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BEYOND THE SURFACE: INVESTOR BASE, RISK-TAKING AND FRAGILITY IN OPEN-END FUNDS

by Valerio Della Corte*, Raffaele Gallo*, Taneli Mäkinen** and Francesco Palazzo*

Abstract

We study how the composition of a fund's investor base shapes its response to a liquidity shock affecting its liabilities rather than its portfolio. In May 2018, capital losses on Italian sovereign bonds prompted large-scale redemptions by Italian insurers from European bond funds holding almost no Italian assets. Funds with more long-term investors replaced them with other euro-area insurers and pension funds, keeping flows and portfolios stable. Funds dominated by short-term investors suffered outflows and increased their exposure to high-yield bonds to attract performance-sensitive investors, reversing the usual precautionary de-risking strategy. Investor composition may therefore shape the effects of liability-side shocks, concentrating run-prone investors and risky assets in the same funds.

JEL Classification: G11, G22, G23.

Keywords: fund liquidity risk, investor composition, insurance companies, capital regulation.

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1. Introduction¹

Liquidity mismatches make open-end funds (OEFs) vulnerable to runs: shares are generally redeemable daily, while many underlying assets – particularly corporate bonds – are costly to liquidate under stress. Large redemptions can force asset sales at depressed prices, transmitting shocks across markets and amplifying stress (Manconi et al., 2012; Chernenko and Sunderam, 2020; Falato et al., 2021). As with bank deposits, redeemable liabilities create a first-mover advantage: in the event of large outflows, the trading costs – often significant for illiquid securities such as corporate bonds – are ultimately borne by remaining investors (Jin et al., 2022). Empirical evidence shows that OEFs can act procyclically (Timmer, 2018; Fricke and Wilke, 2023) and contribute to market fragility (Jiang et al., 2022), particularly when they hold less-liquid assets.

The extent of this fragility may depend not only on a fund’s portfolio but also on the composition of its investor base. Long-Term (LT) investors – such as households, insurance companies, and pension funds – tend to exhibit more stable redemption behavior than Short-Term (ST) investors, such as other mutual funds.² Prior research finds that funds with a larger LT investor base experience smaller outflows following adverse performance or market shocks (Cella et al., 2013; Schmidt et al., 2016; Allaire et al., 2023; Della Corte and Santioni, 2023; Fricke et al., 2026).

Existing evidence thus establishes that investor types differ systematically in redemption behavior and that ownership composition predicts outflows under stress (Schmidt et al., 2016; Allaire et al., 2023; Fricke et al., 2026). Yet because the shocks studied so far combine liability-side and asset-side stress, three questions remain unanswered. First,

¹The views expressed in this paper are those of the authors and should not be considered as reflecting those of Banca d’Italia, the Eurosystem or the IMF. While retaining full responsibility for all remaining errors and omissions, the authors wish to thank A. De Vincenzo, F. Fecht, S. Federico, L. Goldberg, G. Lorranth, A. Polo, A. Rosolia, all participants to IBRN meetings, Banca d’Italia-IVASS Conference on “Banking, insurance and financial stability”, ESMA Research Conference “Understanding investment funds: Developments and risks in the EU fund industry”, and EIEF seminar for helpful comments and suggestions.

²Insurance companies often act as market stabilizers in the corporate bond market (Apicella et al., 2022; Chodorow-Reich et al., 2021; Coppola, 2025).

does investor composition shape how funds absorb a shock originating solely on the liability side? Second, which investors step in to replace those who exit? Third, do fund managers adjust their portfolios toward the types of investors they are most likely to attract? Together, these margins determine whether a liquidity shock is absorbed within the fund or instead leads to a persistent reallocation of fragility across funds.

This paper addresses these questions by examining how the ex ante composition of a fund's investor base governs its response to a liquidity shock that originates on the liability side and is unrelated to the fund's performance. Such a shock forces adjustment along two margins. The first is the investor margin: the capital that leaves can be replaced by similar LT investors or by more performance-sensitive ones, but prospective LT investors might be reluctant to enter a fund dominated by ST holders, whose future redemptions would impose trading costs on those who remain. The second is the portfolio margin: a fund that cannot attract replacement long-term capital can instead increase portfolio risk, since higher expected returns make it more attractive to the ST investors it can still reach. Focusing on corporate bond funds – funds more exposed to liquidity risk as redeemable liabilities meet illiquid assets – we show that both margins operate and interact: after the shock, liquidity and market risk become concentrated precisely in the funds whose investor base was most fragile to begin with.

To verify the interaction of redeemable liabilities and asset illiquidity, unlike prior studies that focus primarily on flow-performance dynamics, we leverage a quasi-natural experiment induced by an exogenous political shock in Italy that affected a key subset of long-term institutional investors – insurance companies (ICs), the very sector the literature portrays as a stabilizer of fund flows – without directly impacting fund performance. Relying on this exogenous liquidity shock for funds, and thanks to the availability of extensive granular micro-to-security-level data, we examine how investor base characteristics for European bond funds shape net flows and portfolio adjustments, shedding light on the mechanisms driving investor-fund matching and their implications for financial

stability.

Specifically, our liquidity shock for funds originates from the unexpected formation of a coalition government in Italy after the May 2018 general election, which caused a sharp increase in Italian sovereign bond yields. This increase significantly reduced the capital ratios of domestic life ICs, major holders of euro area mutual funds.³ Italian ICs have two relevant features for our analysis. First, a substantial portion of their non-unit-linked (with-profits or traditional) portfolios — which bear investment risk for ICs — was invested in mutual fund shares but with limited direct exposure to Italian securities. Second, these ICs' portfolios were also heavily invested in domestic sovereign bonds and other Italian assets. Following the rise in bond yields, the market value of these assets fell by over 5 percent, resulting in a large capital ratio shock (about 35 percentage points on average).

Consistent with the literature on the shock-absorbing role of insurance companies, we find that Italian ICs did not sell their distressed sovereign bonds after the increase in yields. Instead, facing capital ratio declines, they selectively divested mutual fund shares – reducing their exposure by approximately 15 percent on average – and corporate bonds, which carry higher capital charges. These divestments were concentrated in their non-unit-linked portfolios, where insurers bear investment risk and capital requirements are higher, while no comparable adjustment occurred in unit-linked portfolios — a within-insurer comparison that acts as a built-in falsification test for the capital-driven interpretation. This pattern reflects an active de-risking strategy aimed at restoring capital ratios rather than responses to fund performance.

This capital-driven portfolio adjustment is unrelated to fund performance and offers a quasi-natural experiment to examine the effects of an exogenous capital supply shock on mutual funds. Crucially, our fund-level analysis is restricted to funds with minimal

³Italian insurance companies are the largest holders of mutual funds among euro area insurance companies after their German and French peers.

direct holdings of Italian securities, so that their portfolios were untouched and the shock reaches them only through the liability side. Specifically, we analyze how other investors respond to such shocks and the extent to which fund managers adjust asset allocations. To isolate the role of first-mover advantage, we compare corporate bond funds, exposed to high liquidity risk and run incentives as they are characterized by redeemable shares and illiquid assets, with two benchmarks that differ in their exposure to first-mover incentives: (i) equity funds, which face lower fire-sale risk as they have redeemable shares but invest in more liquid assets; and (ii) corporate bonds, which are not subject to redemption-driven runs as they are generally illiquid assets but held in non-redeemable structures.

We find that investor composition shapes fund responses primarily in corporate bond funds. Those with a larger share of ST investors are less likely to attract new LT capital following liquidity shocks: highly exposed funds with ST-dominated bases lost about 12 percentage points of insurer ownership, partially replaced by other investment funds, and suffered net outflows of about 6.5 percent of assets, whereas funds with LT-dominated bases lost about 4 percentage points, offset by inflows from other euro-area insurers and pension funds, leaving net flows about flat. These findings are consistent with LT investors anticipating higher future trading costs caused by a performance-sensitive investor base. This evidence is confirmed also by employing a matched sample of ST and LT funds with similar asset-side characteristics and a more granular partition of fund investor categories. In contrast, this pattern is absent in equity funds and in direct holdings of corporate bonds, highlighting the key role of redeemable liabilities combined with asset illiquidity.

When LT investors withdraw, corporate bond funds with more run-prone investor bases increase portfolio risk by investing in high-yield bonds and shedding safe assets – likely to attract ST inflows and partially offset outflows – raising the potential for risk concentration. Conversely, funds with higher LT investor shares effectively replace redemptions with new LT inflows and do not change significantly their portfolio allocation. This

contributes to the literature on precautionary de-risking documented after outflows (Cutura et al., 2025): whether a fund de-risks or increases risk-taking after losing investors depends on the remaining investor base.

These findings show that a liquidity shock sorts investors across run-prone bond funds: LT investors gravitate toward funds with stable investor bases, while ST investors concentrate in the most fragile ones. This sorting interacts with managerial risk-taking to generate sharply different portfolio responses across funds, reinforcing the fragility of those already most exposed to runs. Our evidence, however, goes beyond a reshuffling of fund ownership. The shock leaves an imprint on balance sheets within the non-bank financial sector: funds with less stable liabilities actively shift into riskier securities, so that liability-side fragility and asset-side risk come to reside in the same intermediaries. Because portfolio adjustments by open-end funds are a primary channel through which redemptions are transmitted to asset markets, this concentration of risks bears directly on financial stability.

These results underscore the importance of mitigating the first-mover advantage in run-prone funds, and also call for incorporating information on investor base composition into regulatory assessments of fund resilience, complementing traditional portfolio-focused metrics. The recommendations of FSB (2023) and IOSCO (2025) calibrate funds' redemption terms to the liquidity of their assets alone — a design that may overlook investor behavior. Our results show why the assessment of the investor base is crucial: among bond funds almost identical on the asset side, post-shock outcomes diverged sharply with the liability side, so asset-only categorization misclassifies fragility. An investor-base metric — the fund-sector analogue of the banking Net Stable Funding Ratio (NSFR) — would address this ex ante, while liquidity management tools (LMTs) such as swing pricing and redemption gates, by lowering the outflow externality that deters replacement LT investors, address it ex post (Jin et al., 2022; Capponi et al., 2025).

Our paper contributes to several strands of literature. First, it relates to research on

funds' liquidity risk management. Building on the literature on funds' flow-performance relationships (Sirri and Tufano, 1998; Chevalier and Ellison, 1997; Goldstein et al., 2017), recent studies highlight significant heterogeneity in investors' responsiveness (Fricke et al., 2026; Jin et al., 2022; Fricke and Wilke, 2023; Allaire et al., 2023; Cella et al., 2013; Schmidt et al., 2016) and suggest that some investors' responsiveness may also reflect strategic-interaction considerations in fund flows (Fricke et al., 2026). Relative to these works, we add three elements: a shock that reaches funds only through the liability side, so that redemptions are unbundled from performance and asset values; the replacement margin — which investors arrive after others leave — rather than only the redemption margin; and the managers' portfolio response conditional on the clientele they can realistically attract. In line with the prediction that a higher concentration of first movers raises system-wide vulnerability (Capponi et al., 2025), we show that these margins jointly affect fragility across funds. The shock originates outside the fund sector: capital-pressure-driven portfolio adjustments by Italian ICs lead to redemptions also from funds with limited direct exposure to Italian assets. This setting allows us to compare funds exposed to the same exogenous redemption shock but with different pre-shock investor bases. We show that funds with more performance-sensitive investors (i.e., a steeper flow-performance relationship) experience weaker stabilizing inflows and increase portfolio risk to attract this type of investor. Thus, we document the consequences for fund fragility and risk-taking depend on the composition of the fund's remaining investors.

Second, our paper relates to the literature on the investment behavior of insurance companies (Apicella et al., 2022; Chodorow-Reich et al., 2021; Coppola, 2025), particularly papers examining the effects of capital considerations for these intermediaries (Ellul et al., 2015; Becker and Ivashina, 2015; Becker et al., 2022; Merrill et al., 2021). Consistent with this literature, which primarily focuses on the corporate bond market, we find that ICs did not amplify shocks in the distressed segment (i.e., the sovereign bond market). However, capital constraints may drive spillover effects to other asset classes initially

unaffected by the shock but subject to higher capital charges. We emphasize the importance of distinguishing between unit-linked portfolios (i.e., related to policies in which the investment risk is borne by the policyholder) and non-unit-linked ones – a distinction often overlooked in empirical analyses due to data availability – to properly assess these dynamics. Recent analyses document that ICs’ ownership stabilizes fund flows on average, while conjecturing that this force weakens when insurers’ own health deteriorates (Fecht et al., 2025). Our setting provides causal evidence for precisely this reversal: when capital constraints bind, the archetypal shock absorber becomes the originator of a correlated redemption shock, transmitted through the capital charges attached to otherwise unaffected asset classes.

Finally, we contribute to the extensive literature on shock transmission across financial intermediaries. While theoretical contributions have explored direct linkages (Allen and Gale, 2000; Freixas et al., 2000) and fire-sale dynamics (Acemoglu et al., 2021; Caballero and Simsek, 2013; Greenwood et al., 2015), empirical work has largely focused on measuring interconnectedness (Billio et al., 2012; Girardi et al., 2021; Duarte and Eisenbach, 2021; Ellul et al., 2022; Cetorelli et al., 2023). Our study provides novel micro-level evidence showing how portfolio adjustments by insurance companies, driven by capital considerations, propagate shocks to other (initially unaffected) non-bank financial intermediaries (NBFIs). By exploiting a political shock, already employed in other studies (Bagattini et al., 2023; Anaya Longaric et al., 2025), we focus on funds holding essentially no distressed assets and that are hit exclusively through their ownership structure, which is what allows us to isolate the liability-side channel.

The remainder of the paper proceeds as follows. Section 2 describes our datasets. Section 3 documents insurers’ capital-driven de-risking and the within-insurer falsification test. Section 4 develops the hypotheses and presents the fund-level results on investor sorting, net flows, and portfolio risk, together with placebo evidence from equity funds and directly held corporate bonds. Section 5 discusses policy implications, and Section 6

concludes.

2. Data

Our empirical analysis combines four complementary datasets that, taken together, provide a rare micro-to-security-level view of how shocks to Italian insurance companies transmit to financial markets. We link supervisory holdings data on insurers from IVASS (the Italian supervisory authority for insurance companies), characteristics and portfolio holdings of mutual funds from Morningstar, security-level information from the ECB Centralised Securities Database (CSDB), and investor composition from the ECB Securities Holdings Statistics by Sector (SHS-S). This linkage allows us to observe every link of the chain described in the introduction: the capital-driven asset reallocations of insurers, the investor-by-investor re-composition of funds' liability side, and the security-level portfolio response of fund managers – that is, both the investor margin and the portfolio margin of funds' adjustment. Each dataset plays a distinct role – IVASS data reveal insurers' exposures and liability composition, Morningstar captures fund-level adjustments, CSDB enriches security characteristics, and SHS-S identifies the investor base – allowing us to quantify both direct and indirect channels of shock propagation.

The remainder of this section provides a detailed description of each source. Our sample period goes from 2017-Q2 to 2019-Q2, centered around the political shock that occurred in 2018-Q2 that we consider for our analysis.

2.1. Supervisory data on ICs

We use supervisory information on ICs' holdings provided by IVASS. 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. This within-insurer distinction – typically unavailable in commercial datasets – is what

enables the falsification test of Section 3: the same insurer, hit by the same shock, holds portfolios that differ only in whether market losses fall on its own capital. A security may be reported multiple times in a quarter by an insurer if held in different portfolios. Our analysis focuses on traded securities – corporate and government bonds, listed equity, and shares of open-end mutual funds – while we exclude shares of closed-end funds and unlisted equity. This granularity is crucial for identifying the insurers’ initial exposure to the securities and funds that experienced a liquidity shock.

The dataset also includes accounting variables at the insurer level, such as quarterly Solvency Capital Requirement (SCR) ratios,⁴ 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 historical performance relative to peers).⁵ For each fund, we also collect portfolio-level data on the asset composition (e.g., stocks, bonds and cash) at the security level, when available. By merging these holdings with the IVASS data, we can trace the indirect effects of insurer sales on fund portfolio reallocation, net flows and returns.

⁴The SCR ratio is the main capital requirement for European ICs. It is the ratio of own funds (assets minus liabilities) to the required capital buffer.

⁵We assign a zero value to unrated funds.

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 percent 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: about 73 percent of the total for funds in the unit-linked portfolios and 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. Moreover, Table A.3 shows the portfolio allocation of 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.⁶

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.

$$q_{s,i,p,t} = \frac{MktValue_{i,p,s,t}}{P_{s,t}} \quad (1)$$

where $MktValue_{i,p,s,t}$ 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 from changes driven by price fluctuations.⁷

2.4. Other investors' holdings

We supplement fund characteristics with information on the types of investors holding funds present in the Italian ICs' portfolio, to distinguish between LT and ST investors. This investor base information is what allows us to observe the replacement margin directly: not only which investors leave a fund after the shock, but which investors arrive, sector by sector and quarter by quarter. We retrieve data from the Eurosystem's Securities Holding Statistics by 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

⁶Ratings 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.

⁷CSDB 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.

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

This section documents how a sovereign stress episode converted the fund sector's archetypal stabilizing investor (i.e. ICs) into the source of a correlated redemption shock. In late May 2018, the Italian government bond market experienced severe turbulence following the formation of an unexpected coalition government, which created heightened uncertainty over Italy's fiscal stance and relationship with the EU. In particular, after the March 2018 general election produced a hung parliament, the market surprise stemmed from the formation of a coalition government between two anti-establishment and euro-sceptic parties. The coalition was perceived as advocating an expansionary fiscal agenda and an ambiguous stance toward Italy's relationship with the euro area.⁸ This raised concerns about both debt sustainability and redenomination risk.⁹

The political shock triggered a sharp rise in yields, as foreign investors sold Italian assets heavily. Concerns over the government's potential economic policies pushed the spread between Italian and German ten-year government bonds – a widely used indicator of sovereign market stress – to a peak of about 330 basis points in mid-November.

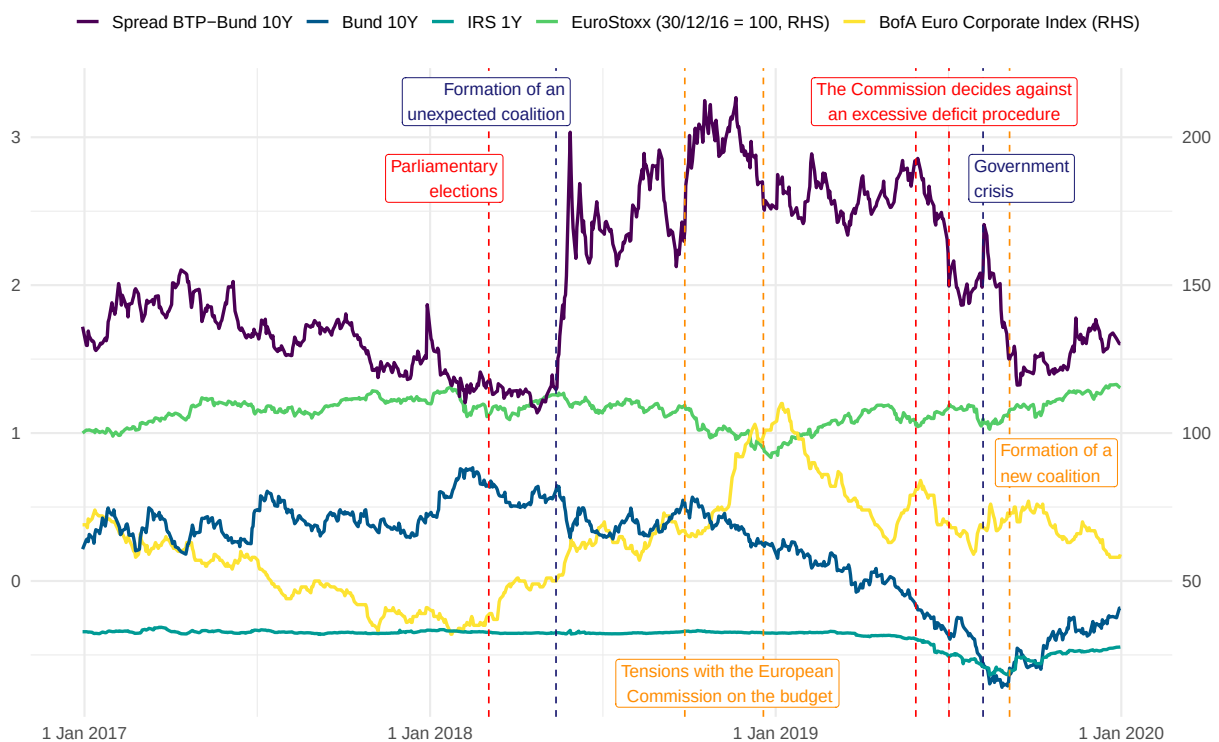
The shock spilled over to broader Italian financial markets, including corporate bonds and equities, but remained largely domestic in scope, as suggested by the low correlations between euro area financial market prices and Italian government bond yields (see Table

⁸See the contemporaneous press coverage, e.g. Financial Times (2018).

⁹The same episode has been exploited as a quasi-natural experiment in the mutual fund literature; see, for example, Bagattini et al. (2023) and Anaya Longaric et al. (2025). Both papers study exposure to the shocked Italian assets themselves – through affiliation with distressed parent groups and through funds' own periphery holdings, respectively. Our analysis is the mirror image: funds holding essentially no Italian assets, reached by the shock exclusively through their ownership structure.

A.4). From early 2019, tensions gradually eased due to a budget compromise between the Italian government and the European Commission, more accommodative ECB policy, and an improved global market environment. Figure 1 plots the 10-year BTP–Bund spread alongside key events. Notably, spreads remained elevated for months before returning to pre-shock levels only in the second half of 2019.

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.

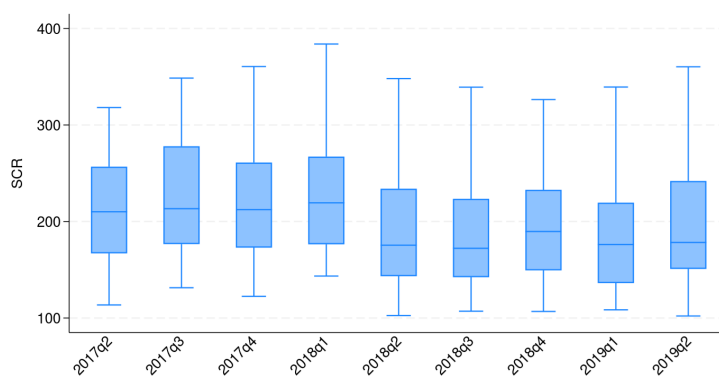
3.2. Hypotheses on ICs investment response to sovereign shock

Italian ICs held a substantial direct exposure to domestic sovereign bonds, which accounted for the majority of their assets, along with significant holdings of other Italian

securities. In contrast, their indirect exposure through fund shares was relatively limited (see Appendix B for a description of ICs portfolios).

The sharp and unexpected rise in yields in mid-2018 directly eroded the market value of ICs' assets. Under Solvency II rules, asset values are marked to market when calculating the SCR ratio.¹⁰ As a result, the shock caused an immediate drop in SCR ratios. On average, SCR ratios fell by around 35 percentage points between the first and second quarters of 2018 (Figure 2). After the shock, the entire distribution shifted downward: the median and the interquartile range declined, indicating deterioration across the broader cross-section.

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. The central line in each box denotes the median, the box edges indicate the first and third quartiles, and the whiskers capture the dispersion of the distribution excluding outliers.

Previous research (Ellul et al., 2011, 2015) shows that capital constraints shape institutional investors' trading behavior: unexpected capital losses can trigger portfolio de-risking if doing so alleviates the impact on capital ratios. In our setting, however, the scope for such adjustments differs sharply between ICs' two main portfolio types.

In unit-linked portfolios asset values are matched by equivalent liabilities, so market losses pass through to policyholders without affecting the IC's capital. Because the capital absorption for market risk is essentially zero, selling riskier assets in these portfolios

¹⁰Appendix C presents a short introduction to Solvency II capital requirements.

would not improve SCR ratios. In contrast, for non-unit-linked portfolios, backing traditional life policies, liabilities are valued at risk-free rates. The sovereign spread shock reduced the value of Italian securities in these portfolios without a corresponding decline in liabilities, shrinking available capital. Here, selling riskier assets lowers capital charges and boosts the SCR ratio. Indeed, the distressed asset itself – domestic sovereign debt – attracts no spread-risk charge under the Solvency II standard formula, so selling it yields little capital relief, whereas fund shares and corporate bonds carry the highest charges. If capital constraints drive the adjustment, de-risking should travel along the regulatory capital gradient rather than the distress gradient – a prediction we test below.

This leads to our first hypothesis to be tested.

Hypothesis 1 (H1). *Following the sovereign shock, ICs sold fund shares with higher capital charges in their non-unit-linked (capital-intensive) portfolios. No analogous adjustments occurred in unit-linked portfolios.*

We further expect heterogeneity based on pre-shock portfolio composition. ICs with greater exposure to Italian securities in their non-unit-linked portfolios suffered larger capital losses and thus had stronger incentives to de-risk.

Hypothesis 2 (H2). *ICs with higher pre-shock exposure to Italian securities engaged in more aggressive de-risking – selling proportionally more high-capital-charge fund shares – in their non-unit-linked portfolios. No such adjustment should occur in unit-linked portfolios.*

Finally, initial capital buffers could, in principle, influence de-risking intensity: ICs closer to the regulatory minimum might react more strongly. In practice, most ICs in our sample maintained substantial buffers even after the shock, so we expect this effect to be limited. Nonetheless, we test for it as a potential secondary source of heterogeneity.

3.3. Empirical tests

To test H1, we categorize funds held by Italian ICs into two groups based on their capital charges, reflecting their riskiness under Solvency II regulatory standards. This

classification draws on either Morningstar fund categories or portfolio holdings data. Specifically, we define the *Riskier* category to include all equity and non-government fixed-income funds. Mixed and miscellaneous funds are included in this category only if their fund-level capital absorption (estimated by applying Solvency II risk weights to the underlying securities) lies in the top quartile of the distribution within these categories, corresponding to a capital charge above 21 percent. Overall, about 80 percent of the funds in ICs' portfolios fall into the *Riskier* category. We construct a dummy variable *Riskier*, equal to one if the fund falls into this riskier category, and zero otherwise.¹¹ Our identification strategy exploits variation in holdings of *Riskier* versus safer funds around the sovereign shock in May 2018. We estimate the following panel regression model (Equation 2) for each portfolio p (N for non-unit, U for unit portfolio) over the sample period 2017-Q3 to 2019-Q2:

$$\ln(q_{s,i,p,t}) = \sum_{\tau} \beta_{p,\tau} (Riskier_s * \mathbf{1}_{t=\tau}) + \gamma_{p,t} \mathbf{X}_{s,t} + \theta_{s,i,p} + \mu_{i,p,t} + \epsilon_{s,i,p,t} \quad (2)$$

where $\ln(q)$ denotes the log of the quantity of fund share s held by insurer i in portfolio p at quarter t . The coefficients $\beta_{p,\tau}$ capture the time-varying differential effect of holding *Riskier* funds (i.e., equity funds, non-government fixed income funds, as well as mixed and miscellaneous ones with a Solvency II capital charge above 21 percent) relative to safer ones. The vector $\mathbf{X}_{s,t}$ includes time-varying fund level controls for exposure to Italian securities, net flows, Morningstar five-star rating (a proxy for fund performance), and

¹¹Our choice of using a dummy variable for identifying *Riskier* funds is based on several reasons. First, a dummy variable based on funds' investment categories allows us to estimate the model considering a larger sample of funds given the lower coverage of funds' holdings data. Second, since Italian ICs' portfolios are skewed towards government bonds securities, any fund with a different allocation is, from their perspective, riskier and significantly more costly in terms of capital charges. Third, while we could construct an alternative continuous variable relying on a look-through approach for funds for which we have portfolio holdings, doing so would assume that ICs have a larger information set than, especially smaller ones, actually have. ICs may calculate capital charges required by regulators based on mutual funds broad categories rather than their precise portfolios. That said, our test of H1 holds if we replace the dummy *Riskier* with the fund's capital charge calculated on portfolio holdings data.

fund size. We include fixed effects at the security-insurance-portfolio level ($\theta_{s,i,p}$) to control for average holdings, and insurance-portfolio-time fixed effects ($\mu_{i,p,t}$) to absorb all time-varying shocks at the insurance portfolio level. Standard errors are clustered at the insurance and fund levels.

This specification allows us to examine dynamic changes in holdings of *Riskier* funds before and after the shock while controlling for confounding factors and unobserved heterogeneity. Figure 3 plots the quarterly estimates of $\beta_{p,\tau}$ for both portfolios. Before the shock, no significant differences in holdings of *Riskier* funds emerge in either portfolio, satisfying the parallel trend assumption. Immediately after the shock, we observe a substantial and persistent decline in holding of *Riskier* funds but only in the non-unit portfolio, which has greater capital requirement implications for ICs. The unit-linked portfolio shows no such effect.

The timing and portfolio-specific nature of this de-risking behavior provide initial evidence that Italian ICs' decisions to sell *Riskier* funds were driven by capital constraints induced by the sovereign shock rather than by deteriorating fund performance or liquidity concerns.

To confirm the robustness of our results to the *Riskier* classification, we adopt a more restrictive definition that considers only funds in the top quartile of capital charges across all fund categories held by ICs in 2018-Q1, corresponding to a higher average capital charge threshold of about 29 percent. This approach, which relies on detailed portfolio holdings and thus reduces sample size, yields qualitatively identical results (see Figure A.1 in the Appendix).

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



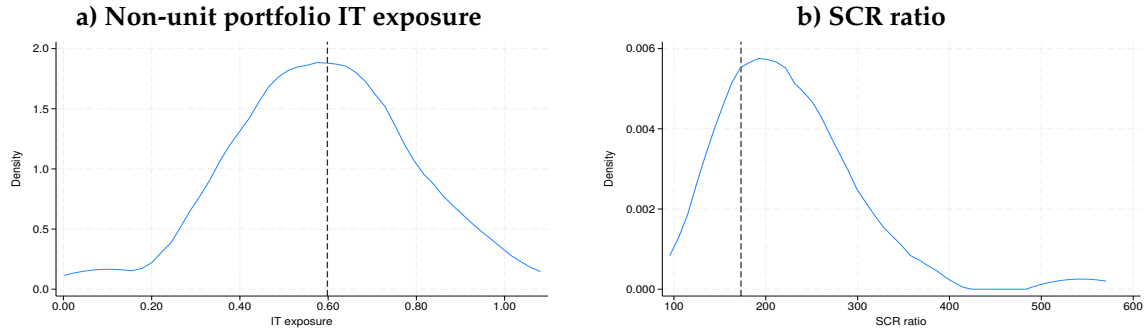
Notes: panels (a) and (b) depict the results of Equation 2 for riskier funds included in the non-unit portfolio and in the unit-linked one, respectively. The dashed vertical line indicates the last pre-shock period. The dots report the point estimate of the coefficients for each quarter. Confidence bands are at the 90% level based on standard errors clustered at the insurance and fund levels.

To investigate cross-sectional heterogeneity in de-risking behavior (Hypothesis 2), we exploit variation in ICs' initial exposure to Italian sovereign securities within their non-unit portfolios. Following this approach, we partition ICs into two groups based on their pre-shock (2018-Q1) share of Italian securities held in the non-unit portfolio (see Figure 4, panel a): those below the median exposure (*LowExpIT*, approximately below 60 percent) and those above (*HighExpIT*). Prior analyses confirm that ICs with higher Italian exposure experienced significantly larger capital losses after the shock – on average 30 percent greater than those with lower exposure – validating this grouping (Appendix C).

To examine the role of initial capital adequacy, we further classify ICs according to their SCR ratios in the pre-shock period (Figure 4, panel b), dividing them into those below the 25th percentile (approximately 180 percent; *LowSCR*) and those above (*HighSCR*). This conservative threshold isolates ICs more vulnerable to capital shortfalls given the right-skewed SCR distribution. Combining these classifications yields four distinct IC groups, detailed in Table A.5 alongside their portfolio investment shares.

Our specification builds on the baseline model in Equation 2 by incorporating interaction terms that capture the joint effects of fund riskiness ($Riskier_s$), post-shock timing

Figure 4: Italian insurance companies' distribution of their exposure to Italian securities and SCR ratio



$(Post_t)$, portfolio type ($NonUnit_p$), and IC exposure to Italian securities ($HighExpIT_i$):

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

The vector $\mathbf{X}_{s,t}$ controls for time-varying fund characteristics including Italian exposure, net flows, and Morningstar five-star ratings using time-varying coefficients $\gamma_{p,t}$. Fixed effects $\theta_{s,i,p}$ and $\mu_{i,p,t}$ capture security–insurer–portfolio and insurer–portfolio–time variation, respectively. In more saturated 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 . We cluster standard errors at the insurer–portfolio–time level.

Table 2 presents estimation results. Column (1) replicates the baseline model (Equation 2), which does not differentiate across $HighExpIT$ ICs. Consistent with Hypothesis 1 and with quarterly evidence presented in Figure 3, the coefficient of $Riskier * Post * NonUnit$ indicates a significant 15 percent greater decline in holdings of *Riskier* funds post-shock in non-unit portfolios, with no significant effect in unit portfolios (captured by $Riskier * Post$). This effect persists and even intensifies when controlling for fund

category-time fixed effects (column 2) and security-time ones (column 3).

In columns (4)–(6) we introduce $HighExpIT_i$ interactions, as described in Equation 3. Critically, the interaction term $Riskier * Post * NonUnit * HighExpIT$ in columns (4) and (5) reveals that ICs with higher Italian exposure implement substantially stronger de-risking, with a more than 30 percent reduction in *Riskier* fund holdings in their non-unit portfolios with respect to their unit ones. The effect remains directionally consistent but loses statistical significance under the most stringent security-time fixed effects in column (6), likely reflecting reduced sample size and statistical power.

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 . The sample includes Italian insurance companies' holdings of fund shares across non-unit-linked and unit-linked portfolios between 2017-Q3 and 2019-Q2. Standard errors are clustered at the insurer-portfolio-time level. p -values in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

As a robustness check, we analyze the extensive and intensive margins of de-risking using the Davis-Haltiwanger growth rate of fund holdings (Davis and Haltiwanger, 1992; Peydró et al., 2021), defined as:¹²

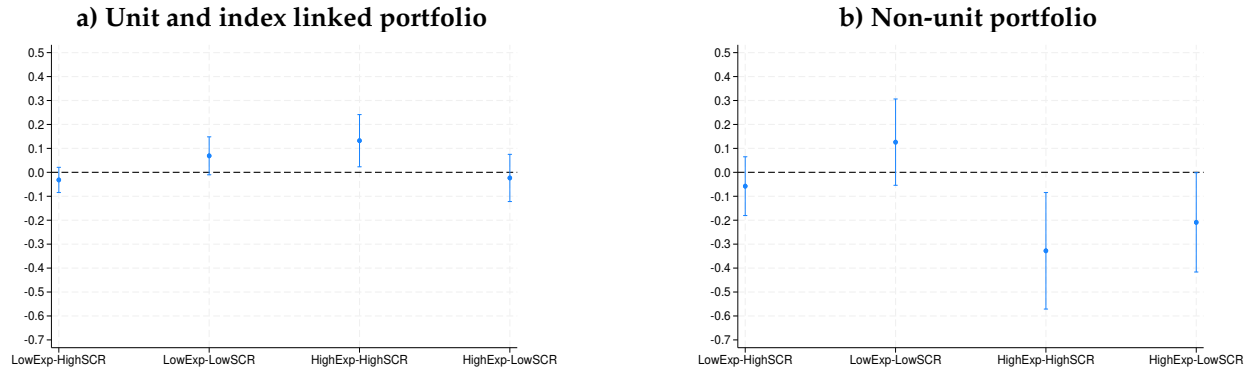
$$NetBuys_{s,i,p,t} = \frac{q_{s,i,p,t} - q_{s,i,p,t-1}}{\frac{1}{2} * (q_{s,i,p,t} + q_{s,i,p,t-1})} \quad (4)$$

¹²This variable ranges in the interval $[-2;2]$, allowing the inclusion of initial purchases and total sales of fund shares.

This measure captures proportional quarterly changes in fund quantities, accommodating both initial acquisitions and full divestitures. Estimating Equation 2 with *NetBuys* as the dependent variable (Figure A.2) confirms significant post-shock reductions in *Riskier* fund purchases in non-unit portfolios, reinforcing our main findings.¹³

Finally, we test whether initial capital levels modulate de-risking by extending Equation 3 with interactions between *Riskier * Post * NonUnit * HighExpIT* and *LowSCR*, the dummy for ICs with pre-shock SCR below the 25th percentile. Figure 5 reports marginal effects of *Riskier* holdings changes across the four groups formed by crossing *HighExpIT* and *LowSCR* after the shock. Consistent with expectations, unit-linked portfolios (panel a) show negligible heterogeneity. In the non-unit portfolio (panel b), ICs with higher exposure to Italian securities exhibit substantial, statistically significant reductions in *Riskier* fund holdings, independent of their initial capital adequacy. The absence of a stronger effect for low-SCR ICs suggests that both relatively more and less capitalized insurers had strong incentives to restore capital, minimizing cross-sectional differences in de-risking intensity.

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 between *Riskier * Post * NonUnit * HighExpIT* and *LowSCR* in order to identify the four groups of ICs differentiated by their exposure to Italian securities and SCR ratio, outlined in Table A.5. Confidence bands are at the 90% level based on standard errors clustered at the insurance-portfolio-time level.

Overall, these results show that ICs' initial exposure to Italian sovereign risk in their

¹³Unreported tests show that also estimates of Equation 3 are robust to adopting *NetBuys* as the dependent variable.

non-unit portfolios drove heterogeneous de-risking behavior, while initial capital levels had limited influence. Moreover, the unit-linked portfolio remained largely unaffected, reinforcing the capital-driven nature of the adjustment. The unit-linked portfolios – same insurers, same shock, no capital at stake – thus behave exactly as the falsification test predicts, and the sales that generate the liquidity shock for funds travel along the capital-charge gradient, not the distress gradient. This orthogonality to fund fundamentals is exploited in the next section as we focus on funds affected by the shock purely through the liability side.

4. Fund responses to the liability-side shock: investor sorting and portfolio adjustment

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 them differently based on the pre-shock prevalence of LT or ST investors among their shareholders. Following prior research (Schmidt et al., 2016; Fricke et al., 2026; Allaire et al., 2023), we categorize ICs, pension funds and households as LT investors, while mutual funds and non-residents are classified as ST investors.¹⁴ Although all impacted funds had a liability-side exposure to Italian ICs, the composition of their remaining investor base varied considerably, even among funds with similar portfolios.

To develop our hypotheses, we build on three well-established findings from the literature. First, mutual fund managers have strong incentives to maximize assets under management (AUM), as this directly affects their compensation (Chevalier and Ellison, 1997). These incentives are likely to shape portfolio adjustments in response to unex-

¹⁴Classifying non-residents as short-term reflects a data constraint – SHS-S provides no sectoral breakdown outside the euro area – but is supported by direct evidence: fund shares held more by non-domestic investors suffered substantially larger redemptions in March 2020 (Allaire et al., 2023), and cross-border investors behave procyclically in euro area stress episodes (Anaya Longaric et al., 2025).

pected outflows (Cutura et al., 2025).

Second, the redeemable-at-demand structure of fund liabilities, coupled with the timing and incidence of trading costs, creates strategic complementarities and a first-mover advantage for investors. When large outflows occur, the remaining investors bear a disproportionate share of trading costs, which are especially high for illiquid assets (Chen et al., 2010). This mechanism is particularly relevant for corporate bond funds, which face illiquid secondary markets (i.e., trading costs rise sharply when large bond positions are liquidated quickly) and exhibit a concave flow–performance relationship, as their outflows are highly sensitive to bad performance (Goldstein et al., 2017).¹⁵

Third, recent studies show that investor behavior differs systematically by investment horizon (Allaire et al., 2023; Fricke et al., 2026; Fricke and Wilke, 2023). ST investors – such as other mutual funds – trade more actively and exhibit a steeper flow–performance relationship than LT investors, such as ICs and households, who adjust holdings less frequently. As a result, LT investors tend to bear the externalities of outflows triggered by more reactive ST investors within the same fund. Anticipating these externalities, prospective LT investors have reason to avoid funds dominated by performance-sensitive holders in the first place – a deterrence mechanism that operates on entry decisions, before any run occurs.

Taking these three facts together, the next hypothesis concerns the investor margin: who, if anyone, replaces the capital that Italian ICs withdraw. Redemptions by Italian ICs mechanically reduced the share of LT investors, unless offset by new inflows from similar long-term holders. An increased proportion of ST investors heightens the first-mover advantage, raising run risk (Chen et al., 2010), especially for funds that already had a low LT share before the shock. This shift may deter prospective LT investors, who expect higher future costs from outflow externalities during downturns (Fricke et al., 2026).

¹⁵Equity mutual funds, holding securities traded in much more liquid secondary markets, are generally less subject to the first-mover advantage, leading to a convex flow–performance relationship (Chevalier and Ellison, 1997; Sirri and Tufano, 1998).

Hypothesis 3 (H3). *After exogenous sales from Italian ICs, highly exposed bond funds with a larger ST investor base fail to attract replacement capital from other LT investors and experience net outflows; highly exposed funds with a larger LT base replace the departing insurers with similar investors and keep net flows stable.*

The last hypothesis concerns the portfolio margin, where the literature offers two opposing benchmarks. The precautionary benchmark predicts de-risking: because bond fund investors are highly sensitive to poor performance (Goldstein et al., 2017), managers sell risky bonds and hoard safe, liquid assets after outflows to meet further redemptions (Morris et al., 2017; Cutura et al., 2025). The catering benchmark predicts the opposite for funds left with a performance-sensitive clientele: since the flow–performance relationship is steeper when ST investors dominate (Fricke and Wilke, 2023), managers of such funds have an incentive to increase risk in order to lift returns and attract the only investors they can realistically reach. Which force prevails should therefore depend on the pre-shock investor base.

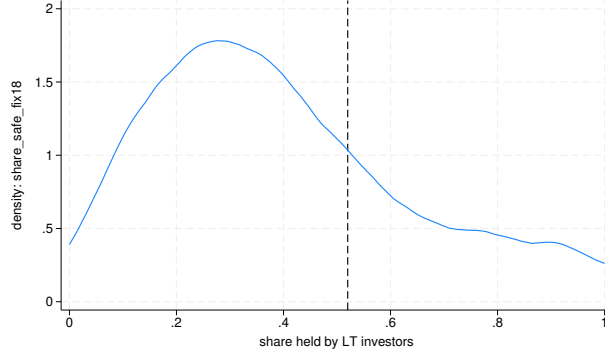
Hypothesis 4 (H4). *After exogenous sales from Italian ICs, highly exposed bond funds with more ST investors increase portfolio risk (catering), while highly exposed funds with more LT investors leave their allocation unchanged (no precautionary de-risking is needed once redemptions are replaced).*

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

We classify funds in the non-unit portfolio of Italian ICs according to their pre-shock investor composition. Specifically, we define a dummy variable, *HighShareLTInv*, equal to 1 for funds in the top quartile of the distribution of long-term (LT) investors in Q1-2018 (i.e., above 52 percent). Funds below this threshold are classified as having a low share of LT investors (Figure 6).

Building on the insurer-level results in Section 3, we measure each fund’s indirect exposure to the Italian sovereign shock via IC holdings. To isolate investor-side effects, we

Figure 6: **Distribution of the share held by long-term investors at the end of 2018-Q1 for funds in our sample**



restrict the sample in two ways. First, we retain only funds in the non-unit portfolio with low direct holdings of Italian securities, excluding the top decile of the distribution (i.e., funds with roughly more than 20 percent of assets in Italian securities at Q1-2018).¹⁶ This restriction is what makes the shock liability-only: the funds' portfolios are essentially untouched by the Italian repricing, while their owners are not. Subsequent adjustments are therefore attributable to investor behavior – the de-risking by Italian ICs – rather than to the funds' own sovereign holdings. Second, given that ICs disproportionately sold shares in funds with higher capital charges, we restrict attention to *Riskier* funds. After these filters, the sample comprises 478 funds out of the 609 in the original non-unit portfolio.

For each fund f in this sample, we compute $FundExp$ – a liability-side exposure measure – by taking a weighted average of each insurer's share of Italian securities held in the non-unit portfolio ($ExpIT$), where weights are the share of fund f held by Italian IC i .¹⁷

$$FundExp_f = \sum_i \frac{ItICHoldings_{i,f}}{TotNetAssets_f} \cdot ExpIT_i \quad (5)$$

The mean value of $FundExp$ in 2018-Q1 is about 5 percent. However, the distribution is highly skewed: only a small subset of funds is significantly exposed to the Italian

¹⁶Results are also robust when excluding the top quartile (i.e., above 10 percent).

¹⁷Since 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 5.

sovereign shock through their IC holdings, with the 90th percentile reaching approximately 10 percent. To identify funds that are materially exposed to the shock, we define exposure thresholds based on the interquartile range (IQR) of net flows in the pre-shock period (2017-Q2 to 2018-Q1), which corresponds to 10 percent of total assets in our sample. For corporate bond funds (241 intermediaries), which our analysis mainly focuses on, we construct the indicator variable *HighExpFund*, which equals 1 for funds with *FundExp* exceeding twice the IQR (i.e., above 20 percent, which roughly corresponds to the 95th percentile).¹⁸

4.3. The investor margin: investor sorting and net flows (H3)

In this section, we investigate whether, following the sovereign shock, the divestment from riskier securities by Italian ICs affected not only the composition of funds' investor bases but also fund-level outcomes, such as net flows and performance. We focus primarily on corporate bond funds and then compare these patterns with those observed for equity funds and corporate bonds. As discussed in Section 4.1, the combination of redeemable liabilities and illiquid underlying assets makes corporate bond funds particularly susceptible to first-mover incentives. In contrast, equity funds, while similarly redeemable, are less exposed to liquidity risk because their underlying assets are more liquid; corporate bonds, although illiquid, do not involve strategic complementarities in investor redemption decisions. These latter two cases thus serve as useful benchmarks for isolating the role of first-mover incentives in shaping equilibrium outcomes.

Accordingly, in the first step of our analysis, we examine, for each *Riskier* fund f in quarter t , five key outcomes: (i) the share held by Italian ICs in their non-unit-linked portfolios (*ShareItIC*); (ii) the share held by other long-term investors (*ShareOthLongTerm*), including Italian ICs' unit-linked portfolios, other euro area ICs, pension funds, and

¹⁸This threshold balances the trade-off between the number of funds considered exposed to the shock (those with *HighExpFund* = 1) and the magnitude of the shock itself. Our results are robust to the use of slightly lower or higher thresholds.

households; (iii) the share held by short-term investors (*ShareShortTerm*), primarily mutual funds and foreign investors; (iv) the quarterly net flows received by the fund divided by the lagged value of its total assets (*NetFlows*); and (v) the fund's total returns (*Returns*).¹⁹

To assess the differential effects of the liquidity shock associated with the sovereign yield spike, we estimate the following regression model:

$$Y_{f,t} = \beta_0 Post_t * HighExpFund_f + \beta_1 Post * HighShareLTInv_f + \beta_2 Post_t * HighExpFund_f * HighShareLTInv_f + \gamma_t X_{f,t} + \mu_f + \theta_{cat(f),t} + \epsilon_{f,t} \quad (6)$$

where the dependent variable $Y_{f,t}$ is one of the five outcomes listed above.

The main explanatory variables include: *HighExpFund*, a dummy for whether fund f had a pre-shock exposure to Italian ICs' non-unit portfolios above the 95th percentile of the bond fund distribution of *FundExp* (i.e., around 20 percent, a value equal to around 2 IQR of the distribution of pre-shock net flows); *HighShareLTInv*, a dummy for whether fund f had a high share of long-term investors in the pre-shock period (i.e., above 52 percent); *Post*, a dummy equal to one for quarters following the shock. The coefficient β_0 captures the post-shock change in outcome $Y_{f,t}$ for funds with high exposure to Italian ICs and predominantly short-term investor bases. The coefficient β_1 measures the differential response for funds with low IC exposure but higher shares of long-term investors. The coefficient β_2 represents the additional effect for funds with both high exposure to Italian ICs and a long-term investor base. The omitted reference group consists of funds with low IC exposure and predominantly short-term investor holdings.

The specification includes a vector of fund-level controls, $X_{f,t}$, interacted with time dummies. These include indicators for the fund's 5-star Morningstar rating – the score

¹⁹Investor base information is obtained from SHS-S and supervisory data for Italian ICs, disaggregated by portfolio. Due to limited sectoral detail, non-euro area investors cannot be classified and are therefore excluded from the long-term investor group. Data on net flows and returns come from Morningstar.

based on funds' historical performance²⁰ – and legal domicile. To control for time-invariant unobserved heterogeneity, we include fund fixed effects μ_f , and we account for time-varying shocks across fund segments using fund-category-by-time fixed effects $\theta_{cat(f),t}$, based on Morningstar's Global Categories as in Giannetti and Jotikasthira (2024). Summary statistics describing the distribution of funds by Global Category and the prevalence of high and low long-term investor shares prior to the shock are provided in Table A.6.

We first present the results on corporate bond funds, those more susceptible to liquidity risk and to the inefficiencies deriving from run-prone incentives. Consistent with prior evidence at the insurance level, the results in column (1) of Table 3 point out that funds with high exposure to Italian ICs (*HighExpFund*) experienced a significant reduction in the share held by Italian ICs in their non-unit portfolios following the shock. This decline was most pronounced for funds with a high share of ST investors, which saw a 12 percentage points drop relative to the reference group (i.e., funds with low IC exposure and a high ST share). In contrast, for *HighExpFund* funds with a high share of LT investors, the decrease was smaller (about 4 percentage points). Funds with low IC exposure and a high LT investor share showed no significant change.

Turning to other LT investors (Table 3, column 2), we find no significant post-shock change for *HighExpFund* funds with a high ST investor share, although the point estimate is negative. However, for those with a high LT investor share, the increase is statistically significant (about 3 percentage points), effectively offsetting the decline in Italian IC holdings.

²⁰In an unreported robustness check, we further verify that our results remain unchanged when controlling for funds' past quarterly returns.

Table 3: **Change in the investor base and performance of *Riskier* bond funds**

	(1)	(2)	(3)	(4)	(5)
	ShareItIC	ShareOthLongTerm	ShareShortTerm	NetFlows	Returns
Post x HighExpFund	-0.1231*** (0.0000)	-0.0023 (0.7994)	0.1206*** (0.0000)	-0.0647*** (0.0002)	0.0075** (0.0257)
Post x HighShareLTInv	0.0039 (0.6785)	0.0101 (0.3709)	-0.0213 (0.2035)	-0.0008 (0.9494)	0.0027 (0.1285)
Post x HighExpFund x HighShareLTInv	0.0810*** (0.0000)	0.0275* (0.0873)	-0.1215*** (0.0000)	0.0891*** (0.0000)	-0.0058 (0.1567)
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	0.9815	0.9698	0.9596	0.3338	0.5326
Observations	1588	1582	1566	1862	1851

Notes: columns (1)-(5) display estimates of Equation 6 by focusing on the following dependent variables, respectively: (i) the share held by Italian ICs in their non-unit-linked portfolios (*ShareItIC*); (ii) the share held by other long-term investors (*ShareOthLongTerm*); (iii) the share held by short-term investors (*ShareShortTerm*); (iv) the quarterly net flows received by the fund by the lagged value of its total assets (*NetFlows*); and (v) the fund's total returns (*Returns*). The sample includes *Riskier* bond funds with low direct exposure to Italian securities (241 funds), over the sample period 2017-Q3 and 2019-Q2. We control for fund-level variables (Morningstar rating, domicile, and category) interacted with time dummies and fund fixed effects. Standard errors are clustered at the fund level. *p*-values in parentheses; *** *p* < 0.01, ** *p* < 0.05, * *p* < 0.1.

The share of ST investors increased sharply for *HighExpFund* funds with a low LT investor base, rising by roughly 12 percentage points relative to the reference group (Table 3, column 3). In contrast, other fund types, including *HighExpFund* funds with a high LT share, showed no significant change in ST investor holdings.

The compositional shifts were mirrored in net flows. Only *HighExpFund* funds with a low LT investor share experienced statistically significant outflows, with net flows falling by about 6.5 percentage points relative to the reference category (Table 3, column 4). This suggests that sales by Italian ICs were only partially replaced by inflows from ST investors, while LT investors, if anything, reduced their exposure. By contrast, *HighExpFund* funds with a high LT investor share maintained relatively stable net flows, with a modest and statistically insignificant post-shock increase (about 2 percentage points), implying that ICs' sales were on average fully offset by other LT investors.

Regarding performance (Table 3, column 5), *HighExpFund* funds with a low LT investor share recorded a 0.7 percentage point return increase relative to the baseline. The corresponding figure for funds with a high LT investor share was not significant. These findings are consistent with the portfolio reallocations discussed in Section 4.4 and antic-

ipated by Hypothesis H4.

Taken together, the results support Hypothesis H3: following the shock, corporate bond funds with less stable investor bases – i.e., lower shares of LT investors – struggled to compensate for IC redemptions through new inflows from other LT investors.²¹ Read jointly, columns (1)–(4) describe a sorting: the long-term capital that leaves high-exposure, ST-dominated funds is replaced by other investment funds, while long-term capital concentrates in funds that already had stable bases. A one-off liability shock thus polarizes the cross-section of investor composition – LT capital gravitates toward stable-base funds, ST capital toward fragile ones. These findings are consistent with our central hypothesis: the investor base composition is a key determinant of how funds absorb liquidity shocks when there is the simultaneous presence of illiquid assets and redeemable liabilities.

4.3.1. *Additional results and robustness tests*

The results shown in Table 3 remain robust across a set of additional robustness checks and placebo tests described below.

Propensity score matching. Summary statistics in Table A.7 show that, before the shock, funds with a high share of LT investors were broadly similar to funds with a low share of LT investors in terms of portfolio allocation, but were substantially smaller. To ensure that our results are not driven by differences in pre-shock asset-side characteristics or fund size, we re-estimate our main specification using a matched sample of LT- and ST-investor funds.²² Table A.8 shows that our main findings are unchanged in this matched

²¹Figures A.3–A.7 report marginal effects for *HighExpFund* funds by initial investor composition, based on time-varying coefficient models. They confirm that investor base dynamics varied systematically depending on the pre-shock investor structure.

²²Specifically, our matching procedure improves comparability across funds with a high LT investor share (treated) and the other ones. We estimate a propensity score matching by employing the nearest neighborhood caliper matching approach, by accounting for fund characteristics in March 2018: fund size, the share of bonds rated below BBB-, the share of investment-grade bonds rated A+ to BBB-, the share of corporate bonds rated AA- or above, the share of cash and highly rated sovereign bonds, the share of equity, the share of other funds. Observations are then weighted by the inverse of the estimated propensity score to balance the distribution of covariates across treated and control funds.

sample.

More detailed investor categories. Table A.9 shows that our results hold when we use more granular investor categories. The estimates indicate that, for *HighExpFund* with a high LT investor share, the increase in other LT investors is mainly driven by ICPFs located in other euro area countries, while the share held by (Italian and euro area) households remains broadly unchanged. By contrast, for *HighExpFund* with a high ST investor share, the expansion of ST investors is attributable to other investment funds, while there is no meaningful change in the share held by investors located outside the euro area.

Moreover, by relying on this more granular definition of fund investor categories, we estimate a model by adopting as the dependent variable the share of the fund f held by the investor category j in quarter t . For each investor category j , we estimate our interaction terms between *Post*, *HighExpFund* and *HighShareLTInv*. In this equation we are able to include: investor category-time fixed effects, Morningstar category-investor category-time fixed effects, fund-investor type fixed effects in order to account for time-varying shocks across investor categories, the evolving preference of each investor type toward specific fund categories, and the time-invariant relationship between a specific fund and each investor category, respectively. We also control for fund characteristics interacted with time dummies: 5-star Morningstar ratings, legal domicile, and lagged net flows. Figure A.8 confirms our main findings: for funds with a high LT investor share, the decline in the share of Italian ICs is compensated by ICPFs located in other euro area countries; while the share held by other investment funds significantly rise for funds with a high ST investor base.

Differences in sales by Italian ICs. Results shown in Table 3 raise the additional question of whether resilience of funds with high LT investor share is driven primarily by replacement inflows of other LT investors (column 2) or by lower initial redemptions by Italian ICs. To investigate to what extent ICs take into account funds' investor base composition in their divestment decision we go back to the analysis at the ICs' portfolio level

and estimate a modified Equation 2 in the non-unit-portfolio focusing on the interaction of *Riskier* with *HighShareLTInv* and *Post*. A statistically significant and positive coefficient of the triple interaction would suggest that Italian ICs strategically decide to divest relatively more from funds that cater to ST clientele. However, we find a coefficient not statistically different from zero (Table A.10), suggesting that the investor base composition did not affect Italian ICs' divestment choices in their fund portfolio. This is an identification result in its own right: the incidence of the shock is uniform across investor bases, so the divergent outcomes documented above cannot reflect insurers selecting which funds to sell. The divergence arises entirely on the demand side – from who steps in afterwards.

Placebo test on equity funds and corporate bonds. To further validate the mechanism related to the first-mover advantage, we extend our analysis to two asset classes that are less prone to run-like dynamics: equity mutual funds (230 funds) and corporate bonds (3,885 securities). These asset classes serve as useful benchmarks, as they differ systematically from bond funds in how their underlying characteristics influence liquidity risk, investor behavior, and redemption incentives.

Specifically, equity funds provide an important comparison group for two reasons. First, their liabilities are similarly redeemable on demand, yet their assets – equities – are far more liquid than corporate bonds. Second, investors in equity funds are thus less exposed to fire-sale externalities and have weaker incentives to redeem early. As a result, first-mover dynamics are expected to be muted.

Analogous to the bond fund analysis, we define a dummy variable *HighExpFund* to identify funds ex ante more exposed to the shock. Given that Italian ICs have a relatively smaller footprint in equity funds, we adjust the definition of exposure to identify a meaningful set of highly exposed funds. Specifically, we set *HighExpFund* equal to one for funds with *FundExp* values above one IQR of pre-shock net flows for equity funds (approximately 9 percent).

Table 4 reports the results of Equation 6 for equity funds. Our findings show that *HighExpFund* equity funds experienced a statistically significant reduction in holdings by Italian ICs post-shock. However, and in contrast to the bond fund case, the magnitude of this decline is not significantly affected by the pre-shock share of long-term investors. This is consistent with the absence of strategic complementarities in redemptions when underlying assets are more liquid. The result reinforces our interpretation of the bond fund findings: the stabilizing role of LT investors matters precisely when first-mover incentives are present.

Table 4: Change in the investor base of equity funds

	(1)	(2)	(3)	(4)	(5)
	ShareItIC	ShareOthLongTerm	ShareShortTerm	NetFlows	Returns
Post x HighExpFund	-0.0232* (0.0656)	0.0088 (0.4597)	0.0142 (0.3457)	-0.0048 (0.8580)	0.0031 (0.4448)
Post x HighShareLTInv	-0.0086* (0.0879)	-0.0161 (0.1600)	0.0248** (0.0408)	0.0232* (0.0594)	0.0007 (0.8446)
Post x HighExpFund x HighShareLTInv	0.0240 (0.3203)	-0.0364 (0.1848)	0.0216 (0.4207)	0.0189 (0.5836)	-0.0018 (0.7827)
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	0.9727	0.9671	0.9589	0.3150	0.8429
Observations	1581	1580	1563	1581	1578

Notes: columns (1)–(5) report estimates from Equation 6 by focusing on the following dependent variables, respectively: (i) the share held by Italian ICs in their non-unit-linked portfolios (*ShareItIC*); (ii) the share held by other long-term investors (*ShareOthLongTerm*); (iii) the share held by short-term investors (*ShareShortTerm*); (iv) the quarterly net flows received by the fund by the lagged value of its total assets (*NetFlows*); and (v) the fund’s total returns (*Returns*). The sample includes *Riskier* equity funds with low direct exposure to Italian securities (230 funds), over the sample period 2017-Q3 and 2019-Q2. We control for fund-level variables (Morningstar rating, domicile, and category) interacted with time dummies and fund fixed effects. Standard errors clustered at the security level. *p*-values in parentheses; *** *p* < 0.01, ** *p* < 0.05, * *p* < 0.1.

Corporate bonds represent the second benchmark asset class. They are similar to bond mutual funds in terms of illiquidity and capital charges for insurers, but differ crucially in that they are not held via open-end fund structures. Hence, investors in corporate bonds are not exposed to the same first-mover incentives since their individual redemptions do not impose externalities on other investors.

Focusing on the sample of corporate bonds held by Italian ICs in their non-unit portfolios, we extend our analysis by computing a bond-level exposure variable, *BondExp*, a bond-level measure of exposure to the Italian shock through Italian ICs’ holdings, ob-

tained by weighting each insurer's shock exposure ($ExpIT$) by its share of the bond's outstanding amount. To identify bonds with materially high exposure, we define the dummy variable $HighExpBond$, which equals 1 for securities with an exposure above the 95th percentile of the $BondExp$ distribution – consistent with the percentile threshold used in defining the $HighExpFund$ variable for bond funds. Similarly, we define $HighShareLTInv$, which is a dummy equals 1 for bonds with a share of long-term investors above 52 percent.

We estimate Equation 6 using these variables, and by focusing on the following dependent variables: $ShareItIC$, $ShareOthLongTerm$, and $ShareShortTerm$. We include bond-specific controls (rating and maturity buckets), bond fixed effects, and issuer-time fixed effects to capture issuer-specific shocks.

Consistent with our expectations, results reported in Table 5 show that $HighExpBond$ corporate bonds experienced a significant reduction in holdings by Italian ICs after the shock (column 1), reflecting the same de-risking behavior observed for other asset classes. However, unlike the case of bond funds, this reduction does not vary significantly with the investor base composition. Additionally, there is no significant change in holdings by other LT or ST investors (columns 2–3 of Table 5). These findings support the idea that the stabilizing role of LT investors – observed in the bond fund sample – operates specifically in the presence of first-mover advantage mechanisms.

These placebo tests confirm the mechanism underlying our main findings: the stabilizing effect of LT investors is significant only in the presence of run-prone redemption incentives. Equity funds and corporate bonds help isolate this channel by offering settings where such incentives are limited or absent. The fact that the investor base composition does not predict post-shock dynamics in these asset classes strengthens our interpretation that, for bond mutual funds, the first-mover problem is central to understanding redemptions, flows, and performance following a liquidity shock.

Table 5: Change in the investor base of corporate bonds

	(1)	(2)	(3)
	ShareItIC	ShareOthLongTerm	ShareShortTerm
Post x HighExpBond	-0.0052* (0.0901)	-0.0036 (0.4255)	0.0072 (0.3196)
Post x HighShareLTInv	-0.0016*** (0.0000)	-0.0117*** (0.0000)	0.0005 (0.8127)
Post x HighExpBond x HighShareLTInv	0.0031 (0.5329)	0.0154** (0.0475)	0.0023 (0.8316)
Issuer*Time FE	Yes	Yes	Yes
Rating*Time FE	Yes	Yes	Yes
Res. maturity*Time FE	Yes	Yes	Yes
Security FE	Yes	Yes	Yes
Adj. R-squared	0.9889	0.9916	0.9857
Observations	26603	26597	25329

Notes: columns (1)–(3) report estimates from Equation 6 for corporate bonds by replacing *HighExpFund* with *HighExpBond* and focusing on the following dependent variables, respectively: (i) the share held by Italian ICs in their non-unit-linked portfolios (*ShareItIC*); (ii) the share held by other long-term investors (*ShareOthLongTerm*); (iii) the share held by short-term investors (*ShareShortTerm*). The sample includes corporate bonds held by Italian ICs in their non-unit portfolios (3,885 securities), over the sample period 2017-Q3 and 2019-Q2, and excludes bonds issued by Italian issuers. We control for bond-specific variables (rating and maturity buckets) interacted with time dummies, bond fixed effects, and issuer-time fixed effects. Standard errors clustered at the security level. *p*-values in parentheses; *** *p* < 0.01, ** *p* < 0.05, * *p* < 0.1.

4.4. The portfolio margin: risk-taking and catering (H4)

In this section, we assess how the portfolio allocation of bond funds responded to the liquidity shock induced by Italian ICs' sales, focusing on the role of the investor base composition, as stated in Hypothesis H4, that is, we turn from the investor margin to the portfolio margin. Specifically, we test whether, after significant redemptions by Italian ICs, corporate bond funds with a more stable investor base (i.e., higher share of LT investors) responded differently in terms of portfolio risk-taking compared to those with a less stable base.

We classify each fund's portfolio across six asset categories: *BondHY* (bonds rated below BBB-), *Bond A-BBB* (non-Italian investment-grade bonds rated A+ to BBB-), *CorpBond AAA-AA* (corporate bonds rated AA- or above), *SafeAsset* (cash and sovereign bonds rated AA- or above), *Equity* (non-Italian stocks), and *FundShares* (holdings of other funds). Italian securities are included in a separate category, *IT*, as they were directly affected by the shock.²³ To ensure sufficient portfolio information, we exclude funds for which more

²³The categories *Equity* and *FundShares* are only marginal in our sample, so the classification effectively ranks assets by liquidity and risk. See Table A.3.

than 30 percent of portfolio holdings are unclassified (e.g., derivatives or unlisted assets), resulting in a sample of 216 funds.

Equation 7 describes our baseline model.

$$\begin{aligned} AssetShare_{f,j,t} = & \beta_{0,j} Post_t * HighExpFund_f + \beta_{1,j} Post_t * HighShareLTInv_f \\ & + \beta_{2,j} Post_t * HighExpFund_f * HighShareLTInv_f + \gamma_t X_{f,t} \\ & + \mu_{j,t} + \zeta_{f,j} + \theta_{cat(f),j,t} + \epsilon_{f,j,t} \end{aligned} \quad (7)$$

where *AssetShare* is the share of fund *f*'s portfolio allocated to asset category *j* in quarter *t*, computed holding securities' prices constant at 2018-Q1 in order to consider only active trading.²⁴ For each asset category *j*, our two main coefficients of interest are: $\beta_{0,j}$, which represents the post-shock changes for funds with high exposure to Italian ICs and predominantly short-term investor base, and $\beta_{2,j}$, which captures the additional post-shock shift in portfolio allocation for funds highly exposed to Italian ICs and with a large LT investor base. The control vector $X_{f,t}$ includes fund characteristics interacted with time dummies: 5-star Morningstar ratings, legal domicile, and lagged net flows.

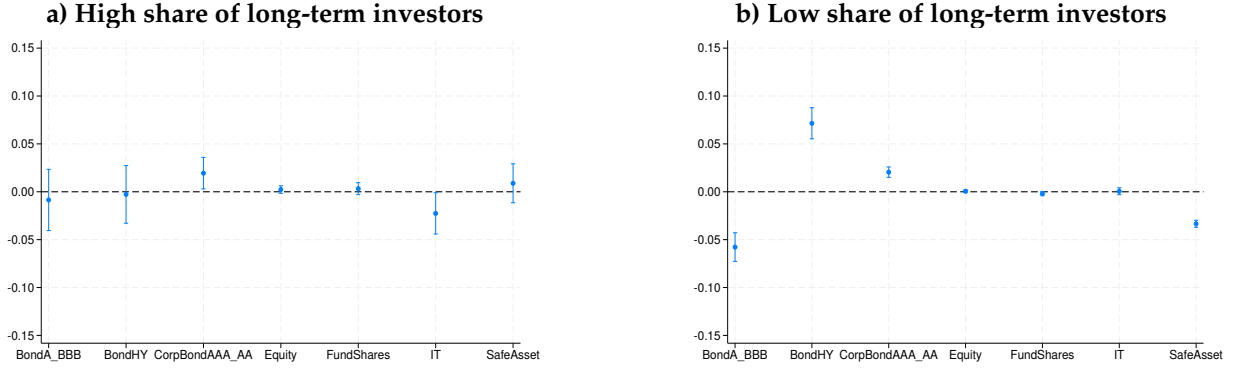
Moreover, we include: asset category-time fixed effects ($\mu_{j,t}$), Morningstar category-asset class-time fixed effects ($\theta_{cat(f),j,t}$), fund-asset category fixed effects ($\zeta_{f,j}$). These controls allow us to account for time-varying shocks across asset categories, the evolving preferences of each fund category toward specific asset classes, and time-invariant preferences of each fund to each asset category, respectively.

Figure 7 presents the results, split by funds with high (panel a) and low (panel b) shares of LT investors. Panel (a) shows that highly exposed corporate bond funds with a high share of LT investors did not significantly change their portfolio allocation. As documented in Section 4.3.1, these funds benefited from continued net inflows from LT investors, suggesting that – in the absence of performance shocks – preserving their ex-

²⁴This methodology is coherent with that employed when studying ICs' portfolio reallocation in Section 3. These results hold even computing shares at market prices.

isting asset allocation is sufficient to counterbalance outflows from Italian ICs.

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



Notes: panels (a) and (b) shows the results of Equation 7. Panel (a) reports the marginal effect for highly exposed funds with a share of long-term investors in the top quartile of the distribution ($\beta_{0,j} + \beta_{2,j}$). Panel (b) shows the marginal effect for highly exposed funds with a lower share of long-term investors ($\beta_{0,j}$). The dependent variable, *AssetShare*, is the share of fund *f*'s portfolio allocated to asset category *j* in quarter *t*, computed holding securities' prices constant at 2018-Q1. We control for fund characteristics interacted with time dummies: 5-star Morningstar ratings, legal domicile, and lagged net flows. We also include asset category-time fixed effects, Morningstar category-asset class-time fixed effects, fund-asset category fixed effects. The sample includes only riskier bond funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities and for which we have information on at least 70 percent of their portfolio. Confidence bands are at the 90% level based on standard errors clustered at the fund level.

In contrast, panel (b) shows that highly exposed corporate bond funds with a lower share of LT investors responded to the same shock by increasing their exposure to riskier assets, particularly high-yield corporate bonds and a reduction in safe assets. This reallocation reflects an active increase in portfolio risk rather than a mechanical response to redemptions. This behavior appears consistent with attempts to boost short-term performance and attract return-sensitive investors, such as mutual funds, a strategy supported by performance and inflow patterns observed in Section 4.3.1.

These findings are further confirmed when we allow the treatment effects to vary by quarter (Figure 8). Highly exposed funds began adjusting their portfolios immediately after the shock, mirroring the timing of shifts in the investor base composition (see Figures A.3, A.4, and A.5).

Finally, to address the possibility that risk-taking of funds with a low share of LT investors mechanically reflects the sale of safer assets, we replicate the analysis using holding amounts (i.e., the log of the value of each asset category, computed holding securities'

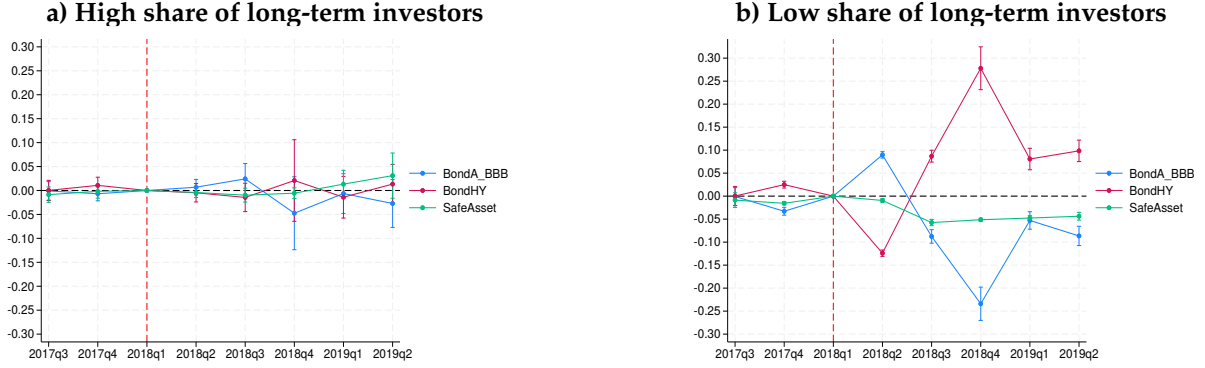
prices constant at 2018-Q1) rather than portfolio shares. The results reported in Figure A.9 confirm that funds with a high share of ST investors increased their high-yield holdings in levels after the shock.²⁵ Hence, the risk-taking of these funds is not driven solely by a denominator effect or by the liquidation of safer assets to meet redemptions, supporting the interpretation that funds with a high share of ST investors actively increase risk exposure following the shock.

Taken together, these results support Hypothesis H4. The composition of a fund's investor base shapes how it adjusts portfolio risk in response to liquidity shocks. Among funds exposed to a liability-side liquidity shock, only those with fewer LT investors – who are more exposed to a performance-sensitive investor base – respond by increasing risk to attract inflows of ST investors.

Notably, the sign of the response reverses the precautionary benchmark: after outflows, bond funds typically de-risk to prepare for further redemptions (Morris et al., 2017; Cutura et al., 2025). Here, only the funds left with performance-sensitive clientel increase risk-taking – the catering benchmark – so whether a fund de-risks or takes more risk after losing investors depends on who remains inside it.

²⁵To ease the interpretation of results, in each panel we also reported the average portfolio share of each asset category, allowing us to assess the relative importance of the corresponding coefficient within the fund portfolio.

Figure 8: Marginal effect of *HighExpFund* over time on the portfolio share of the main categories of assets for *Riskier* bond funds, broken down by investor base



Notes: panels (a) and (b) shows the results of Equation 7 by introducing a time-varying coefficient for each group. Panel (a) reports the quarterly marginal effect for highly exposed funds with a share of long-term investors in the top quartile of the distribution ($\beta_{0,j} + \beta_{2,j}$). Panel (b) shows the quarterly marginal effect for highly exposed funds with a lower share of long-term investors ($\beta_{0,j}$). The dependent variable, *AssetShare*, is the share of fund *f*'s portfolio allocated to asset category *j* in quarter *t*, computed holding securities' prices constant at 2018-Q1. We control for fund characteristics interacted with time dummies: 5-star Morningstar ratings, legal domicile, and lagged net flows. We also include asset category-time fixed effects, Morningstar category-asset class-time fixed effects, fund-asset category fixed effects. The sample includes only riskier bond funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities and for which we have information on at least 70 percent of their portfolio. The dots report the point estimate of the coefficients for each quarter. The dashed vertical line indicates the last pre-shock period. Confidence bands are at the 90% level based on standard errors clustered at the fund level.

5. Discussion and policy implications

Our findings show that the composition of a fund's investor base plays a decisive role in shaping its response to an exogenous liquidity shock. The adjustment operates along the two margins identified in the introduction: who replaces the capital that leaves (the investor margin), and how managers reposition the portfolio toward the investors the fund can attract (the portfolio margin). Following large redemptions from Italian insurance companies, corporate bond funds with a higher pre-shock share of LT investors successfully compensated outflows by attracting new inflows from similar investor types, with no need to change their asset allocation. In contrast, funds with more ST investors struggled to replace the LT clientele, experienced persistent net outflows, and increased portfolio risk, likely to appeal to performance-sensitive investors.

These dynamics are consistent with the first round of a self-reinforcing mechanism: following the shock, funds with a larger short-term investor base became more concentrated in run-prone investors and shifted toward riskier assets, a combination that would

plausibly increase their vulnerability to future shocks. The observed divergence in both investor composition and portfolio risk persists over the year covered by our sample, suggesting that a liability-side shock does not simply dissipate but re-sorts the distribution of fragility across funds.

These results extend the literature on run-like incentives in open-end funds in two ways. First, they show that run-like incentives operate *ex ante*, on the replacement margin: the prospect of bearing future first-mover costs deters stable investors from entering funds with performance-sensitive clienteles, so that liquidity risk builds up on the liability side before any run occurs. Second, they identify a previously underexplored link between liability composition and managers' portfolio choices (the catering margin), highlighting an additional channel for systemic risk concentration.

Our results speak directly to the international framework for open-end fund resilience. The recommendations of FSB (2023) and IOSCO (2025) calibrate funds' redemption terms and their expected use of liquidity management tools to the liquidity of fund assets, grouping funds into categories along this single dimension. The evidence in this paper shows that focusing only on this dimension may be insufficient: among corporate bond funds facing the same redemption shock with comparable portfolios, post-shock outcomes diverged sharply with the composition of the liability side. Liquidity risk assessments should therefore complement asset-based categories with an investor-base metric – akin to the NSFR in banking, which explicitly considers the stability of counterparties – measurable at the fund level from existing security-holdings statistics. Such an approach targets the build-up of vulnerabilities *ex ante*, rather than only mitigating run risk *ex post*, and supervisory practice is already moving in this direction: recent analyses monitor the stabilizing role of household ownership during market stress (European Central Bank, 2025) and of insurer ownership conditional on insurers' own financial health (Fecht et al., 2025).

Liquidity management tools play a complementary role, and our mechanism clari-

fies where it lies. Tools that reduce first-mover advantages – swing pricing, anti-dilution levies, redemption gates – do more than slow redemptions: by lowering the outflow externality that prospective LT investors expect to bear, they operate on the replacement margin, making it easier for funds to rebuild a stable base after a shock and weakening managers’ incentives to increase portfolio risk in order to attract performance-sensitive inflows (Jin et al., 2022). Since the aggregate vulnerability of the fund sector rises with the concentration of first movers (Capponi et al., 2025), the expected use of these tools could be calibrated not only to asset liquidity, as under the current framework, but also to the fragility of the investor base within each asset category.

These insights are particularly relevant given the growing cross-holdings among funds (Fricke and Wilke, 2023), the run-proneness of the fund sector itself as an investor in other funds (Allaire et al., 2023), and the potential for correlated redemptions across intermediaries. By addressing vulnerabilities at the liability side before shocks occur, regulators could limit the concentration of systemic risk in the subset of funds most susceptible to runs.

6. Conclusions

This paper exploits an exogenous liquidity shock to euro-area mutual funds – triggered by large redemptions from Italian insurance companies – to examine two margins of adjustment – the investor margin and the portfolio margin – with security-level granularity.

Using detailed micro-to-security level data, we show that the stability of a fund’s investor base is a key determinant of resilience. Bond funds with a greater share of long-term investors avoided large net outflows by attracting similar investor types – the departing Italian insurers were replaced by other euro-area ICPFs – without changing their portfolio allocation. Funds dominated by short-term investors, instead, failed to replace long-term investors’ outflows and increased portfolio risk – losing about 6.5 percent of

assets to net outflows, seeing the short-term share of their ownership rise by some 12 percentage points, and actively tilting toward high-yield bonds to cater to the performance-sensitive clientele they could still attract. These findings demonstrate that run-like incentives create liability-side sorting that concentrates systemic vulnerabilities in funds with a more unstable investor base and a riskier asset allocation.

While our analysis focuses on fund-level portfolio responses, an important avenue for future research is to examine potential security-level effects in stress periods. In our empirical setting, highly exposed funds do not appear to engage in fire sales; instead, they tilt their portfolios toward riskier assets following the liability-side shock. Future work could test whether, in broader market downturns, vulnerabilities of funds with unstable investor bases and risky asset allocations translate into security-level fragility.

From a regulatory perspective, two implications stand out. First, resilience frameworks calibrated on asset liquidity alone – the approach underlying current international standards – may be incomplete: two funds with identical portfolios can sit at opposite ends of the fragility distribution, so investor-base composition belongs alongside portfolio risk in fund assessments. Second, liquidity management tools that reduce first-mover advantages operate on the replacement margin as well as the redemption margin: by lowering the externality that deters prospective long-term investors, they help fragile funds rebuild stable bases – while the stability provided by long-term investors remains, ultimately, only as sound as those investors’ own balance sheets.

Overall, our results underscore the importance of integrating liability-side considerations into the design of both supervisory frameworks and fund-level risk management practices.

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A. Internet Appendix: Additional tables and figures

Table A.1: Italian insurance companies 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 10th, 25th, 75th, 90th 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
<i>Panel A: mutual funds held by ICs (non-unit-linked portfolio)</i>								
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
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
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
Net flows (%)	5998	0.66	-0.05	-10.91	-4.89	5.4	15.37	7.91
Net returns (%)	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
Riskier (dummy)	6162	0.83	1	0	1	1	1	0.38
FundExp	5658	0.05	0.01	0	0	0.04	0.13	0.11
<i>Panel B: mutual funds held by ICs (unit-linked portfolio)</i>								
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
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
Fund characteristics								
Fund size (Eur mln)	32604	923	332	45	116	877	2129	2210
Net flows (%)	28850	0.44	-0.72	-10.94	-5.64	5.53	15.67	8.23
Net returns (%)	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
Riskier (dummy)	30901	0.82	1	0	1	1	1	0.38

Notes: the table reports, for each variable, the mean, standard deviation, median and 10th, 25th, 75th, 90th 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 4.4). *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: **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
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
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 10th, 25th, 75th, 90th percentile and number of unique mutual fund-time-observations. Shares of fund assets invested in a specific category (as defined in Section 4.4) considering the sample of funds included in the regression Equation 7.

Table A.4: **Correlations of financial market prices with Italian government bond yields**

		Gov. bond yield - IT		
		2-year	5-year	10-year
Corp. bond spread - Financials	IT	0.54	0.57	0.48
	EA excl. IT	0.12	0.11	0.01
Corp. bond spread - Non-financials	IT	0.25	0.22	0.07
	EA excl. IT	-0.05	-0.07	-0.15
Euro Stoxx - Financials	IT	-0.39	-0.46	-0.45
	EA excl. IT	-0.24	-0.28	-0.23
Euro Stoxx - Non-financials	IT	-0.31	-0.37	-0.38
	EA excl. IT	-0.19	-0.24	-0.23
2-year gov. bond yield	DE	-0.40	-0.38	-0.26
	FR	-0.20	-0.18	-0.08
	ES	0.29	0.34	0.39
2-year EUR swap rate	EA	0.05	0.07	0.14
5-year gov. bond yield	DE	-0.30	-0.27	-0.14
	FR	-0.13	-0.08	0.07
	ES	0.24	0.30	0.36
5-year EUR swap rate	EA	-0.14	-0.09	0.06
10-year gov. bond yield	DE	-0.20	-0.17	-0.02
	FR	-0.01	0.05	0.20
	ES	0.42	0.52	0.64
10-year EUR swap rate	EA	-0.06	-0.01	0.14

Notes: the table reports the correlation coefficients between different financial market indicators and Italian government bond yields. Corporate bond spreads refer to market value weighted asset swap spreads of the constituents of the iBoxx EUR Corporates index, sourced from Markit. The Euro Stoxx indices, constructed using data from LSEG, are the free float market capitalization weighted price indices of the index constituents. Government bond yields refer to the yields to maturities of the Bloomberg benchmark bonds. Swap rates are the fixed rates on EONIA interest rate swaps, sourced from Bloomberg. The correlations are calculated using daily changes between January 1, 2018 and December 31, 2019.

Table A.5: **Insurance companies classification for Italian exposure and SCR ratio**

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

Table A.6: **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	61	25
Global Fixed Income	44	12
Emerging Markets Fixed Income	41	4
Fixed Income Miscellaneous	28	9
US Fixed Income	15	4
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 52 percent). We marked with a 3* cases in which the number of funds is three or less than three.

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
<i>Panel A: Low share of long-term investors</i>								
Bond HY	526	0.39	0.38	0.03	0.11	0.64	0.8	0.29
Bond A-BBB	526	0.35	0.32	0.07	0.12	0.53	0.7	0.23
Bond corp. AAA-AA	526	0.05	0.01	0	0	0.06	0.14	0.08
Safe assets	526	0.11	0.03	0	0.01	0.13	0.3	0.2
Foreign equity	526	0	0	0	0	0	0	0.01
Italian securities	526	0.04	0.02	0	0	0.06	0.11	0.05
Fund shares	526	0.02	0	0	0	0.04	0.08	0.03
Bond corp.	526	0.59	0.74	0.09	0.31	0.87	0.93	0.32
Other (n.a.)	526	0.04	0.04	-0.03	0.01	0.08	0.13	0.09
Fund size (Eur mln)	525	2609	1669	233	789	3389	6438	3050
Net flows (%)	394	3.93	2.87	-6.19	-1.76	10.52	15.67	7.86
Net returns (%)	524	0.34	0.38	-1.38	-0.36	1.23	2.14	1.52
<i>Panel B: High share of long-term investors</i>								
Bond HY	147	0.36	0.24	0.01	0.04	0.5	0.83	0.49
Bond A-BBB	147	0.35	0.32	0.02	0.09	0.55	0.81	0.28
Bond corp. AAA-AA	147	0.04	0	0	0	0.03	0.07	0.12
Safe assets	147	0.11	0.03	0	0.01	0.13	0.37	0.18
Foreign equity	147	0.03	0	0	0	0	0	0.16
Italian securities	147	0.07	0.06	0	0	0.12	0.16	0.09
Fund shares	147	0.02	0	0	0	0.03	0.09	0.06
Bond corp.	147	0.63	0.77	0.06	0.28	0.88	0.92	0.49
Other (n.a.)	147	0.01	0.03	-0.01	0.01	0.08	0.13	0.33
Fund size (Eur mln)	145	421	174	67	102	457	1083	532
Net flows (%)	109	2.29	0.59	-7.81	-1.08	4.98	15.67	7.28
Net returns (%)	145	0.33	0.22	-1.54	-0.31	1.19	2	1.58

Notes: the table reports, for each variable, the mean, standard deviation, median and 10th, 25th, 75th, 90th percentile and number of mutual fund-time observations. Shares of fund assets invested in a specific category (as defined in Section 4.4) in the pre-shock periods considering the sample used to estimate Equation 7.

Table A.8: **Change in the investor base and performance of *Riskier* bond funds by adopting the matched sample**

	(1)	(2)	(3)	(4)	(5)
	ShareItIC	ShareOthLongTerm	ShareShortTerm	NetFlows	Returns
Post x HighExpFund	-0.1412*** (0.0000)	-0.0096 (0.5256)	0.2102*** (0.0000)	-0.0648*** (0.0040)	0.0078** (0.0257)
Post x HighShareLTInv	0.0105 (0.1453)	0.0147 (0.1761)	-0.0486*** (0.0070)	-0.0057 (0.6253)	0.0011 (0.6122)
Post x HighExpFund x HighShareLTInv	0.1052*** (0.0002)	0.0273 (0.1140)	-0.1892*** (0.0000)	0.0652*** (0.0058)	-0.0050 (0.2296)
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	0.9921	0.9776	0.9738	0.3768	0.6032
Observations	1224	1089	1090	1284	1284

Notes: columns (1)-(5) display estimates of Equation 6. The sample includes the matched sample of *Riskier* bond funds with low direct exposure to Italian securities. Specifically, our matching procedure improves comparability across funds with a high LT investor share (treated) and the other ones by implementing an inverse probability weighting (IPW) approach based on propensity scores. We estimate a propensity score matching by employing the nearest neighborhood caliper matching approach, by accounting for fund characteristics in March 2018: size, the share of bonds rated below BBB-, the share of investment-grade bonds rated A+ to BBB-, the share of corporate bonds rated AA- or above, the share of cash and highly rated sovereign bonds, the share of equity, the share of other funds. Observations are then weighted by the inverse of the estimated propensity score to balance the distribution of covariates across treated and control funds. Standard errors are clustered at the fund level. p -values in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.9: **Change in the investor base of *Riskier* bond funds by investor type**

	(1)	(2)	(3)	(4)
	ShareHouseholds	ShareEaICPFs	ShareIFs	ShareExtraEa
Post x HighExpFund	-0.0036 (0.6135)	0.0012 (0.8602)	0.0896*** (0.0000)	0.0119 (0.5290)
Post x HighShareLTInv	0.0023 (0.8111)	0.0079 (0.2152)	0.0009 (0.9374)	-0.0088 (0.1703)
Post x HighExpFund x HighShareLTInv	0.0008 (0.9300)	0.0267** (0.0297)	-0.1022*** (0.0000)	-0.0129 (0.4503)
Fund contr.*Time	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
IF category-Time FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.9851	0.9634	0.9345	0.9104
Observations	1582	1582	1582	1582

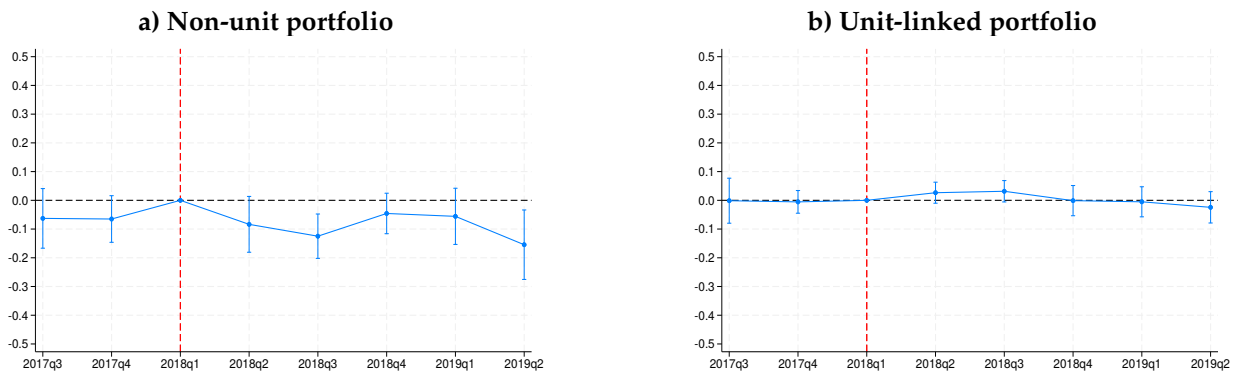
Notes: columns (1)-(4) display estimates of Equation 6 by focusing on the following dependent variables, respectively: (i) the share held by Italian and euro area households (*ShareHouseholds*); (ii) the share held by euro area insurance companies and pension funds, excluding Italian ones (*ShareEaICPFs*); (iii) the share held by Italian and euro area investment funds (*ShareIFs*); (iv) the share held by investors located outside the euro area (*ShareExtraEa*). The sample includes *Riskier* bond funds with low direct exposure to Italian securities (241 funds), over the sample period 2017-Q3 and 2019-Q2. We control for fund-level variables (Morningstar rating, domicile, and category) interacted with time dummies and fund fixed effects. Standard errors are clustered at the fund level. p -values in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A.10: 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)
	$\ln q$
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

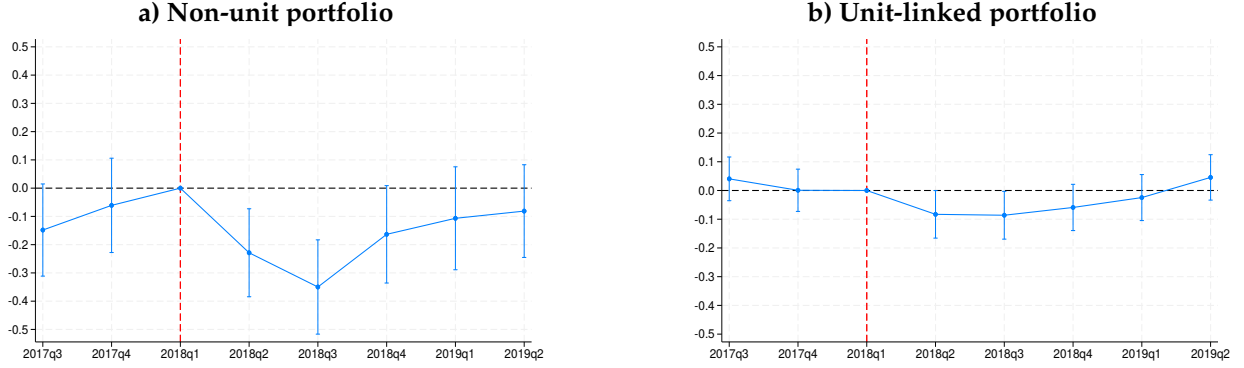
Notes: the table shows results of Equation 2 obtained by focusing on funds in the non-unit portfolio and interacting *Riskier* and *Post* with *HighShareLTInv*, which is a dummy equal to 1 for funds with a high proportion of long-term investors (above 52 percent) in 2018-Q1. The dependent variable is $\ln q$, 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; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A.1: Change in Italian ICs' holdings of *Riskier* funds between portfolios (using a threshold of the capital charge of the fund in 2018-Q1 of 29% to define a fund as *Riskier*)



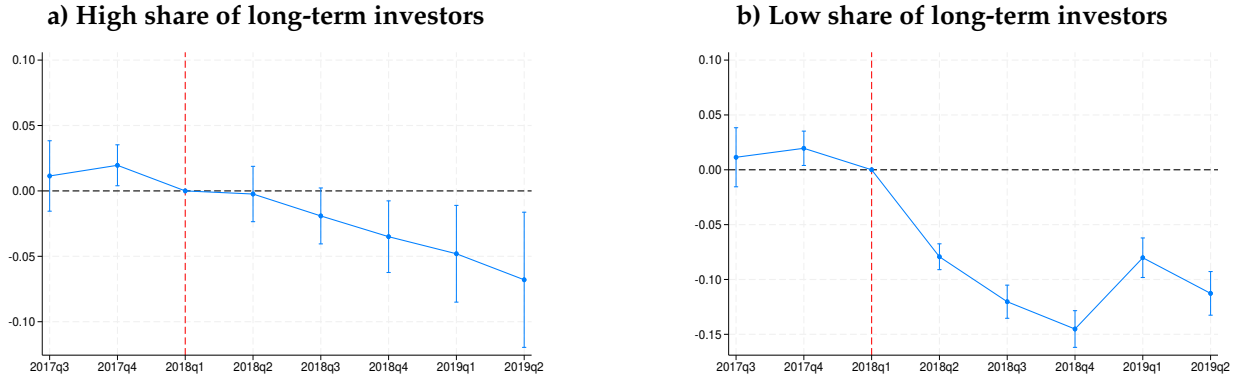
Notes: panels (a) and (b) depict the results of Equation 2 for riskier funds included in the non-unit portfolio and in the unit-linked one, respectively. The dashed vertical line indicates the last pre-shock period. The dots report the point estimate of the coefficients for each quarter. Confidence bands are at the 90% level based on standard errors clustered at the insurance and fund levels.

Figure A.2: Change in Italian ICs' holdings of *Riskier* funds between portfolios by adopting the Davis-Haltiwanger growth rate



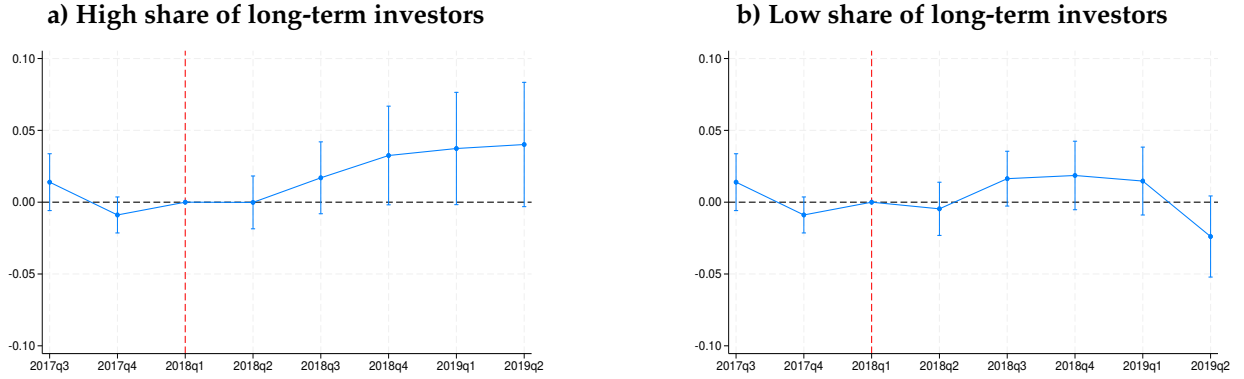
Notes: panels (a) and (b) depict the estimated coefficients of Equation 2 for riskier funds included in the non-unit portfolio and in the unit-linked one, respectively, estimated by adopting *NetBuys* as the dependent variable. *NetBuys* is equal to $\frac{q_{s,i,p,t} - q_{s,i,p,t-1}}{\frac{1}{2} * (q_{s,i,p,t} + q_{s,i,p,t-1})}$. The model includes IC-time-portfolio and security-portfolio fixed effects as well as fund controls and IF category dummies interacted with time. The dashed vertical line indicates the last pre-shock period. The dots report the point estimate of the coefficients for each quarter. Confidence bands are at the 90% level based on standard errors clustered at the fund and time levels.

Figure A.3: Marginal effect of *HighExpFund* on *ShareItIC*



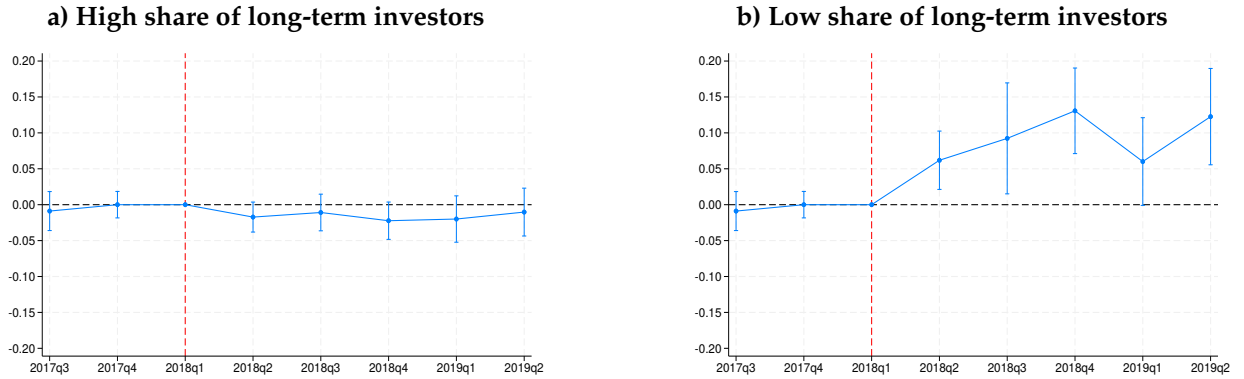
Notes: the figure shows the results of Equation 6 by adopting *ShareItIC* as the dependent variable and by introducing a time-varying interaction term between *Riskier*, *HighExpFund* and *HighShareLTInv*. Panel (a) reports results for funds with a share of long-term investors in the top quartile of 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. The dots report the point estimate of the coefficients for each quarter. The dashed vertical line indicates the last pre-shock period. Confidence bands are at the 90% level based on standard errors clustered at the fund level.

Figure A.4: Marginal effect of *HighExpFund* on *ShareOthLongTerm*



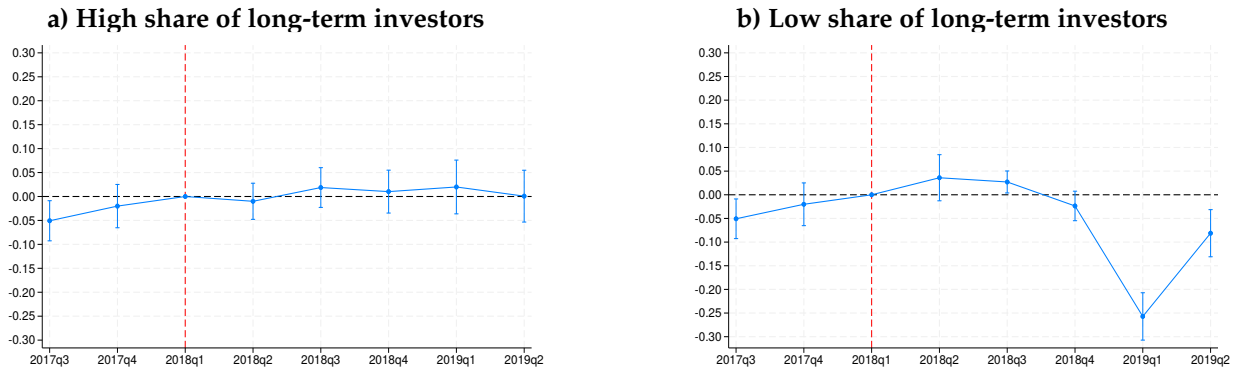
Notes: the figure shows the results of Equation 6 by adopting *ShareOthLongTerm* as the dependent variable and by introducing a time-varying interaction term between *Riskier*, *HighExpFund* and *HighShareLTinv*. Panel (a) reports results for funds with a share of long-term investors in the top quartile 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. The dots report the point estimate of the coefficients for each quarter. The dashed vertical line indicates the last pre-shock period. Confidence bands are at the 90% level based on standard errors clustered at the fund level.

Figure A.5: Marginal effect of *HighExpFund* on *ShareShortTerm*



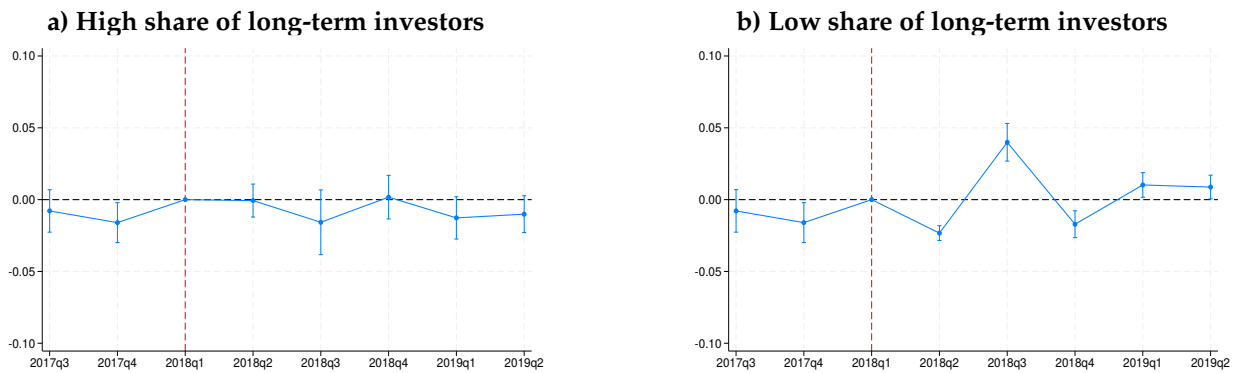
Notes: the figure shows the results of Equation 6 by adopting *ShareShortTerm* as the dependent variable and by introducing a time-varying interaction term between *Riskier*, *HighExpFund* and *HighShareLTinv*. Panel (a) reports results for funds with a share of long-term investors in the top quartile 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. The dots report the point estimate of the coefficients for each quarter. The dashed vertical line indicates the last pre-shock period. Confidence bands are at the 90% level based on standard errors clustered at the fund level.

Figure A.6: Marginal effect of *HighExpFund* on the net flows of *Riskier* funds, broken down by investor base



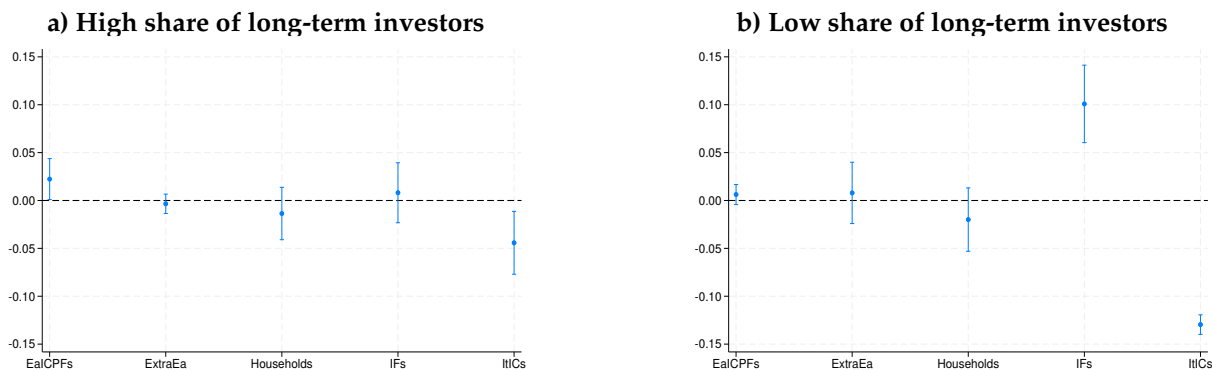
Notes: the figure shows the results of Equation 6 by adopting *NetFlows* as the dependent variable and by introducing a time-varying interaction term between *Riskier*, *HighExpFund* and *HighShareLTinv*. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the 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. The dots report the point estimate of the coefficients for each quarter. The dashed vertical line indicates the last pre-shock period. Confidence bands are at the 90% level based on standard errors clustered at the fund level.

Figure A.7: Marginal effect of *HighExpFund* on returns of *Riskier* funds, broken down by investor base



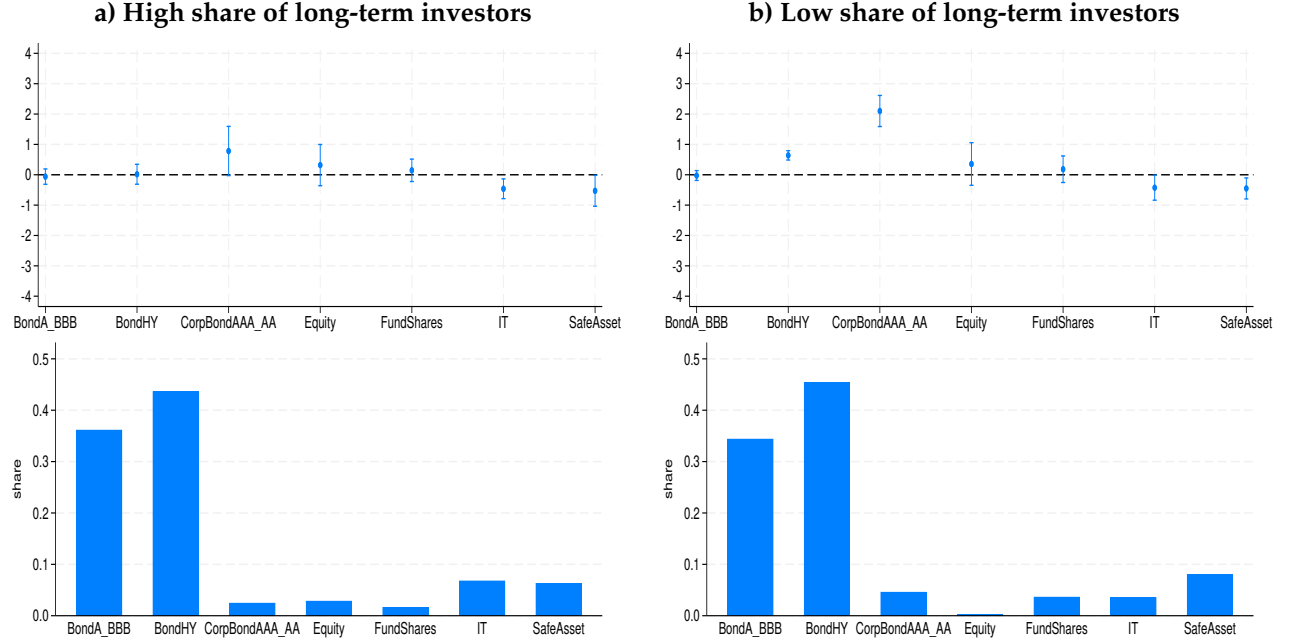
Notes: the figure shows the results of Equation 6 by adopting *Returns* as the dependent variable and by introducing a time-varying interaction term between *Riskier*, *HighExpFund* and *HighShareLTinv*. Panel (a) reports results for funds with a share of long-term investors in the top quartile of the 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. The dots report the point estimate of the coefficients for each quarter. The dashed vertical line indicates the last pre-shock period. Confidence bands are at the 90% level based on standard errors clustered at the fund level.

Figure A.8: Marginal effect of *HighExpFund* on the share held by each investor category of *Riskier* bond funds



Notes: panels (a) and (b) shows the results of an equation estimated by adopting as the dependent variable the share of the fund f held by each investor category j in quarter t . For each investor category j , we estimate our interaction terms between *Post*, *HighExpFund* and *HighShareLTInv*. We control for fund characteristics interacted with time dummies: 5-star Morningstar ratings, legal domicile, and lagged net flows. We also include investor category-time fixed effects, Morningstar category-investor category-time fixed effects, fund-investor category fixed effects. The sample includes only riskier bond funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities and for which we have information on at least 70 percent of their portfolio. Panel (a) reports the marginal effect for highly exposed funds with a share of long-term investors in the top quartile of the distribution. Panel (b) shows the marginal effect for highly exposed funds with a lower share of long-term investors. Confidence bands are at the 90% level based on standard errors clustered at the fund level.

Figure A.9: Marginal effect of *HighExpFund* on the log amount of the main categories of assets for *Riskier* bond funds, broken down by investor base



Notes: panels (a) and (b) shows the results of Equation 7. Panel (a) reports the marginal effect for highly exposed funds with a share of long-term investors in the top quartile of the distribution ($\beta_{0,j} + \beta_{2,j}$). Panel (b) shows the marginal effect for highly exposed funds with a lower share of long-term investors ($\beta_{0,j}$). The dependent variable, *LogAmount*, is the logarithm of the value of asset category j held by fund f in quarter t , computed holding securities' prices constant at 2018-Q1. We control for fund characteristics interacted with time dummies: 5-star Morningstar ratings, legal domicile, and lagged net flows. We also include asset category-time fixed effects, Morningstar category-asset class-time fixed effects, fund-asset category fixed effects. The sample includes only riskier bond funds included in the non-unit portfolio of Italian ICs with low direct holdings of Italian securities and for which we have information on at least 70 percent of their portfolio. Confidence bands are at the 90% level based on standard errors clustered at the fund level. Each panel also reports the average portfolio share of each asset category in 2018-Q1, in order to assess its relative importance within the fund portfolio.

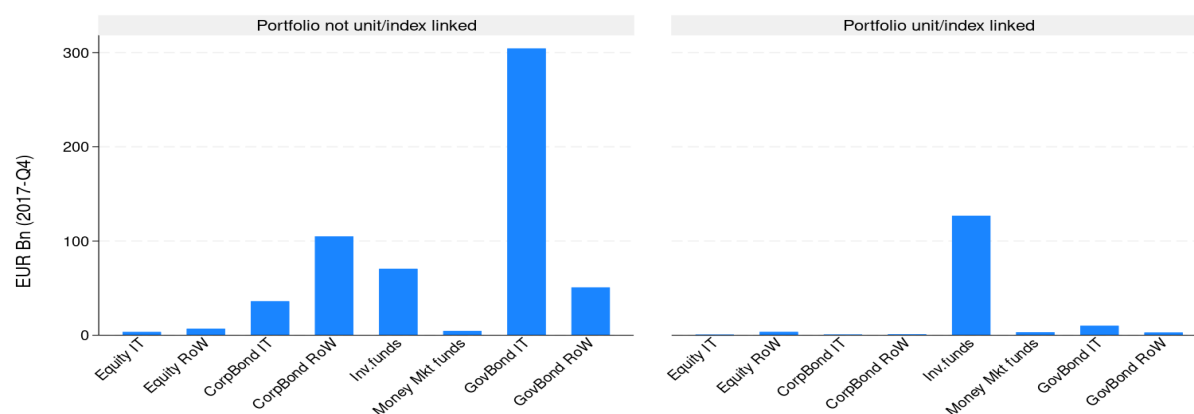
B. Internet Appendix: An overview of the Italian insurance sector

B.1. Portfolio allocation before the shock

At the end of 2017, Italian insurance companies' total assets were approximately €921 billion. 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. Indeed, 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.10, left panel). On the other hand, unit-linked portfolios consist almost entirely of mutual fund shares (Figure B.10, right panel).

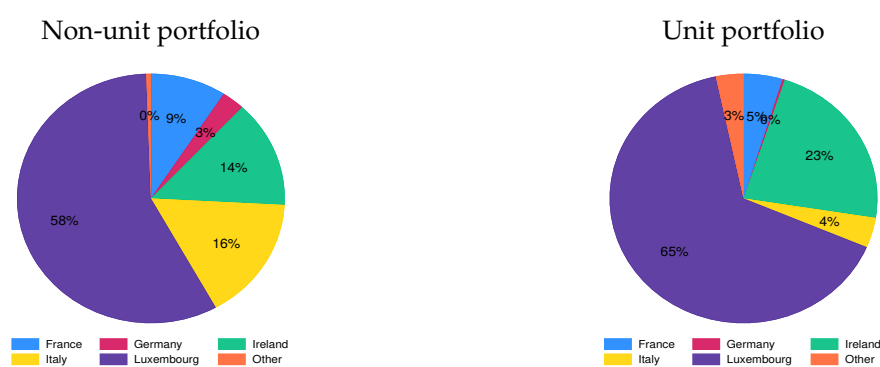
Figure B.10: Aggregate portfolio break-down by security type of Italian ICs (2017-Q4)



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

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.11). 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.11: Asset under management by domicile of funds held by Italian ICs (2017-Q4)



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

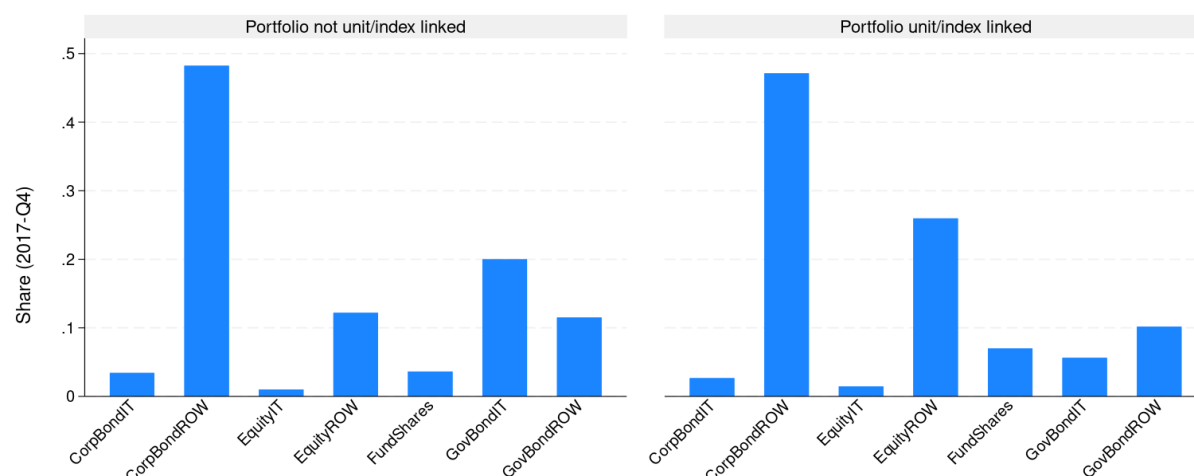
The differences in the composition of the two portfolios are only partially reflected in the mutual funds' underlying asset allocation. Investment funds in the non-unit-linked portfolio tend to allocate more to asset classes other than domestic government bonds, compared to the insurance sector's direct holdings.²⁶ 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.12).

This suggests that insurance companies use their investment fund holdings to diversify internationally, increasing their exposure to the corporate sector while maintaining

²⁶The 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.

relatively limited equity exposure.²⁷

Figure B.12: **Portfolio composition of funds held by Italian ICs (2017-Q4)**



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

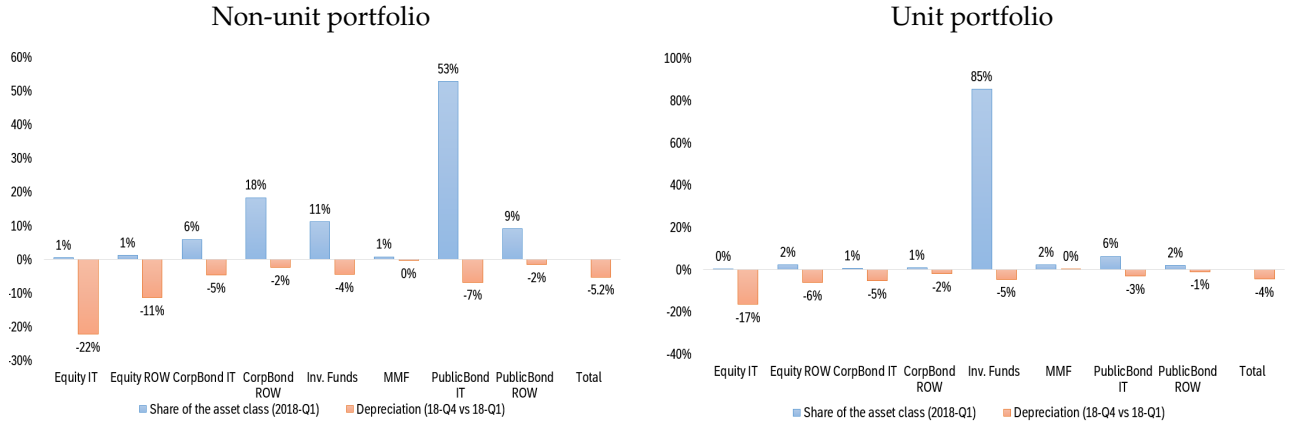
B.2. Impact of sovereign shock on ICs' portfolios

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.13).

As pointed out in 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

²⁷Interestingly, 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 share 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.13: **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 related to life-insurance policies.

shock.

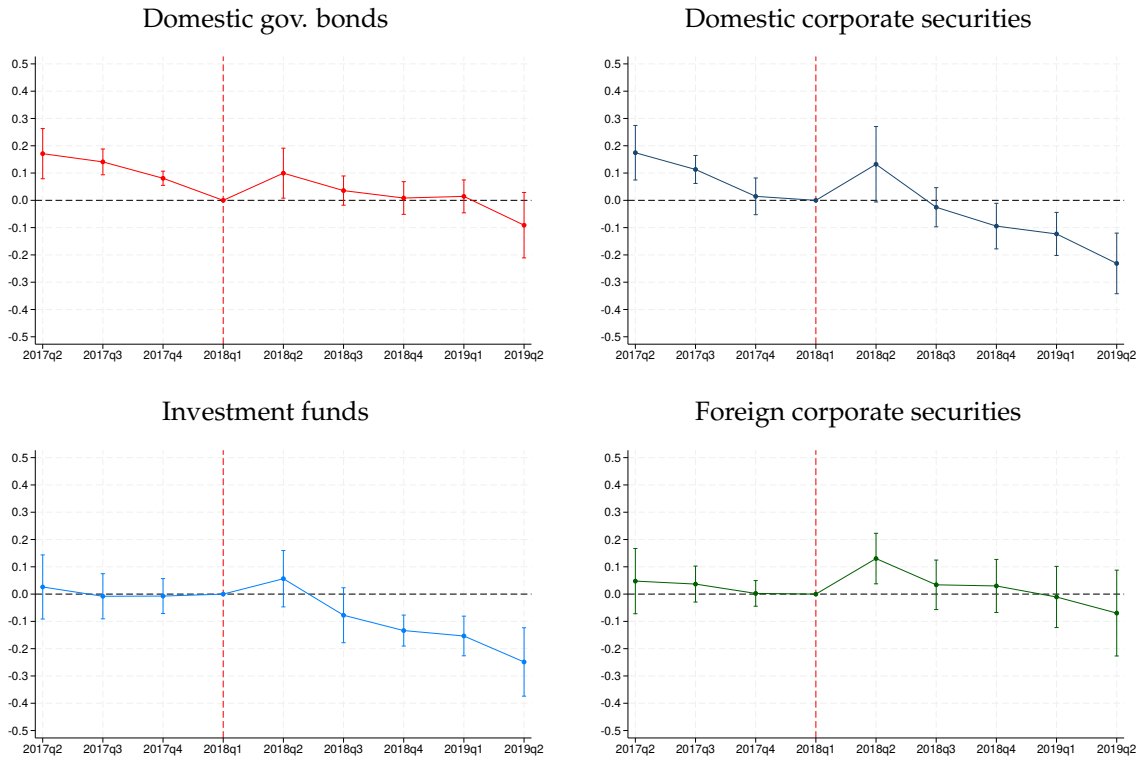
Specifically, we calculate the quantity of each security held in each quarter (see Section 2.3), multiplied by its price at the end of 2018-Q1. We then sum the values of securities across asset categories: investment funds, money market funds, foreign corporate securities, foreign government securities, domestic corporate securities, and domestic government bonds. This allows us to examine changes in holdings, net of price effects. The regression model is as follows:

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

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 time-invariant observed and unobserved characteristics specific to an IC-category pair (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 IC (e.g., total assets and subscriptions). Standard errors are double-clustered at the IC and

asset category levels.

Figure B.14: Investment patterns relative to foreign government bonds



Notes: the four charts depict the results of Equation B.1 for each asset category. The money market funds category is not plotted but it does not show any particular pattern over the period. The dots report the point estimate of $\beta_{cat,t}$ for each quarter. The dashed vertical line indicates the last pre-shock period. Confidence bands are at the 90% level based on standard errors clustered at the asset category and insurance company level.

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.²⁸

The results of this regression are summarized in Figure B.14. On average, ICs did not significantly adjust their holdings of domestic government bonds. However, they

²⁸We 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.

reduced their investments in riskier and more capital-absorbing asset categories, particularly shares of investment funds and domestic corporate securities.

C. Internet Appendix: 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.11. Importantly, government bonds issued by sovereigns in the European Economic Area (EEA) carry no capital charge for spread risk, irrespective of their rating.

The increase in Italian government bond yields in 2018 affected the capital held by Italian ICs by decreasing the market value of their assets.

To understand the extent to which the heterogeneous exposure to Italian securities

Table C.11: **Capital requirements in submodules of market risk**

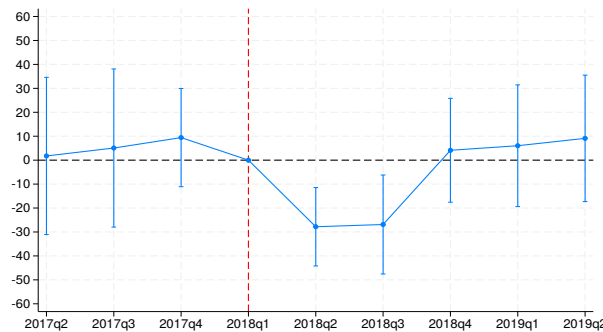
Submodule	Charge (%)	Notes
Equity	30	40% for non-OECD and non-EEA exposures
Currency	25	
Property	25	
Spread	0.9–60	E.g., 12.5% for a BBB-rated bond with a 5-year duration
Interest rate		variable duration gap $\times \Delta$ risk-free rates of 25–75%

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.

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 their SCR ratio in the immediate aftermath of the sovereign shock. To do this, we estimate the following panel regression for the SCR ratio (Equation C.1):

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

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.15: **SCR ratio for highly exposed ICs**

Notes: The figure depicts the results of Equation C.1. The dots report the point estimate of the coefficients for each quarter. The dashed vertical line indicates the last pre-shock period. Confidence bands are at the 90% level based on standard errors clustered at the insurance level.

Our results show that *HighExpIT* ICs experienced an immediate average reduction of 30 percentage points in their SCR ratio relative to the *LowExpIT* group (Figure C.15).

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.