IC	Share non-unit inv. (%)	Share unit inv. (%)
LowExpIT-HighSCR	17	34.9	37.8
LowExpIT-LowSCR	8	12.2	9.8
HighExpIT-HighSCR	19	50.4	21.7
HighExpIT-LowSCR	5	2.5	30.7

Table A.4: **Change in Italian ICs' holdings of $Riskier$ funds in the non-unit portfolio across funds with high and low share of long-term investors**

	(1) lnq
Riskier x Post	-0.2822**
	(0.0166)
Post x HighShareLTinv	-0.1795
	(0.2303)
Riskier x Post x HighShareLTinv	0.1856
	(0.2580)
IC-Time FE	Yes
IC-Sec. FE	Yes
Fund contr.*Time	Yes
Adj. R-squared	0.9850
Observations	5675

Notes: the table shows results of Equation 2 obtained by focusing on funds in the non-unit portfolio and replacing $NonUnit$ with $HighShareLTInv$, which is a dummy equal to 1 for funds with a high proportion of long-term investors (above 58 percent) in Q1-2018. The dependent variable is lnq, which is the log-quantity of fund s held by insurer i in quarter t. Standard errors are clustered at the insurer and fund level. p-values in parentheses; *** p <0.01, ** p <0.05, * p <0.1.

Table A.5: **No. of bond funds by MS category and share of long-term investors**

MS global category	Low share Long-Term inv.	High share Long-Term Inv.
Europe Fixed Income	66	20
Global Fixed Income	46	10
Emerging Markets Fixed Income	43	3∗
Fixed Income Miscellaneous	29	8
US Fixed Income	16	3∗
Asia Fixed Income	3∗	3∗

Notes: the table reports for each Morningstar global category of corporate bond funds the number of funds in the top quartile of the distribution of the share of long-term investors (i.e. above 59 per cent). We marked with a 3∗ cases in which the number of funds is three or less than three.

Table A.6: **Bond funds' portfolio allocation - all periods**

Variable	N	Mean	Median	10^{th} P.	25^{th} P.	75^{th} P.	90^{th} P.	St.Dev
Bond HY	1447	0.41	0.38	0.03	0.13	0.66	0.82	0.32
Bond A-BBB	1447	0.34	0.32	0.05	0.12	0.53	0.69	0.24
Bond corp. AAA-AA	1447	0.04	0	0	0	0.05	0.13	0.08
Safe assets	1447	0.1	0.03	0	0.01	0.11	0.31	0.18
Foreign equity	1447	0.01	0	0	0	0	0	0.07
Italian securities	1447	0.04	0.02	0	0	0.07	0.12	0.06
Bond other sovereign	1447	0.18	0.02	0	0	0.22	0.69	0.28
fund shares	1447	0.02	0	0	0	0.04	0.08	0.04
Bond corp.	1447	0.61	0.77	0.08	0.31	0.88	0.93	0.34
Other (n.a.)	1447	0.03	0.03	-0.02	0	0.06	0.11	0.13
Fund size (Eur mln)	1444	2139	1194	106	352	2646	5188	2781

Notes: the table reports, for each variable, the mean, standard deviation, median and 10^{th}, 25^{th}, 75^{th}, 90^{th} percentile and number of unique mutual fund-time-observations. Shares of fund assets invested in a specific category (as defined in Section 4.3.2) considering the sample of funds included in the regression Equation 6.

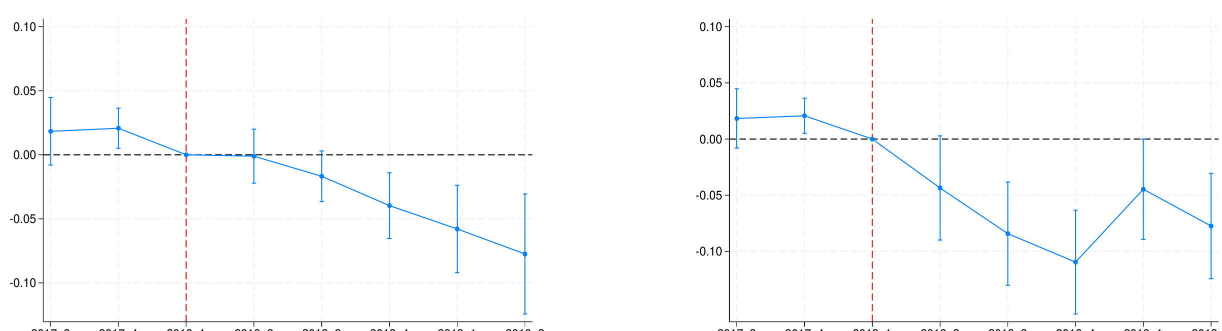
Table A.7: **Bond funds' portfolio allocation before the shock and LT investors' share**

Variable	N	Mean	Median	10^{th} P.	25^{th} P.	75^{th} P.	90^{th} P.	St.Dev
Panel A: Low share of long-term investors								
Bond HY	552	0.39	0.38	0.04	0.11	0.65	0.8	0.29
Bond A-BBB	552	0.35	0.32	0.07	0.12	0.53	0.7	0.23
Bond corp. AAA-AA	552	0.05	0.01	0	0	0.06	0.14	0.08
Safe assets	552	0.11	0.03	0	0.01	0.12	0.29	0.19
Foreign equity	552	0	0	0	0	0	0	0.01
Italian securities	552	0.04	0.02	0	0	0.07	0.11	0.05
Bond other sovereign	552	0.18	0.02	0	0	0.22	0.69	0.28
Fund shares	552	0.02	0	0	0	0.04	0.08	0.03
Bond corp.	552	0.6	0.75	0.1	0.32	0.87	0.93	0.31
Other (n.a.)	552	0.04	0.04	-0.03	0.01	0.08	0.13	0.09
Fund size (Eur mln)	550	2530	1610	226	733	3299	6223	3005
Panel B: High share of long-term investors								
Bond HY	121	0.34	0.21	0.01	0.04	0.45	0.83	0.52
Bond A-BBB	121	0.35	0.29	0.02	0.08	0.57	0.83	0.3
Bond corp. AAA-AA	121	0.04	0	0	0	0.03	0.06	0.13
Safe assets	121	0.13	0.03	0	0.01	0.15	0.43	0.19
Foreign equity	121	0.04	0	0	0	0	0	0.18
Italian securities	121	0.08	0.06	0	0	0.12	0.19	0.09
Bond other sovereign	121	0.12	0.04	0	0	0.1	0.52	0.22
Fund shares	121	0.02	0	0	0	0.01	0.09	0.06
Bond corp.	121	0.6	0.7	0.06	0.25	0.88	0.93	0.53
Other (n.a.)	121	0	0.04	0	0.01	0.09	0.14	0.36
Fund size (Eur mln)	120	324	159	62	97	340	828	423

Notes: the table reports, for each variable, the mean, standard deviation, median and 10^{th}, 25^{th}, 75^{th}, 90^{th} percentile and number of mutual fund-time observations. Shares of fund assets invested in a specific category (as defined in Section 4.3.2) in the pre-shock periods considering the sample used in the regression Equation 6.

Figure A.1: **Marginal effect of $HighExpFund$ on $ShareItIC$**

a) High share of long-term investors **b) Low share of long-term investors**

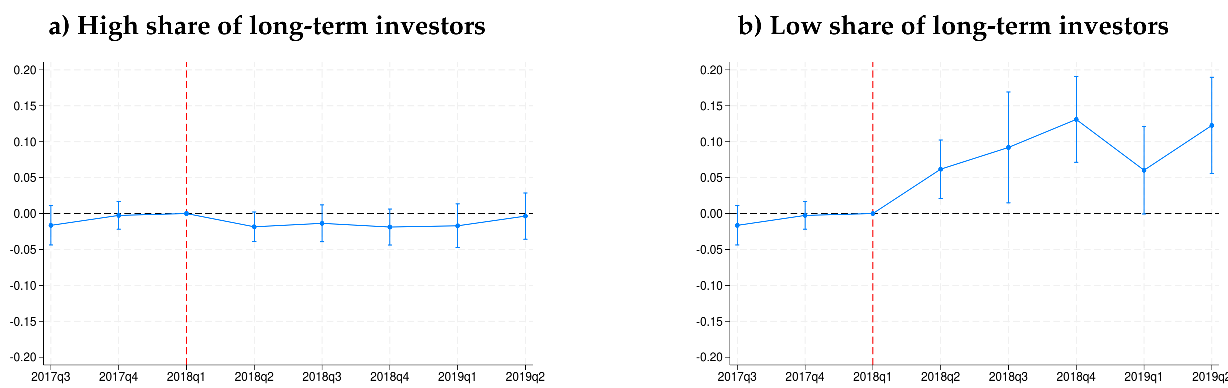


Notes: the figure shows the results of Equation 5 by adopting $ShareItIC$ as the dependent variable and by introducing a time-varying interaction term between $Riskier$, $HighExpFund$ and $HighShareLTinv$. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the distribution; panel (b) shows results for funds with a lower share of long-term investors. The sample includes only riskier funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities. Standard errors are clustered at the fund level.

Figure A.2: **Marginal effect of** $HighExpFund$ **on** $OthShareLongTerm$

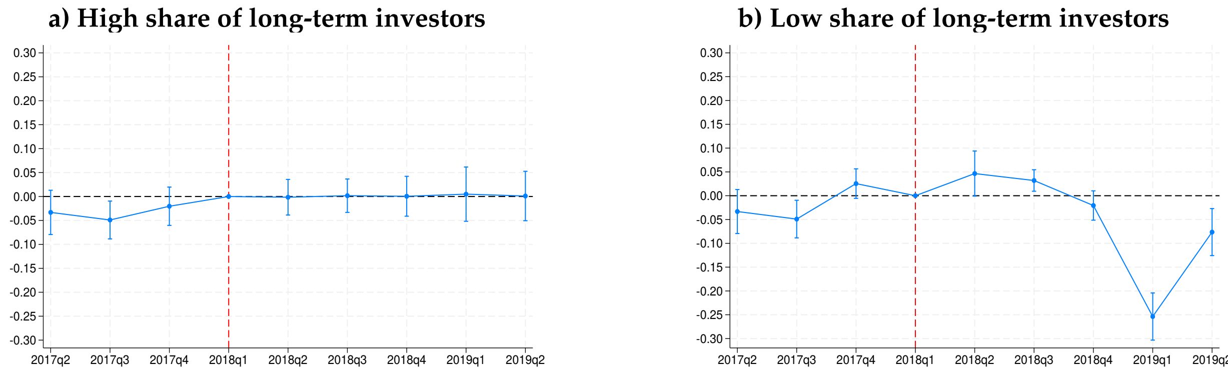
Notes: the figure shows the results of Equation 5 by adopting $OthShareLongTerm$ as the dependent variable and by introducing a time-varying interaction term between $Riskier$, $HighExpFund$ and $HighShareLTinv$. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the distribution; panel (b) shows results for funds with a lower share of long-term investors. The sample includes only riskier funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities. Standard errors are clustered at the fund level.

Figure A.3: **Marginal effect of** $HighExpFund$ **on** $ShareShortTerm$



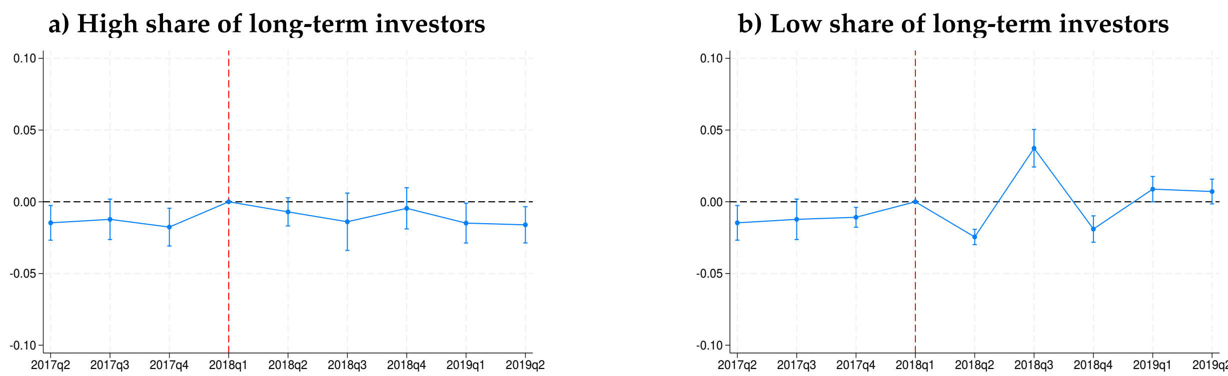
Notes: the figure shows the results of Equation 5 by adopting $ShareShortTerm$ as the dependent variable and by introducing a time-varying interaction term between $Riskier$, $HighExpFund$ and $HighShareLTinv$. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the distribution; panel (b) shows results for funds with a lower share of long-term investors. The sample includes only riskier funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities. Standard errors are clustered at the fund level.

Figure A.4: **Marginal effect of $HighExpFund$ on the net flows of $Riskier$ funds, broken down by investor base**



Notes: the figure shows the results of Equation 5 by adopting $NetFlows$ as the dependent variable and by introducing a time-varying interaction term between $Riskier$, $HighExpFund$ and $HighShareLTinv$. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the distribution; panel (b) shows results for funds with a lower share of long-term investors. The sample includes only riskier funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities. Standard errors are clustered at the fund level.

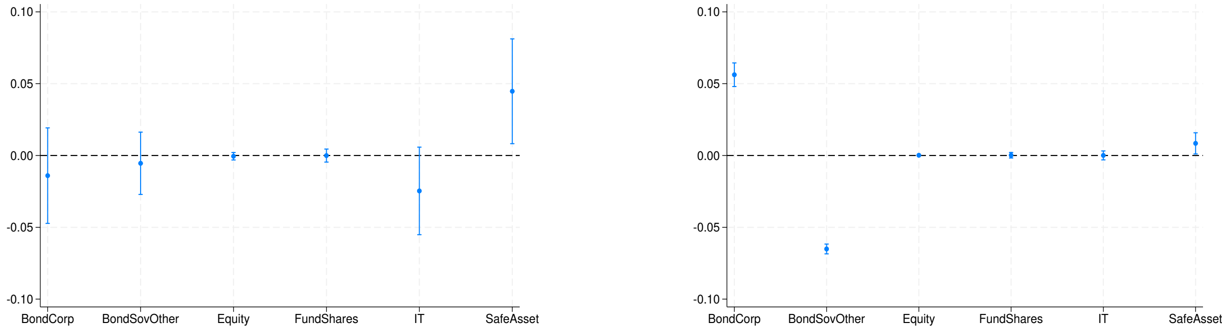
Figure A.5: **Marginal effect of $HighExpFund$ on returns of $Riskier$ funds, broken down by investor base**



Notes: the figure shows the results of Equation 5 by adopting $Returns$ as the dependent variable and by introducing a time-varying interaction term between $Riskier$, $HighExpFund$ and $HighShareLTinv$. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the distribution; panel (b) shows results for funds with a lower share of long-term investors. The sample includes only riskier funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities. Standard errors are clustered at the fund level.

Figure A.6: **Marginal effect of $HighExpFund$ across an alternative classification of the main categories of assets for $Riskier$ bond funds, broken down by investor base**

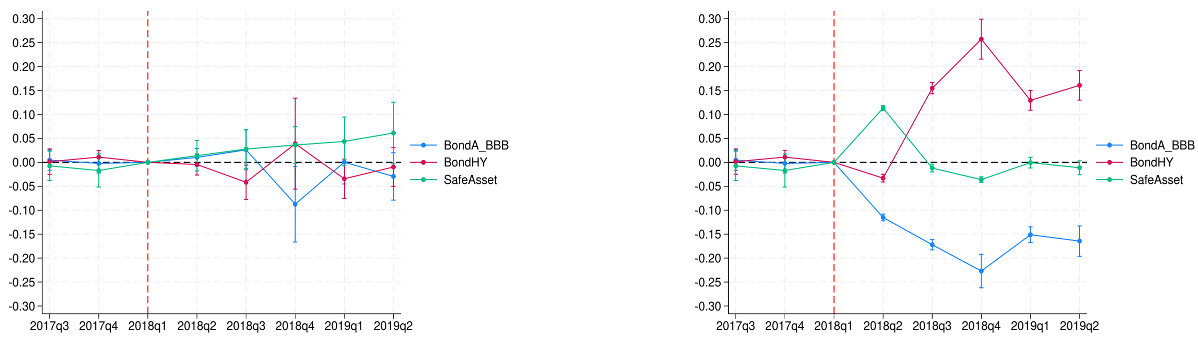
a) High share of long-term investors **b) Low share of long-term investors**



Notes: panels (a) and (b) shows the results of Equation 6 for an alternative classification of the main categories of assets. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the distribution; panel (b) shows results for funds with a lower share of long-term investors. The sample includes only riskier bond funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities. Standard errors are clustered at the fund level.

Figure A.7: **Marginal effect of $HighExpFund$ across time on the main categories of assets for $Riskier$ bond funds, broken down by investor base**

a) High share of long-term investors **b) Low share of long-term investors**



Notes: panels (a) and (b) shows the results of Equation 6 by introducing a time-varying coefficient for each group. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the distribution; panel (b) shows results for funds with a lower share of long-term investors. The sample includes only riskier bond funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities. Standard errors are clustered at the fund level.

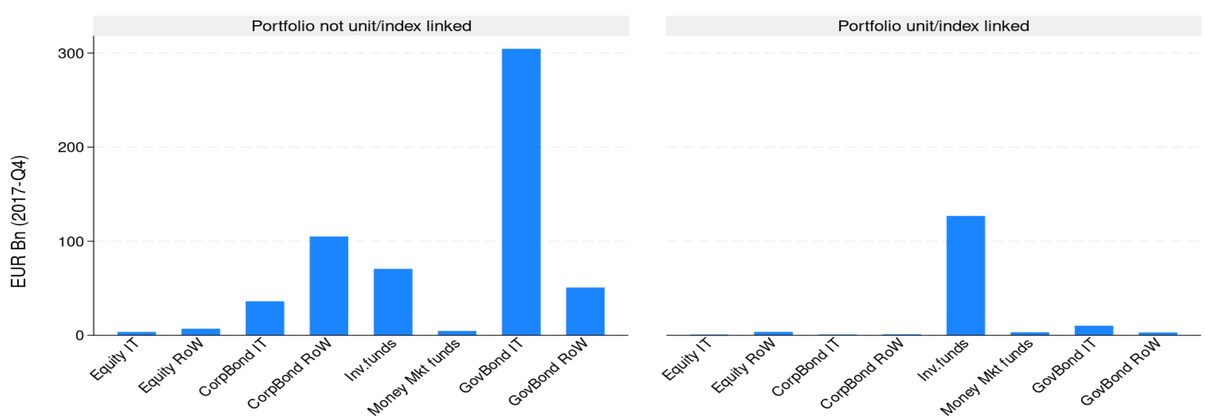
B. An overview of the Italian insurance sector

B.1. Portfolio allocation before the shock

At the end of 2017, Italian insurance companies held approximately €921 billion in total assets. The majority of these assets were linked to technical provisions for life policies (€684 billion), of which €146 billion was attributed to unit-linked or index-linked policies. Within the life insurance segment, a key distinction exists between two types of products: with-profits policies and unit-linked or index-linked policies. In with-profits policies, the insurer guarantees a minimum return to the policyholder, whereas in unit-linked or index-linked policies, the investment risk is fully transferred to the policyholder. These two types of liabilities also differ in volatility: with-profits policies are generally more stable, while unit-linked policies, which can be redeemed at short notice, tend to be more volatile sources of funding.

Italian government bonds make up the largest portion of insurance companies' holdings in their non-unit-linked portfolios, followed by significant investments in foreign corporate bonds and mutual fund shares (Figure B.8, left panel). On the other hand, unit-linked portfolios consist almost entirely of mutual fund shares (Figure B.8, right panel).

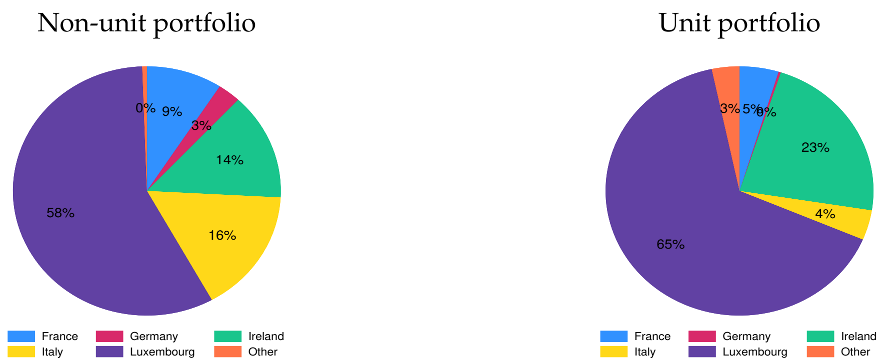
Figure B.8: **Aggregate portfolio break-down by security type**



Notes: authors' calculations based on the Centralised Securities Database from ECB and supervisory data from IVASS.

A large proportion of the mutual funds held by Italian insurance companies are domiciled in Luxembourg and Ireland – the two main financial hubs of the euro-area mutual fund industry, as noted by Beck et al. (2024) – regardless of the portfolio type. However, there is a higher share of Italy-domiciled mutual funds in the non-unit-linked portfolio (Figure B.9). We then apply a look-through approach using Morningstar data on mutual fund holdings to compare the portfolio composition of mutual funds held for unit-linked and non-unit linked liabilities.

Figure B.9: **Asset under management by funds' domicile**



Notes: authors' calculations based on the Centralised Securities Database from ECB and confidential supervisory data from IVASS. Only assets related to life-insurance policies are considered.

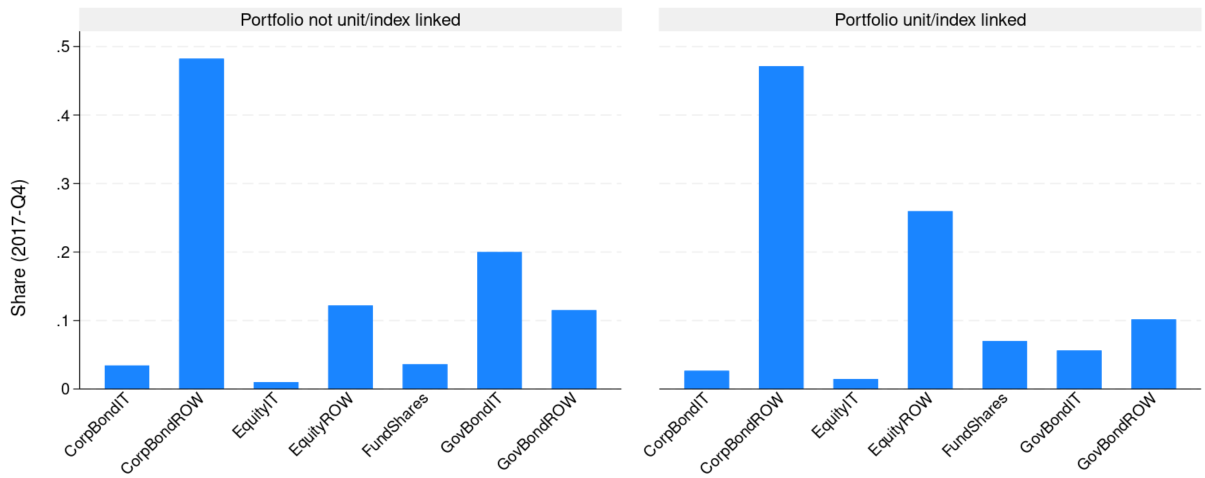
The differences in the composition of the two portfolios are only partially reflected in the mutual funds' underlying asset allocation. Investment funds in the non-unit-linked portfolio tend to allocate more to asset classes other than domestic government bonds, compared to the insurance sector's direct holdings.[20] Additionally, investment funds in both unit-linked and non-unit-linked portfolios allocate similarly to foreign corporate bonds, though non-unit-linked funds invest less heavily in foreign equities (Figure B.10).

This suggests that insurance companies use their investment fund holdings to diversify internationally, increasing their exposure to the corporate sector while maintaining relatively limited equity exposure.[21]

[20]The still substantial share of domestic government bonds in indirect holdings is largely driven by a couple of funds held by one insurer. By contrast, the median fund has minimal exposure to Italian sovereign bonds.

[21]Interestingly, while government bonds dominate the domestic securities held by the insurance sector, this is not the case for foreign securities, where foreign corporate bonds hold a much larger weight than foreign government bonds. This indicates that the Italian insurance sector is less prone to the "domestic projection bias" identified by Du et al. (2023).

Figure B.10: **Investment funds portfolio composition**



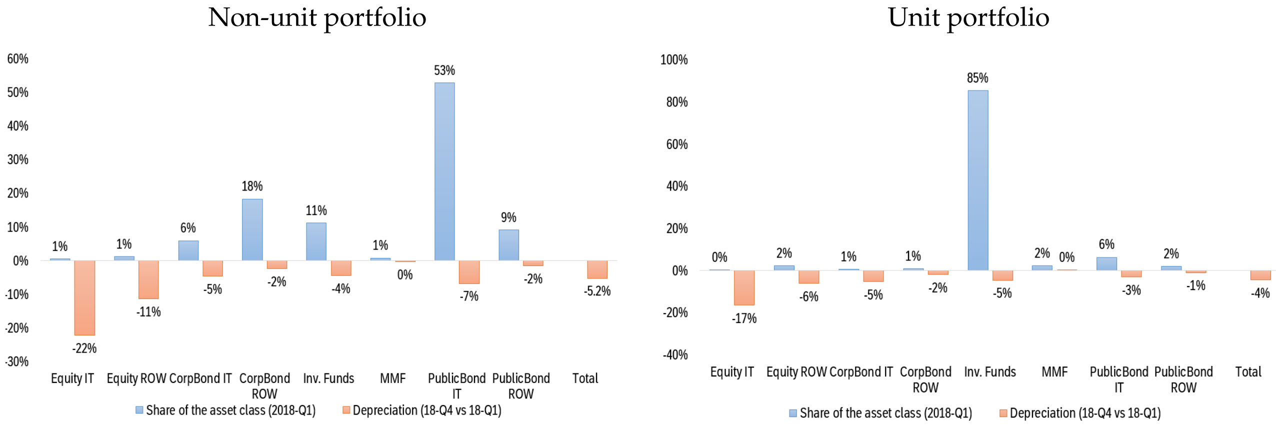
Notes: authors' calculations based on the Centralised Securities Database from ECB, supervisory data from IVASS and the Centralised Securities Database from ECB.

B.2. Impact of sovereign shock on ICs' portfolios

By maintaining the portfolio composition as of March 2018 (just before the shock) and accounting for market price changes through the end of 2018, we estimate that the market value of assets in the insurance sector's non-unit-linked portfolio dropped by over 5 percent, mainly due to the fall in domestic government bond prices. In comparison, the unit-linked portfolio saw a slightly smaller decline of around 4 percent (Figure B.11).

As pointed out in the section 3, Italian ICs engaged in a de-risking strategy on their mutual fund holdings in the non-unit portfolio. In this Appendix we show that Italian ICs engaged in a de-risking strategy also for other asset classes in their non-unit portfolio, by performing a regression analysis at a higher level of aggregation. In this way, we observe the average investment patterns in ICs' non-unit-linked portfolios before and after the shock. To do this, we calculate the quantity of each security held in each quarter (see Section 2.3), multiplied by its price at the end of 2018-Q1. We then sum the values of securities across asset categories: investment funds, money market funds, foreign corporate securities, foreign government securities, domestic corporate securities, and domes-

Figure B.11: **Depreciation of assets held by the Italian insurance sector by liabilities and asset category**



Notes: authors' calculations based on IVASS data and CSDB. We keep unchanged the nominal amount of securities held by the insurance sector at the end of 2018-Q1 and calculate the change in the market values only due to price adjustments. We consider only assets held for life-insurance policies.

tic government bonds. This allows us to examine changes in holdings, net of price effects. The regression model is as follows:

$$\ln(Stock_{i,cat,t}) = \sum_{t=17q3}^{T=19q2} \beta_{cat,t} D_t + \theta_{i,cat} + \theta_{i,t} + \epsilon_{i,cat,t} \tag{B.1}$$

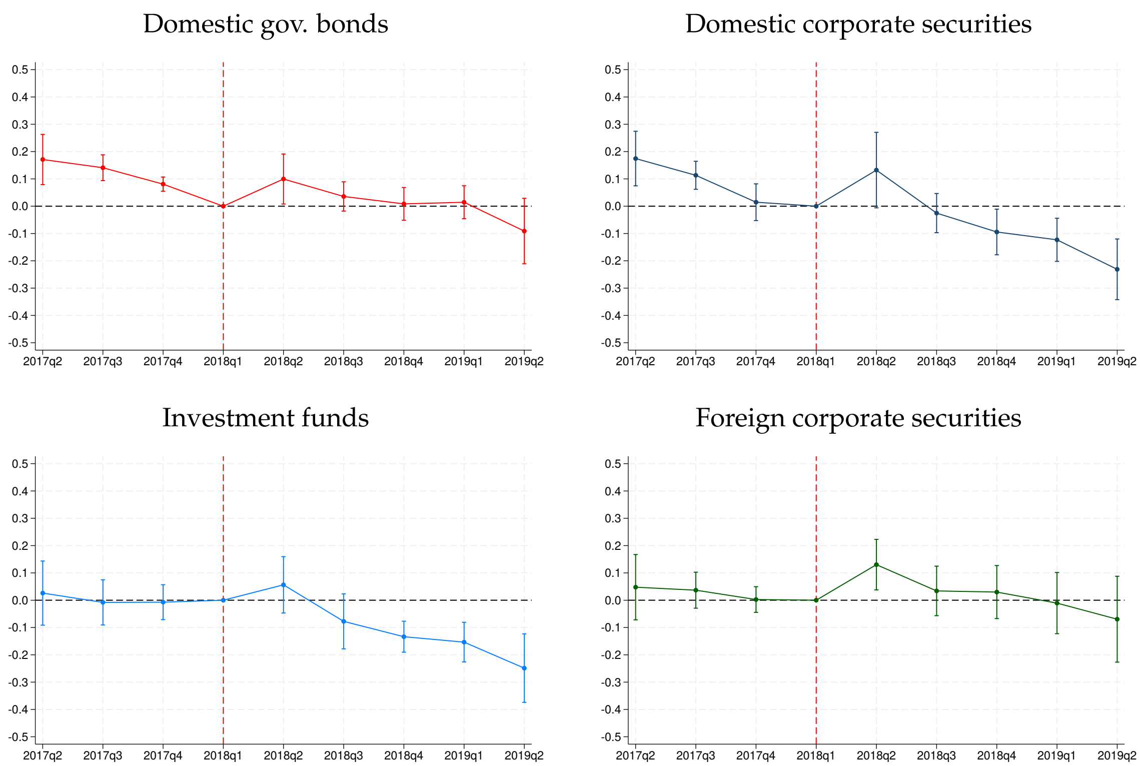
where $Stock_{i,cat,t}$ is the value of the asset held by IC i in category cat at time t (based on market prices at the end of 2018-Q1), and D_t represents time dummies for each period from 2017-Q2 to 2019-Q2. The terms $\theta_{i,cat}$ and $\theta_{i,t}$ represent IC-category and IC-time fixed effects. The former controls for observed and unobserved characteristics specific to an IC-category pair that do not change over time (e.g., an insurer's tendency to invest in certain asset classes), whereas the latter controls for factors common to all asset categories for a given insurer (e.g., total assets and subscriptions). Standard errors are double-clustered at the insurance company and asset category levels.

The benchmark period is 2018-Q1, right before the shock, and the reference asset category is "foreign government securities," which can be considered the safest in the insurance portfolio in that period. The coefficient $\beta_{cat,t}$ measures the average percentage difference in the amount held of each asset category, net of price adjustments, relative to

2018-Q1 and foreign government securities.[22]

The results of this regression are summarized in Figure B.12. On average, ICs did not significantly adjust their holdings of domestic government bonds. However, they reduced their investments in riskier and more capital-absorbing asset categories, particularly shares of investment funds and domestic corporate securities.

Figure B.12: **Investment patterns relative to foreign government bonds**



Notes: the charts plot the $\beta_{cat,t}$ for each asset category estimated with model in Equation B.1. The money market funds category is not plotted but it does not show any particular pattern over the period. Confidence bands are at the 90% level based on standard errors clustered at the asset category and insurance company level.

[22]We only consider securities that either do not mature or are issued during the sample period. To ensure the results are not driven by outliers, we exclude the top and bottom 5 percent of changes in holdings, which are typically due to small insurers holding negligible amounts of certain assets in some periods.

C. Capital requirements and portfolio reallocation following the shock

The Solvency II Directive specifies the minimum capital requirements (Solvency Capital Requirements, SCRs) of ICs in the European Union, in terms of a value-at-risk measure. More specifically, the Directive stipulates that each IC must hold enough capital to cover the losses that may occur due to changes in the market values of its assets and liabilities over the following year with a confidence level of 99.5 percent. ICs may compute their SCRs either using an internal model or the standard formula, and most of them rely on the latter, at least partly (Grochola and Schlütter, 2024). The standard formula quantifies the SCR by aggregating capital requirements in different risk modules, the most important of which are market risk, life underwriting, health underwriting, non-life underwriting and counterparty risk.

In the market risk module, the standard formula specifies a minimum capital requirement due to changes in the value of the insurer's assets. The SCR of the market risk module is obtained by aggregating the capital requirements in its submodules: interest rate risk, equity risk, spread risk, currency risk, property risk, concentration risk and illiquidity risk. For Italian ICs, capital requirements for market risk are mainly attributable to their exposures to spread, equity, currency and property risk (Banca d'Italia, 2020). The capital requirements in these submodules are summarized in Table C.8. Importantly, government bonds issued by sovereigns in the European Economic Area (EEA) carry no capital charge for spread risk, irrespective of their rating.

Table C.8: Capital requirements in submodules of market risk.

Submodule	Charge (%)	Notes
Equity	30	40% for non-OECD and non-EEA exposures
Currency	25	
Property	25	
Spread	0.9–60	E.g., 12.5% for a BBB-rated bond with a 5-year duration
Interest rate		variable duration gap × Δ risk-free rates of 25–75%

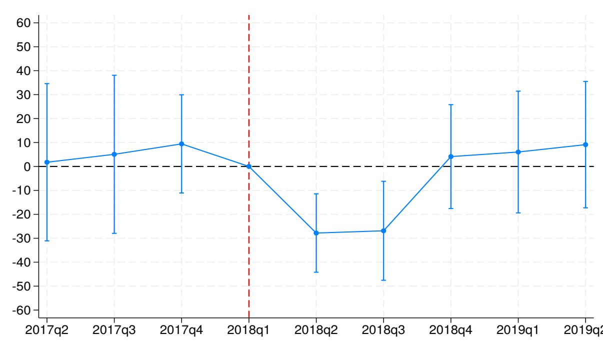
Notes: The spread risk submodule refers to the capital charges for corporate bonds (which are decreasing in the rating and increasing in the duration of the bonds), those for structured products are higher for non-investment-grade exposures.

The increase in the spreads of Italian government bonds in 2018 affected the capital held by Italian insurance corporations by decreasing the market value of their assets. To understand the extent to which the heterogenous exposure to Italian securities in the non-unit portfolio across ICs differentially affected the SCR dynamics in the post-shock period, we test whether the $HighExpIT$ group – those with greater exposure to Italian securities – suffered a larger drop in SCR in the immediate aftermath of the sovereign shock. To do this, we estimate the following panel regression for the SCR ratio (Equation C.1):

$$SCR_{i,t} = \sum_t \beta_t HighExpIT_i + \mu_i + \gamma_t + \epsilon_{i,t} \tag{C.1}$$

where we include time-invariant insurance fixed effects (μ_i) and time fixed effects (γ_t) to account for heterogeneity in each IC's initial SCR ratio and for common shocks, including those stemming from significant domestic securities exposure.

Figure C.13: **SCR ratio for highly exposed ICs**



Notes: the figure depicts the results of Equation C.1. The dashed vertical line indicates the last pre-shock period. Standard errors are clustered at the insurance level.

Our results show that ICs $HighExpIT$ ICs experienced an immediate average reduction of 30 percentage points in their SCR ratio relative to the $LowExpIT$ group (Figure C.13). However, this reduction was statistically significant only in the two quarters following the shock. Over time, they managed to increase their SCR ratios, although the sovereign spread remained elevated throughout the sample period. This evidence suggests that a de-risking strategy was implemented, aimed at reducing minimum capital requirements, and ultimately improving the SCR ratio.