Getting Called:
The Risks of Investor Liquidity Provision to Private Funds*

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Abstract

Institutional investors commit trillions of dollars to private funds. These commitments give fund managers discretion to call capital on short notice, effectively making investors their liquidity providers. Using novel data on insurers' $370 billion private fund investments, this paper studies the risk of unexpected capital calls. Specifically, I examine the portfolio implications of capital call shocks and the resulting spillovers to public asset markets. I show that capital calls are difficult to predict and that unexpected calls are substantial. Nevertheless, I find no evidence that insurers build liquidity buffers ex ante. Instead, they adjust their portfolios only ex post, primarily by selling risky corporate bonds. These portfolio decisions are driven by regulatory capital considerations. Moreover, capital-call-induced corporate bond sales cause negative price impacts, especially for bonds with high risk weights. These spillover effects are amplified when capital call shocks are concentrated or coincide with other episodes of market stress. Counterfactual stress tests reveal significant aggregate losses under extreme scenarios. Overall, the findings highlight the liquidity risk embedded in private fund commitments and its implications for financial fragility.

Keywords: capital call, private fund, liquidity transformation, liquidity management, institutional investor, financial fragility, insurance company, corporate bond, risk-based capital.
JEL Classification: G11, G22, G23, G28, G32

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1 Introduction

Private funds such as private equity, private debt, and real estate funds manage over $10 trillion in private assets (McKinsey, 2024). Investors behind these funds are predominantly institutional investors, such as insurance companies and pension funds. Understanding the asset allocation and the risk management of these institutional investors and their implications for financial markets more broadly is critical in the wake of the rise of private fund investments. One distinctive feature of private fund investment is that investors make a binding commitment to contribute capital upon receiving capital calls from fund managers. This structure effectively makes institutional investors the liquidity providers to private funds, exposing investors to the risk of unexpected capital calls.

The total amount of uncalled private fund commitments reached $3.7 trillion in 2023 (McKinsey, 2024), on par with unused corporate credit lines from banks (Federal Reserve Board, 2020). Policymakers have expressed concerns about potential systemic risk arising from capital calls. For example, the Federal Reserve warns that "unanticipated calls may pose a liquidity risk for some investors, potentially forcing them to sell other assets to raise liquidity" (Federal Reserve Board, 2023). Similarly, the International Monetary Fund notes that significant capital calls in a downside scenario could spill over to other markets and the broader economy (IMF, 2024). Yet there is little evidence to assess the validity or severity of these concerns. Using novel data on insurers' $370 billion private fund investments, this paper provides the first evidence on how investors manage their portfolios in view of capital call risk and on the resulting spillover effects on public asset markets.

While akin to banks' credit line drawdown risk, capital call risk poses a distinct challenge for private fund investors, who lack banks' structural advantages in managing liquidity provision.[1] A conservative strategy would be to build liquidity buffers ex ante. By holding sufficient liquid assets, investors can meet capital calls without resorting to selling relatively illiquid assets when shocks occur. The trade-off, however, is the lower returns associated with liquid assets. If investors opt to rebalance their portfolios ex post, they must decide which assets to sell. Beyond liquidity considerations, a key factor is the portfolio risk implication. Substituting liquid safe assets for private funds increases portfolio risk, which could be too costly due to regulations or internal risk management mandates. The interactions

[1] Banks' unique advantages of liquidity provision include: (1) stable deposit inflows (Kashyap et al., 2002; Gatev and Strahan, 2006), (2) government-backed deposit insurance (Pennacchi, 2006), and (3) ex post risk management through covenants (Sufi, 2009; Acharya et al., 2014; Greenwald, 2019; Chodorow-Reich and Falato, 2022).

among liquidity, opportunity costs, and risk considerations thus pose a complex portfolio management problem. How investors manage capital call risk remains an open empirical question that this paper aims to explore.

In this paper, I use insurance companies as a laboratory to shed light on the implications of unexpected capital calls. Not only do insurers provide unique data coverage, but the industry has also undergone a profound transformation, with growing involvement in private funds and a shift toward more opaque private assets, raising concerns about systemic risk (BIS, 2025). In that context, I provide the following main novel findings. I first show that fund-level capital calls are difficult to predict and that insurers are unable to smooth idiosyncratic capital call risk through diversification. As a result, investor-level unexpected calls remain substantial. In spite of this, insurers do not appear to build liquidity buffers ex ante. Instead, they adjust their portfolios only ex post, primarily by selling risky corporate bonds. I show that this rebalancing behavior is driven by regulatory capital considerations. Guided by these observed portfolio adjustments, I then examine the spillover effects on the corporate bond market. I find sizable negative price impacts arising from bond sales triggered by capital call shocks, particularly for bonds with high risk weights. Moreover, these spillover effects are amplified when capital call shocks are correlated and coincide with other market stresses.

One key challenge is linking private fund capital calls to investors' portfolio holdings. I address this problem by introducing novel data from insurers' Schedule BA statutory filings. Schedule BA reports "Other Long-Term Invested Assets," which include alternative investments such as private funds. Schedule BA filings are largely unexplored because they are messy and lack consistent asset identifiers.[2] I develop a multi-stage algorithm to overcome these difficulties. The algorithm utilizes the panel structure of the holdings data to detect potential name inconsistencies. It then applies a customized name standardization procedure together with a large language model–based fuzzy matching method. I also conduct extensive manual checks and corrections to ensure data quality.

Schedule BA offers several key advantages over other common datasets. First, to my knowledge, Schedule BA is the only dataset that links investors' private fund investments to position-level holdings in the rest of their portfolio, covering all asset classes including public equities, Treasuries, corporate bonds, and more. Second, as a mandatory regulatory filing, it provides the complete universe of private fund holdings for all U.S. insurers. By contrast, most existing datasets rely on Freedom of Information

[2] To my knowledge, the only existing study that uses Schedule BA data is Foley-Fisher et al. (2023), which studies insurers' CLO investments.

Act (FOIA) requests to public pension funds, which offer only limited coverage (Harris et al., 2014; Brown et al., 2015; Begenau et al., 2020). Third, Schedule BA provides granular, audited information on private fund investments, including capital calls, distributions, uncalled commitments, fair value, and even secondary market sales.

Another key challenge is measuring unexpected capital calls. While expected capital calls can be planned for in advance, unexpected calls force investors to adjust their portfolios on short notice. Therefore, only unexpected capital calls resemble exogenous shocks. To measure plausibly unexpected capital calls, I first estimate expected capital calls at the fund level using a statistically optimal forecasting model, which I describe in more detail below. I then aggregate these fund-level forecasts to the investor level. The unexpected capital call is defined as the positive component of the difference between actual and expected investor-level capital calls. I only account for the positive part because the paper focuses on the implications of unexpected demands for liquidity.

For the forecasting model, I evaluate a set of state-of-the-art machine learning methods to capture potential nonlinear predictive patterns in capital call dynamics. The candidate models include LASSO, Decision Trees, Random Forest, LightGBM, and XGBoost. In addition, I consider two-stage hurdle models to address the issue of zero-inflated capital call data (Tobin, 1958; Cragg, 1971). I include a wide range of predictors, which fall into four categories: (1) macroeconomic variables, such as GDP growth and interest rates; (2) public market variables, such as S&P 500 returns and credit spreads; (3) private market variables, such as aggregate PE deal volume and fundraising amount; and (4) fund-specific characteristics, such as fund age, type, and lagged cash flows. The final model is selected based on out-of-sample (OOS) forecasting performance using rolling windows.

I begin the analysis by providing descriptive statistics on insurers' private fund investments and capital calls. By the end of 2023, insurers' total exposure to private funds reached \$370 billion, comprising \$270 billion in invested assets and \$100 billion in uncalled commitments. On average, private funds account for about 3% of insurers' portfolios. However, the distribution is highly right-skewed, with some insurers allocating more than 10% to private funds. Turning to capital calls, the aggregate amount received by insurers has steadily increased over time, reaching approximately \$10 billion per quarter in 2023. On average, about 10% of uncalled commitments are expected to be called in the subsequent quarter. The time-series variation in unexpected calls is substantial, with some quarters exceeding \$5 billion. Moreover, unexpected calls also exhibit considerable cross-sectional dispersion and pronounced right skewness.

To understand the sources of this variation, I perform a variance decomposition. The expected component of the capital call rate, defined as the fraction of uncalled commitments called in the current quarter, explains less than 10% of the total variation. I then further decompose the unexpected component into investor-specific, time-specific, and idiosyncratic components. The majority of the variation in unexpected calls is idiosyncratic. This finding aligns with the fund-level forecasting results: even the best-performing forecasting model achieves an OOS R^2 of only 7.4%. This low OOS R^2 underscores the unpredictable nature of capital calls, even for complex machine learning models. Moreover, the fact that unexpected calls remain largely idiosyncratic even at the investor level suggests that investors are unable to smooth fund-level uncertainty through diversification.[3] Overall, these results highlight a fundamental dilemma of private fund investing: capital calls are highly unpredictable at the fund level, yet investors cannot diversify away this exposure. As a result, unexpected capital calls remain substantial at the investor level.

I next examine how insurers manage their portfolios in response to capital-call risk. I begin by testing whether they build liquidity buffers ex ante. If this is their strategy, three testable predictions follow: first, there should be a positive correlation between uncalled commitments and liquid asset holdings; second, liquid asset holdings should increase around the time investors make abnormally large new commitments; third, liquid asset holdings should decline when capital call shocks occur, as these buffers are drawn down. Using multiple definitions of liquid assets, I find no support for any of these predictions. These results suggest that insurers do not seem to rely on ex ante buffers to manage the liquidity demand from private fund commitments. A likely explanation is the low return on liquid assets: the opportunity cost of holding liquidity buffers outweighs the transaction costs of selling assets ex post.

Indeed, when capital call shocks materialize, I find that insurers rebalance their portfolios mostly by selling bonds.[4] For every dollar of capital calls, bond holdings decline by approximately 76 cents. There are no changes in cash or Treasury holdings, both statistically and economically. I then analyze

[3]This lack of diversification is largely a structural feature of the private fund market. First, the private fund market is heavily relationship-based, which limits investors' ability to commit to a broad set of funds beyond the general partners they know. Second, high minimum commitment requirements constrain the number of funds to which investors can commit. This is consistent with the findings of Gredil et al. (2021) based on pension fund data.

[4]A potential caveat is that I observe holdings only at a quarterly frequency and thus cannot capture potential intra-quarter dynamics. While insurers might initially use cash or Treasuries to meet an immediate capital call, my results reveal the ultimate source of funding insurers choose to meet capital calls, which is more relevant for understanding the implications for broader financial markets.

which types of bonds investors choose to liquidate. The evidence shows that investors primarily sell corporate bonds. Moreover, when I break bonds down by risk category using NAIC designations, I find that sales are concentrated in NAIC 2 and NAIC 3 categories, which correspond to BBB-rated and high-yield (HY) bonds, respectively. I find no evidence of front running and the portfolio adjustments are persistent.

Selling risky corporate bonds may first appear counterintuitive, as more liquid assets such as Treasuries would seem the more natural choice to liquidate. This suggests that considerations beyond simple transaction costs drive insurers' portfolio rebalancing decisions. One potential explanation is that insurers prioritize preserving their regulatory capital. The key regulatory metric used to assess the financial health of insurance companies is the Risk-Based Capital (RBC) ratio. Prior research has shown that the RBC ratio is critical for insurers (Ellul et al., 2011; Koijen and Yogo, 2015; Becker and Ivashina, 2015; Ellul et al., 2015; Merrill et al., 2021; Becker et al., 2022).[5] Under the current regulatory framework, the RBC ratio is calculated solely on the basis of on-balance-sheet assets and does not account for off-balance-sheet items such as uncalled commitments. As a result, funding an unexpected capital call by selling low-risk-weight assets would raise insurers' required capital and significantly deteriorate the RBC ratio. In contrast, selling risky corporate bonds would help mitigate the deterioration in the RBC ratio. In other words, RBC regulations make insurers view risky corporate bonds as the closest substitutes for private funds.

I provide three pieces of evidence in support of this explanation. First, insurers facing tighter regulatory capital constraints are more likely to sell bonds with higher risk weights, whereas less constrained insurers tend to fund capital calls using cash and more liquid bonds. Second, using position-level data, I find that insurers are more likely to sell bonds with large unrealized gains when facing unexpected capital calls. The reason is that most bonds on insurers' balance sheets are valued at historical cost rather than mark-to-market (Ellul et al., 2015). Selling a bond with unrealized gains increases insurers' book equity value and thus improves the RBC ratio. Finally, I find that the realized impact of unexpected capital calls on the RBC ratio is smaller for constrained insurers, indicating that they actively manage their portfolios to mitigate the negative effects of capital calls. Overall, these results highlight that regulations play a central role in shaping insurers' portfolio responses to capital

[5] Though most insurers are above the minimum RBC ratio cutoff (Ge, 2022), fluctuations in the RBC ratio still matter, as they influence the frequency of regulatory exams and actions, as well as credit ratings, financing costs, and product pricing (Sen, 2023).

call shocks.

Finally, I examine the motivating question raised by policymakers: Do asset sales induced by unexpected capital calls generate spillovers to public asset markets? Because insurers mainly sell corporate bonds, I focus on the corporate bond market. Intuitively, bonds more heavily held by investors facing larger unexpected capital calls should experience greater selling pressure and negative price impacts. To test this, I construct a bond-level measure of exposure to unexpected capital calls in the same spirit as the flow-induced trade-pressure measure commonly used in the literature (Lou, 2012). Consistent with the hypothesis, I find that a one-standard deviation increase in capital call shock exposure leads to a 0.85 bps increase in yield spreads, confirming the spillover channel. The effects are mostly concentrated in BBB and HY bonds, consistent with insurers' rebalancing decisions. Moreover, the spillover effects are amplified during periods of market stress, such as COVID-19: the average spillover effect is nearly three times larger in the first quarter of 2020 than in normal periods.

While the reduced-form estimates identify the average spillover effect, policymakers are often concerned with outcomes under more extreme stress scenarios. I provide suggestive evidence from counterfactual stress tests using the recent demand-system approach to asset pricing pioneered by Koijen and Yogo (2019). Utilizing the corporate bond market demand system estimated by Bretscher et al. (2024), I approximate the price impacts under two illustrative counterfactuals: (1) uncalled commitments are twice as large, and (2) capital-call shocks are highly correlated across insurers. For each scenario, I run 10,000 simulations based on the historical distribution of capital call rates and compute the 1% Value-at-Risk (VaR) for the average changes in bond spreads. The simulations indicate that doubling insurers' uncalled commitments would increase the 1% VaR from roughly 2 bps to about 6 bps. The effect of correlated shocks is even stronger, with the 1% VaR reaching nearly 10 bps, or an aggregate loss of about $8.7 billion. These hypothetical scenarios have not been observed historically and the goal of this exercise is to illustrate how capital-call-induced selling could amplify stress in credit markets and potentially contribute to financial fragility.

Taken together, the paper highlights the risks posed by unexpected capital calls. The commitment structure of private funds positions investors as effective liquidity providers. Fulfilling this liquidity-provision role presents investors with a complex portfolio management problem. Their decisions are shaped by transaction costs, opportunity costs, risk management considerations, and, critically, regulatory constraints. These portfolio responses ultimately shape the direction and magnitude of spillovers to public markets. This paper provides the first systematic evaluation of these dynamics. I focus on insurance companies because of the unique data availability. While the exact portfolio adjustments may vary across investor types, the key message is likely generalizable: unexpected capital calls induce non-trivial portfolio rebalancing and spillovers to public markets.

Related Literature This paper first contributes to the extensive literature on private funds by providing the first empirical evidence on how investors manage their portfolios in response to capital call shocks. Existing studies that focus directly on capital calls are limited and almost entirely focus on the fund rather than the investor side. Closely related, Braun et al. (2023) show that university endowments with large uncalled commitments and low liquidity buffers underperformed their peers during the 2008 financial crisis. Both studies highlight the liquidity risk embedded in private fund commitments. My paper differs by examining both ex ante and ex post portfolio adjustments in light of unexpected capital calls, as well as the resulting spillovers to public asset markets. Robinson and Sensoy (2016) document the cyclicality of fund-level calls and link countercyclical calls to fund performance, while Li (2025) finds that liquidity shocks experienced by investors can cause delays in capital calls and subsequent investments. Maurin et al. (2023) model the capital call structure as an optimal solution to fund managers' moral hazard problem. More broadly, the paper also relates to studies examining the performance implications of cash flow uncertainty in private funds (e.g., Brown et al., 2021, 2024). Additionally, this paper contributes by incorporating a wide range of machine learning methods into capital call forecasting, complementing existing research on predicting fund-level cash flows (Takahashi and Alexander, 2002; Jeet, 2020; Cao, 2023; Jeet, 2024).

This paper also relates to studies on investors' portfolio allocation strategies, a central problem in finance (Markowitz, 1952; Merton, 1969). Focusing on private funds, prior works have examined the optimal allocation with illiquid private funds (Ang et al., 2014; Giommetti and Sorensen, 2024). Gourier et al. (2024) develop and calibrate a dynamic portfolio allocation model with ex ante capital commitments and stochastic capital-call timing, showing that commitment-quantity risk is substantial, causing under-allocation to private funds and welfare losses. Chen et al. (2025) incorporate additional key institutional features, such as regulatory constraints, into a dynamic model of private asset allocation. Korteweg and Westerfield (2022) provides a thorough literature review. This paper provides new empirical evidence of how investors dynamically adjust their portfolio allocation when facing unexpected capital call shocks.

The second literature this paper speaks to is on liquidity transformation and financial fragility by financial intermediaries. Financial fragility can arise when agents offer highly liquid liabilities while holding less liquid assets. This problem has been extensively examined in the context of banks (e.g., Diamond and Dybvig, 1983; Goldstein and Pauzner, 2005). Since the Global Financial Crisis, growing attention has also been extended to nonbank financial institutions including money market funds (e.g., Kacperczyk and Schnabl, 2013; Schmidt et al., 2016), fixed-income mutual funds (e.g., Chen et al., 2010; Goldstein et al., 2017; Choi et al., 2020; Falato et al., 2021; Ma et al., 2022), Exchange-Traded Funds (e.g., Pan and Zeng, 2017; Koont et al., 2025), insurance companies (e.g., Ellul et al., 2022; Chodorow-Reich et al., 2021), and pension funds (e.g., Jansen et al., 2024; Andonov et al., 2025). Almeida et al. (2014) provide a conceptual framework and survey for corporate liquidity management. This paper examines the liquidity management and financial-stability implications arising from a unique form of liquidity provision: institutional investors' capital commitments to private funds.

Third, this paper also speaks to the literature on cross-asset spillovers. Since the global financial crisis, a rapidly growing body of research has studied how risks originating in one asset class can spill over into otherwise unrelated asset classes. For instance, Manconi et al. (2012) document contagion from asset-backed securities to corporate bonds during the crisis. Capponi and Larsson (2015) demonstrate that bank deleveraging activities generate spillover effects on otherwise unrelated assets held by the same banks. Ellul et al. (2015) show that insurers experiencing high mark-to-market losses disproportionately sell unrelated bonds with unrealized gains, transmitting shocks across markets. More broadly, Harvey et al. (2025) identify predictable price co-movements between bonds and equities resulting from portfolio rebalancing activities. This paper introduces the capital-call-induced portfolio rebalancing as a novel spillover channel connecting private assets and public markets. It serves as a first step toward understanding how capital calls affect the interconnectedness between private funds and the public market.

Finally, this paper contributes to the literature studying the implications of risk-based capital regulations. Specific to insurers, Ellul et al. (2011), Ellul et al. (2015), Merrill et al. (2021) and Becker et al. (2022) find that RBC requirements and mark-to-market accounting affect insurers' incentives to sell downgraded assets as they impose higher regulatory capital costs. Becker and Ivashina (2015) demonstrate that, conditional on credit ratings, insurers' portfolios are biased towards bonds with higher yields. In terms of real effects, Koijen and Yogo (2015) show that statutory reserve levels led to extraordinary pricing behaviors for annuity and life insurance products during the financial crisis. Sen (2023) shows how regulatory treatments affect insurers' hedging behaviors. This paper is the first to examine how RBC requirements affect insurers' response to capital call shocks. Furthermore, this paper offers valuable policy insights by highlighting the need to incorporate off-balance-sheet exposures, such as uncalled commitments, when assessing insurers' risk and liquidity management under capital regulations.

Paper Outline The remainder of the paper is organized as follows. Section 2 introduces the institutional background. Section 3 describes the data sources, cleaning procedures, and sample construction. Section 4 explains the key empirical methods. Section 5 performs descriptive analysis. Section 6 studies investors' portfolio adjustments, while Section 7 examines the spillover effects. Section 8 concludes.

2 Institutional Background

2.1 Private Fund Investment

Institutional investors have rapidly expanded their allocation to private funds. Data from the SEC private fund statistics reveal that the total assets under management (AUM) in private funds (a combination of PE, VC, and real estate funds) have grown from approximately $2 trillion in 2013 to around $8.5 trillion by early 2024 (Figure 1 Subfigure (a)). Large financial institutions are the primary investors in private funds. As shown in Figure 1 Subfigure (b), the largest identifiable investor type is pension funds, which account for approximately 25% of the market. Sovereign wealth funds follow, representing around 10%, while insurance companies and nonprofit institutions (such as university endowments) each hold about 5%. Individuals only account for a very small share of the market.[6] Some institutional investors have extremely high allocations to private funds. According to a report by Private Equity International, as of the end of 2024, Temasek Holdings was the largest investor in the private fund space, with more than $148 billion allocated, accounting for 58% of its portfolio.

[Insert Figure 1]

[6] See Balloch et al. (2025) for evidence about retail investors in the private fund market.

2.2 Capital Commitment and Capital Call

Private funds are typically structured as limited partnerships. In this arrangement, private fund investors, known as Limited Partners (LPs), contribute capital but are not involved in the fund's operations. The General Partner (GP), usually the private equity firm, is responsible for sourcing, managing, and exiting investments. The relationship between the GP and the LPs is formally defined in the Limited Partnership Agreement (LPA), which specifies the fund's terms, governance structure, and the rights and responsibilities of all parties.

Unlike investing in public securities or other delegated vehicles such as mutual funds, LPs in private funds do not transfer the full amount of their investment upfront. Instead, at the fund's inception, each LP makes a *Capital Commitment*, which is a binding promise to provide capital upon *Capital Call* request, up to the total committed amount. Throughout the life of the fund, the GP makes capital calls to LPs to finance investments, cover fund expenses, or pay management fees. The remaining uncalled portion of the commitment, which is the total commitment minus cumulative capital calls, is commonly referred to as "dry powder" by practitioners. In most cases, the full commitment is called within the first three to five years of the fund's life, a phase known as the "investment period," during which the GP builds the portfolio. As investments mature and are exited, the GP returns proceeds to LPs in the form of distributions, which typically increase in the later years of the fund's life.

The LPA grants the GP the authority to call capital at its discretion, subject to two restrictions. First, each capital call must be made pro rata based on each LP's initial commitment. Second, the total amount called cannot exceed the committed amount. From the LP's perspective, both the timing and the amount of each capital call are uncertain. Once a capital call is issued, LPs must transfer the required amount to the GP within a short notice period, typically between five and ten days. Failure to meet a capital call within the required period constitutes a default. The penalties for default are severe and may include interest charges, suspension of future distributions, forced sale of the LP's interest, or forfeiture of existing stakes (Litvak, 2004 and Banal-Estano et al., 2016).[7] In addition to financial consequences, defaulting on a capital call can cause significant reputational damage, potentially limiting the LP's future investment. Due to these punitive consequences, defaults on capital calls are exceptionally rare in practice.

An instructive parallel can be drawn between private fund capital call structure and a bank's credit

[7] Also see the LPA template by the Institutional Limited Partners Association: Link.

line. In this analogy, the LP acts as the lender and the GP as the borrower. By committing capital at the fund's inception, the LP effectively extends a line of credit to the GP, with the maximum limit being the total committed amount. Importantly, as with credit lines, the borrower (GP) retains discretion over both the timing and the amount of each drawdown. Consequently, LPs face liquidity and risk management challenges similar to those of banks.

Lastly, some GPs may use capital call facilities, which are credit lines obtained from banks and secured by investors' capital commitments. These facilities allow GPs to fund investments immediately and repay the loan using proceeds from subsequent capital calls. Maturities typically range from 30 days to one year. The main advantage of using capital call facilities is that they enable GPs to deploy capital more efficiently and help reduce the frequency of capital calls, thereby lowering administrative burden. However, they have also been criticized for inflating reported performance and reducing transparency. Albertus et al. (2024) provides a detailed introduction to the institutional background. Importantly, such facilities do not necessarily make capital calls smoother or more predictable. First, as capital calls are consolidated to match with loan repayment, each drawdown will be larger. Second, because these loans are short-term and usually cannot be rolled over, GPs still need to issue capital calls regularly. Given that the data used in this paper are at quarterly frequency, the impact of capital call facilities on the analysis is likely limited.

2.3 Private Fund Cash Flow and Valuation

Private funds exhibit distinctive cash flow dynamics due to their capital call structure. A typical private fund has a lifecycle of 10 to 15 years and is characterized by two main phases: the investment period and the harvest period. During the investment period, capital calls dominate as the GP builds the portfolio. From the perspective of LPs, these capital calls represent negative cash flows. Consequently, the cumulative net cash flow becomes increasingly negative during the early years of the fund. As the fund matures and its investments are exited, it transitions into the harvest period, during which distributions, positive cash flows to LPs, dominate. Over time, as distributions accumulate, the cumulative net cash flow breaks even and eventually turns positive. This unique cash flow pattern is commonly referred to as the "J-curve."

Figure IA.1 provides a real-world fund example to illustrate the cash flow pattern. Capital calls and distributions are represented in blue and red bars. The blue and red lines capture the cumulative capital call and distribution. The fund began with an investment period lasting from its inception in 2007 until roughly 2013. During this phase, cash flows were dominated by capital calls, as the fund gradually drew down its $10 million of committed capital to build its portfolio. The harvest period began around 2012, with distributions increasing significantly. The fund reached breakeven in mid-2015 as cumulative net cash flow (the green line) started to turn positive. Eventually, the fund had generated a cumulative net cash flow of approximately $9 million.

One key challenge in private fund investment is the unavailability of market prices. As most assets held by private funds are illiquid and not frequently traded, it is hard to assess the mark-to-market valuation of the investment. Further, the secondary market for private funds is still limited, which makes it hard to use secondary market prices to infer the fair value of the fund (Jenkinson et al., 2013; Chakraborty and Ewens, 2018; Barber and Yasuda, 2017; Brown et al., 2019).[8]

Despite the fact that fair values are often smoothed or potentially manipulated, they remain central to assessing both the performance and risk of private fund investments. This is particularly important for investors such as insurance companies, for whom fair values are used in calculating Risk-Based Capital (RBC). Under standard accounting frameworks such as GAAP and IFRS, investors are required to record the fair value of private fund investments for which capital has already been called. Uncalled commitments, by contrast, are not reflected on insurers' balance sheets.[9] When capital is called, it is recorded as an additional investment and thus mechanically increases the reported fair value. Subsequent gains or losses on these investments are reflected through fair value adjustments. Distributions are treated as disposal of investment and reduce the fair value accordingly.

3 Data and Sample Construction

3.1 Insurers' Private Fund Investment Data

The primary data source for insurers' private fund investments is Schedule BA from the statutory filings. I obtained the raw Schedule BA data from S&P Capital IQ Pro. Schedule BA reports insurers' "Other Long-Term Invested Assets," a broad category that includes investments not reported in the

[8] Nadauld et al. (2019) find that the average secondary-market discount for PE is 13.8%, with much larger discounts during crisis periods. The liquidity risk highlighted in this paper is distinct: private fund investments are not only illiquid, but also liquidity-demanding.

[9] This differs from the banking regulation. Under the Basel III framework, banks are required to convert such uncalled commitments into on-balance-sheet equivalents using a credit conversion factor (CCF) before applying a risk weight. In contrast, current U.S. insurance regulations focus exclusively on the on-balance-sheet exposure.

other investment schedules.[10] Schedule BA is specifically designed to cover alternative investments such as private funds. Other typical investments reported in Schedule BA include hedge funds, joint ventures, surplus notes, and residual tranches of structured finance vehicles.

One key challenge in using Schedule BA data is the absence of a unique and consistent asset identifier. Investments are reported only by asset name, which often contains inconsistencies, abbreviations, and typographical errors. For my analysis, it is essential that each private fund investment be assigned a consistent identifier across time, as many parts of the analysis rely on tracking lagged values or constructing time series at the fund level. To address this issue, I implement a multi-stage cleaning process. Appendix IA.2 provides a detailed explanation of the procedures. Here I briefly summarize the key steps. First, I manually examine a subset of the raw data to identify common variations in naming conventions and recurring typographical errors. Based on this review, I develop an algorithm to standardize fund names, correcting for frequently observed inconsistencies. Next, for standardized names, I identify potential inconsistencies using the panel structure of the data. In many cases, a fund that appears only sporadically or terminates abruptly is the result of inconsistent naming rather than an actual investment exit. These suspicious cases are flagged for further investigation. I then submit the flagged fund names to a large language model (LLM) to perform fuzzy name matching. A key advantage of using an LLM over traditional string-based fuzzy matching algorithms is that the LLM can incorporate contextual and external knowledge, including internet-based information. This capability is particularly valuable in this setting, where many funds have similar names despite being distinct entities. Relying solely on textual similarity can result in frequent matching errors. Additionally, fund names may change due to mergers, acquisitions, or rebranding, often leading to substantially different names. In such cases, LLM-based matching is the only viable approach for correctly identifying name continuity. After applying the LLM matching, I manually review the remaining unmatched or ambiguous fund names and manually reconcile the inconsistency if possible. Lastly, I assign a unique fund identifier to each cleaned fund name and conduct a thorough review of the final sample to ensure the resulting panel dataset is reliable.

After obtaining unique fund identifiers, I identify all private fund holdings using both the reported asset type and a screening algorithm based on reported fund names. For each private fund investment, I extract the initial investment date and the total commitment amount. I also obtain GP names and

[10] Other investment schedules include Schedule A for real estate, Schedule B for mortgages, and Schedule D for bonds and stocks.

fund types by feeding the fund names to an LLM.[11] I then collect quarterly transaction data, including capital calls, distributions, and sales of fund stakes. Finally, I construct the quarterly fair value for each investment.[12] Computing quarterly fair values requires additional steps because individual fund-level fair value is only available annually. But since transaction data are reported quarterly, I can back out the quarterly fair value. Specifically, I calculate the quarterly fair value by starting from the year-end value and adjusting it with the cumulative quarterly transactions, including capital calls, distributions, and disposals. One important caveat is that fair value adjustments, such as unrealized gains and losses and other-than-temporary impairments, are only reported annually. To estimate the quarterly fair value, I assume that these annual adjustments are evenly distributed across quarters, such that each quarter reflects one fourth of the annual adjustment. Appendix IA.2 provides additional details on the data cleaning and sample construction procedures.

My dataset offers several important advantages over traditional data sources used in the literature. First, because Schedule BA is a mandatory filing for all U.S. insurance companies, the dataset provides comprehensive coverage of private fund investments for each insurer. In contrast, traditional data sources often rely on Freedom of Information Act (FOIA) requests or voluntary disclosures from GPs. While these sources may offer detailed fund-level information, they are typically incomplete at the investor level. Moreover, depending on the data vendor and subscription level, traditional datasets often cover only certain fund types. By contrast, my dataset covers all private fund types, including private equity, venture capital, private debt, real estate, and infrastructure. Second, this novel dataset allows me to link each insurer's private fund holdings to its full financial statements and other portfolio holdings, such as bond and equity positions. This enables an analysis of how insurers manage their overall portfolios in response to private fund investments, which is not possible using existing datasets. Third, because traditional data sources rely heavily on FOIA requests, their LP coverage is concentrated among public pension funds, with limited representation of insurance companies. My dataset therefore offers the first comprehensive, investor-level view of private fund investments by insurers, one of the most important institutional investors in the financial system.

[11] Specifically, I classify funds into six types: private equity, venture capital, private debt, real estate, infrastructure and others.

[12] Insurers are required to report book-adjusted carrying value (BACV) under SAP. For private fund investments, BACV is equivalent to fair value, as all insurers are required to use fair value accounting for these holdings. For the remainder of the paper, I use fair value to refer to BACV.

3.2 Other Data

Insurer Financial and Portfolio Data I obtain financial information on insurance companies from statutory filings through S&P Capital IQ Pro. All variables are aggregated at the insurance group level by insurance type. Key variables include: (1) financial statement items such as total assets, liabilities, capital and surplus, and net income; (2) insurer-level aggregate investment amounts by asset class, including bonds, stocks, mortgages, cash, and others; (3) position-level data on bond holdings, including par value held, fair value adjustments, reported bond types, and NAIC designations; and (4) the annual regulatory risk-based capital (RBC) ratio. Most financial variables are scaled by lagged total assets. I also obtain A.M. Best insurer ratings.

Corporate Bond Data I collect corporate bond characteristics such as issuance date, maturity, outstanding amount, and credit ratings from Mergent FISD. Monthly bond transaction data such as yield, liquidity, and trading volume are obtained from the WRDS Bond Return Database. I calculate bond yield spreads by subtracting the maturity-matched Treasury yield from each bond's yield. All monthly variables are converted to a quarterly frequency by taking quarter-end observations to align with the frequency of the holdings data. These bond-level data are then merged with insurer holding-level data using bond CUSIP.

Other Variables Most macroeconomic and public market data are obtained from the Federal Reserve Economic Data (FRED). Specifically, I collect data on GDP, inflation, Treasury yields, public equity market returns, price-dividend ratios, corporate bond spread indices, and the VIX index. All variables are converted to quarterly frequency. I also use aggregate private fund statistics from the SEC's Private Fund Statistics Reports. I also gather additional private equity and venture capital data from PitchBook. Lastly, I collect data on U.S. private equity market fundraising, deal activity, and internal rates of return (IRR) from PitchBook's quarterly U.S. Private Equity reports.

3.3 Sample Construction

I restrict the sample to insurers that report at least one private fund investment. Following the literature, I aggregate insurers at the insurance group level for each insurer type (Life and P&C). The sample period is from 2008 to 2023, as transaction data are only available starting in 2008. I restrict insurers to those that have positive and non-missing asset and equity values (Capital & Surplus). I also require the annual RBC ratio to be non-missing. The final sample includes 506 unique insurer groups (220 life insurers and 286 P&C insurers) and 6,501 unique private funds. Table 1 provides summary statistics.

[Insert Table 1]

4 Empirical Methods

This section describes two key empirical methods in this paper: (1) measuring unexpected capital calls, and (2) main regression specifications.

4.1 Measuring Unexpected Capital Calls

The main explanatory variable is the investor-level unexpected capital call. There are several reasons to focus on the unexpected component rather than the total capital call. First, investors have some control over total capital calls, as the primary driver is the level of uncalled commitments. For instance, investors who are increasing their exposure to private funds will naturally anticipate higher capital calls due to more recent commitments. This endogeneity introduces identification concerns. In contrast, the unexpected component of capital calls resembles a random shock and is thus more plausibly exogenous. Second, unexpected capital calls are of greater concern to investors because they require immediate portfolio adjustments without prior planning. Expected capital calls, on the other hand, can be managed in advance through strategies such as internal cash flow netting.[13] As a result, the expected and unexpected components of capital calls are likely to have distinct implications for investors' portfolio management.

I adopt a bottom-up approach to plausibly measure investor-level unexpected capital calls. Specifically, I first forecast the amount of capital calls for each individual fund, and then aggregate the fund-level forecasts to the investor level. The unexpected component of capital calls is defined as the difference between realized calls and my measure of investor-level expected calls. This approach

[13] Internal cash flow netting, or "commitment pacing", is a liquidity management strategy in which an LP uses distributions received from older vintage funds to fund capital calls from younger funds, thereby reducing the need to hold cash or rebalance the portfolio. This strategy helps smooth cash flows at the portfolio level (PitchBook, 2022). However, it relies on cash flow forecasting. As a result, it is effective primarily for managing expected capital calls, while unexpected capital calls still need to be funded through other means. For more details about the industry practice, see the report by PitchBook: Link.

takes advantage of the more granular fund-level information and improves predictive performance.[14] Effectively, I assume that investors form expectations based on the best available statistical forecasts. This approach also assumes that investors have the same information set as the econometrician.[15] In the subsections below, I explain the exact implementation in more detail.

4.1.1 Forecasting Models

To predict the fund-level capital call, I generalize the classical Takahashi-Alexander (TA) model (Takahashi and Alexander, 2002) to incorporate state-of-the-art forecasting techniques. Let j index fund and t index time.[16] The amount of next-period capital called, $C_{j,t+1}$, can be expressed as equation (1):

$$C_{j,t+1} \equiv U_{j,t} \times RC_{j,t+1}, \tag{1}$$

where $U_{j,t}$ is the uncalled commitment from the end of the previous period and $RC_{j,t+1}$ is the fund- and time-specific capital call rate.[17] Since $U_{j,t}$ is known, the expected capital call can be expressed as

$$\mathbb{E}_t[C_{j,t+1}] = U_{jt} \times \mathbb{E}_t[RC_{j,t+1}] \tag{2}$$

I use the statistically optimal forecast to measure $\mathbb{E}_t[RC_{j,t+1}]$. Hence, the task is to forecast $RC_{j,t+1}$ at time t. Focusing on forecasting $RC_{j,t+1}$ rather than $C_{j,t+1}$ offers practical advantages as the RC is more stationary over time and less sensitive to fund size, making it more suitable for forecasting and cross-sectional comparisons. Formally, the forecasting model is as follows:

$$RC_{j,t+1} = f\left(\mathbf{X}_{j,t}\right) + \varepsilon_{j,t+1},$$

where $f(\cdot)$ is the nonlinear function to be estimated and $\mathbf{X}_{j,t}$ is the vector of predictors. $\mathbf{X}_{j,t}$ includes four categories of variables: (1) macroeconomic indicators such as GDP growth, inflation, and Treasury yields; (2) public market indicators such as S&P 500 returns, corporate bond spreads, and the VIX index; (3) private market indicators including aggregate private equity fundraising, deal activity, and

[14]The results are qualitatively similar if I directly forecast investor-level capital calls.

[15]While in rare cases some very large LPs, or those serving on investment committees, may possess superior information, most investors do not receive any inside information. This is consistent with my conversation with a fund manager. Furthermore, if investors systematically received inside information about future capital calls, we would expect to observe front-running in their portfolio adjustments. However, the results presented later show that this is not the case.

[16]Let a represent the fund's age, where $a = 0$ signifies the fund's inception. Fund age is directly linked to calendar time t by the relation $t = t_0 + a$, where t_0 is the inception period. For simplicity, I index all variables by calendar time t.

[17]In the original TA model, $RC_{j,t}$ is simplified as a stepwise function of fund age: $RC_{j,t} \approx RC(Age)$.

average internal rates of return; and (4) fund-specific characteristics such as fund type, fund age, vintage year, fund size, GP identity, and lagged capital call rates. The predicted value is denoted as $\widehat{RC}_{j,t+1}$.

Machine learning methods are well-suited for this task, as $f(\cdot)$ can be highly nonlinear. Moreover, these methods naturally capture the effects of the investment-period mandate on capital call rates.[18] I employ a set of classical machine learning methods: LASSO, Decision Tree, Random Forest, LightGBM, and XGBoost. To conserve space, I delegate a more detailed explanation of the models to Appendix IA.3. Here, I provide a short introduction to the key intuition of each model: (1) LASSO is a linear model that performs variable selection by penalizing the inclusion of less important predictors; (2) Decision Tree recursively partitions the data based on predictor values to create a flowchart-like structure for prediction; (3) Building on decision trees, Random Forest constructs and averages many independent trees to improve predictive accuracy and control for overfitting; (4) LightGBM and XGBoost are more sophisticated gradient-boosting models that build trees sequentially, with each new tree correcting the errors of the previous one, allowing the model to learn complex patterns and often lead to state-of-the-art performance. I do not consider more complex methods like neural networks, given their "black box" nature. Furthermore, classical gradient-boosting methods are usually more effective and efficient for structured tabular data without requiring significant tuning and computational cost.

A key challenge in forecasting capital calls is the prevalence of zeros (Lambert, 1992). Such data are called zero-inflated. To address this issue, I adopt a two-stage hurdle model, which can improve performance when handling zero-inflated data (Tobin, 1958; Cragg, 1971; Mullahy, 1986). This approach separates the forecasting problem into two distinct steps. The first stage is a classification task to predict the probability that a capital call will be non-zero. The second stage is a regression task to predict the magnitude of the capital call, conditional on it being positive. The final forecast, $\widehat{RC}_{j,t+1}$, is the product of these two predictions:

1. Probability of a non-zero call: $\Pr\left(RC_{j,t+1} > 0 \mid \mathbf{X}_{j,t}\right) = g_1\left(\mathbf{X}_{jt}\right) = \hat{p}_{j,t+1}$
2. Magnitude of a non-zero call: $\mathbb{E}\left[RC_{j,t+1} \mid RC_{j,t+1} > 0, \mathbf{X}_{j,t}\right] = g_2\left(\mathbf{X}_{jt}\right) = \hat{\mu}_{j,t+1}$
3. Final prediction: $\widehat{RC}_{j,t+1} = \hat{p}_{j,t+1} \cdot \hat{\mu}_{j,t+1}$

[18] For example, a typical LPA specifies the investment period as the first five years. If a fund still has substantial uncalled commitment near the end of the fourth year, we would expect a faster pace of capital calls in the fifth year. Machine learning methods, such as a simple decision tree, can automatically incorporate such patterns without the need to model the relationship explicitly.

I also consider a simple linear model with five variables as the benchmark, as specified in equation (3). The five variables are the lagged capital call rate, lagged uncalled commitments, fund age, fund size, and fund type. These variables are chosen because they are the five most important predictors identified by the best-performing machine learning model, discussed in more detail in the next subsection.

$$\mathbb{E}_t\left[RC_{j,t+1}\right] = \alpha + \beta_1 RC_{j,t} + \beta_2 \text{Uncalled}_{j,t} + \beta_3 \text{Fund Age}_{j,t} + \beta_4 \text{Fund Size}_j + \text{Fund Type}_j \tag{3}$$

4.1.2 Forecasting Outcomes

The models are trained annually using a 5-year rolling window. For example, to forecast the capital call in 2019, the models are trained using data from 2014 Q1 to 2018 Q4. Thus, all forecasting results are out-of-sample. Additionally, to avoid losing observations in my main sample, all models are first trained and tested on the Preqin data, which also provides fund-level cash flow information similar to my data. The advantage is that the Preqin data start in the 1990s, allowing me to have an out-of-sample forecasting model ready at the beginning of my sample.[19] For machine learning models that require tuning of hyperparameters, I apply standard cross-validation procedures using the data before the first 5-year training sample (sample before 2003). All hyperparameters are chosen once and remain constant thereafter. I delegate a more detailed description to the online Appendix IA.3.

To evaluate model performance, I compute the average R^2 for each estimation window. Table 2 shows the results. Models are ranked based on the average out-of-sample R^2. The best model is the two-stage LightGBM with an average out-of-sample R^2 of 7.4%. As expected, the two-stage hurdle models have superior performance. Predictor importance for the top 20 predictors in the best-performing model is shown in Figure 2. Predictor importance quantifies each variable's contribution to reducing the model's prediction error, measured by its average gain. Predictors with higher average gain are more important in explaining the model's predictions. Variables that are intuitively important for predicting capital calls, such as lagged uncalled commitments, lagged capital calls, fund age and fund size, rank among the top predictors.

[Insert Table 2]

[Insert Figure 2]

[19]The results are qualitatively similar if I directly estimate the model using my sample. But I would have to start my main sample in 2013 (or even later if I use cross-validation to choose hyperparameters).

Interestingly, the performance gains from machine learning models over the linear benchmark are surprisingly modest. The best-performing model improves the out-of-sample R^2 by just 0.9%. This suggests that the underlying predictive relationship is largely linear and that the capital call process features a low signal-to-noise ratio. While nonlinear interactions and patterns may exist, this modest improvement implies that they are either weak or unstable over time, making them difficult for machine learning models to exploit consistently out-of-sample. This finding aligns with the institutional knowledge that capital calls are at GPs' discretion and driven by idiosyncratic factors such as investment opportunities and strategy. From LPs' perspective, capital calls therefore often resemble idiosyncratic shocks. Nonetheless, I use the best model (two-stage LightGBM) to predict the capital call rate in the subsequent analysis.[20]

4.1.3 Aggregating to the Investor-level

Using the best predictive model, the expected fund-level capital call amount at period t is computed as

$$\mathbb{E}_t\left[C_{ij,t+1}\right] = U_{ijt} \times \mathbb{E}_t[RC_{j,t+1}] = U_{ijt} \times f\left(\mathbf{X}_{jt}\right),$$

where $U_{i,j,t-1}$ is the amount of uncalled commitment for fund j and investor i at the end of $t-1$. Then, the investor-level expected capital call is computed as

$$ExpCall_{it} = \sum_j \mathbb{E}_t\left[C_{i,j,t+1}\right]$$

Let the realized capital call be denoted as $Call_{it}$. Then, the investor-level unexpected capital call is the difference between the realized capital call and the expected one. Since this paper focuses on the liquidity shock imposed by unexpected capital calls, I only take the positive component of the unexpected capital calls.[21] Formally, the unexpected capital call, $UnexpCall_{it}$, is defined as in equation (4). Section 5 provides more description of the unexpected capital call measures.

$$UnexpCall_{it} = \max\{Call_{it} - ExpCall_{it}, 0\} \tag{4}$$

[20] All results remain similar if I use the linear benchmark model. Robustness of some key results is tabulated in the Appendix.

[21] Negative unexpected capital calls represent positive cash flow shocks, to which investors may respond differently. Therefore, focusing only on the positive component makes the interpretation cleaner.

Figure IA.8 displays predicted and actual capital calls over the fund lifecycle. The red lines represent the actual average capital calls, while the blue lines show the corresponding model predictions. The blue area represents the 95% confidence interval of the predicted values. Panel (a) plots the capital call rate (RC), which follows a bell-shaped pattern: it begins at roughly 6% in the first year, increases to about 13% by year five, and declines thereafter. Panel (b) shows cumulative capital calls as a percentage of total commitments. On average, 20% is called by the end of year one, and approximately 80% is called within the first five years. The close alignment between the red and blue lines provides validation for the prediction model.

4.2 Main Regression Specification

The main regression model is at the insurer–time level. Specifically, the specification is as follows:

$$\Delta Y_{i,t} = \beta_1 UnexpCall_{it} + \beta_2 ExpCall_{it} + \beta_3 Dist_{it} + Controls + \gamma_i + \alpha_t + \epsilon_{it} \tag{5}$$

The main dependent variables are changes in portfolio allocations. The key explanatory variable is the unexpected capital call, $UnexpCall_{it}$. I also include the expected capital call, $ExpCall_{it}$, to examine how investors manage the capital calls that are anticipated. I control for distributions, $Dist_{it}$, as distributions are positive cash flow shocks that also affect portfolio allocation.[22] Additional controls include lagged expected and unexpected capital calls, lagged distributions, lagged private fund allocations, asset growth, return on assets, insurer size, capital and surplus, leverage ratio, and the previous year-end RBC ratio.

One potential concern is that omitted variables might bias the estimation, as this empirical approach only relies on fixed effects and control variables.[23] For an omitted factor to bias the estimation, it

[22]Another way to control for distributions is to directly use net cash flows, defined as distributions minus capital calls. While net cash flows indeed represent the ultimate cash flow shocks investors experience from their private fund investments, I choose to separate capital calls and distributions in the main specifications for several reasons. First, combining capital calls and distributions may create identification concerns. Unexpected capital calls are plausibly exogenous, as they largely stem from the stochastic timing of private investments. Distributions, however, are directly influenced by public equity market conditions (e.g., exits through IPOs or M&A), which could introduce omitted-variable bias. For instance, if we observe a reduction in equity holdings following a negative cash flow shock driven by low distributions, that effect is likely confounded by equity market downturns. Second, focusing on capital calls allows me to isolate the liquidity shock channel. Distributions represent positive cash inflows, to which investors may respond very differently. Combining the two would therefore blur the interpretation. Third, it is substantially more difficult to measure the unexpected component of distributions, since the model would need to predict not only distribution rates but also growth rates, increasing the risk of measurement error. Nonetheless, I show in the Appendix that the results are robust when using net cash flows instead.

[23]Reverse causality is unlikely, as capital calls are initiated by GPs.

must satisfy two conditions: (1) be correlated with both unexpected capital calls and changes in portfolio allocations, and (2) disproportionately affect certain investors (not absorbed by time fixed effects). There are several reasons why I do not think omitted variable bias poses a serious threat to my analysis. First, unexpected capital calls are constructed as the residuals from the machine learning prediction model and are therefore unpredictable by nature. Second, GPs, not LPs, control the timing of capital calls, and commitments are made well before capital is drawn, making it unlikely that investors can adjust calls in response to their own contemporaneous shocks. Third, I am not aware of any economically plausible omitted factors that could jointly drive unusually high capital calls and systematic portfolio rebalancing.[24]

Lastly, to fully account for the dynamic effects of unexpected capital calls, I estimate a local projection following Jordà (2005). The local projection method estimates the dynamic impulse response of an outcome variable to shocks at different horizons. Specifically, this approach directly regresses the cumulative changes in the outcome variable on current shocks. My model specification is as follows:

$$Y_{i,t+h} - Y_{i,t-1} = \beta_1^h UnexpCall_{it} + \beta_2^h ExpCall_{it} + \beta_3^h Dist_{it} + Controls + \gamma_i + \alpha_t + \epsilon_{it} \tag{6}$$

5 Descriptive Statistics

5.1 Insurers' Portfolio Allocation

Table 1, Panel A, presents summary statistics on insurers' portfolio allocations, while Figure IA.9 plots aggregate allocations separately for life and P&C insurers. Long-term bonds are the largest asset class for both groups, accounting for 70% of life insurers' portfolios and 50% of P&C insurers' portfolios. Among bond types, industrial bonds, primarily corporate bonds, dominate, comprising 50% of life and 20% of P&C allocations. Both groups hold approximately 5% in Treasury securities. Other long-term bond holdings include mortgage-backed securities and municipal bonds. A key difference between the two is equity exposure: P&C insurers allocate about 30% to public equities, while life insurers invest only 5%. In contrast, life insurers hold 15% in mortgage loans, whereas P&C insurers' exposure to mortgages is minimal. Both groups hold about 5% in cash and cash equivalents. Lastly, both groups have steadily increased their allocation to Schedule BA assets, reaching approximately 6% of their

[24] I specifically discuss potential confounders such as interest rates in the context of my findings later.

portfolios by the end of the sample period.

5.2 Insurers' Private Fund Investment

Figure 3 plots the aggregate private fund investments held by U.S. insurance companies. Insurers have significantly increased their allocations to private funds, rising from less than 50 billion dollars in 2005 to over 360 billion dollars by the end of 2023. The blue bars in the figure represent the book-adjusted fair value of these investments. As of 2023, the on-balance-sheet book value of insurers' private fund holdings exceeded 260 billion dollars. As discussed earlier, the capital call structure of private funds implies that a portion of committed capital remains off-balance-sheet until it is called. The red bars in the figure represent these uncalled commitments. By the end of 2023, the total uncalled commitments held by insurers were approximately 100 billion dollars. The orange line plots the ratio of uncalled commitments to on-balance-sheet book value. This ratio began at around 50 percent in 2005, reflecting the early stage of insurers' involvement in the private fund market as they built up their portfolios. As insurers' private fund portfolios matured, the ratio declined and stabilized at around 30%.

[Insert Figure 3]

Figure 4 presents the distribution of private fund allocations across insurers. Panel (a) shows box plots of private fund allocations by year, measured as a percentage of total assets. Each box represents the interquartile range (IQR), with the bottom and top edges corresponding to the first and third quartiles. The horizontal dark blue line inside each box denotes the median, while the red triangle indicates the mean. The vertical lines extending from the boxes (whiskers) show the range of the data, excluding outliers. Individual observations beyond the whiskers are plotted as light gray dots. Private fund allocations by insurers have increased steadily over time, particularly after 2020. By the end of 2023, the median allocation is approximately 2%, the average is around 3%, and the third quartile reaches about 4%. The data also reveal substantial heterogeneity and skewness. For example, in 2023, the upper whisker extends to roughly 8%—more than twice the interquartile range—and several outliers exceed 10%. Panel (b) shows a binned scatter plot of private fund allocations versus insurer size, measured by total assets. There is a general positive correlation between insurer size and private fund allocation. However, a few small insurers allocate a disproportionately large share of their assets to private funds.

[Insert Figure 4]

5.3 Investor-level Capital Call Dynamics

Figure 5 subfigure (a) plots the time series of the aggregate amounts of total (red line), expected (green line), and unexpected (blue bars) capital calls. From 2008 to 2024, expected capital calls in the insurance sector rose from about $3 billion per quarter to over $10 billion, reflecting insurers' expansion into private fund investments. Notably, the expected capital call series closely tracks the realized capital calls, supporting the validity of the forecasting method. Subfigure (b) scales capital calls by uncalled commitments to remove the underlying time trend. The aggregate expected capital call rate is almost a flat line around 10%, indicating that about 10% of the remaining commitments are called each quarter. In contrast, the total capital call rate displays substantial fluctuation over time, with notable spikes in 2008, 2012, 2015, and 2021. For instance, the call rate reached 18% in the first quarter of 2013. The total amount of unexpected calls, as defined in Equation (4), is below $2 billion during normal periods but can exceed $5 billion in certain quarters.

[Insert Figure 5]

Figure 6 presents the distribution of investor-level capital calls. Panel A shows capital call rates, while Panel B displays capital call amounts as a share of insurers' total portfolios. Within each panel, subfigures (a) through (c) show total capital calls and the unexpected and expected components, respectively. Consistent with the aggregate patterns, the average capital call rate is around 10%, which is also the average expected rate. About 10% of observations show zero capital call rates, more commonly among investors with only a few private fund commitments. The distribution is highly right-skewed: the 90th, 95th, and 99th percentiles reach approximately 20%, 30%, and 55%, respectively. Around 60% of observations have unexpected capital call rates equal to zero, meaning realized capital calls do not exceed expectations. Conditional on receiving a positive unexpected call, the average unexpected capital call rate is approximately 12%. The distribution of capital call amounts as a share of insurers' total portfolios is more dispersed, as it reflects variation in portfolio size and private fund exposure across investors. On average, capital calls equal 0.2% of portfolio value. At the upper tail, the 90th, 95th, and 99th percentiles are 0.5%, 0.7%, and 1%, respectively.

[Insert Figure 6]

Figure 7 plots the distribution of unexpected capital calls over time. The pattern mirrors that of Figure 5, with the distribution shifting upward during periods of high aggregate capital calls. Still, the cross-sectional dispersion remains wide each quarter. The 99th percentile frequently reaches 1%, highlighting that some insurers face large unexpected calls even when aggregate capital calls are moderate.

[Insert Figure 7]

To further understand the sources of variation in investor-level capital calls, I conduct a variance decomposition. Table 3 Panel A presents results for capital call amounts scaled by investors' portfolio size, while Panel B reports results for capital call rates. For capital call amounts, the expected component accounts for approximately 60% of the total variation, largely driven by cross-sectional differences in uncalled commitments. In contrast, for capital call rates, the expected component explains less than 10% of the total variation. By construction, the positive part of unexpected capital calls accounts for roughly half of the remaining variation. I further decompose the unexpected component into investor-specific, time-specific, and idiosyncratic elements. Specifically, I compute the R^2 from regressions with insurer fixed effects to capture investor-specific variation, with time fixed effects to capture time-specific variation, and use the residual from a two-way fixed effects model to measure the idiosyncratic component. Approximately 16% of the variation is investor-specific, 4.2% is time-specific, and 78% is idiosyncratic. These results suggest that, although investor-level capital calls display some aggregate patterns, most of the variation remains idiosyncratic.

[Insert Table 3]

The high degree of idiosyncratic variation in capital calls suggests that investors are significantly under-diversified with respect to capital call risk. A common explanation is that the high costs of selecting and managing a large number of private fund investments make it impractical to hold a fully diversified "market portfolio" of private funds (Brown et al., 2024; Gredil et al., 2021). The unpredictable and idiosyncratic nature of capital calls implies that investors face substantial risk from unexpected capital call shocks. Motivated by this, the next section examines the portfolio management challenges posed by such shocks.

6 Portfolio Effects

6.1 Ex Ante Liquidity Buffers

Given the inherent unpredictability of capital calls, a conservative approach is to hold sufficient cash or liquid asset buffers in anticipation of future drawdowns. However, maintaining large buffers can be costly, especially when capital calls are more unpredictable. Investors may be forced to hold low-yield assets over extended periods. Moreover, it is unclear how much of a buffer is optimal. The most conservative strategy would require holding a buffer equal to 100% of uncalled commitments, but such an approach is impractical. In practice, determining the optimal buffer remains an unsolved issue.[25] Thus, how investors manage capital calls ex ante remains an open empirical question.

I begin by examining whether investors prepare for future capital calls by holding liquid asset buffers. If that is the case, we would expect a positive correlation between cash holdings and uncalled commitments. Figure 8 presents bin-scatter plots where the x-axis shows uncalled commitments and the y-axis shows liquid asset holdings. Panels (a) through (d) consider four definitions of liquid assets: cash, Treasury bonds, NAIC 1 bonds (e.g., A–AAA rated corporate bonds), and a composite measure combining all three. Across all definitions, the correlations are either flat or slightly negative, which suggests no ex ante liquid asset buffer in preparation for future capital calls.

[Insert Figure 8]

Table 4 presents the formal regression analysis. In Panel A, I regress liquid asset holdings on uncalled commitments. None of the estimated coefficients are statistically significant, and three are negative. To test whether investors increase liquid buffers following new commitments, I examine changes in liquid assets after new commitments in Panel B. Again, the results are statistically insignificant. Figure 9 further illustrates the dynamic effects and confirms the results. Together, these findings suggest that, on average, investors do not appear to hold liquid asset buffers ex ante in anticipation of future capital calls.[26]

[Insert Table 4]

[Insert Figure 9]

[25] For example, PitchBook provides clients with solutions for capital call forecasting and liquidity management. See link.

[26] These results are consistent with the findings of Andonov et al. (2025), which show that public pension funds also maintain low liquidity buffers despite facing potential negative cash flow shocks.

6.2 Ex Post Portfolio Adjustments

Next, I examine how investors rebalance their portfolios in response to capital calls. The dependent variables are changes in portfolio allocations across major asset classes: private funds, long-term bonds, cash, mortgage loans, equities, and a residual category. Since the data only provide insurers' end-of-quarter holdings, I cannot observe intraquarter portfolio adjustments. For example, consider a scenario in which an investor initially uses cash to meet a capital call and later in the quarter sells corporate bonds to restore the original cash level. In such cases, my analysis would primarily capture the bond-selling activity, not the immediate use of cash. Therefore, the results should be interpreted as reflecting the impact of capital calls on investors' equilibrium portfolio allocations, rather than their immediate liquidity responses. While the latter is more relevant for studying short-term liquidity risk, the former offers more insights regarding the longer-term portfolio implications of capital calls.

Table 5 presents the results. Panel A reports the effects of total capital calls. As expected, capital calls lead to significant increases in private fund allocations, while distributions lead to significant decreases. The coefficients suggest that a 1% capital call results in an approximate 0.6% increase in private fund allocation, whereas a 1% distribution leads to a 0.9% decrease. More interestingly, column (2) shows that a 1% capital call is associated with a 0.5% reduction in long-term bond holdings. Column (3) indicates a 0.25% decline in cash holdings, although this estimate is not statistically significant. Columns (4) through (6) show no meaningful changes in other asset classes, such as mortgage loans and equities. Taken together, the results suggest that investors meet capital calls primarily by reducing their holdings in long-term bonds and, to a lesser extent, cash. For distributions, although the estimates are not significant, the direction of the coefficients suggests that proceeds are reinvested into cash, bonds, and other residual asset categories. Figure 10 presents the dynamic effects using local projections as in equation (6).

[Insert Table 5]

[Insert Figure 10]

Panel B separates expected and unexpected components. The results for unexpected capital calls closely mirror those for total capital calls: investors primarily reduce allocations to long-term bonds. In contrast, the coefficients for expected capital calls are statistically insignificant and much smaller in magnitude. This is consistent with the earlier discussion that expected calls are managed ex ante through strategies such as internal cash flow netting. Such an approach eliminates the need for investors to adjust their portfolios when expected calls are realized. As a result, expected capital calls generate little explanatory variation in portfolio shifts, leading to small and insignificant regression coefficients. Appendix IA.1 provides a simulation that illustrates how commitment strategies can mute the estimated effect of expected calls.

Additionally, Figure 11 presents the dynamic effects using local projections as in Equation (6). The results suggest that the effects of unexpected capital calls on portfolio allocations are persistent. Notably, while not statistically significant, investors continue to reduce long-term bond holdings in the subsequent quarter, while beginning to rebuild cash balances. This pattern is consistent with the notion that investors seek to maintain a stable level of cash. After partially funding the capital call with cash in the first quarter, they appear to offset that drawdown by selling additional bonds in the following quarters, thereby returning cash holdings to pre-shock levels.

[**Insert Figure 11**]

Omitted variables are unlikely to drive these findings. An important driver of changes in bond holdings is movements in interest rates. Time fixed effects may not be sufficient if interest rate changes disproportionately affect bond holdings for certain insurers. An increase in interest rates typically leads to a decline in bond allocations, either mechanically through price decreases or through active rebalancing. However, for most private funds, such as buyout and real estate funds, higher interest rates tend to reduce capital calls, because many private deals rely on access to credit markets for leverage.[27] This pattern is the opposite of my findings. Furthermore, the fact that the coefficients on changes in private fund allocations and bond allocations are roughly one-to-one provides additional support that the estimated effects are likely causal.

The next question is which types of long-term bonds investors are selling in response to capital calls. Table 6 presents the regression results, and Figure 12 displays the corresponding dynamic effects. In Panel A, long-term bonds are first broken into four types: Treasury bonds, industrial bonds, non-Treasury government agency bonds, and others. Only industrial bonds show a statistically significant decline, with a 1% unexpected capital call resulting in a 0.75% reduction in allocation, which is close

[27]The only exception may be private debt funds. For example, higher interest rates can create additional investment opportunities for distressed lending strategies. I rule out this concern by conducting two robustness checks: (1) excluding private debt funds and (2) focusing on subsamples with no changes in interest rates. All results remain unchanged.

to 100% of the total impact of capital calls on long-term bond holdings. Additionally, columns (5) and (6) further divide industrial bonds into corporate and non-corporate segments, revealing that nearly all the reduction occurs in corporate bonds. These results together imply that investors predominantly liquidate corporate bonds to meet unexpected capital calls.[28]

Another dimension that may influence insurers' bond-selling decisions is the NAIC designation, which directly affects the RBC risk weight. Panel B of Table 6 presents the results. Columns (1) through (6) correspond to NAIC designations 1 through 6. Bonds with an NAIC 1 designation are considered the safest and most liquid, while those with NAIC 6 are the riskiest and least liquid. The associated RBC risk weights are summarized in the Appendix. Interestingly, the coefficients on unexpected capital calls are statistically insignificant for NAIC 1 bonds, indicating that insurers generally avoid liquidating these assets. In contrast, capital calls significantly reduce holdings in all other categories. The largest reduction is seen in NAIC 2 bonds, which correspond to BBB-rated corporate bonds. The impact on NAIC 3 through NAIC 6 bonds—primarily HY bonds—is also statistically significant but smaller in magnitude. These findings are consistent with Ge and Weisbach (2021), which shows that insurers shift away from risky corporate bonds when facing negative shocks. Taken together, these findings suggest that insurers fund unexpected capital calls not by selling their most liquid bonds, but rather by liquidating BBB-rated and some high-yield corporate bonds.

[**Insert Table 6**]

[**Insert Figure 12**]

6.3 Mechanism Analysis

Why do insurers choose to sell risky corporate bonds to fund capital calls? If their objective were to minimize transaction costs, they would likely sell Treasury securities or use cash. One potential explanation is that insurers aim to preserve their RBC ratios. As described in Section 2.3, under the current regulatory framework, only private fund investments that are already called and held on the balance sheet are recognized in the RBC calculation, while uncalled commitments are excluded. Since called private fund investments receive a 30% risk weight—the highest among common asset classes—unexpected capital calls increase capital requirements. If insurers were to fund capital calls by

[28] These results are consistent with Andonov et al. (2025), which also find that public pension funds do not rely on cash or Treasuries when facing negative cash flow shocks.

using cash or highly liquid assets such as Treasury securities or NAIC 1 bonds—both of which have a 0% risk weight—they would be replacing the lowest-cost assets with the highest-cost ones. This substitution leads to a significant increase in required capital and a deterioration in the RBC ratio.

The above explanation suggests that insurers facing tighter regulatory capital constraints are more likely to fund capital calls by selling bonds with higher risk weights. To test this hypothesis, following Sen (2023), I divide insurers into two groups based on whether their RBC ratio is above or below the median within their insurer type (Life or P&C) in each period. Insurers with below-median RBC ratios face tighter regulatory capital constraints. Table 7 presents the results, and Figure 13 reports the corresponding dynamic effects estimated using local projections. Panels A and C show the outcomes for the low-RBC group, while Panels B and D correspond to the high-RBC group. Consistent with the hypothesis, insurers with tighter regulatory capital constraints are more likely to sell bonds in response to unexpected capital calls, whereas those with looser constraints tend to rely more on cash. Further breakdown by bond category reveals that constrained insurers are particularly likely to sell BBB and HY bonds to fund unexpected capital calls, again consistent with the hypothesis.

[Insert Table 7]

[Insert Figure 13]

In addition to selling bonds with high risk weights, insurers may also preserve their RBC ratios by selling bonds with high unrealized gains. Since most bonds are held at historical cost rather than marked to market (Ellul et al., 2015), selling a bond with unrealized gains will increase equity and improve the RBC ratio. Based on this reasoning, I hypothesize that insurers facing tighter regulatory capital constraints are more likely to sell bonds with high unrealized gains. To test this, I use position-level data and estimate a regression where the dependent variable equals one if a bond is sold. The analysis is conducted at the insurer-bond-time level. To isolate the effect of unrealized gains, I include tight fixed effects. Bond-by-time fixed effects control for bond-specific time-varying characteristics, including performance, coupon, maturity, and credit quality. This allows me to compare the sale decisions of two insurers holding the same bond at the same time but with different unrealized gains due to different purchase prices. I also include insurer-by-time fixed effects to absorb time-varying insurer-specific factors, such as capital position and liquidity needs.

Table 8 presents the results, with Panel A showing the full sample, Panel B the low-RBC group, and Panel C the high-RBC group. First, in line with earlier findings from the insurer-level analysis, the interaction between unexpected calls and NAIC designation is significantly positive, indicating that insurers tend to offload bonds with higher regulatory risk weights when facing unexpected capital calls. The coefficient on unrealized gains is significantly negative, indicating that, in general, insurers are less likely to sell bonds with large unrealized gains. This finding is intuitive, as insurers are typically buy-and-hold investors and have little incentive to sell well-performing bonds under normal conditions. Notably, the interaction term between unexpected capital calls and unrealized gains is significantly positive. This implies that, when faced with unexpected calls, insurers are more likely to sell bonds with high unrealized gains, consistent with the hypothesis.

Additionally, I include a measure of bond illiquidity along with the corresponding triple interaction terms in column (3) to assess how insurers balance the trade-off between transaction costs and the impact on their RBC ratios. The interaction between unexpected capital calls and illiquidity is significantly positive, indicating that insurers are more likely to sell illiquid bonds in response to capital calls. While this finding may appear counterintuitive, it likely reflects the fact that bonds with higher risk weights also tend to be less liquid. Importantly, both triple interaction terms are significantly negative. This suggests that, conditional on the same NAIC designation and unrealized gains, insurers are less likely to sell illiquid bonds, which is intuitive. Taken together, these results imply that insurers prioritize preserving their RBC ratios over minimizing transaction costs when deciding which assets to liquidate in response to unexpected capital calls.

[**Insert Table 8**]

Another way to validate insurers' incentive to preserve their RBC ratios is to examine the realized impact. The hypothesis is that insurers facing tighter capital constraints should experience smaller realized declines in their RBC ratios following unexpected calls due to their efforts to preserve the RBC ratio. Table 9 presents the results. Consistent with this hypothesis, the coefficient on unexpected capital calls is statistically insignificant for the low-RBC group but significantly negative for the high-RBC group. This suggests that constrained insurers actively manage their RBC ratios when facing unexpected capital calls, whereas unconstrained insurers do not.

[**Insert Table 9**]

7 Spillovers

In this section, I examine whether portfolio rebalancing induced by unexpected capital calls generates spillover effects to other parts of the financial market. In particular, as previous results show insurers mostly sell corporate bonds, I focus my analysis on the corporate bond market. The central hypothesis is that bonds more heavily held by insurers with larger unexpected calls should experience temporary price declines due to selling pressure.

7.1 Measuring Bond-level Capital Call Exposure

To test this hypothesis, I first construct a bond-level measure of exposure to insurers' unexpected capital calls, $Exposure_{it}$, which is effectively an ownership-weighted average of unexpected calls across insurers. The formal definition of $Exposure_{it}$ is provided in Equation (7). $Ownership_{ij,t-1}$ denotes insurer j's lagged ownership share of bond i, and $UnexpCall_{jt}$ represents the dollar amount of unexpected calls for insurer j at time t. This step assumes that non-insurance bondholders face no capital calls or do not use corporate bonds to meet capital calls.[29] Hence, the results can be viewed as a lower bound. I then scale this weighted average by the lagged amount outstanding for bond i to account for differences in bond sizes. Finally, I take the log, as the distribution of the raw measure is highly dispersed. The Appendix shows the distribution of $Exposure_{it}$.

$$Exposure_{it} = \log\left(1 + \frac{\sum_j Ownership_{ij,t-1} \times UnexpCall_{jt}}{Outstanding_{i,t-1}}\right) \tag{7}$$

The intuition behind $Exposure_{it}$ is similar to the flow-induced trade-pressure measure commonly used in the literature (Lou, 2012). Insurers' unexpected capital calls are plausibly exogenous to bond fundamentals. Furthermore, each bond's exposure to the capital call shock is determined by its lagged ownership. Hence, $Exposure_{it}$ should satisfy the exclusion restriction and can be used as an IV. For instance, to estimate the effect of insurers' selling activity on bond prices, one could regress bond yields on the amount of bond holdings sold by insurers. This is similar to approaches used in the price elasticity literature (e.g., Chaudhary et al. 2023). To isolate the price impact arising specifically from capital calls, $Exposure_{it}$ can serve as an instrument for the insurer sales variable. The corresponding

[29] Given that corporate bonds are largely held by insurance companies and mutual funds, this assumption is reasonable. The caveat is that I exclude pension funds, which invest in both private funds and corporate bonds.

two-stage least squares (2SLS) specification is shown in Equation (8).

$$\begin{aligned} \Delta YieldSpread_{it} &= \beta \Delta \widehat{Holdings}_{it} + Controls_{it} + FEs + \epsilon_{it} \\ \Delta Holdings_{it} &= \gamma Exposure_{it} + Controls_{it} + FEs + u_{it} \end{aligned} \tag{8}$$

7.2 Spillover Results

Table 10 presents the results of the spillover tests. Columns (1) through (3) assess the validity of the exposure measure by testing whether bonds with higher exposure to capital call shocks experience greater selling pressure from insurance companies. In column (1), the dependent variable is the total amount of shares sold by insurers, scaled by bond size. Column (2) examines the extensive margin. In both cases, the coefficient on $Exposure_{it}$ is significantly positive, indicating that bonds with higher exposure are more likely to be sold by insurers. Column (3) provides a more direct test by examining changes in insurers' ownership. The coefficient on $Exposure_{it}$ is significantly negative, suggesting that bonds with greater capital call exposure experience a decline in insurance ownership over time. In economic terms, a one-standard-deviation increase in $Exposure_{it}$ is associated with a 0.3% decline in insurer ownership.

[Insert Table 10]

Next, I examine whether the selling pressure induced by capital calls leads to price impacts. In column (4), I regress the change in yield spread on the bond-level exposure measure. The coefficient on $Exposure_{it}$ is significantly positive, consistent with the hypothesis that bonds with higher exposure experience price declines. Economically, a one-standard-deviation increase in $Exposure_{it}$ is associated with a 0.85 basis point increase in yield spread. To further test this relationship, I use $Exposure_{it}$ as an instrument for the change in insurers' holdings. The resulting coefficient can be interpreted as a price elasticity. Column (5) reports the second-stage results, with column (3) showing the first stage. The Kleibergen–Paap F-statistic is 32, exceeding the conventional threshold for a strong instrument (Stock and Yogo, 2005). As expected, the coefficient is significantly negative, indicating a downward-sloping demand curve.

Next, I examine the dynamic effects using the local projection framework described in Equation 6. Figure 14 displays the results, with Subfigures (a) through (c) corresponding to Columns (3) to (5) in

Table 10. For insurers' holdings, the coefficients remain stable following the initial decline at period $t = 0$, indicating that insurers do not reverse the reduction in holdings in subsequent quarters. In contrast, the effect on yield spreads appears to be short-lived. Only the contemporaneous coefficient is statistically significant, and it becomes insignificant in the following period. This pattern is consistent with the interpretation of capital call as a transitory shock for certain investors. The immediate price impact reflects limited liquidity in the corporate bond market and the presence of inelastic demand, while the reversal suggests the influence of slow-moving capital.

[Insert Figure 14]

Finally, I examine the heterogeneity of the spillover effects. As shown in Section 6.2, investors do not sell bonds randomly; instead, insurers tend to sell bonds with higher risk weights to mitigate the negative impact on their RBC ratios. Holding everything else constant, bonds with higher risk weights are therefore expected to face greater selling pressure. Moreover, such bonds are, by definition, more illiquid. As demonstrated in Bretscher et al. (2024), illiquid bonds exhibit larger price impacts in response to a given demand shock. Taken together, these insights suggest that bonds with higher risk weights should experience stronger spillover effects from capital call shocks. To test this hypothesis, I interact the exposure measure z_{it} with indicator variables for each bond's NAIC category. These categories are based on credit ratings following Li (2024).[30] Specifically, $NAIC1$ corresponds to bonds rated A to AAA, $NAIC2$ includes bonds rated BBB, and $NAIC3$ comprises lower-rated bonds corresponding to NAIC categories 3 through 6.

Table 11 presents the results. Columns (1) and (3) report regressions of changes in insurers' holdings and yield spreads on the interaction between z_{it} and the NAIC risk-weight indicator variables. For bonds with an NAIC designation of 1, the spillover effects are relatively weak, with coefficients either insignificant or only marginally significant at the 10% level. NAIC 2 bonds (i.e., BBB-rated) exhibit the strongest spillover effects. For the same level of exposure, the selling pressure for NAIC 2 bonds is about four times greater than that for NAIC 1 bonds, and the associated price impact is more than ten times larger. Bonds with lower credit ratings (NAIC 3–6) also experience significant spillover effects, though of smaller magnitude compared with NAIC 2. Column (4) reports the 2SLS estimates to directly compare price elasticities (first-stage results are in Appendix Table IA.10). Overall, these

[30] I do not use the actual NAIC designations because they may vary across investors, become outdated, or be affected by regulatory changes (Kirti and Singh, 2025).

results align with the findings in Section 6.2, which shows that insurers predominantly sell BBB and HY bonds.

[Insert Table 11]

Lastly, the spillover effects could be amplified when capital call shocks coincide with broader adverse market events. During such periods, already-depressed liquidity conditions may exacerbate the price impact of additional selling pressure as other investors may be unwilling to provide liquidity. On the other hand, investors may choose to use cash rather than sell corporate bonds to meet capital calls, which could lead to smaller spillover effects. Therefore, the overall impact remains an empirical question. I use the COVID-19 pandemic to test this hypothesis, as the corporate bond market experienced severe stress and liquidity shortages (Falato et al., 2021; Kargar et al., 2021). To capture this effect, I interact a COVID dummy (equal to one for 2020 Q1) with $Exposure_{it}$. Columns (2) and (5) report OLS results, and Column (6) presents the 2SLS estimates. The coefficient on insurers' holdings is slightly smaller during this period, possibly reflecting insurers' reluctance to sell corporate bonds in stressed markets. Despite this, the coefficient is still significantly negative. The estimated price impacts are nearly three times larger than in normal periods. These findings support the idea that spillover effects are amplified when capital call shocks coincide with broader adverse shocks.

This finding has important implications for financial stability. As shown in Section 5, most of the variation in capital calls is idiosyncratic, meaning that some investors may still experience large capital calls during periods of market stress. Indeed, a closer look at Figure 7 shows that certain insurers faced unexpected capital calls as large as 1% of their total assets in 2020 Q1. These "inconvenient" capital calls can trigger large spillover effects. Actually, some industry reports have documented that some private credit funds issued abnormally high capital calls during the first quarter of 2020, particularly in senior debt and distressed debt strategies.[31] As private fund investments continue to grow, the risk of such "inconvenient" capital calls may pose a threat to financial stability.

7.3 Counterfactual Stress Tests

While the reduced-form estimates identify the average spillover effect, policymakers are often concerned with outcomes under more extreme stress scenarios. In this section, I provide suggestive evidence from

[31] See MSCI.

simulated stress tests using the recent demand-system approach to asset pricing pioneered by Koijen and Yogo (2019). To conserve space, I briefly outline the key steps in the simulation procedure and leave further details to Appendix IA.5.

I begin with insurers' actual holdings at 2019Q4, as the Bretscher et al. (2024) sample ends in 2020Q3, and I want to avoid the COVID period. For each bond, I observe the holdings across all investors. The demand elasticities and other coefficients of the demand system are directly taken from Bretscher et al. (2024).[32] I link all insurers (both life and P&C) to my dataset to obtain their uncalled private fund commitments as of 2019Q4.[33] Next, for each insurer, I randomly draw a capital call rate from the historical distribution. In the baseline simulations, these draws are independent across insurers. Guided by the empirical findings in Section 6.2, I assume that capital calls are funded through corporate bond sales, with the composition of sales determined by the regression estimates. Given these inputs, the demand system computes new equilibrium prices for all bonds. I then calculate the average change in yield spreads across bonds. The simulation is repeated 10,000 times, and I report the 1% VaR.

In addition to the baseline, I consider two stress scenarios: (1) uncalled commitments are twice as large, and (2) capital-call shocks are concentrated. The first scenario is implemented by doubling each insurer's uncalled commitments. For the second scenario, in each simulation, I randomly select half of the insurers to experience capital call rates drawn from the top quartile of the historical distribution.

I report the main results here and provide full details in the appendix. Under the baseline scenario, the 1% VaR is roughly 2 basis points—an economically meaningful change given the size of the corporate bond market. Doubling insurers' uncalled commitments increases the 1% VaR to about 6 basis points. The effect of concentrated shocks is even larger, with the 1% VaR reaching nearly 10 basis points, corresponding to an aggregate loss of roughly $8.7 billion. Admittedly, these hypothetical stress scenarios have not been observed historically. The goal is not to forecast precise outcomes, but rather to illustrate the underlying mechanism: capital-call-induced selling can amplify stress in credit markets and potentially contribute to financial fragility.

[32] I thank the authors for generously providing their code and coefficient estimates.

[33] Effectively, I assume that all other investor types have no uncalled commitments to private funds. Because pension funds also allocate to both private funds and corporate bonds, my estimates should be viewed as a lower bound.

8 Conclusion

The funding structure of private funds makes their investors effective liquidity providers, exposing them to the risk of unexpected capital calls. Utilizing novel data, this paper provides the first systematic examination of insurers' liquidity management practices and the resulting spillovers to public asset markets. Importantly, the findings reveal that investors do not necessarily manage capital call risk in a way that promotes financial stability. Their portfolio decisions are shaped not only by transaction and opportunity costs, but also by risk management considerations and, critically, regulatory constraints. Investors' portfolio responses ultimately shape the direction and magnitude of spillovers to public markets.

This paper focuses on insurance companies because of the unique data availability. While the exact portfolio adjustments may differ across investor types, the key message is likely generalizable: unexpected capital calls induce nontrivial portfolio rebalancing and spillovers to public markets. As private markets continue to expand, capital calls could emerge as a new threat to financial stability. In addition, the rise of private credit could also amplify the spillover effects of capital calls, as calls from private credit funds tend to be more countercyclical. This paper offers an important first step toward understanding how private fund capital calls affect the broader financial market. Further research is needed to assess the full implications.

References

Acharya, Viral, Heitor Almeida, Filippo Ippolito, and Ander Perez, 2014, Credit lines as monitored liquidity insurance: Theory and evidence, *Journal of financial economics* 112, 287–319.

Albertus, James F, Matthew Denes, and Yingxiang Li, 2024, Capital call facilities, *The Palgrave Encyclopedia of Private Equity* 1–6.

Almeida, Heitor, Murillo Campello, Igor Cunha, and Michael S Weisbach, 2014, Corporate liquidity management: A conceptual framework and survey, *Annu. Rev. Financ. Econ.* 6, 135–162.

Andonov, Aleksandar, Kristy AE Jansen, and Joshua D Rauh, 2025, When cash flows turn negative: Liquidity-driven selling by pension funds, *Available at SSRN 5498920* .

Ang, Andrew, Dimitris Papanikolaou, and Mark M. Westerfield, 2014, Portfolio Choice with Illiquid Assets, *Management Science* 60, 2737–2761.

Balloch, Cynthia, Federico Mainardi, Sangmin Oh, and Petra Vokata, 2025, Democratizing private markets: Private equity performance of individual investors, *Available at SSRN 5319498* .

Banal-Estano, Albert, Filippo Ippolito, and Sergio Vicente, 2016, Default penalties in private equity partnerships, *Available at SSRN 1022023* .

Barber, Brad M, and Ayako Yasuda, 2017, Interim fund performance and fundraising in private equity, *Journal of Financial Economics* 124, 172–194.

Becker, Bo, and Victoria Ivashina, 2015, Reaching for Yield in the Bond Market, *The Journal of Finance* 70, 1863–1902.

Becker, Bo, Marcus M Opp, and Farzad Saidi, 2022, Regulatory Forbearance in the U.S. Insurance Industry: The Effects of Removing Capital Requirements for an Asset Class, *The Review of Financial Studies* 35, 5438–5482.

Begenau, Juliane, Claudia Robles-Garcia, Emil Siriwardane, and Lulu Wang, 2020, An empirical guide to investor-level private equity data from preqin, *Available at SSRN 3764895* .

BIS, 2025, The transformation of the life insurance industry: systemic risks and policy challenges, Bis papers no. 161.

Braun, Reiner, Mark Jansen, and Ludovic Phalippou, 2023, Consequences of unfunded capital commitments: Evidence from university endowments, *SSRN* .

Bretscher, Lorenzo, Lukas Schmid, Ishita Sen, and Varun Sharma, 2024, Institutional Corporate Bond

Pricing, *Review of Financial Studies* Forthcoming.

Brown, Gregory, Robert Harris, Wendy Hu, Tim Jenkinson, Steven N. Kaplan, and David T. Robinson, 2021, Can investors time their exposure to private equity?, *Journal of Financial Economics* 139, 561–577.

Brown, Gregory W, Oleg R Gredil, and Steven N Kaplan, 2019, Do private equity funds manipulate reported returns?, *Journal of Financial Economics* 132, 267–297.

Brown, Gregory W., Robert S. Harris, Tim Jenkinson, Steven N. Kaplan, and David T. Robinson, 2015, What Do Different Commercial Data Sets Tell Us About Private Equity Performance?

Brown, Gregory W., Andrei S. Gonçalves, and Wendy Hu, 2024, The Private Capital Alpha, *Working Paper* .

Cao, Wen, 2023, A Latent Factor Cash Flow Model for Alternative Investment Funds, *SSRN Electronic Journal* .

Capponi, Agostino, and Martin Larsson, 2015, Price Contagion through Balance Sheet Linkages, *The Review of Asset Pricing Studies* 5, 227–253.

Chakraborty, Indraneel, and Michael Ewens, 2018, Managing performance signals through delay: Evidence from venture capital, *Management Science* 64, 2875–2900.

Chaudhary, Manav, Zhiyu Fu, and Jian Li, 2023, Corporate bond multipliers: Substitutes matter, *Available at SSRN* .

Chen, Hui, Giovanni Gambarotta, Simon Scheidegger, and Yu Xu, 2025, A Dynamic Model of Private Asset Allocation, *Working Paper* .

Chen, Qi, Itay Goldstein, and Wei Jiang, 2010, Payoff complementarities and financial fragility: Evidence from mutual fund outflows, *Journal of financial economics* 97, 239–262.

Chodorow-Reich, Gabriel, and Antonio Falato, 2022, The loan covenant channel: How bank health transmits to the real economy, *The Journal of Finance* 77, 85–128.

Chodorow-Reich, Gabriel, Andra Ghent, and Valentin Haddad, 2021, Asset insulators, *The Review of Financial Studies* 34, 1509–1539.

Choi, Jaewon, Saeid Hoseinzade, Sean Seunghun Shin, and Hassan Tehranian, 2020, Corporate bond mutual funds and asset fire sales, *Journal of Financial Economics* 138, 432–457.

Cragg, John G, 1971, Some statistical models for limited dependent variables with application to the demand for durable goods, *Econometrica* 829–844.

Diamond, Douglas W, and Philip H Dybvig, 1983, Bank runs, deposit insurance, and liquidity, *Journal of political economy* 91, 401–419.

Ellul, Andrew, Chotibhak Jotikasthira, Anastasia Kartasheva, Christian T Lundblad, and Wolf Wagner, 2022, Insurers as Asset Managers and Systemic Risk, *The Review of Financial Studies* 35, 5483–5534.

Ellul, Andrew, Chotibhak Jotikasthira, and Christian T. Lundblad, 2011, Regulatory pressure and fire sales in the corporate bond market, *Journal of Financial Economics* 101, 596–620.

Ellul, Andrew, Chotibhak Jotikasthira, Christian T. Lundblad, and Yihui Wang, 2015, Is Historical Cost Accounting a Panacea? Market Stress, Incentive Distortions, and Gains Trading, *The Journal of Finance* 70, 2489–2538.

Falato, Antonio, Itay Goldstein, and Ali Hortaçsu, 2021, Financial fragility in the covid-19 crisis: The case of investment funds in corporate bond markets, *Journal of Monetary Economics* 123, 35–52.

Federal Reserve Board, 2020, Financial stability report, Board of Governors of the Federal Reserve System.

Federal Reserve Board, 2023, Financial stability report, Board of Governors of the Federal Reserve System.

Foley-Fisher, Nathan, Nathan Heinrich, and Stéphane Verani, 2023, Are us life insurers the new shadow banks?, *Available at SSRN 3534847* .

Gatev, Evan, and Philip E Strahan, 2006, Banks' advantage in hedging liquidity risk: Theory and evidence from the commercial paper market, *The journal of finance* 61, 867–892.

Ge, Shan, 2022, How Do Financial Constraints Affect Product Pricing? Evidence from Weather and Life Insurance Premiums, *The Journal of Finance* 77, 449–503.

Ge, Shan, and Michael S. Weisbach, 2021, The role of financial conditions in portfolio choices: The case of insurers, *Journal of Financial Economics* 142, 803–830.

Giommetti, Nicola, and Morten Sorensen, 2024, Optimal Allocation to Private Equity, *Working Paper* .

Goldstein, Itay, Hao Jiang, and David T Ng, 2017, Investor flows and fragility in corporate bond funds, *Journal of Financial Economics* 126, 592–613.

Goldstein, Itay, and Ady Pauzner, 2005, Demand–deposit contracts and the probability of bank runs, *the Journal of Finance* 60, 1293–1327.

Gourier, Elise, Ludovic Phalippou, and Mark M. Westerfield, 2024, Capital Commitment, *The Journal* *of Finance* 79, 3407–3457.

Gredil, Oleg, Yan Liu, and Berk A. Sensoy, 2021, Diversifying Private Equity, *SSRN* .

Greenwald, Daniel, 2019, Firm debt covenants and the macroeconomy: The interest coverage channel, *SSRN* .

Harris, Robert S., Tim Jenkinson, and Steven N. Kaplan, 2014, Private Equity Performance: What Do We Know?, *The Journal of Finance* 69, 1851–1882.

Harvey, Campbell R., Michele G. Mazzoleni, and Alessandro Melone, 2025, The Unintended Consequences of Rebalancing, *Working Paper* .

IMF, 2024, Global Financial Stability Report, April 2024.

Jansen, Kristy AE, Sven Klingler, Angelo Ranaldo, and Patty Duijm, 2024, Pension liquidity risk, *Working Paper* .

Jeet, Vishv, 2020, Modeling Private Investment Cash Flows With Market Sensitive Periodic Growth, *SSRN Electronic Journal* .

Jeet, Vishv, 2024, Enhancement to the Takahashi and Alexander's Cash Flow Model, *Working Paper* .

Jenkinson, Tim, Miguel Sousa, and Rüdiger Stucke, 2013, How fair are the valuations of private equity funds?, *Available at SSRN 2229547* .

Jordà, Òscar, 2005, Estimation and inference of impulse responses by local projections, *American economic review* 95, 161–182.

Kacperczyk, Marcin, and Philipp Schnabl, 2013, How safe are money market funds?, *The Quarterly Journal of Economics* 128, 1073–1122.

Kargar, Mahyar, Benjamin Lester, David Lindsay, Shuo Liu, Pierre-Olivier Weill, and Diego Zúñiga, 2021, Corporate bond liquidity during the covid-19 crisis, *The Review of Financial Studies* 34, 5352–5401.

Kashyap, Anil K, Raghuram Rajan, and Jeremy C Stein, 2002, Banks as liquidity providers: An explanation for the coexistence of lending and deposit-taking, *The Journal of finance* 57, 33–73.

Kirti, Divya, and Akshat Singh, 2025, The Insurer Channel of Monetary Policy, *Working Paper* .

Koijen, Ralph S. J., and Motohiro Yogo, 2015, The Cost of Financial Frictions for Life Insurers, *American Economic Review* 105, 445–475.

Koijen, Ralph SJ, and Motohiro Yogo, 2019, A demand system approach to asset pricing, *Journal of Political Economy* 127, 1475–1515.

Koont, Naz, Yiming Ma, Lubos Pastor, and Yao Zeng, 2025, Steering a ship in illiquid waters: Active management of passive funds, *The Review of Financial Studies* 38, 2887–2935.

Korteweg, Arthur, and Mark M. Westerfield, 2022, Asset Allocation with Private Equity, *Foundations and Trends in Finance* .

Lambert, Diane, 1992, Zero-inflated poisson regression, with an application to defects in manufacturing, *Technometrics* 34, 1–14.

Li, Yingxiang, 2025, Liquidity Shocks and Private Equity Investment, *Working Paper* .

Li, Ziang, 2024, Long Rates, Life Insurers, and Credit Spreads, *Working Paper* .

Litvak, Kate, 2004, Governance through exit: default penalties and walkaway options in venture capital partnership agreements, *Willamette L. Rev.* 40, 771.

Lou, Dong, 2012, A flow-based explanation for return predictability, *The Review of Financial Studies* 25, 3457–3489.

Ma, Yiming, Kairong Xiao, and Yao Zeng, 2022, Mutual fund liquidity transformation and reverse flight to liquidity, *The Review of Financial Studies* 35, 4674–4711.

Manconi, Alberto, Massimo Massa, and Ayako Yasuda, 2012, The role of institutional investors in propagating the crisis of 2007–2008, *Journal of Financial Economics* 104, 491–518.

Markowitz, Harry M., 1952, Portfolio selection, *The Journal of Finance* 7, 77–91.

Maurin, Vincent, David T Robinson, and Per Strömberg, 2023, A theory of liquidity in private equity, *Management science* 69, 5740–5771.

McKinsey, 2024, Global private markets report: Private markets in a slower era, McKinsey & Company Report.

Merrill, Craig B., Taylor D. Nadauld, René M. Stulz, and Shane M. Sherlun, 2021, Were there fire sales in the RMBS market?, *Journal of Monetary Economics* 122, 17–37.

Merton, Robert C, 1969, Lifetime portfolio selection under uncertainty: The continuous-time case, *The review of Economics and Statistics* 247–257.

Mullahy, John, 1986, Specification and testing of some modified count data models, *Journal of econometrics* 33, 341–365.

Nadauld, Taylor D., Berk A. Sensoy, Keith Vorkink, and Michael S. Weisbach, 2019, The liquidity cost of private equity investments: Evidence from secondary market transactions, *Journal of Financial Economics* 132, 158–181.

Pan, Kevin, and Yao Zeng, 2017, Etf arbitrage under liquidity mismatch, *Available at SSRN 3723406* .

Pennacchi, George, 2006, Deposit insurance, bank regulation, and financial system risks, *Journal of Monetary Economics* 53, 1–30.

PitchBook, 2022, Allocator solutions: Cash flow forecasting and commitment pacing, Technical report, PitchBook.

Robinson, David T., and Berk A. Sensoy, 2016, Cyclicality, performance measurement, and cash flow liquidity in private equity, *Journal of Financial Economics* 122, 521–543.

Schmidt, Lawrence, Allan Timmermann, and Russ Wermers, 2016, Runs on money market mutual funds, *American Economic Review* 106, 2625–2657.

Sen, Ishita, 2023, Regulatory Limits to Risk Management, *The Review of Financial Studies* 36, 2175–2223.

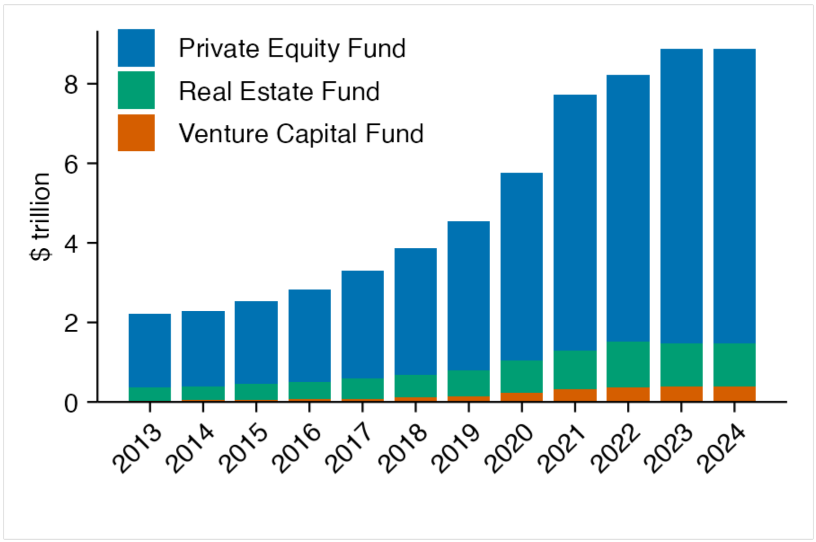
Stock, James, and Motohiro Yogo, 2005, Asymptotic distributions of instrumental variables statistics with many instruments, *Identification and inference for econometric models: Essays in honor of Thomas Rothenberg* 6, 109–120.

Sufi, Amir, 2009, Bank lines of credit in corporate finance: An empirical analysis, *The Review of Financial Studies* 22, 1057–1088.

Takahashi, Dean, and Seth Alexander, 2002, Illiquid Alternative Asset Fund Modeling, *The Journal of Portfolio Management* 28, 90–100.

Tobin, James, 1958, Estimation of relationships for limited dependent variables, *Econometrica* 24–36.

(a) Assets Under Management



(b) Ownership

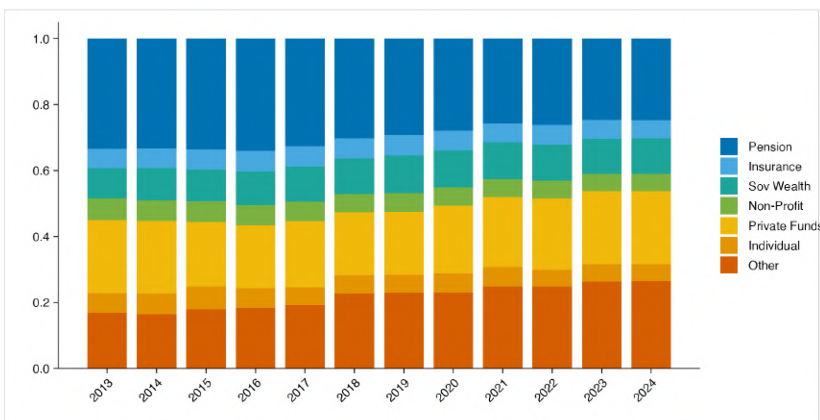
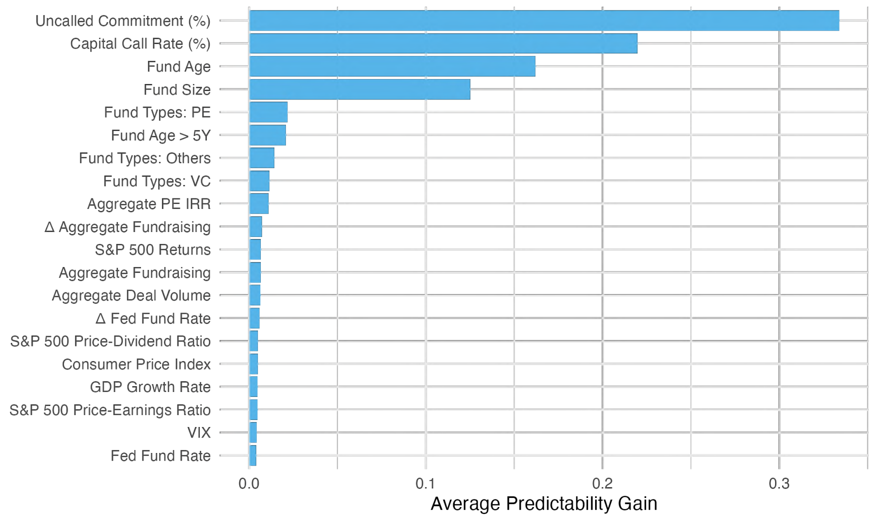


Figure 1: Aggregate Private Fund Investments

This figure plots the total assets under management for different private fund types (Private Fund Statistics Report Table 2.1) from the SEC Private Fund Statistics. According to the definition provided by the SEC, "private equity fund" includes private debt funds. Subfigure (a) plots the total assets under management for different private fund types, and Subfigure (b) plots ownership by different investor types. Private fund types are defined by the SEC according to the instructions of Form ADV (Instruction Part 1A, Item 6.e(2)).

(a) First-stage Classification



(b) Second-stage Regression

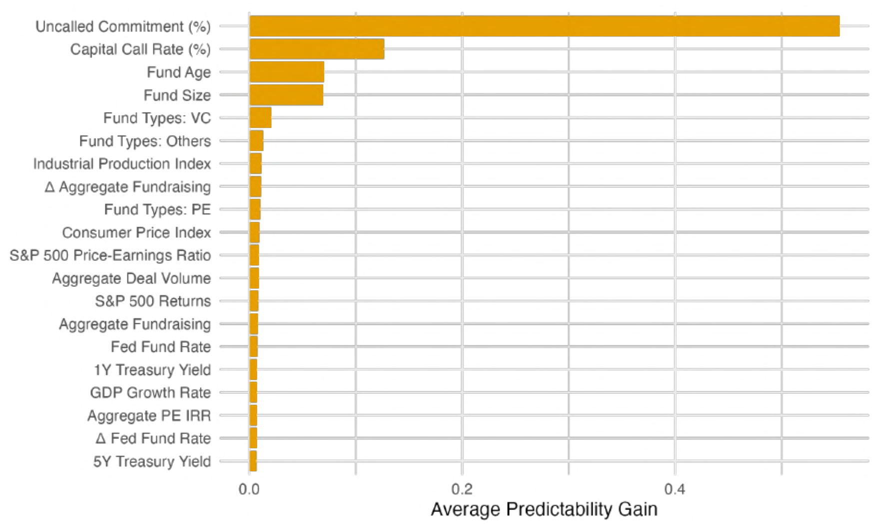


Figure 2: Predictor Importance

This figure presents the predictor (feature) importance for the top 20 predictors in the best-performing machine learning model (two-stage LightGBM). Predictor importance quantifies each variable's contribution to reducing the model's prediction error, measured by its average gain across all splits. Predictors with higher average gain play a greater role in explaining the model's prediction outcomes. Panel (a) reports results for the first-stage classification task, and Panel (b) for the second-stage regression task.

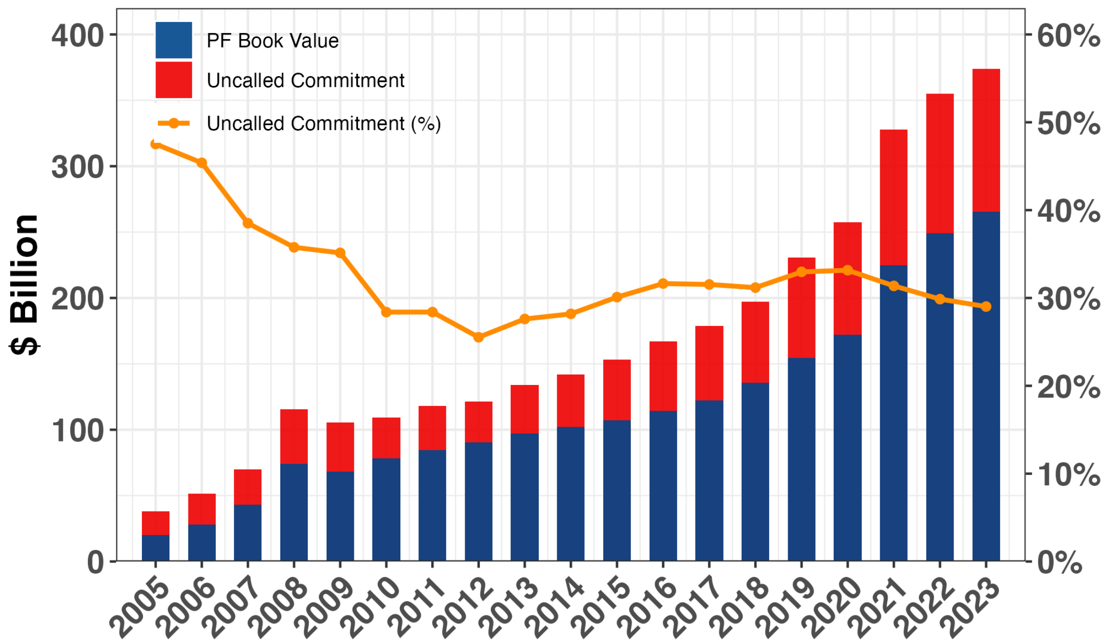
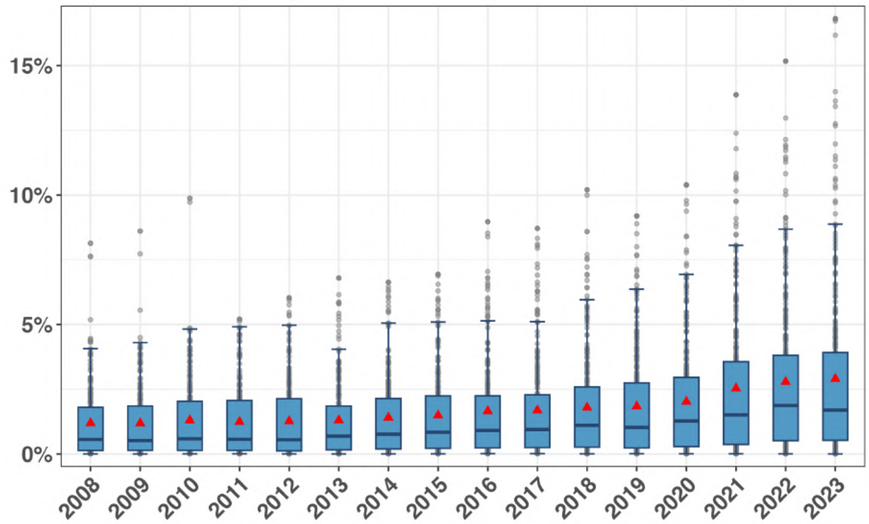


Figure 3: Insurers' Aggregate Private Fund Investments and Uncalled Commitments

This figure plots insurers' aggregate private fund investments. The blue bars (left axis) represent the book-adjusted carrying value (fair book value), and the red bars (left axis) represent the additional uncalled commitments. The orange line (right axis) shows the ratio of uncalled commitments to the book-adjusted carrying value.

(a) Distribution of Private Fund Allocations



(b) Size vs Private Fund Allocations

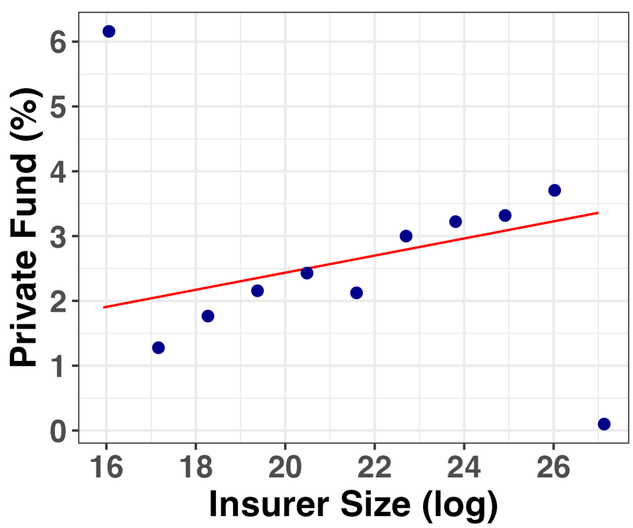
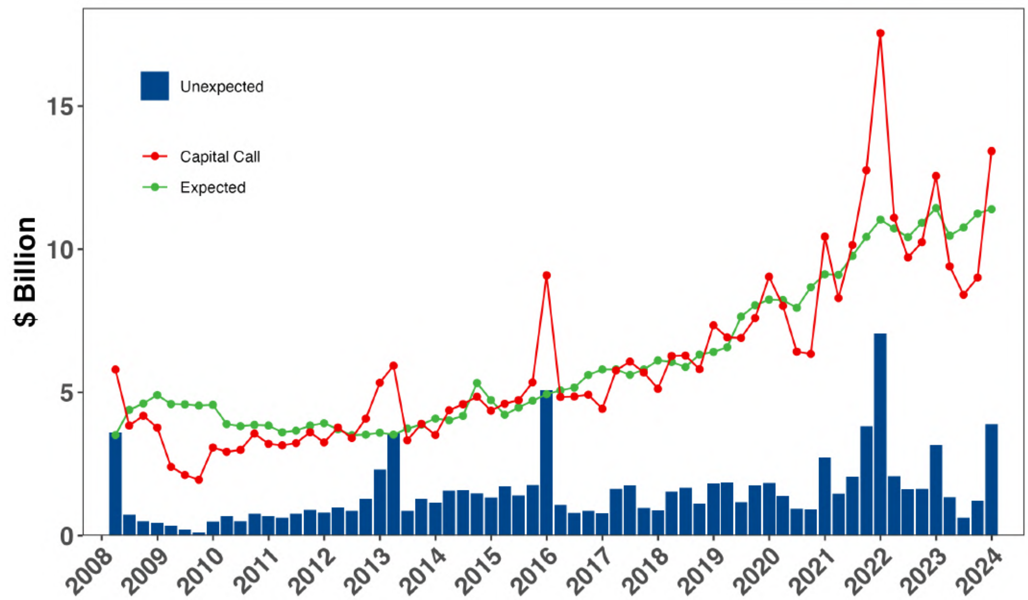


Figure 4: Distribution of Insurers' Private Fund Allocations

This figure shows the distribution of insurer-level private fund allocations. Panel A presents box plots of private fund allocations (measured as a percentage of total assets) by year from 2008 to 2023. Each box represents the interquartile range (IQR), with the bottom and top edges indicating the first and third quartiles, respectively. The horizontal dark blue line within each box denotes the median, while the red triangle represents the mean. The vertical lines extending from the boxes—known as whiskers—indicate the range of the data, excluding outliers. Individual observations beyond the whiskers are shown as light gray dots. Panel B displays a binned scatter plot of private fund allocations against insurer size. The x-axis measures insurer size in terms of total assets, and the y-axis shows the corresponding private fund allocation. A fitted line is included to illustrate the relationship. Private fund allocations are winsorized at the 1st and 99th percentiles within each year.

(a) Capital Calls



(b) Capital Call Rates

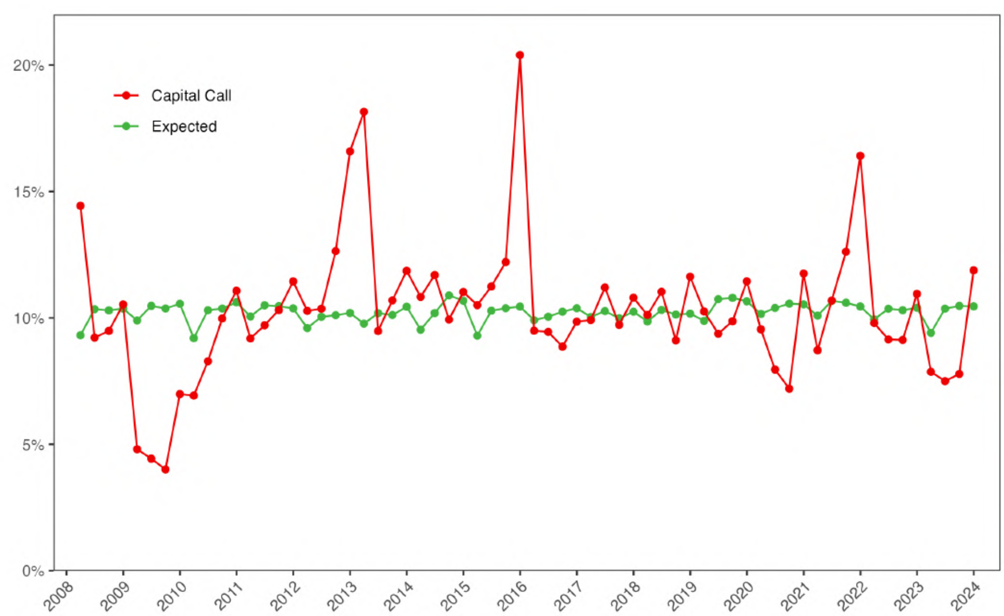


Figure 5: Time Series of Aggregate Capital Calls

This figure plots the time series of aggregate capital calls received by insurers. Subfigure (a) plots the dollar amount of capital calls. Total capital calls are represented by the red line, expected capital calls by the green line, and unexpected capital calls by the blue bars. The aggregate unexpected capital calls are the sum of insurer-level unexpected calls. Subfigure (b) plots the time series of the capital call rate, which is defined as the capital call divided by the uncalled commitment from the end of the previous period. The total capital call rates are shown in red, and the expected capital call rates are shown in green.

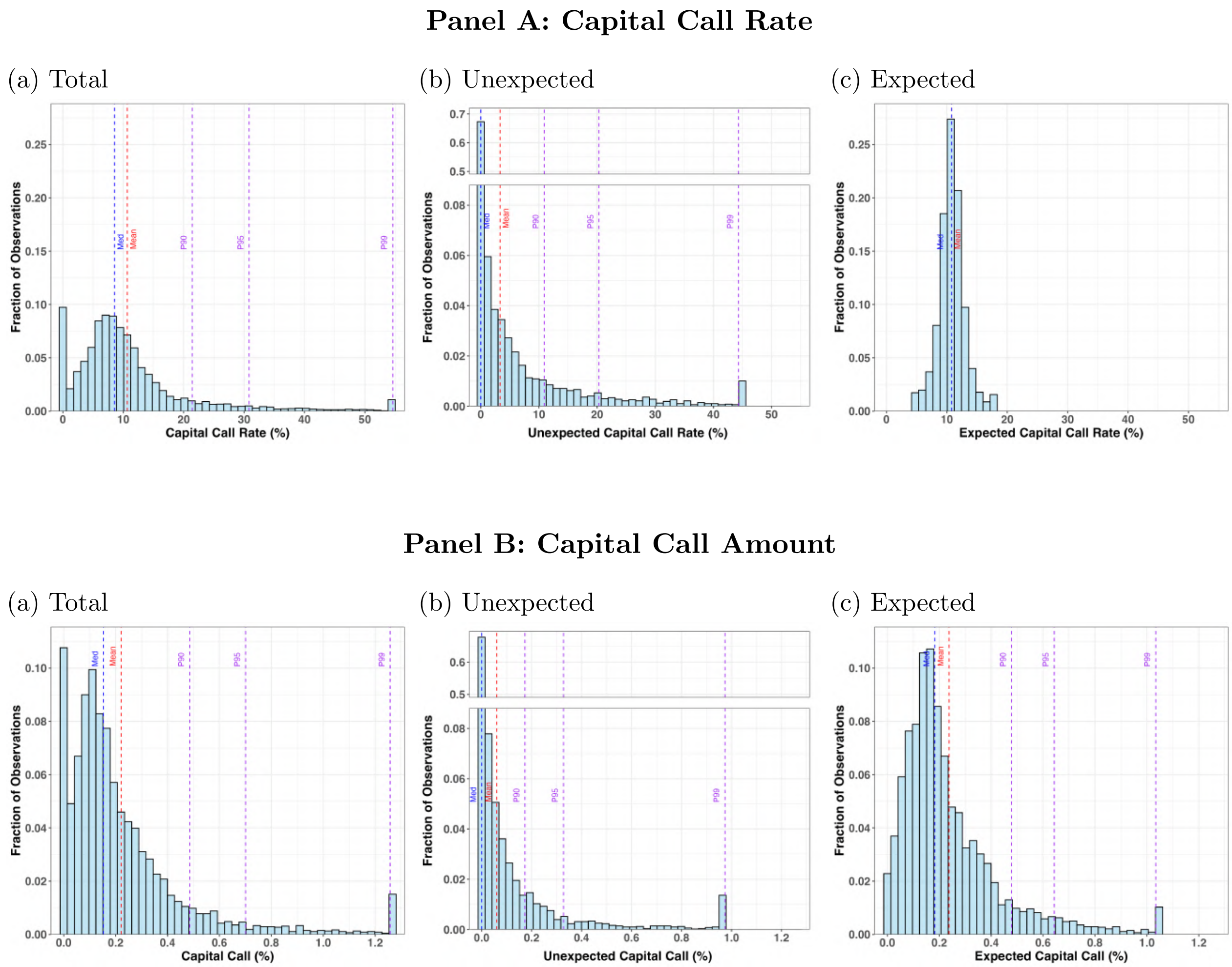
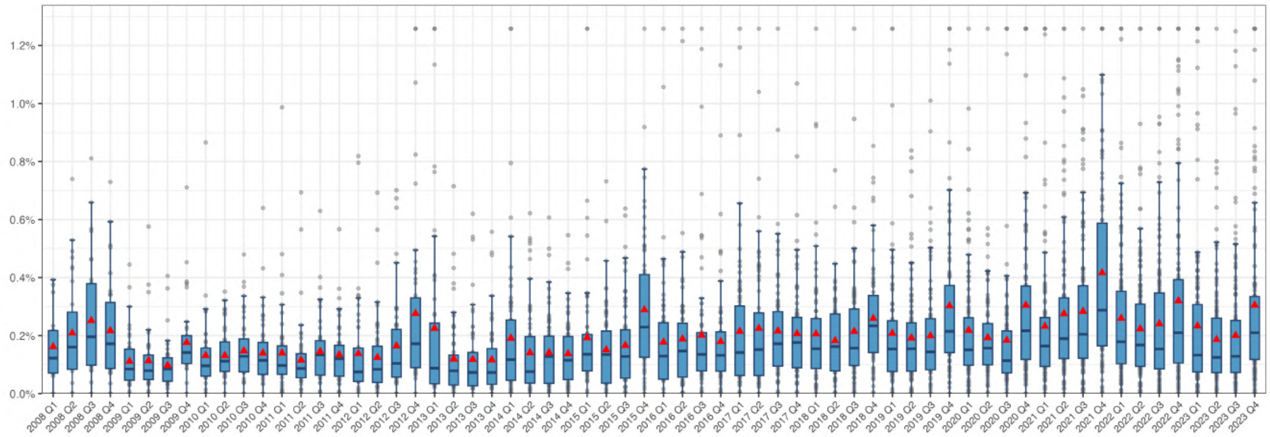


Figure 6: Distribution of Investor-level Capital Calls

This figure shows the distribution of insurer-level capital calls. Panel A plots capital call rates (capital calls scaled by the previous period-end uncalled commitments), while Panel B plots capital call amounts (scaled by the previous period-end insurer portfolio size). Subfigure (a) presents the total capital calls, Subfigure (b) shows the unexpected component, and Subfigure (c) shows the expected component. The y-axis reflects the fraction of observations. All variables are winsorized at the 1st and 99th percentiles. In Panel A, observations with missing or zero lagged uncalled commitments are dropped. In Subfigure (b), as over half of the observations have unexpected capital calls equal to zero, the y-axis is broken into two parts for readability. The blue and red vertical dashed lines represent the median and mean, respectively. From left to right, the three purple dashed lines represent the 90th, 95th, and 99th percentiles of the distribution.

(a) Capital Calls



(b) Unexpected Capital Calls

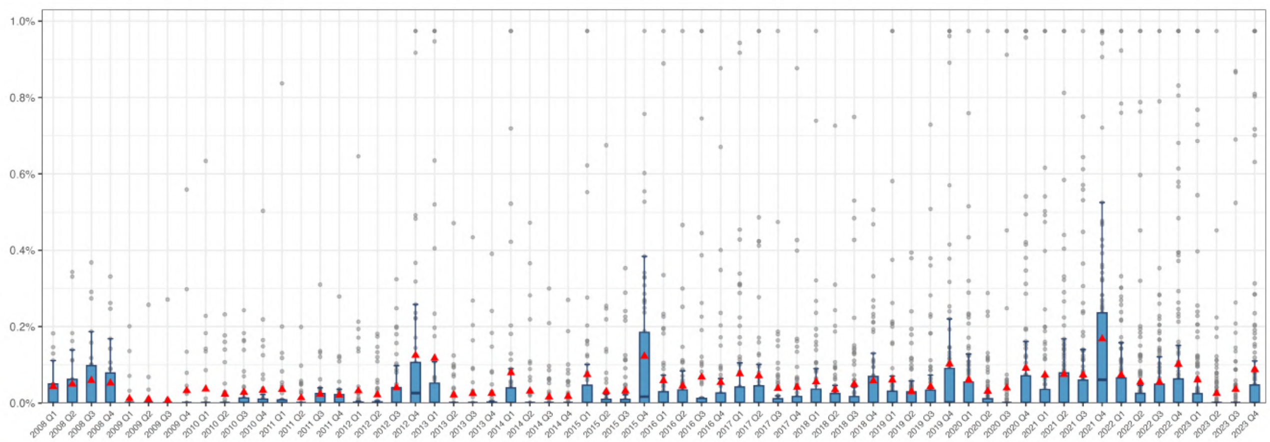


Figure 7: Investor-level Capital Call Distribution over Time

This figure plots the distribution of insurer-level capital calls over time using box plots, where Subfigure (a) shows the total capital calls and Subfigure (b) shows the unexpected component. Each box represents the interquartile range (IQR), with the bottom and top edges corresponding to the first and third quartiles. The short horizontal dark blue line inside each box denotes the median, while the red triangle indicates the mean. The vertical lines extending from the boxes (whiskers) show the range of the data, excluding outliers. Individual observations beyond the whiskers (outliers) are plotted as light gray dots. Capital calls are scaled by the previous period-end insurer portfolio size.

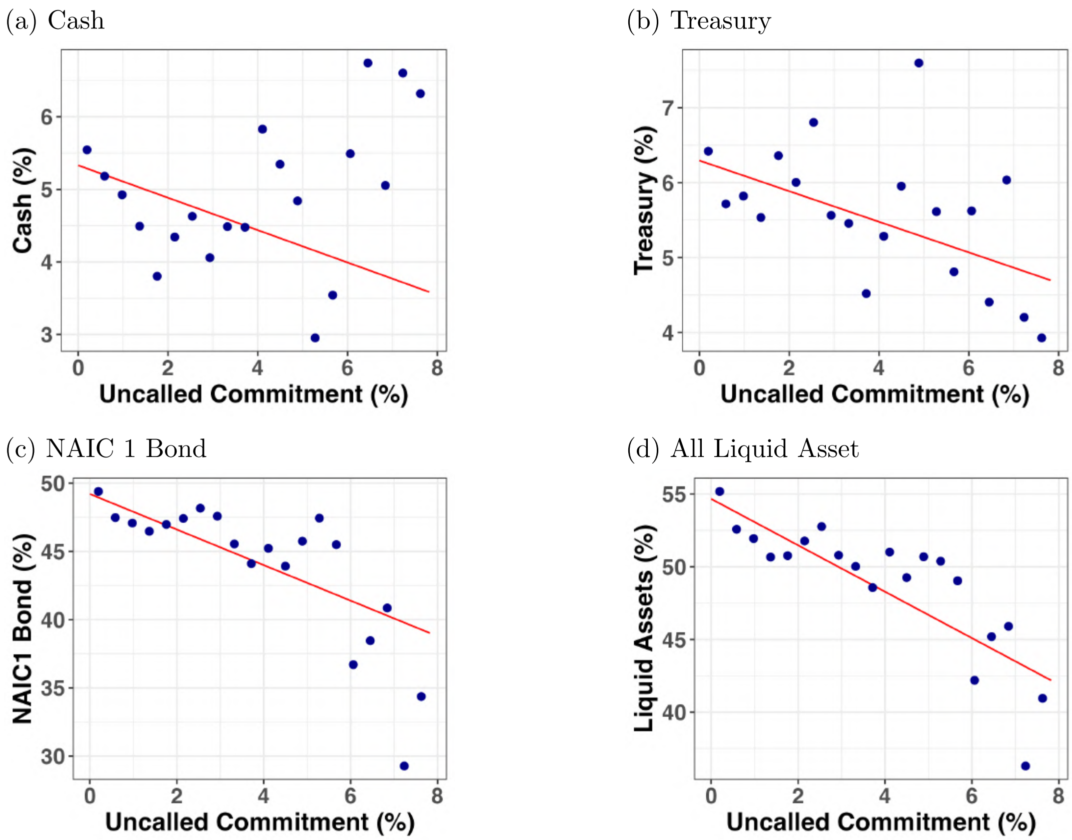


Figure 8: Liquidity Buffers and Uncalled Commitments

This figure presents a binned scatter plot of insurers' liquid asset holdings against their uncalled commitments. Subfigures (a) through (d) correspond to cash and cash equivalents, Treasury bonds, NAIC 1–designated bonds, and the combination of all three.

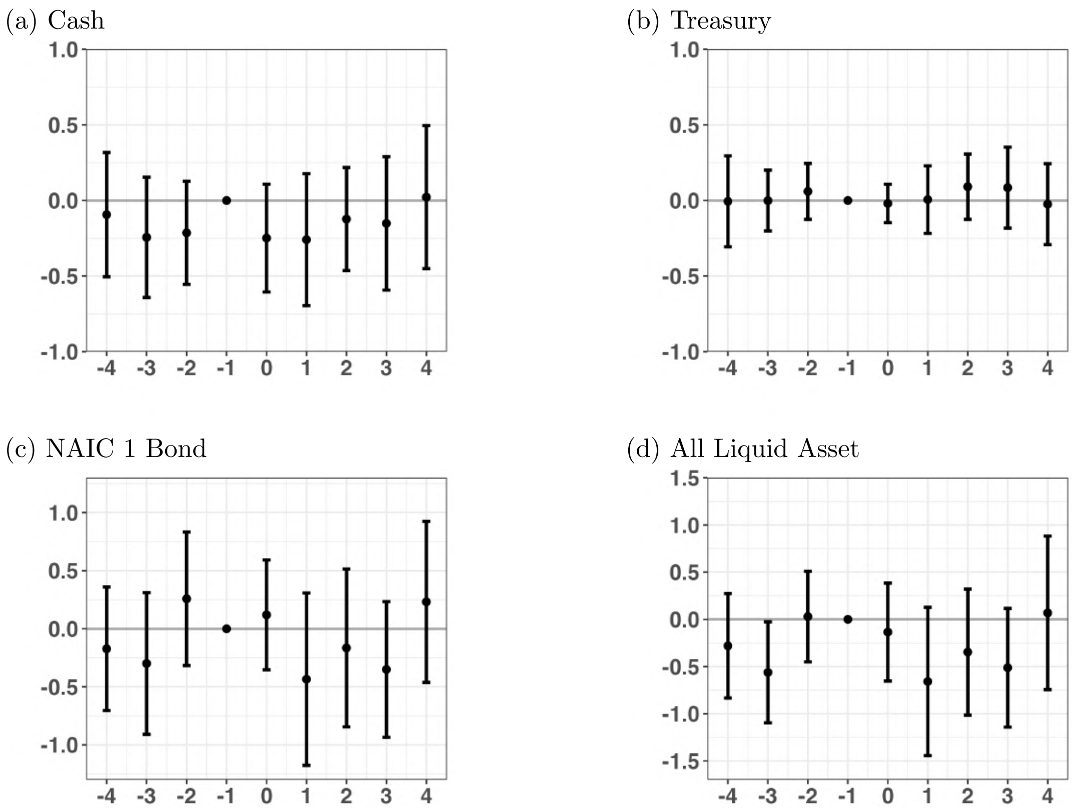


Figure 9: New Commitments and Liquid Asset Dynamics

This figure shows the dynamic effects of abnormal new commitments on investors' liquid asset holdings. Abnormal new commitments are defined as quarterly new commitments minus the rolling average over the past four quarters. Subfigures (a) through (d) correspond to cash and cash equivalents, Treasury bonds, NAIC 1–designated bonds, and the combination of all three. Coefficients are estimated using local projections as defined in Equation (6). Controls include log insurer size, asset growth, return on assets, leverage ratio, and the prior year-end RBC ratio. I also control for four lags of capital calls, distributions, and abnormal new commitments. Insurer and time (calendar year–quarter) fixed effects are included in all specifications. Standard errors are double-clustered at the insurer and time levels. Error bars represent the 95% confidence interval.

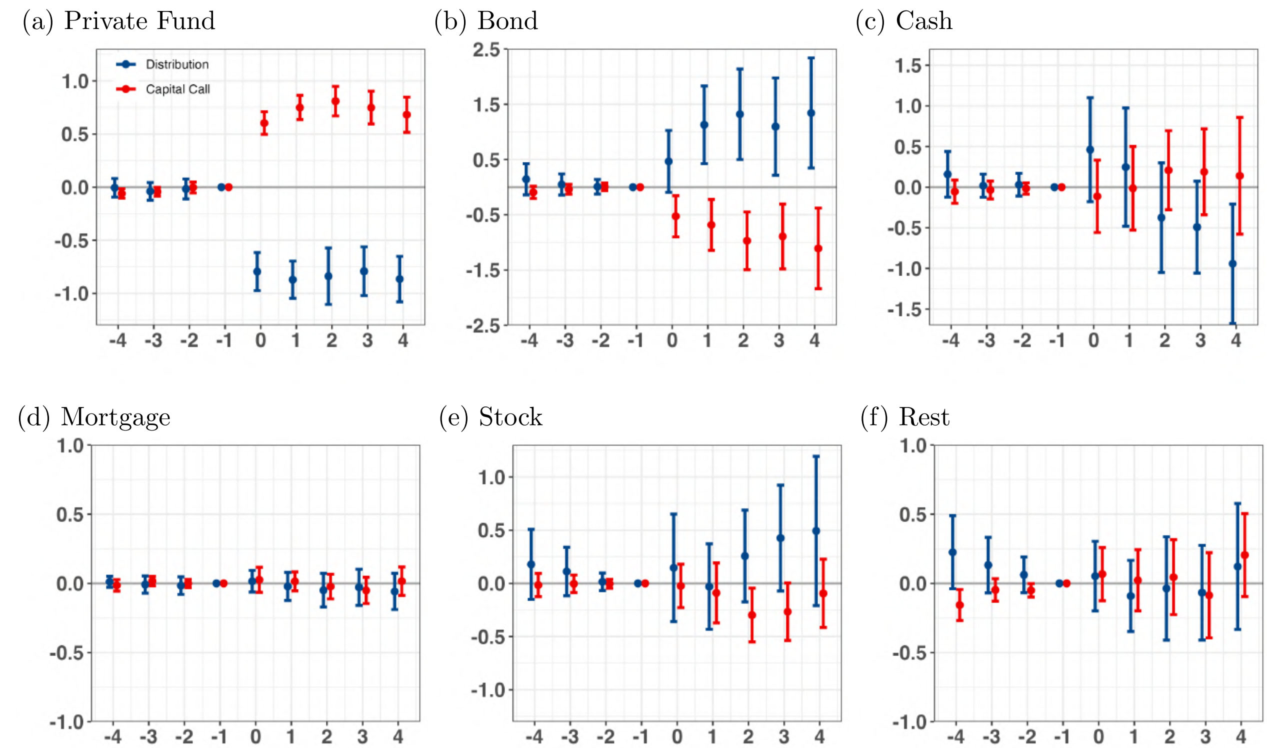


Figure 10: Dynamic Portfolio Effects of Capital Calls and Distributions

This figure shows the dynamic effects of capital calls on insurers' portfolio allocations. Subfigures (a)–(f) correspond to private funds, long-term bonds, cash and cash equivalents, mortgage loans, stocks, and all other assets. Coefficients are estimated using the local projection method defined in Equation (6). Estimates for capital calls are shown in red, and those for distributions are shown in blue. Controls include log insurer size, asset growth, return on assets, leverage ratio, and the prior year-end RBC ratio. I also control for four lags of capital calls, distributions, and dependent variables (dropped for periods –2 to –4). Insurer and time (calendar year–quarter) fixed effects are included in all specifications. Standard errors are double-clustered at the insurer and time levels. Error bars represent the 95% confidence interval.

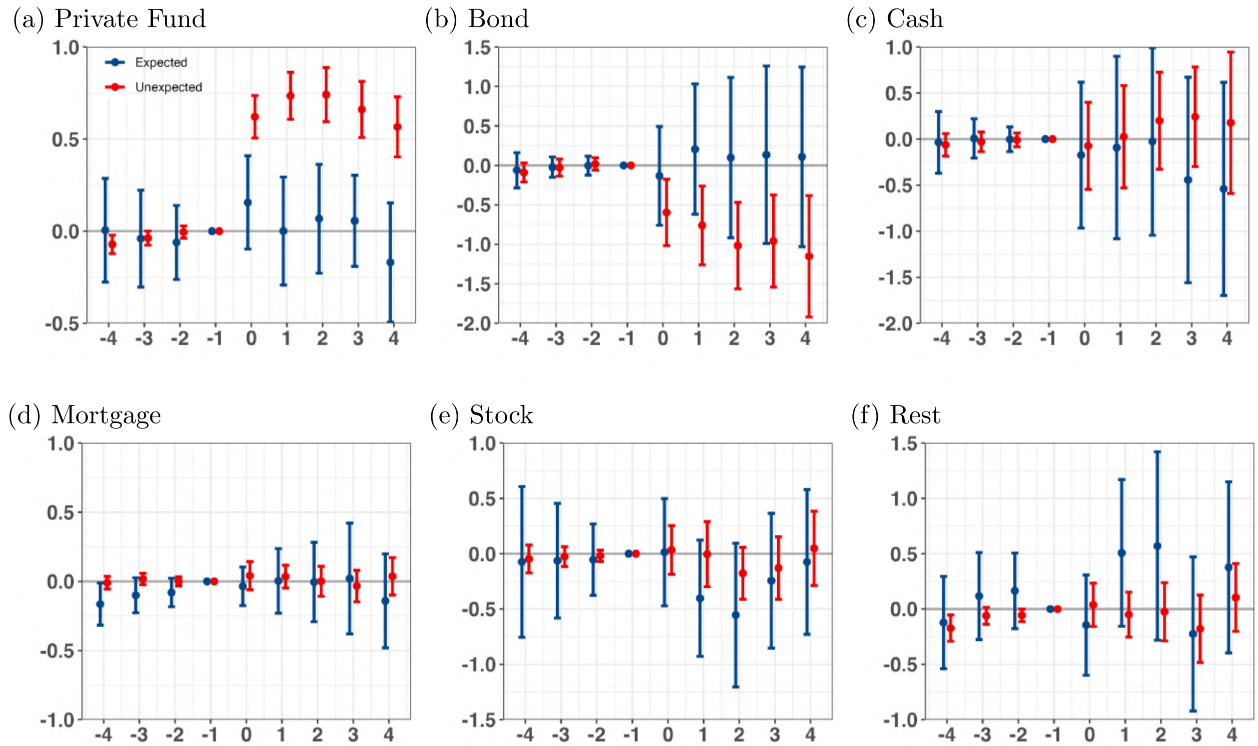


Figure 11: Dynamic Portfolio Effects of Expected vs. Unexpected Capital Calls

This figure shows the dynamic effects of unexpected capital calls on insurers' portfolio allocations. Subfigures (a)–(f) correspond to private funds, long-term bonds, cash and cash equivalents, mortgage loans, stocks, and all other assets. Coefficients are estimated using the local projection method defined in Equation (6). Estimates for unexpected capital calls are shown in red, and those for expected capital calls are shown in blue. Controls include log insurer size, asset growth, return on assets, leverage ratio, and the prior year-end RBC ratio, as well as distributions and four lags of expected calls, unexpected calls, distributions, and the dependent variable (excluded for periods –2 to –4). All specifications include insurer and time (calendar year–quarter) fixed effects. Standard errors are double-clustered at the insurer and time levels. Error bars represent the 95% confidence interval.

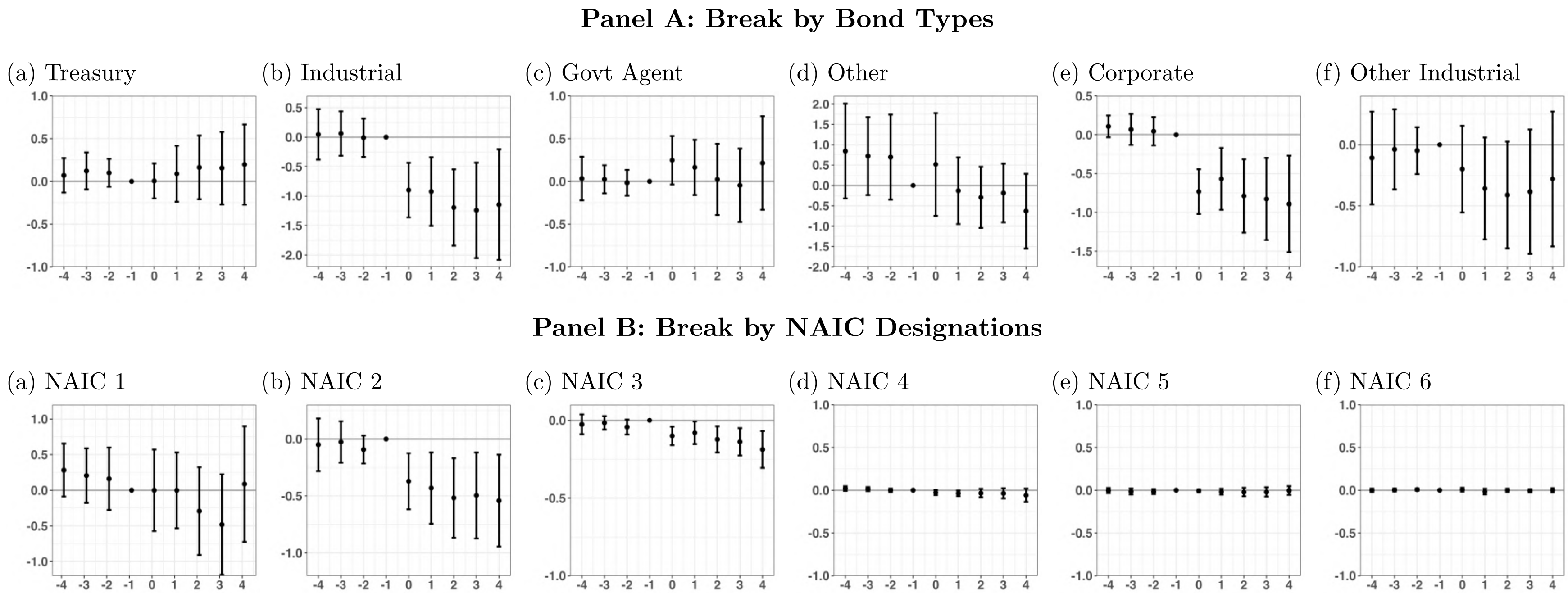


Figure 12: Dynamic Effects on Bond Allocations

This figure shows the dynamic effects of unexpected capital calls on insurers' bond holdings. In Panel A, Subfigures (a) to (d) correspond to Treasury bonds, industrial bonds, other non-Treasury government-related bonds (primarily MBS and municipal bonds), and all other bonds. Subfigures (e) and (f) further split industrial bonds into corporate bonds and other industrial bonds (e.g., CLOs). Panel B classifies bonds by NAIC designation, with Subfigures (a) to (f) corresponding to NAIC designations one through six. Coefficients are estimated using the local projection method defined in Equation (6). Controls include log insurer size, asset growth, return on assets, leverage ratio, and the prior year-end RBC ratio, as well as distributions and four lags of expected calls, unexpected calls, distributions, and the dependent variable (excluded for periods –2 to –4). Insurer and time (calendar year–quarter) fixed effects are included. Standard errors are double-clustered at the insurer and time levels. Error bars represent the 95% confidence interval.

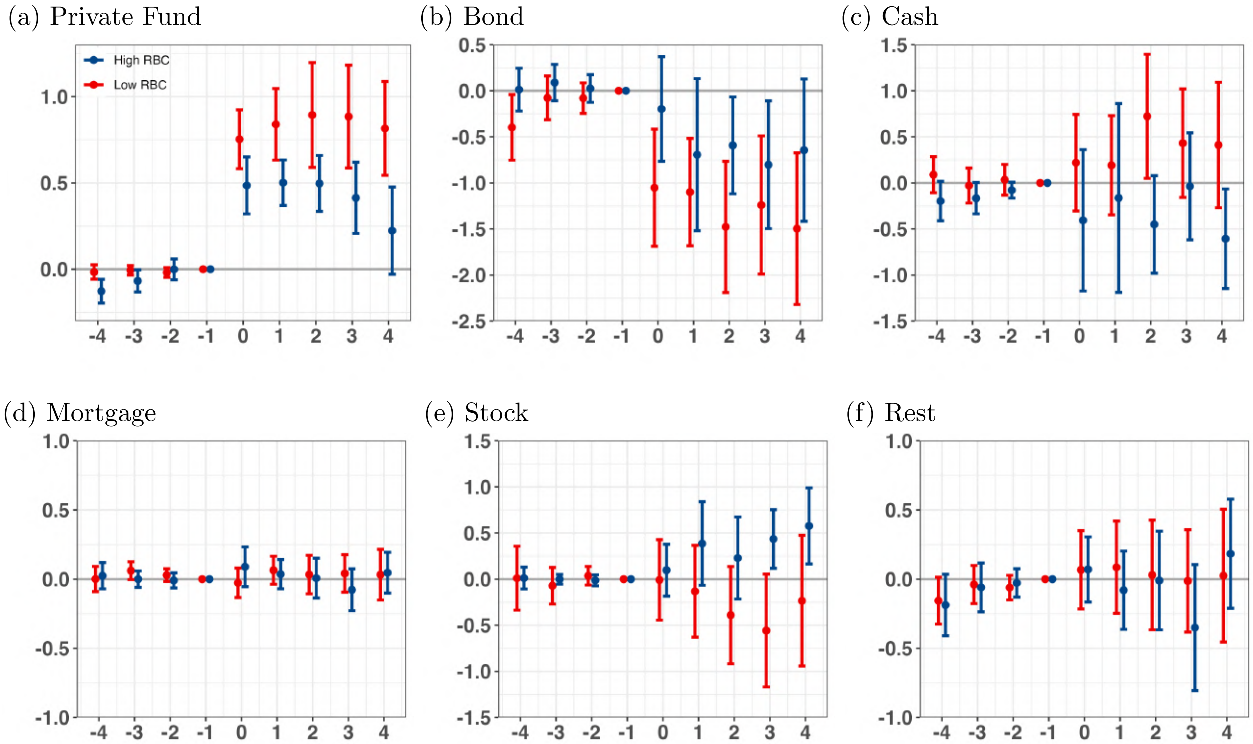
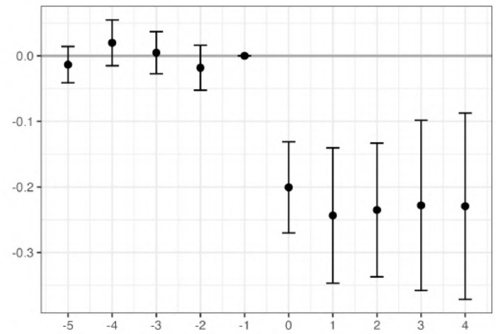


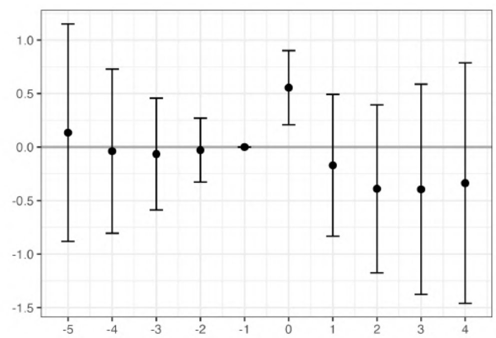
Figure 13: Dynamic Portfolio Effects: High vs. Low RBC Ratios

This figure shows how regulatory capital affects insurers' portfolio adjustments when facing capital call shocks. The sample is split equally based on insurers' prior year-end Risk-Based Capital (RBC) ratio. An insurer is classified as having a low (high) RBC ratio if its prior year-end ratio is below (above) the median, computed by insurer type (Life or P&C) and year. Estimates for the low-RBC group are shown in red, and those for the high-RBC group are shown in blue. Subfigures (a)–(f) correspond to private funds, long-term bonds, cash and cash equivalents, mortgage loans, stocks, and all other assets. Coefficients are estimated using the local projection method defined in Equation (6). Controls include log insurer size, asset growth, return on assets, leverage ratio, and the prior year-end RBC ratio, as well as distributions and four lags of expected calls, unexpected calls, distributions, and the dependent variable (excluded for periods –2 to –4). All specifications include insurer and time (calendar year–quarter) fixed effects. Standard errors are double-clustered at the insurer and time levels. Error bars represent the 95% confidence interval.

(a) Insurer Holdings



(b) Yield Spread: OLS



(c) Yield Spread: 2SLS

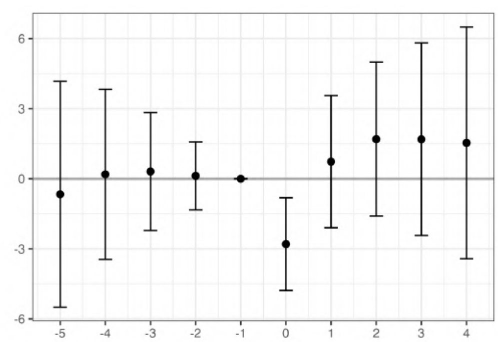


Figure 14: Dynamic Spillover Effects

This figure explores the dynamic spillover effects of asset sales induced by capital calls. Subfigure (a) plots results for insurers' holdings (corresponding to Column (3) of Table 10), Subfigure (b) plots the results for yield spreads using OLS (corresponding to Column (4) of Table 10), and Subfigure (c) plots the results for yield spreads using 2SLS (corresponding to Column (5) of Table 10). Control variables include bond size, duration, credit ratings, bid–ask spread, and par-value trading volume. Bond and time fixed effects are included. Error bars represent the 90% confidence interval, and standard errors are double-clustered at the bond and time levels.

Table 1: Summary Statistics

Variable	N	Mean	SD	P1	P25	Med	P75	P99
Capital Call (%)	15716	0.22	0.24	0.00	0.08	0.15	0.28	1.26
Expected Capital Call (%)	15716	0.24	0.19	0.00	0.12	0.18	0.30	1.03
Unexpected Capital Call (%)	15716	0.06	0.16	0.00	0.00	0.00	0.04	0.97
Capital Call Rate (%)	15716	10.67	9.76	0.00	5.15	8.54	12.88	54.62
Expected Capital Call Rate (%)	15716	10.79	2.23	4.69	9.62	10.79	11.92	18.19
Unexpected Capital Call Rate (%)	15716	3.30	7.87	0.00	0.00	0.00	2.30	44.32
Private Fund ($ M)	15716	521.98	1647.34	0.00	3.85	27.57	232.45	8531.47
Private Fund (%)	15716	2.02	8.53	0.00	0.22	1.04	2.72	11.48
Number Private Fund	15716	44.53	93.40	1.00	2.00	6.00	32.00	497.00
Uncalled Commit ($ M)	15716	227.27	657.14	0.00	0.00	7.56	116.34	3835.37
Distribution ($ M)	15716	22.19	104.89	0.00	0.00	0.29	5.75	431.02
Insurer Size ($B)	15716	21.74	49.71	0.02	1.00	3.59	18.04	272.06
RBC Ratio (%)	15716	1609.68	33255.85	250.78	590.20	830.90	1089.26	3345.23
Leverage	15716	7.52	8.55	1.35	2.37	3.43	9.68	45.01
Bond (%)	15716	69.04	16.25	9.74	61.48	71.75	80.04	94.04
NAIC 1 (%)	15716	50.14	73.92	4.46	38.74	48.61	59.95	86.78
NAIC 2 (%)	15716	17.52	50.67	0.00	7.23	14.79	24.50	52.61
NAIC 3 (%)	15716	1.87	6.10	0.00	0.33	1.42	2.73	8.10
NAIC 4 (%)	15716	0.84	1.29	0.00	0.01	0.41	1.21	5.51
NAIC 5 (%)	15716	0.28	0.70	0.00	0.00	0.07	0.30	3.41
NAIC 6 (%)	15716	0.10	0.77	0.00	0.00	0.00	0.07	1.04
Industrial (%)	15716	42.41	86.93	0.00	24.26	41.32	57.14	85.34
Corporate Bond (%)	15716	22.43	49.40	0.00	10.58	19.64	30.51	60.35
Other Industrial (%)	15716	19.98	39.19	0.00	8.88	18.12	28.43	52.05
Treasury (%)	15716	6.53	16.73	0.00	1.39	3.92	8.07	39.34
Other Govt Related (%)	15716	19.75	28.90	0.01	7.47	15.06	28.39	65.31
Other Bond (%)	15716	2.19	8.17	0.00	0.12	0.94	2.80	14.98
Cash (%)	15716	5.68	8.22	-0.67	1.59	3.28	6.48	40.18
Mortgage (%)	15716	3.89	6.15	0.00	0.00	0.06	6.50	21.93
Stock (%)	15716	13.24	13.63	0.00	2.79	8.85	20.17	64.61
Rest (%)	15716	6.14	10.17	-0.26	2.47	4.76	8.37	24.90
Exposure	373484	1.56	1.31	0.00	0.39	1.34	2.44	5.23
Yield Spread (bps)	373484	189.07	187.74	15.55	83.30	133.17	216.95	1208.47
Bond Size ($M)	373484	714.38	643.26	46.27	314.49	500.00	900.00	3000.00
Time-to-Maturity	373484	9.75	9.89	0.15	3.04	6.13	13.86	31.03
Ratings	373484	8.28	3.01	1.00	6.00	8.00	10.00	17.00
Bid-Ask Spread (bps)	373484	45.27	50.60	2.30	18.10	32.30	56.00	217.90
Trading Volume ($M)	373484	144.13	253.83	0.51	23.54	68.32	167.64	1106.63
Insurer Ownership (%)	373484	25.47	18.50	0.25	10.07	22.17	37.65	75.79
Insurer Sell ($M)	373484	4.38	14.01	0.00	0.00	0.00	2.50	61.06

Table 2: Capital Call Prediction Model Summary

This table reports the performance of forecasting models. Root Mean Squared Error (RMSE) is measured as the percentage improvement relative to the linear benchmark model. Columns (1) and (2) report the in-sample performance, and Columns (3) and (4) report the out-of-sample performance. The linear benchmark model includes five variables: fund age, log fund size, fund type, the lagged capital call rate, and the fraction of uncalled commitments as a share of total commitments. The detailed definitions of the other models are shown in the Appendix.

	In-sample		Out-of-sample	
Model	RMSE (%)	R^2 (%)	RMSE (%)	R^2 (%)
Two-Stage LightGBM	5.47	16.11	0.48	7.40
Two-Stage Random Forest	21.68	42.43	0.47	7.38
Two-Stage XGBoost	5.63	16.40	0.35	7.16
XGBoost	6.92	18.69	0.12	6.72
One-Stage LightGBM	5.21	15.65	0.07	6.62
Linear Benchmark	0.00	6.05	0.00	6.50
Random Forest	43.79	70.31	-0.14	6.23
Two-Stage LASSO	-0.21	5.64	-0.46	5.64
LASSO	-0.50	5.11	-0.77	5.05
Two-Stage Tree	2.09	9.98	-2.17	2.40
Decision Tree	3.80	13.18	-3.30	0.22

Table 3: Variance Decomposition

This table presents the results of the variance decomposition analysis. Panel A reports results for the level of capital calls, scaled by the lagged insurer portfolio size, while Panel B focuses on the capital call rate. In each panel, the first row shows the share of the total variance attributable to the expected and unexpected components. Note that the unexpected capital call captures only the positive deviation from the expected call. Hence, the sum of the expected and unexpected components does not add up to 100%. For each of the three components, I further decompose the variance into investor-specific, time-specific, and idiosyncratic components. This is done by estimating a series of fixed-effects regressions: an insurer fixed-effects model to isolate investor-level variation, a time fixed-effects model to capture common temporal variation, and a two-way fixed-effects model whose residuals represent the idiosyncratic component. The proportion of variance explained by each source is computed as the model's R^2 relative to the total variance of the respective component.

Panel A: Capital Call Amount			
	Total	Expected	Unexpected
Share of Total Variance	100%	63.3%	20.7%
Insurer-FE Share	44.1%	62.2%	16.8%
Time-FE Share	6.7%	5%	4.2%
Residual Share	49.1%	32.5%	78.3%
Panel B: Capital Call Rate			
	Total	Expected	Unexpected
Share of Total Variance	100%	8.3%	48.2%
Insurer-FE Share	27%	23.8%	23.5%
Time-FE Share	7.6%	2.9%	5.8%
Residual Share	64.8%	73.1%	70.4%

Table 4: Private Fund Commitments and Liquidity Buffers

This table examines whether insurers use liquid asset buffers to prepare for future capital calls. Columns (1)–(4) correspond to cash & cash equivalents, Treasury bonds, NAIC 1–designated bonds, and the combination of all three. Panel A regresses the level of liquid asset allocations on the level of uncalled commitments. Panel B regresses the change in liquid asset allocations on quarterly abnormal new commitments, defined as new commitments minus the rolling average over the past four quarters. Controls include log insurer size, asset growth, return on assets, leverage ratio, and the prior year-end RBC ratio. Panel B also controls for capital calls, distributions, and four lags of abnormal new commitments. Insurer and time (calendar year–quarter) fixed effects are included in all specifications. Standard errors are double-clustered at the insurer and time levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Uncalled Commitments and Liquid Asset Holdings

	Holdings (%)			
	Cash	Treasury	NAIC 1 Bond	All Liquid Asset
	(1)	(2)	(3)	(4)
Uncalled Commitment (%)	0.128	0.040	−0.688**	−0.478**
	(0.104)	(0.110)	(0.285)	(0.206)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128
Adjusted R^2	0.750	0.797	0.522	0.849

Panel B: New Commitments and Liquid Asset Holdings

	ΔHoldings (%)			
	Cash	Treasury	NAIC 1 Bond	All Liquid Asset
	(1)	(2)	(3)	(4)
Abnormal New Commitment	−0.276	−0.076	0.024	−0.256
	(0.200)	(0.079)	(0.263)	(0.290)
Controls	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128
Adjusted R^2	−0.003	0.206	0.320	0.734

Table 5: Portfolio Effects of Capital Calls

This table examines insurers' portfolio adjustment decisions when facing capital call shocks. The dependent variable is the change in the percentage allocation to each asset class. Columns (1)–(6) correspond to private funds, long-term bonds, cash and cash equivalents, mortgage loans, stocks, and all other assets. Panel A reports results for total capital calls, controlling for distributions. Panel B decomposes capital calls into expected and unexpected components. All regressions control for four lags of capital calls (expected and unexpected in Panel B), distributions, and the dependent variable. Additional controls include log insurer size, asset growth, return on assets, leverage ratio, and the prior year-end RBC ratio. Insurer and time (calendar year–quarter) fixed effects are included. Standard errors are double-clustered at the insurer and time levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Capital Calls vs Distributions

	$\Delta Holdings(\%)$					
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Capital Call	0.604***	−0.571***	−0.134	−0.022	0.031	0.017
	(0.054)	(0.197)	(0.206)	(0.101)	(0.027)	(0.101)
Distribution	−0.799***	0.418	0.338	0.055	0.004	0.079
	(0.092)	(0.288)	(0.258)	(0.192)	(0.032)	(0.229)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.432	0.148	0.119	0.392	0.098	0.114

Panel B: Expected vs. Unexpected Capital Calls

	$\Delta Holdings(\%)$					
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Unexpected Capital Call	0.622***	−0.646***	−0.120	0.040	0.041	−0.023
	(0.059)	(0.220)	(0.219)	(0.107)	(0.031)	(0.104)
Expected Capital Call	0.158	−0.165	−0.202	−0.043	0.036	0.011
	(0.130)	(0.310)	(0.427)	(0.235)	(0.048)	(0.269)
Distribution	−0.765***	0.349	0.336	0.085	0.008	0.052
	(0.094)	(0.281)	(0.252)	(0.193)	(0.032)	(0.234)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.424	0.149	0.119	0.392	0.098	0.117

Table 6: Capital Calls and Bond Allocations

This table examines how insurers adjust long-term bond allocations when facing unexpected capital call shocks. The dependent variable is the change in the percentage allocation to each bond group. Panel A classifies bonds by type. Columns (1)–(4) correspond to Treasury bonds, industrial bonds, other non-Treasury government-related bonds (primarily MBS and municipal bonds), and all other bonds. Columns (5) and (6) further split industrial bonds into corporate bonds and other industrial bonds (e.g., CLOs). Panel B classifies bonds by NAIC designation, with columns (1)–(6) corresponding to NAIC designations one through six. All regressions control for four lags of expected calls, unexpected calls, distributions, and the dependent variable. Additional controls include log insurer size, asset growth, return on assets, leverage ratio, and the prior year-end RBC ratio. Insurer and time (calendar year–quarter) fixed effects are included. Standard errors are double-clustered at the insurer and time levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Break by Bond Types

	$\Delta Holdings(\%)$					
	Treasury	Industrial	Govt Agent	Other	Corporate	Non-Corporate
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.005	−0.900***	0.246*	0.518	−0.731***	−0.207
	(0.104)	(0.236)	(0.144)	(0.642)	(0.147)	(0.181)
Expected Capital Call	0.041	−0.228	0.535	1.131	−0.004	−0.322
	(0.232)	(0.612)	(0.365)	(1.892)	(0.322)	(0.481)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.288	0.126	0.680	0.460	0.452	0.043

Panel B: Break by NAIC Designations

	$\Delta Holdings(\%)$					
	NAIC 1	NAIC 2	NAIC 3	NAIC 4	NAIC 5	NAIC 6
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.0002	−0.372***	−0.100***	−0.028*	−0.007	0.007
	(0.289)	(0.127)	(0.031)	(0.015)	(0.008)	(0.011)
Expected Capital Call	0.788	0.046	−0.081	0.008	−0.017	0.059
	(0.965)	(0.301)	(0.088)	(0.048)	(0.024)	(0.045)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.334	0.090	0.0004	0.159	0.057	0.171

Table 7: Regulatory Capital and Portfolio Rebalancing

This table examines how regulatory capital affects insurers' portfolio adjustments when facing capital call shocks. The sample is split equally based on insurers' prior year-end Risk-Based Capital (RBC) ratio. An insurer is classified as having a low (high) RBC ratio if its prior year-end ratio is below (above) the median, computed by insurer type (Life or P&C) and year. Panels A and C report results for the low-RBC group, while Panels B and D report results for the high-RBC group. Panels A and B present results for capital calls and distributions, corresponding to Panel A of Table 5. Panels C and D present results for unexpected and expected capital calls, corresponding to Panel B of Table 5. All regression specifications are identical to those in Table 5.

Panel A: Low RBC Ratio						
	Private Fund	Bond	Cash	Mortgage	Stock	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Call	0.759***	−1.044***	0.211	−0.015	−0.002	0.051
	(0.076)	(0.305)	(0.283)	(0.209)	(0.034)	(0.139)
Distribution	−0.756***	0.442	0.353	0.209	−0.005	−0.547
	(0.120)	(0.436)	(0.368)	(0.294)	(0.038)	(0.347)
Observations	6,050	6,050	6,050	6,050	6,050	6,050
Adjusted R^2	0.315	0.096	0.107	0.266	0.116	0.066
Panel B: High RBC Ratio						
	Private Fund	Bond	Cash	Mortgage	Stock	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Call	0.489***	−0.166	−0.494	0.004	0.057*	−0.002
	(0.076)	(0.253)	(0.314)	(0.132)	(0.032)	(0.117)
Distribution	−0.897***	0.442	0.142	−0.097	0.039	0.941***
	(0.121)	(0.293)	(0.343)	(0.223)	(0.043)	(0.330)
Observations	6,078	6,078	6,078	6,078	6,078	6,078
Adjusted R^2	0.537	0.239	0.155	0.512	0.098	0.213
Panel C: Low RBC Ratio – Unexpected vs. Expected						
	Private Fund	Bond	Cash	Mortgage	Stock	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.774***	−1.111***	0.262	−0.034	0.005	0.044
	(0.091)	(0.332)	(0.272)	(0.218)	(0.039)	(0.160)
Expected Capital Call	0.491***	−0.722	0.592	−0.061	−0.038	−0.460
	(0.163)	(0.630)	(0.444)	(0.377)	(0.067)	(0.369)
Observations	6,050	6,050	6,050	6,050	6,050	6,050
Adjusted R^2	0.303	0.095	0.107	0.266	0.116	0.067
Panel D: High RBC Ratio – Unexpected vs. Expected						
	Private Fund	Bond	Cash	Mortgage	Stock	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.496***	−0.210	−0.512	0.108	0.070*	−0.057
	(0.081)	(0.293)	(0.359)	(0.147)	(0.038)	(0.110)
Expected Capital Call	0.097	0.085	−0.596	0.057	0.051	0.178
	(0.137)	(0.328)	(0.684)	(0.222)	(0.073)	(0.295)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,078	6,078	6,078	6,078	6,078	6,078
Adjusted R^2	0.532	0.240	0.156	0.512	0.099	0.221

Table 8: Which Bonds do Insurers Sell?

This table studies which bonds insurers sell when facing unexpected capital calls. The sample is at the insurer–bond–year–quarter level. The dependent variable is an indicator equal to one if a bond is sold partially or fully in quarter t. I only consider active sales, excluding passive disposals such as redemptions, scheduled paydowns, and maturities. Panel A reports the results for different bond types. *NAIC* denotes NAIC bond designations, ranging from 1 to 6. *Unrealized G&L* is the percentile rank (ranging from zero to one) of the unrealized gain or loss for each bond holding at the previous year-end. Specifically, unrealized gain or loss is calculated as the difference between the reported fair value and the book-adjusted carrying value at the previous year-end, scaled by the book-adjusted carrying value. *Illiquidity* is the lagged bond bid–ask spread. The interaction terms between *Unexpected Capital Call* and bond characteristics capture insurers' relative propensity to sell bonds with certain characteristics when facing unexpected capital calls. Other controls include a low-RBC-ratio indicator, bond size, time to maturity, lagged bond trading volume, and lagged bond bid–ask spread. Columns (1)–(3) include bond, insurer, and time (calendar year–quarter) fixed effects. Columns (4)–(6) include bond-by-time and insurer-by-time fixed effects. Standard errors clustered at the bond-by-time level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.054***	0.037***	0.031***			
	(0.005)	(0.006)	(0.006)			
Unexpected Capital Call × NAIC	0.008***	0.008***	0.006**	0.034***	0.036***	0.049***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
Unexpected Capital Call × Unrealized G&L		0.033***	0.041***		0.061***	0.108***
		(0.006)	(0.007)		(0.005)	(0.007)
Unexpected Capital Call × Illiquidity			0.022***			0.146***
			(0.008)			(0.015)
Unexpected Capital Call × NAIC × Illiquidity			0.002			-0.038***
			(0.002)			(0.007)
Unexpected Capital Call × Unrealized G&L × Illiquidity			-0.021**			-0.126***
			(0.009)			(0.011)
NAIC	0.005***	0.005***	0.004***			
	(0.0007)	(0.0007)	(0.0008)			
Unrealized G&L	-0.016***	-0.018***	-0.022***	-0.010***	-0.014***	-0.016***
	(0.0010)	(0.0010)	(0.001)	(0.0009)	(0.0009)	(0.001)
Low RBC Ratio	0.006***	0.006***	0.006***			
	(0.0006)	(0.0006)	(0.0006)			
Trading Volume	0.005***	0.005***	0.005***			
	(0.0002)	(0.0002)	(0.0002)			
Illiquidity	-0.002***	-0.002***	-0.006***			
	(0.0003)	(0.0003)	(0.0008)			
Bond Size	-0.011***	-0.011***	-0.011***			
	(0.001)	(0.001)	(0.001)			
Time-to-Maturity	0.085	0.085	0.085			
	(0.065)	(0.065)	(0.065)			
NAIC × Illiquidity			0.0004			
			(0.0003)			
Unrealized G&L × Illiquidity			0.007***			0.005***
			(0.0008)			(0.001)
Bond FE	Yes	Yes	Yes	No	No	No
Insurer FE	Yes	Yes	Yes	No	No	No
Time FE	Yes	Yes	Yes	No	No	No
Bond-by-Time FE	No	No	No	Yes	Yes	Yes
Insurer-by-Time FE	No	No	No	Yes	Yes	Yes
Observations	8,851,969	8,851,969	8,851,969	8,851,969	8,851,969	8,851,969
Adjusted R^2	0.106	0.106	0.106	0.3352	0.335	0.336

Table 9: Capital Calls and Risk-Based Capital Ratios

This table examines how capital calls affect insurers' Risk-Based Capital (RBC) ratios. Columns (1)–(3) use the full sample; Columns (4)–(6) use the subsample of insurers with low RBC ratios; and Columns (7)–(9) use the subsample with high RBC ratios. An insurer is classified as having a low (high) RBC ratio if its prior year-end ratio is below (above) the median, computed by insurer type (Life or P&C) and year. The sample is annual because RBC ratios are reported only at year-end. The dependent variable is the log RBC ratio. In Columns (1), (4), and (7), the key explanatory variable is the private fund allocation. In Columns (2), (5), and (8), the key explanatory variable is the annual total capital call, controlling for annual total distributions. In Columns (3), (6), and (9), the key explanatory variable is the annual total unexpected capital call, controlling for annual total expected capital calls and distributions. Controls include log insurer size, asset growth, return on assets, leverage ratio, and lagged capital calls and distributions. All regressions include insurer and year fixed effects, with standard errors clustered at the insurer level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Full Sample			Low RBC Ratio			High RBC Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Private Fund (%)	−0.011**			−0.006			−0.019***		
	(0.004)			(0.005)			(0.006)		
Capital Call		−0.010			0.011			−0.040***	
		(0.010)			(0.013)			(0.011)	
Unexpected Capital Call			−0.005			0.021			−0.039***
			(0.011)			(0.016)			(0.013)
Expected Capital Call			−0.014			−0.015			−0.026
			(0.013)			(0.019)			(0.016)
Distribution		−0.011	−0.009		0.006	0.008		−0.021	−0.026*
		(0.013)	(0.013)		(0.017)	(0.017)		(0.023)	(0.015)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,183	3,183	3,183	1,588	1,588	1,588	1,595	1,595	1,595
Adjusted R^2	0.891	0.890	0.890	0.816	0.816	0.816	0.803	0.803	0.803

Table 10: Spillovers to the Corporate Bond Market

This table studies spillover effects of asset sales induced by unexpected capital calls. I first construct a bond-level capital call shock exposure measure. Specifically, the measure is defined as

$$\text{Exposure}_{it} = \log\left(1 + \frac{\sum_j Ownership_{ij,t-1} \times UnexpCall_{jt}}{Outstanding_{i,t-1}}\right)$$

where $Ownership_{ij,t-1}$ insurer j's lagged ownership share of bond i, $UnexpCall_{jt}$ is the dollar amount of unexpected calls for insurer j at time t, and $Outstanding_{i,t-1}$ is the lagged bond amount outstanding. Columns (1) to (4) report the results of directly regressing dependent variables on $Exposure_{it}$ using OLS. From Columns (1) to (4), the dependent variables are: amount of share sold by insurers ($Insurer\_Sell$), an indicator equals to one if the amount sold by insurers are non-negative ($1(Insurer\_Sell)$), change of share owned by insurers $\Delta Insurer\_Holdings$, and change of yield spread ($\Delta Yield\_Spread$). Finally, in Column (5), $Exposure_{it}$ is used as instrument for $\Delta Insurer\_Holdings$ in 2SLS model. Specifically, the regression model is as follow:

$$\Delta YieldSpread_{it} = \beta_h \Delta \widehat{Holdings}_{it} + Controls_{it} + FEs + \epsilon_{it}$$
$$\Delta Holdings_{it} = \gamma_h Exposure_{it} + Controls_{it} + FEs + u_{it}$$

Note that Column (3) is the first-stage of Column (5). Controls include bond size, time-to-maturity, credit ratings, lagged log trading volume, lagged bid-ask spreads, lagged insurers ownership. All columns include bond and time fixed (calender year-quarter) effects. Standard errors double clustered at the bond and time level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

	$Insurer\_Sell$	$1(Insurer\_Sell)$	$\Delta Insurer\_Holdings$	$\Delta Yield\_Spread$	
	(1)	(2)	(3)	(4)	(5)
Exposure	0.967***	0.026***	−0.201***	0.555**	
	(0.131)	(0.003)	(0.035)	(0.211)	
$\Delta \widehat{Insurer\_Holdings}$					−2.798**
					(1.210)
Bond Size	0.903***	0.158***	−0.898***	1.221***	−1.323
	(0.155)	(0.007)	(0.187)	(0.434)	(1.485)
Time-to-Maturity	0.469	0.149	−84.049***	−61.767***	−280.084**
	(3.899)	(0.199)	(10.768)	(14.268)	(109.353)
Rating	0.067	−0.001	−0.195***	0.313***	−0.219
	(0.046)	(0.002)	(0.020)	(0.099)	(0.284)
Lag Trading Volume	0.688***	0.029***	−0.092***	−0.318**	−0.732***
	(0.052)	(0.002)	(0.022)	(0.138)	(0.206)
Lag Bid-Ask Spread	0.173	−0.006	−0.041	−0.093	−0.206
	(0.194)	(0.004)	(0.038)	(0.404)	(0.450)
Lag Insurer Ownership	0.260***	0.005***	−0.133***	0.128**	−0.262
	(0.013)	(0.0003)	(0.008)	(0.054)	(0.194)
Controls	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Adjusted R^2	0.084	0.204	0.085	0.869	0.809
Observations	375,546	375,546	355,626	375,546	355,626
Kleibergen-Paap F-Statistic					32

Table 11: Spillover Heterogeneity

This table examines the heterogeneous spillover effects of asset sales induced by unexpected capital call shocks. Columns (1), (3), and (4) report results for bonds with different NAIC designations, where bonds with designations three through six are combined into one group labeled $NAIC3$. Columns (2), (5), and (6) report results for the COVID versus non-COVID periods. In Columns (1) and (2), the dependent variable is the change in the share of a bond held by insurers ($\Delta Insurer_Holdings$). In Columns (3)–(6), the dependent variable is the change in yield spread ($\Delta Yield_Spread$). Columns (1), (3), and (5) present OLS estimates, while Columns (2), (4), and (6) present 2SLS estimates. First-stage results are reported in Table IA.10. Controls include bond size, time to maturity, credit ratings, lagged bid–ask spreads, and lagged insurer ownership. All regressions include bond and time (calendar year–quarter) fixed effects. Standard errors are double-clustered at the bond and time levels. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	$\Delta Insurer\_Holdings$		$\Delta Yield\_Spread$			
	(1)	(2)	(3)	(4)	(5)	(6)
Exposure × $NAIC1$	−0.074*		0.062			
	(0.044)		(0.303)			
Exposure × $NAIC2$	−0.303***		0.853***			
	(0.038)		(0.267)			
Exposure × $NAIC3$	−0.132***		0.668**			
	(0.032)		(0.288)			
Exposure × $COVID$		−0.182***			1.480***	
		(0.034)			(0.303)	
Exposure × $REST$		−0.201***			0.546***	
		(0.036)			(0.219)	
$\Delta \widehat{Holdings \times NAIC1}$				0.914		
				(1.919)		
$\Delta \widehat{Holdings \times NAIC2}$				−2.953**		
				(1.249)		
$\Delta \widehat{Holdings \times NAIC3}$				−1.875		
				(1.738)		
$\Delta \widehat{Holdings \times COVID}$						−8.913***
						(2.014)
$\Delta \widehat{Holdings \times REST}$						−2.771**
						(1.223)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	355,626	355,626	375,546	355,626	375,546	355,626
Adjusted R^2	0.088	0.085	0.869	0.787	0.869	0.799

Internet Appendix for

"Getting Called: The Risks of Investor Liquidity Provision to Private Funds"

Tiange Ye

IA.1 Conceptual Framework

IA.1.1 Illustrative Examples

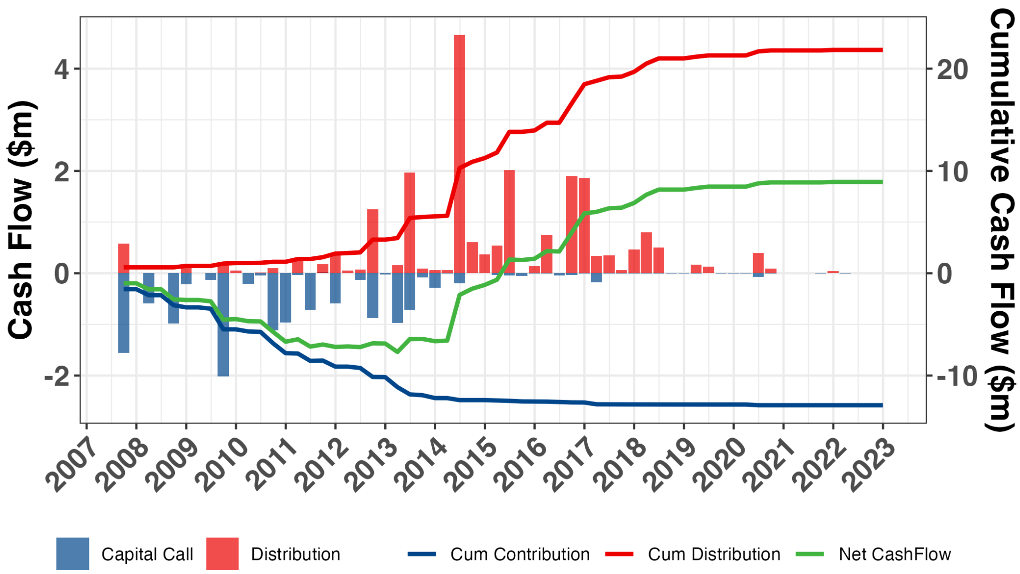
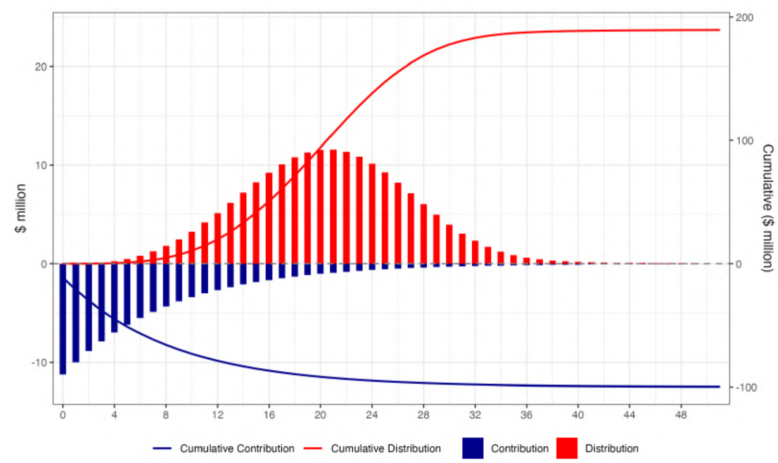


Figure IA.1: Example of Private Fund Cash Flow

This figure shows cash flows from a real private fund. The blue (red) bars represent capital calls (distributions). The blue (red) line plots the cumulative capital calls (distributions). The green line plots the net cash flows.

Panel A: Single fund cash flow



Panel B: Portfolio of private funds

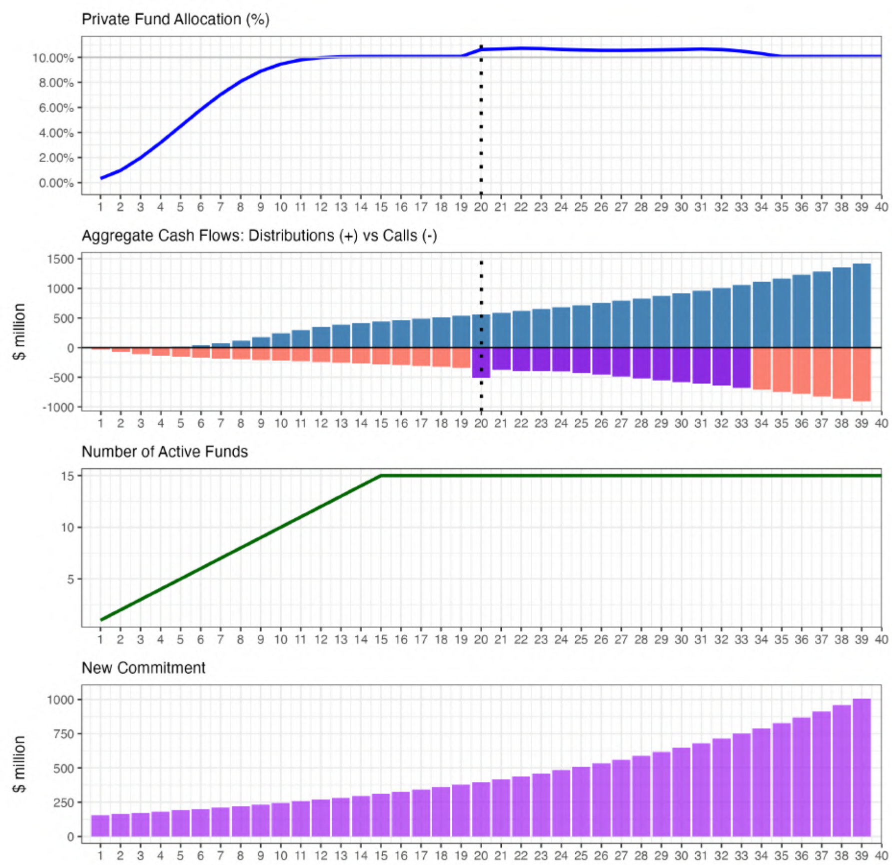


Figure IA.2: An Illustrative Example of a Portfolio of Private Funds

Panel A plots the simulated cash flow of a private fund using the Takahashi and Alexander model. Panel B illustrates a simulated portfolio with a 10% target private fund allocation achieved by repeatedly investing in the fund simulated in Panel A. The first subfigure of Panel B plots the portfolio weight allocated to private funds. The second subfigure plots the aggregate capital calls and distributions at each period. The third subfigure plots the number of active funds. The last subfigure plots the level of new commitments required to achieve a stable 10% target private fund allocation. Additionally, there is an unexpected capital call at period t=20.

IA.1.2 An Illustrative Model

Model Setup I consider a risk-neutral insurer operating over two dates, $t = 0$ and $t = 1$. At $t = 0$, the insurer holds assets A_0 and liabilities L_0, implying initial equity $K_0 = A_0 - L_0$. The asset portfolio consists of three sleeves: risk-free liquid bonds (F), illiquid bonds (I), and private funds (P), with portfolio weights satisfying $\alpha_F + \alpha_I + \alpha_P = 1$. The target allocation at $t = 0$ is $(\bar{\alpha}_I, \bar{\alpha}_P)$, and I assume the insurer is initially at target, so that $\alpha_F = 1 - \bar{\alpha}_I - \bar{\alpha}_P$.

Each asset category carries a regulatory risk weight: $\omega_I, \omega_P, \omega_L$. The required regulatory capital (RBC) is then

$$\widehat{K} = \omega_L L_0 + \omega_I \alpha_I A_0 + \omega_P \alpha_P A_0$$

Then the target RBC ratio is

$$\text{Ratio}^{\text{Target}} = \frac{K_0}{\widehat{K}_0} = \frac{A_0 - L_0}{\omega_L L_0 + \omega_I \bar{\alpha}_I A_0 + \omega_P \bar{\alpha}_P A_0}$$

Asset returns are as follows: $R_I \sim \mathcal{N}\left(\mu_I, \sigma_I^2\right)$ for illiquid bonds, $R_P \sim \mathcal{N}\left(\mu_P, \sigma_P^2\right)$ for private funds, and r_f is the risk-free rate. At $t = 1$, the insurer faces a capital call from its private fund investments of random size $\tau \bar{\alpha}_P A_0$, where $\tau \sim \text{LogNormal}\left(\mu_{\tau'}, \sigma_{\tau'}^2\right)$. At $t = 0$, the insurer chooses $\theta \in [0, 1]$, the fraction of the capital call to be financed by selling illiquid bonds; the remaining share $1 - \theta$ is funded from cash. Selling illiquid bonds entails a proportional transaction cost c per dollar sold. Liabilities L_0 are assumed fixed for simplicity, so equity at $t = 1$ is $K_1 = A_1 - L_0$.

The insurer's objective at $t = 0$ is to maximize expected equity net of a penalty for deviating from the target capital ratio:

$$J(\theta) = \mathbb{E}\left[A_1 - L_0\right] - \tilde{\phi}_{\text{eff}} \mathbb{E}\left[Z^2\right],$$

where $Z \equiv K_1 - \text{Ratio}^{\text{Target}} \widehat{K}_1$ measures the deviation from the desired RBC ratio, and $\widehat{K}_1$ is the required capital at $t = 1$ based on end-of-period exposures. The penalty weight scales with the target ratio as $\tilde{\phi}_{\text{eff}} = k/\text{Ratio}^{\text{Target}}$, so that a lower initial RBC ratio implies a larger penalty. The capital call arrives effectively at the start of $t = 1$, and the post-adjustment portfolio earns returns over the full period. I assume that (τ, R_I, R_P) are independent.

Model Solution End-of-period asset value can be expressed as

$$\begin{aligned} A_1 = & \underbrace{\left(\alpha_F A_0 - (1-\theta)\tau \bar{\alpha}_P A_0\right)(1 + r_f)}_{\text{Liquid bonds}} \\ & + \underbrace{\left(\bar{\alpha}_I A_0 - \theta \tau \bar{\alpha}_P A_0\right)(1 + R_I)}_{\text{Illiquid bonds}} \\ & + \underbrace{\left((1+\tau)\bar{\alpha}_P A_0\right)(1 + R_P)}_{\text{Private funds}} \\ & - \underbrace{c\,\theta \tau \bar{\alpha}_P A_0}_{\text{Transaction cost}}. \end{aligned}$$

Required capital at $t = 1$ is

$$\widehat{K}_1 = \omega_L L_0 + \omega_I \big(\bar{\alpha}_I - \theta\tau\bar{\alpha}_P\big) A_0 + \omega_P (1+\tau)\bar{\alpha}_P A_0.$$

The deviation term Z is affine in θ: $Z = Z_0 + \theta Z_1$, where

$$Z_1 = \tau\bar{\alpha}_P A_0 \left(r_f - R_I - c + \text{Ratio}^{\text{Target}}\omega_I\right),$$

and Z_0 collects all θ-independent terms. The expected equity $\mathbb{E}\left[A_1 - L_0\right]$ is linear in θ:

$$\mathbb{E}\left[A_1 - L_0\right] = \text{Const} + \theta A_0 \bar{\alpha}_P \mathbb{E}[\tau] \left(r_f - \mu_I - c\right),$$

while the expected penalty term is quadratic:

$$\mathbb{E}\left[Z^2\right] = \mathbb{E}\left[Z_0^2\right] + 2\theta\mathbb{E}\left[Z_0 Z_1\right] + \theta^2\mathbb{E}\left[Z_1^2\right].$$

Substituting into the objective and grouping terms yields

$$J(\theta) = C_0 + C_1\theta - C_2\theta^2$$

with

$$\begin{aligned} C_0 &= \text{Const} - \tilde{\phi}_{\text{eff}}\mathbb{E}\left[Z_0^2\right], \\ C_1 &= A_0\bar{\alpha}_P\mathbb{E}[\tau]\left(r_f - \mu_I - c\right) - 2\tilde{\phi}_{\text{eff}}\mathbb{E}\left[Z_0 Z_1\right], \\ C_2 &= \tilde{\phi}_{\text{eff}}\mathbb{E}\left[Z_1^2\right] > 0, \end{aligned}$$

so the objective is strictly concave in θ. The first-order condition $dJ/d\theta = 0$ implies the unconstrained optimum

$$\theta^*_{\text{unc}} = \frac{C_1}{2C_2} = \frac{A_0\bar{\alpha}_P\mathbb{E}[\tau]\left(r_f - \mu_I - c\right) - 2\tilde{\phi}_{\text{eff}}\mathbb{E}\left[Z_0 Z_1\right]}{2\tilde{\phi}_{\text{eff}}\mathbb{E}\left[Z_1^2\right]}.$$

Using $\tilde{\phi}_{\text{eff}} = k/\text{Ratio}^{\text{Target}}$, this can be rewritten as

$$\theta^*_{\text{unc}} = \frac{A_0\bar{\alpha}_P\mathbb{E}[\tau]\left(r_f - \mu_I - c\right)\text{Ratio}^{\text{Target}}}{2k\mathbb{E}\left[Z_1^2\right]} - \frac{\mathbb{E}\left[Z_0 Z_1\right]}{\mathbb{E}\left[Z_1^2\right]}.$$

Imposing the feasibility constraint $0 \leq \theta \leq 1$, the optimal policy is

$$\theta^* = \min\left\{1, \max\left\{0, \theta^*_{\text{unc}}\right\}\right\}.$$

Discussion The optimal θ^* balances two opposing forces. A higher θ implies funding capital calls by selling illiquid bonds rather than using cash. The marginal economic cost of doing so is $A_0\bar{\alpha}_P\mathbb{E}[\tau]\left(r_f - \mu_I - c\right)$, typically negative when $\mu_I + c > r_f$. At the same time, increasing θ affects the expected penalty through $Z = Z_0 + \theta Z_1$, which is the marginal change in the expected penalty. The RBC relief term inside Z_1 makes selling illiquid assets more attractive when capital requirements are binding. Moreover, since the penalty weight scales inversely with the target ratio, a lower target ratio increases the effective penalty and shifts the optimum θ up.

Assuming an interior solution ($\theta^* > 0$), the comparative statics are intuitive. Higher expected illiquid returns or higher transaction costs ($\mu_I \uparrow$ or $c \uparrow$) reduce θ^*, since selling illiquid bonds becomes more costly. A larger penalty coefficient ($k \uparrow$) shifts θ^* upward. A higher target RBC ratio ($\text{Ratio}^{\text{Target}} \uparrow$) reduces $\tilde{\phi}_{\text{eff}}$ and places more weight on the economic term, typically lowering θ^*. The effects of RBC risk weights (ω_I, ω_P) and targeted portfolio allocations ($\bar{\alpha}_I, \bar{\alpha}_P$) are ambiguous because they enter both the required capital and the deviation term Z. A larger expected capital call $\mathbb{E}[\tau]$ magnifies the economic term, whereas higher call volatility increases $\mathbb{E}\left[Z_1^2\right]$, dampening the sensitivity of θ^*.

For illustration, consider the following parameterization: $A_0 = 1000, L_0 = 500$, target allocations $\bar{\alpha}_I = 50\%, \bar{\alpha}_P = 10\%$, and $\bar{\alpha}_F = 40\%$. Risk weights are $\omega_I = 10\%$, $\omega_P = 30\%$, and $\omega_L = 1\%$, implying a target RBC ratio of approximately 588%. Expected returns are $\mu_I = 7\%, \sigma_I = 10\%, \mu_P = 20\%, \sigma_P = 30\%$, with a risk-free rate $r_f = 1\%$. The capital call follows $\tau \sim \log\mathcal{N}\left(\log(0.15) - 0.5(0.4)^2, 0.4^2\right)$, yielding $\mathbb{E}[\tau] \approx 0.15$. The transaction cost is $c = 1\%$, and the penalty coefficient is $k = 0.6$. Figure IA.3 plots the sensitivity analysis.

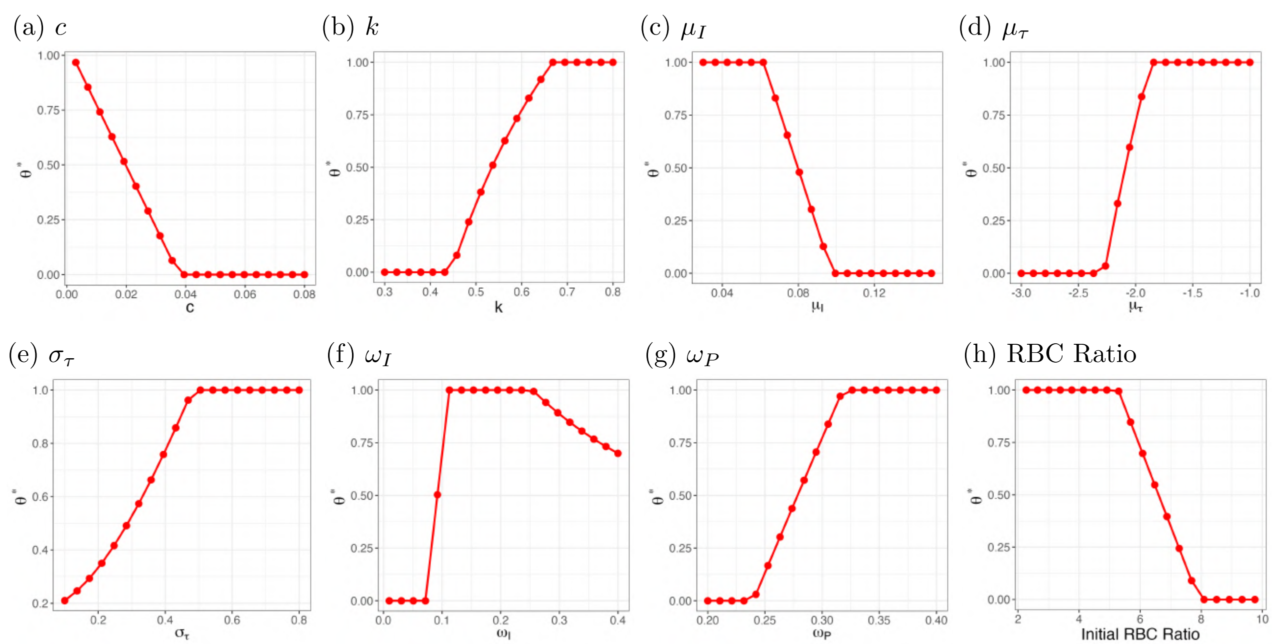


Figure IA.3: Sensitivity Analysis for θ^*

This figure plots the sensitivity analysis for the optimal θ. The baseline parameter choices are: initial asset $A_0 = 1000$, initial liability $L_0 = 500$, target allocation to illiquid bond $\bar{\alpha}_I = 50\%$, target allocation to private fund $\bar{\alpha}_P = 10\%$, target allocation to liquid asset $\bar{\alpha}_F = 40\%$, RBC charges for illiquid assets $\omega_I = 10\%$, RBC charges for private fund $\omega_P = 30\%$, RBC charges for liability $\omega_L = 1\%$, illiquid asset return $\mu_I = 7\%$, $\sigma_I = 10\%$, private fund return $\mu_P = 20\%$, $\sigma_P = 30\%$, capital call $\mu_\tau = \log(0.15) - 0.5 * 0.4^2$, $\sigma_\tau = 40\%$ (i.e., $E(\tau) = 0.15$), transaction cost $c = 1\%$, penalty coefficient $k = 0.6$, risk free rate $r_f = 1\%$. The implied target RBC ratio $\approx 588\%$

IA.2 Data

IA.2.1 Raw Schedule BA Data

This section explains the raw Schedule BA data. I obtained the raw statutory filings data from Capital IQ Pro. Schedule BA reports alternative asset investments, including private fund hedge funds, joint ventures, surplus notes, and residual tranches of structured finance vehicles. Schedule BA has three parts:

Part 1: Other long-term invested assets owned as of December 31 of the current year This part is reported only in the annual report. Figure IA.4 provides an example. Some key variables include:

- Column (2): Asset Name
- Column (8): Date Originally Acquired. For private funds, this can be interpreted as the initial commitment date
- Column (10), (11), (12): Historical Cost Value, Fair Value, and Book-adjusted Carrying Value (BACV). For private funds, BACV should be very close to fair value as almost all private funds are recorded using fair value. I use BACV to compute the on-balance-sheet book value.
- Column (13) to (17): Fair value adjustments
- Column (19): Commitment for Additional Investment. For private funds, it represents the uncalled commitment (dry powder).
- Column (20): Percentage Ownership. I use it to back out the total size of the fund.

Part 2: Other long-term invested assets acquired and additions made during the year (quarter) This part is reported in both the annual and quarterly (first three quarters) reports. Figure IA.5 provides an example. For private funds, it includes initial investment as well as additional contribution through capital call. Some key variables include:

- Column (2): Asset Name
- Column (7): Date Originally Acquired. Similar to Part 1, it is the initial commitment date.
- Column (9): Actual Cost of Time of Acquisition. This column is blank except for the initial commitment. For private funds, it can be interpreted as the contribution at the time of initial commitment.
- Column (10): Additional Investment Made After Acquisition. For private funds, this column represents capital call (contribution).
- Column (12): Commitment for Additional Investment. Similar to part 1, it represents the uncalled commitment.

Part 3: Other long-term invested assets disposed of, transferred, or repaid during the year (quarter) This part is reported in both the annual and quarterly reports. Figure IA.6 provides an example. For private funds, disposal includes secondary market sales, liquidation/termination, and distribution. Some key variables include:

- Column (2): Asset Name.
- Column (5): Nature of Disposal. Common types include distributions, partial disposals, full disposals, secondary market sales, and liquidations or terminations. Most of the time, a partial disposal also represents a distribution.
- Column (7): Disposal Date. Blank for distribution.
- Column (8): Book value from part 1 of last year.
- Columns (9) to (14): Fair value adjustment of the disposed part from the end of last year until the time before disposal. For distribution, it is usually blank.
- Column (15): Book value immediately before disposal. For distribution, it is usually blank.
- Column (16): Proceeds from disposal. I use this as the distribution amount.
- Column (19): Total gain or loss on disposal (difference between column (15) and 16). For distribution, it is usually blank.

ANNUAL STATEMENT FOR THE YEAR 2023 OF THE Forethought Life Insurance Company

SCHEDULE BA - PART 1

Showing Other Long-Term Invested Assets OWNED December 31 of Current Year

1	2	3	Location		6	7	8	9	10	11	12	Change in Book/Adjusted Carrying Value					18	19	20
			4	5								13	14	15	16	17			
CUSIP Identification	Name or Description	Code	City	State	Name of Vendor or General Partner	NAIC Designation, NAIC Designation Modifier and SVO Administrative Symbol	Date Originally Acquired	Type and Strategy	Actual Cost	Fair Value	Book/ Adjusted Carrying Value Less Encumbrances	Unrealized Valuation Increase/ (Decrease)	Current Year's (Depreciation) or (Amortization)/ Accretion	Current Year's Other-Than-Temporary Impairment Recognized	Capitalized Deferred Interest and Other	Total Foreign Exchange Change in Book/ Adjusted Carrying Value	Investment Income	Commitment for Additional Investment	Percentage of Ownership
BGA0UX-6A-9	BUILDERS FACILITY			US	BUILDERS FACILITY		02/01/2021		2,552,614	2,467,536	2,552,617		(128)				438,543		0.000
BGA0XA-V4-2	COMMERCE HOME MORTGAGE FACILITY			US	COMMERCE HOME MORTGAGE FACILITY		10/15/2021		98,401,045	87,435,118	98,401,045		224,512				2,600,199		0.000
BGA0ZN-WU-3	BUILDERS FACILITY II - ABS			US	BUILDERS FACILITY II - ABS		12/20/2021		258,425,111	226,073,828	258,425,671		(19)				12,692,054		0.000
BGA123-X8-9	AGAMERICA 2022-A A - ABS			US	AGAMERICA 2022-A A - ABS		05/19/2022		78,189,020	78,300,000	78,247,074		71,698				4,425,267		0.000
BGA12T-6M-1	GENESIS FACILITY - ABS			US	GENESIS FACILITY - ABS		07/15/2022		52,000,000	49,508,183	52,000,000						3,031,528		0.000
1199999. Non-Registered Private Funds - Mortgage Loans - Unaffiliated									489,567,790	443,784,665	489,626,407		296,063				23,187,591		XXX
BGA10H-SX-1	ERESI WAREHOUSE - ABS			US	ERESI WAREHOUSE - ABS		01/07/2022		218,501	143,489	143,489		(12)				75,047		0.000
GA2308-C7-9	ERESI WAREHOUSE LINE - ABS			US	ERESI WAREHOUSE LINE - ABS		09/01/2023		67,276,199	43,172,182	44,152,706		(47,867)				8,388		0.000
1299999. Non-Registered Private Funds - Mortgage Loans - Affiliated									67,494,700	43,315,671	44,296,195		(47,879)				83,435		XXX
BGA09B-W7-9	TOAMS 2017-1 LLC			DE	TOAMS 2017-1 LLC		03/01/2019		9,000,000	126,454,039	126,454,039	(487,771)							0.000
BGA0QE-DJ-9	BDC EQUITY INVESTMENT			NY	BC Partners Lending Corporation		10/16/2019		9,963,858	10,602,358	10,602,358	638,499					451,205		18.450
BGA0ZT-LZ-1	Landis - Equity			US	Landis - Equity		12/29/2021		2,504,154	4,163,442	2,504,154								0.000
BGA12P-ZT-2	FIDUCIARY EXCHANGE LLC			US	FIDUCIARY EXCHANGE LLC		11/04/2022		8,000,000	7,523,845	7,523,845	(476,155)							4.990
BRS7DA-16-4	TCW/CRESCENT MEZZANINE PARTNER			DE	TCW/Crescent Mezzanine V, LLC		06/24/2010	1											0.298
BRSDHV-FZ-2	GLOBAL ENERGY CAPITAL			US	GEC Capital Group LP		12/08/2011	1	75,160	75,160	75,160	(14,954)						264,218	1.300
BRSFMM-GE-7	PINEBRIDGE STRUCTURED CAPITAL			DE	PineBridge Structured Capital General Pa		08/02/2012	1	376,217	157,142	157,142	(375,319)						27,790	1.100
BRSJ0F-QS-6	OLYMPUS CAP ASIA III LP			DE	Olympus Capital Asia III GP, L.P.		04/01/2013	1	2,473,347	297,008	297,008	12,294					989	433,350	0.500
BRSJ0F-VL-5	KRG CAPITAL FUND IV			DE	KRG Capital Management, L.P.		04/04/2013	1	416,365	416,365	416,365	(1,104)						205,510	0.400
BRSJSD-Q8-5	BRENTWOOD IV			DE	Brentwood Private Equity IV, L.P.		06/28/2013	1	596,082	393,377	393,377	(305,174)						1,574	2.500
GA2309-3B-C	Panamint Power			US	Panamint Power		08/21/2023		97,956,428	99,200,296	99,200,296	1,243,868							0.000
GA2309-57-2	Panamint Capital			US	Panamint Capital		05/27/2022		3,609,600	970,847	970,847	(2,638,753)							47.000
1999999. Joint Venture Interests - Common Stock - Unaffiliated									134,971,211	250,253,879	248,594,591	(2,404,569)					452,194	932,442	XXX
BGA0ZP-NH-7	KKR REAL ESTATE STABILIZED LP			US	KKR REAL ESTATE STABILIZED LP		12/13/2021		973,890	991,375	991,375	203					54,535		0.000
2099999. Joint Venture Interests - Common Stock - Affiliated									973,890	991,375	991,375	203					54,535		XXX
591560-AA-5	METLIFE CAPITAL TRUST IV			NY	METLIFE CAPITAL TRUST IV		03/30/2023		2,058,066	2,153,155	2,053,532		(4,533)				157,500		0.000
2799999. Surplus Debentures, etc - Unaffiliated									2,058,066	2,153,155	2,053,532		(4,533)				157,500		XXX
BGA05E-9S-7	GOODGREEN HOLDINGS 2015-1			US	GOODGREEN HOLDINGS 2015-1		09/20/2022		2,813,164	2,813,164	2,813,164						701,337		0.000
BGA0A1-8X-9	GOODGREEN HOLDINGS 2016-A			US	GOODGREEN HOLDINGS 2016-A		10/25/2016		740,431	740,431	740,431						255,283		0.000
BGA12H-LE-8	AREVIA DEVELOPMENT LOAN FACILITY - ABS			US	AREVIA DEVELOPMENT LOAN FACILITY - ABS		06/03/2022		38,017,299	38,566,882	38,451,441		284,414				2,376,403		0.000
GA2309-98-3	BIRCH CREEK DEVELOPMENT LOAN FACILITY - ABS			US	BIRCH CREEK DEVELOPMENT LOAN FACILITY -		09/28/2023		36,148,041	36,148,041	36,153,797		5,755						0.000
2999999. Collateral Loans - Unaffiliated									77,718,935	78,268,518	78,158,833		290,169				3,333,023		XXX
BGA10S-7B-8	STELLAR DEVELOPMENT LOAN FACILITY - ABS			US	STELLAR DEVELOPMENT LOAN FACILITY - ABS		01/27/2022		54,473,139	53,324,443	54,473,139						3,769,718		0.000
3099999. Collateral Loans - Affiliated									54,473,139	53,324,443	54,473,139						3,769,718		XXX
BRS7KV-H9-7	LEMOORE PACIFIC ASSOCIATES LP		Eagle	ID	Central Valley Coalition for Affordable		06/24/2010	1	309,100	309,100	309,100		(13,428)						28.010
BRS80C-SM-8	WP KEARNEY PALMS II SR APT LP		Westlake Village	CA	WP Kearney Court Phase II, LLC		06/24/2010	1	155,552	155,552	155,552		(20,088)						99.990
BRSCSR-71-5	RED STONE 2011 NATIONAL FD LP		Cleveland	OH	RSEP MW, LLC		08/05/2011	1	248,748	248,748	248,748		(63,648)						0.000
BRSDNC-TM-1	ALLIANT TAX CREDIT PARTNERSHIP		Palm Beach	FL	Alliant Real Estate Investment, LLC		12/22/2011	1	89,136	89,136	89,136		(90,636)						4.000
BRSEST-MT-9	GREAT LAKES CAPITAL FUNDING		Lansing	MI	GLCFH-XXVI, Inc		05/14/2012	1	284,927	284,927	284,927		(248,736)						3.866
BRSHAK-35-3	NATIONAL EQUITY FUND 2012 LP		Chicago	IL	NEF 2012 Fund Manager LLC		01/16/2013	1	329,549	329,549	329,549		(324,120)						4.950
4199999. Non-Guaranteed State Low Income Housing Tax Credit - Unaffiliated									1,417,012	1,417,012	1,417,012		(760,656)						XXX
36268K-AF-3	GSHLT TRUST 2021-A Class F - ABS			US	GSHLT TRUST 2021-A Class F - ABS		12/12/2023		4,408,643	2,929,636	2,929,636	(1,479,007)							0.000
36269U-AF-0	GSHLT TRUST 2021-B Class F - ABS			US	GSHLT TRUST 2021-B Class F - ABS		12/12/2023		464,106	2,193,358	464,106								0.000
61971D-AF-5	MOST TRUST 2020-1 F			US	MOST TRUST 2020-1 F		08/29/2023		16,997,424	24,237,609	16,997,424								0.000

Figure IA.4: Example – Schedule BA Part 1

STATEMENT AS OF SEPTEMBER 30, 2023 OF THE NORTHWESTERN MUTUAL LIFE INSURANCE COMPANY

SCHEDULE BA - PART 2

Showing Other Long-Term Invested Assets ACQUIRED AND ADDITIONS MADE During the Current Quarter

1	2	Location		5	6	7	8	9	10	11	12	13
		3	4									
CUSIP Identification	Name or Description	City	State	Name of Vendor or General Partner	NAIC Designation, NAIC Designation Modifier and SVO Administrative Symbol	Date Originally Acquired	Type and Strategy	Actual Cost at Time of Acquisition	Additional Investment Made After Acquisition	Amount of Encumbrances	Commitment for Additional Investment	Percentage of Ownership
	770511 RIVERSTONE/CARLYLE GLB E&P IV	WASHINGTON	DC	RIVERSTONE/CARLYLE ENERGY PARTNERS IV LP		01/17/2008	3		(24,132)			0.500
	770633 ENCAP ENERGY CAP FD VIII LP	HOUSTON	TX	ENCAP EQUITY FUND VIII GP LP		02/16/2011	3		492			0.230
	770688 RIVERSTONE GLB ENRGY&PWR FND V	NEW YORK	NY	RIVERSTONE ENERGY PARTNERS V LP		05/04/2012	3		22,224		220,343	0.320
	770729 COURT SQUARE CAP PARTNERS III	NEW YORK	NY	COURT SQUARE CAPITAL GP III LLC		10/02/2012	3		14,091		559,142	1.010
	770817 HARBOUR GRP INVESTMENTS VI LP	WILMINGTON	DE	HARBOUR GROUP VI MANAGEMENT CO LLC		10/01/2013	3		46,362		2,043,173	3.050
	770828 CLAYTON DUBILIER & RICE IX LP	GEORGE TOWN	CYM	CD&R ASSOCIATES IX LP		11/21/2013	3		8,361		2,036,401	0.550
	770847 STERLING INVESTMENT PTNRS III	WILMINGTON	DE	STERLING INVSTMNT PTNS MGMT III LLC		01/03/2014	3		217,356		1,720,821	2.840
	770879 CENTRE CAPITAL INVESTORS VI LP	WILMINGTON	DE	CENTRE PARTNERS VI LP		05/30/2014	3		4,656,671		2,653	13.760
	770897 PAINE & PARTNERS CAPITAL FD IV	GEORGE TOWN	CYM	PAINE & PARTNERS CAPITAL FUND IV GP LP		07/23/2014	3		66,844		5,577,393	3.460
	770904 BLUE POINT CAPITAL PTRS III LP	CLEVELAND	OH	BLUE POINT CAPITAL PTRS MGMT III LP		08/18/2014	3		342,467		2,147,050	7.500
	770948 HARVEST PARTNERS STRUCTURED	NEW YORK	NY	HARVEST ASSOCIATES SCF LP		12/31/2014	3		36,426		4,600,787	5.050
	770960 KKR EUROPEAN FUND IV	GEORGE TOWN	CYM	KKR ASSOCIATES EUROPE IV LP		02/26/2015	3		28,619		85,249	0.690
	770980 BAIN CAPITAL EUROPE IV LP	GEORGE TOWN	CYM	BAIN CAPITAL PARTNERS EUROPE IV LP		05/12/2015	3		56,010		2,894,830	0.570
	771032 RIDGEMONT EQUITY PTNS II LP	WILMINGTON	DE	RIDGEMONT EQUITY MGT II LP		11/30/2015	3		99,601		6,017,799	2.940
	771064 GENSTAR CAPITAL PARTNERS VII	WILMINGTON	DE	GENSTAR CAPITAL VII LP		10/01/2015	3		66,802		43,206	1.830
	771078 GRYPHON PARTNERS IV	SAN FRANCISCO	CA	GRYPHON GENPAR IV LP		11/25/2015	3		70,778		3,090,948	3.390
	771080 GRYPHON COINVEST FUND IV LP	SAN FRANCISCO	CA	GRYPHON GENPAR IV LP		11/25/2015	3		6,533		294,657	6.530
	771082 RIVERSIDE STRATEGIC CAP FUND I	WILMINGTON	DE	RSCF I ASSOCIATES LP		10/16/2015	3		631,775		1,186,672	4.790
	771119 AURORA EQUITY PARTNERS V LP	DOVER	DE	AURORA CAPITAL PARTNERS V LP		06/10/2016	3		198,459		8,233,372	5.340
	771121 KELSO INVESTMENT ASSOCIATES IX	DOVER	DE	KELSO GP IX LP		07/07/2016	3		62,700		2,493,123	1.240
	771129 KKR AMERICAS FUND XII LP	GEORGE TOWN	CYM	KKR ASSOCIATES AMERICAS XII LP		10/31/2017	3		44,483		2,869,056	0.190
	771141 HAMILTON LANE NM FUND I LP	WILMINGTON	DE	HAMILTON LANE NM FUND I GP LLC		06/28/2016	3		1,203,572		67,697,083	92.470
	771145 ALPINVEST SECONDARY ONSHORE VI	WILMINGTON	DE	ALPINVEST SECONDARIES VI GP LLC		05/19/2017			177,253		6,028,433	8.770
	771151 WIND POINT PARTNERS VIIIA LP	CHICAGO	IL	WIND POINT INVESTORS VIII LP		06/07/2016	3		78,341		26,868,024	5.240
	771153 JLL PARTNERS FUND VII LP	WILMINGTON	DE	JLL ASSOCIATES VII LP		04/19/2016	3		60,402		3,658,612	2.470
	771172 NYCA INVESTMENT FUND LP	NEW YORK	NY	NYCA INVESTMENTS LLC		06/22/2016	3		125,000		249,999	3.590
	771173 ABRY HERITAGE PARTNERS LP	DOVER	DE	ABRY HERITAGE CAPITAL PARTNERS LP		07/01/2016	3		8,699		451,410	0.730
	771196 BISON CAPITAL PARTNERS V LP	WILMINGTON	DE	BISON CAPITAL PARTNERS V GP LP		09/18/2017	3		817,835		1,176,616	6.860
	771200 NB SECONDARY OPPORTUNITIES IV	NEWARK	DE	NB SECONDARY OPPORTUNITIES ASSOCIATES IV		04/19/2017			940,875		16,200,182	2.790
	771240 ABRY SENIOR EQUITY V LP	DOVER	DE	ABRY SENIOR EQUITY INVESTORS V LP		11/21/2016	3		168,542		255,643	0.790
	771246 LEEDS EQUITY PARTNERS VI LP	WILMINGTON	DE	LEEDS EQUITY ASSOCIATES VI LP		06/02/2017	3		617,770		3,023,600	5.050
	771266 BAIRD CAPITAL GLOBAL FUND I LP	GRAND CAYMAN	CYM	BAIRD CAPITAL GLOBAL FUND MANAGEMENT I		07/11/2017	3		818,916		1,064,076	8.730
	771289 VANCE STREET CAPITAL II LP	DOVER	DE	VS CAPITAL PARTNERS II LLC		04/03/2017	3		90,243		2,001,273	8.170
	771293 GENSTAR CAPITAL PTR VIII LP	WILMINGTON	DE	GENSTAR CAPITAL VIII LP		04/28/2017	3		116,341		2,042,848	2.490
	771309 WHITEHORSE LIQUIDITY PTR I LP	WILMINGTON	DE	WHITEHORSE ASSOCIATES LLP		05/24/2017			1,753		757,189	3.510
	771323 GENSTAR VIII COINVT OAGE FUND	WILMINGTON	DE	GENSTAR CAPITAL VIII LP		10/05/2017	3		20,249		446,731	2.450
	771348 VINTAGE VII LP	WILMINGTON	DE	VF VII ADVISORS LLC		08/28/2017			1,096,879		42,483,446	2.050
	771386 NORDIC CAPITAL IX BETA LP	ST HELIER	JEY	NORDIC CAPITAL IX LIMITED		03/25/2019	3		379,866		4,083,796	1.070
	771388 MIDOCEAN PARTNERS V LP	WILMINGTON	DE	MIDOCEAN ASSOCIATES LP		04/26/2018	3		791,137		2,326,181	3.120
	771390 GTCR FUND XII LP	DOVER	DE	GTCR PARTNERS XII LP		05/04/2018	3		312,130		5,492,116	0.740
	771414 KKR NWM PARTNERSHIP LP	GRAND CAYMAN	CYM	KKR NWM GP LIMITED		06/25/2018	3		2,541,830		20,573,605	91.000
	771422 LINDEN CAPITAL PARTNERS IV LP	DOVER	DE	LINDEN MANAGER IV LP		09/25/2018	3		197,018		3,182,623	5.600
	771424 HARVEST PRTN STRUCT CAP FD II	WILMINGTON	DE	HARVEST ASSOCIATES SCF II LP		06/28/2018	3		2,620,803		6,616,016	4.470
	771430 FRAZIER HC GRTH BUYOUT FD IX	WILMINGTON	DE	FHM GROWTH BUYOUT IX LP		02/27/2019	3		364,000		1,274,000	3.820
	771438 CENTRE CAP INVESTORS VII LP	WILMINGTON	DE	CENTRE PARTNERS VII LP		05/29/2018	3		520,860		3,262,737	10.580
	771454 WHITEHORSE LIQUIDITY PTR II LP	WILMINGTON	DE	WHITEHORSE LIQUIDITY PARTNERS INC		09/21/2018			374,176		3,742,030	3.620
	771464 VESTAR CAPITAL PARTNERS VII LP	GRAND CAYMAN	CYM	VESTAR ASSOCIATES VII LP		04/02/2018	3		749,215		6,826,276	4.250
	771478 PPC FUND II LP	WILMINGTON	DE	PPC FUND GP II LP		04/26/2018	3		121,284		4,315,185	4.090

Figure IA.5: Example – Schedule BA Part 2

STATEMENT AS OF SEPTEMBER 30, 2023 OF THE NORTHWESTERN MUTUAL LIFE INSURANCE COMPANY

SCHEDULE BA - PART 3

Showing Other Long-Term Invested Assets DISPOSED, Transferred or Repaid During the Current Quarter

1	2	Location		5	6	7	8	Change in Book/Adjusted Carrying Value						15	16	17	18	19	20
		3	4					9	10	11	12	13	14						
CUSIP Identification	Name or Description	City	State	Name of Purchaser or Nature of Disposal	Date Originally Acquired	Disposal Date	Book/ Adjusted Carrying Value Less Encum- brances, Prior Year	Unrealized Valuation Increase (De- crease)	Current Year's (Depre- ciation) or (Amorti- zation)/ Accretion	Current Year's Other Than Temporary Impair- ment Recog- nized	Capital- ized Deferred Interest and Other	Total Change in Book/ Adjusted Carrying Value (9+10- 11+12)	Total Foreign Exchange Change in Book/ Adjusted Carrying Value	Book/ Adjusted Carrying Value Less Encum- brances on Disposal	Consid- eration	Foreign Exchange Gain (Loss) on Disposal	Realized Gain (Loss) on Disposal	Total Gain (Loss) on Disposal	Invest- ment Income
	771317 FRONTENAC XI PRIVATE CAP LP	CHICAGO	IL	DISTRIBUTION	04/17/2018										12,213,725				7,452,248
	771323 GENSTAR VIII COINVT OAGE FUND	WILMINGTON	DE	DISTRIBUTION	10/05/2017										237,017				
	771348 VINTAGE VII LP	WILMINGTON	DE	DISTRIBUTION	08/28/2017										3,085,618				812,820
	771350 WALKER STREET MKE FUND LP	WILMINGTON	DE	DISTRIBUTION	08/18/2017										78,791				
	771382 WHLP HOLDING 2 LP	WILMINGTON	DE	DISTRIBUTION	09/26/2017										458,203				
	771386 NORDIC CAPITAL IX BETA LP	ST HELIER	JEY	DISTRIBUTION	03/25/2019										3,566,773	(241,506)		(241,506)	
	771414 KKR NMM PARTNERSHIP LP	GRAND CAYMAN	CYM	DISTRIBUTION	06/25/2018										134,287				
	771422 LINDEN CAPITAL PARTNERS IV LP	DOVER	DE	DISTRIBUTION	09/25/2018										197,018				197,018
	771424 HARVEST PRTN STRUCT CAP FD II	WILMINGTON	DE	DISTRIBUTION	06/28/2018										224,105				
	771438 CENTRE CAP INVESTORS VII LP	WILMINGTON	DE	DISTRIBUTION	05/29/2018										47,734				
	771454 WHITEHORSE LIQUIDITY PTR II LP	WILMINGTON	DE	DISTRIBUTION	09/21/2018										867,261				
	771462 COPPERMINE HOLDINGS LP	WILMINGTON	DE	DISTRIBUTION	03/27/2018										2,426,944				
	771478 PPC FUND II LP	WILMINGTON	DE	DISTRIBUTION	04/26/2018										121,284				121,284
	771480 PROVIDENCE EQUITY PTR VIII LP	GEORGE TOWN	CYM	DISTRIBUTION	07/17/2019										222,112				13,286
	771501 DATUM ONE LP	GEORGE TOWN	CYM	DISTRIBUTION	07/26/2018										222,207				222,207
	771503 INSIGHT VENTURE PARTNERS X LP	GEORGE TOWN	CYM	DISTRIBUTION	08/02/2018										366,453				366,453
	771519 COURT SQUR CAPITAL PART IV LP	NEW YORK	NY	DISTRIBUTION	11/04/2019										541,826				541,826
	771521 KELSO INVEST ASSOCIATES X LP	DOVER	DE	DISTRIBUTION	12/13/2018										2,325,684				47,610
	771523 GOAT HOLDINGS I LP	WILMINGTON	DE	DISTRIBUTION	08/30/2018										2,511,095				
	771537 TPG HEALTHCARE PARTNERS LP	WILMINGTON	DE	DISTRIBUTION	09/30/2019										549				
	771539 TPG PARTNERS VIII LP	WILMINGTON	DE	DISTRIBUTION	09/30/2019										160,808				160,808
	771573 WINDJAMMER SR EQUITY FD V LP	WILMINGTON	DE	DISTRIBUTION	12/28/2018										40,216				
	771604 OAK HILL CAP PTR V ONSHORE LP	GEORGE TOWN	CYM	DISTRIBUTION	12/07/2020										9,105,779				2,139,677
	771608 ENTERGY UTILITY HOLDCO LLC A	WILMINGTON	DE	DISTRIBUTION	10/01/2015										826,875				826,875
	771619 PAINE SCHWARTZ FOOD CHAIN FD V	GEORGE TOWN	CYM	DISTRIBUTION	01/21/2020										2,007,002				1,044,301
	771621 EAGLETREE PARTNERS V ONSHORE	GEORGE TOWN	CYM	DISTRIBUTION	12/18/2020										7,808,415				
	771629 GENSTAR CAPITAL PARTNERS IX LP	WILMINGTON	DE	DISTRIBUTION	07/03/2019										2,480,352				489,329
	771633 LOVELL MINNICK EQUITY PTR V LP	DOVER	DE	DISTRIBUTION	10/25/2019										8,856				8,856
	771635 ENTERGY UTILITY HOLDCO LLC B	WILMINGTON	DE	DISTRIBUTION	10/01/2015										229,688				229,688
	771637 ENTERGY UTILITY HOLDCO LLC C	WILMINGTON	DE	DISTRIBUTION	10/01/2015										499,163				499,163
	771656 VERITAS CAP CREDIT OPP FUND LP	WILMINGTON	DE	DISTRIBUTION	10/30/2019										1,260,600				1,260,600
	771662 WHITEHORSE LIQT PTR FD III	WILMINGTON	DE	DISTRIBUTION	08/06/2019										510,494				318,537
	771668 BLACKSTONE TAC OPP FUND III LP	WILMINGTON	DE	DISTRIBUTION	09/03/2019										853,481				
	771697 ARCLIGHT ENERGY PARTNER VII LP	DOVER	DE	DISTRIBUTION	02/21/2020										4,288,003				2,511,416
	771708 WIND POINT PARTNERS IX A LP	GEORGE TOWN	CYM	DISTRIBUTION	09/06/2019										2,012,431				
	771710 NEW MTN STRATEGIC EQ FUND I LP	WILMINGTON	DE	DISTRIBUTION	03/26/2021										156,390				
	771727 OAKTREE PORT AM FUND HS III LP	WILMINGTON	DE	DISTRIBUTION	06/21/2021										(266,374)				(266,374)
	771737 LINDEN STRUCTURED EQUITY FUND	DOVER	DE	DISTRIBUTION	02/21/2020										2,131,271				144,323
	771743 GREEN EQUITY INVESTORS VIII LP	DOVER	DE	DISTRIBUTION	10/21/2020										128,829				
	771745 CARLYLE EUROPE TECH PARTNER IV	LUXEMBOURG	LUX	DISTRIBUTION	12/31/2019										488,510	(14,891)		(14,891)	
	771766 STERLING INVESTMENT PART IV LP	WILMINGTON	DE	DISTRIBUTION	07/16/2021										11,756,897				716,759
	771778 INSIGHT PARTNERS XI LP	GEORGE TOWN	CYM	DISTRIBUTION	03/25/2020										47,292				
	771780 IVY HILL REVOLVER FUNDING LP	WILMINGTON	DE	DISTRIBUTION	05/19/2020										157,546				157,546
	771781 GIP SPECTRUM FUND LP	WILMINGTON	DE	DISTRIBUTION	06/12/2020										278,566				278,566
	771803 GRYPHON HERITAGE PARTNERS LP	WILMINGTON	DE	DISTRIBUTION	12/15/2020										367,711				
	771806 LEEDS EQUITY PARTNERS VII LP	WILMINGTON	DE	DISTRIBUTION	09/08/2021										2,372				
	771828 KKR DISLOCATION OPP FUND LP	GEORGE TOWN	CYM	DISTRIBUTION	06/22/2020										5,655,002				972,715
	771842 HARVEST PRTN STRUCT CAP FD III	WILMINGTON	DE	DISTRIBUTION	12/18/2020										490,697				

Figure IA.6: Example – Schedule BA Part 3

IA.2.2 Schedule BA Cleaning Procedure

Create Fund ID I create fund identifier (ID) using the following steps:

1. Based on recurring typographical errors and naming variations identified through manual inspection, I develop an algorithm to standardize fund names by correcting these commonly observed inconsistencies. Below, I outline the key steps of the algorithm:
   - **Convert all fund names to lowercase.** This ensures case-insensitive comparisons.
   - **Remove internal ID at the beginning or end of the name.** Some insurers append internal ID to fund names, typically as prefixes or suffixes. I apply the following rules to identify and remove such patterns. Specifically, I drop any leading or trailing numbers longer than six digits. I also drop any leading or trailing unpronounceable tokens longer than six characters that contain a mix of letters and numbers.
   - **Standardize common phrases.** Through manual review, I compile a list of over 50 commonly varying terms and apply consistent transformations. This step is conceptually similar to the Porter stemming algorithm used in natural language processing, but implemented through a manually curated list. By constructing the stemming rules by hand, my algorithm is more flexible and robust. A few illustrative examples are:
     - I drop all phrases referring to *Limited Partnership*, including `LP`, `L.P.`, `limited partner`, `limited partnership`, `prtr`, `ptr`, `ptrs`, etc (more than 100 variations).
     - Phrases such as `American`, `United States`, `US`, `USA`, are standardized to `America`.
     - Phrases such as `Euro`, `Europ`, `European`, are standardized to `Europe`.
     - Phrases such as `Invest`, `Invt`, and `Inve`, are standardized to `Investment`.
     - Phrases such as `Opportunity`, `opp`, `opps`, `opport`, are converted to `Opportunities`.
     - Phrases such as `infra`, `infras`, `infrastruct`, are standardized as `Infrastructure`.
   - **Remove all punctuation marks.**
   - **Trim leading, trailing, extra spaces.**
2. I then identify potential inconsistencies by exploiting the panel structure of the holdings data. Specifically, I flag suspicious cases based on the following criteria:
   - **Rare appearances:** I flag fund names that appear only once or twice in an insurer's portfolio (except when it is likely caused by data truncation). *Example:* Fund A is recorded in Insurer X's portfolio only in 2013, and never before or after.
   - **Missing observations:** I flag fund names that exhibit missing values within what should be a continuous holding period. *Example:* Fund A is held by Insurer X continuously from 2015 to 2023, except for 2017.
   - **Unexplained discontinuation:** I flag fund names that disappear from an insurer's portfolio without any reported sale. *Example:* Fund A was first acquired in 2016 suddenly drops out starting 2019 and no sale is reported.
   - **Delayed first appearance:** I flag fund names where the first appearance occurs substantially after the reported initial acquisition date (except when it is likely caused by data truncation). *Example:* Fund A first appears in the insurer X's portfolio in 2017, but the reported first acquisition year is 2014.

3. Next, I use ChatGPT to standardize the flagged fund names. To simplify the task and ensure consistency, I perform the matching process separately for each insurer. For each insurer, I begin with a panel dataset that contains all fund names previously flagged in Step 2. Note that according to Step 2, all names associated with a given fund will be flagged if any name inconsistency is detected across time. I then identify a subset of fund names to serve as target names. Target names are the most likely correct fund names, which other names will be matched to. A fund name is identified as a target if its number of observed appearances exceeds half of its theoretical appearance count, which I compute based on the reported first acquisition year and the insurer-specific sample window. Specifically, the theoretical appearance count is calculated as the number of years between the fund's acquisition year and the sample end year, capped at 15 to reflect a typical private fund life span. For example, if a fund was first acquired in 2014 and the sample ends in 2023, the theoretical appearance count is 10. Once target names are identified, I use ChatGPT to perform fuzzy matching between non-target names and target names using the following prompt:
4. I manually review all remaining unmatched cases as well as cases with low confidence scores.
5. I repeat steps 2 to 4 multiple times to ensure consistent and accurate name matching.
6. Finally, a unique fund ID is assigned to each unique fund name.

Prompt for Fund Name Match (reformatted for readability)

I have a dataset of private fund names reported by a specific investor. Due to typographical errors, abbreviations, or rebranding, the same fund may appear under multiple names. Your task is to manually review each row where `Target == 0` and determine whether it refers to the same underlying fund as any of the names listed in the rows where `Target == 1`.

Please do not use code or automated string comparison. Instead, consider the following rules:

- Name variations caused by typos and abbreviations.
- Name variations caused by private equity M&A and rebranding.
- Proximity of acquisition dates. If two names refer to the same fund, their reported acquisition date should be close (may not exactly be the same).

For each `Target == 0` row, compare it to the full list of `Target == 1` fund names. Return the final dataset in CSV format with two added columns:

- `MatchedName`: The most likely matching fund name (or "No Match")
- `MatchedScore`: A confidence score from 1 to 5

Important: Please perform this review manually, row by row, using your knowledge and reasoning. Do not use code or fuzzy matching tools.

Identify Private Fund After obtaining the fund ID, I identify private funds in Schedule BA using the following steps:

1. Keep only funds listed under the following categories according to the NAIC instructions:
   - Non-Registered Private Funds
   - Joint Venture, Partnership, or Limited Liability Company Interests
2. Drop assets whose names mention terms such as `Hedge Fund`, `Surplus Debentures`, `Low Income Housing Tax`, or `Tranches`.
3. Drop assets with zero "Commitment for Additional Investment" throughout the sample, except for funds first acquired before 2005 (the start of the annual sample).

Get Quarterly Measure To obtain all relevant variables at the quarterly frequency, I take several additional steps. A key challenge is that the quarterly statutory filings do not include the full list of fund holdings (Part 1). The annual filing provides a complete snapshot of all holdings at year-end as well as the transaction during the year. In contrast, only transaction (Part 2 and 3), such as contribution (capital call), distributions, or disposal, are reported each quarter. To reconstruct a complete panel at the insurer-fund-year-quarter level, I proceed as follows:

1. **Construct a balanced panel.** I begin by creating a complete insurer-fund-year-quarter panel that includes all possible combinations within each period. This ensures that each insurer-fund pair has one row per quarter, regardless of whether the position changed during that quarter.
2. **Merge year-end values from annual reports.** I left join year-end values (e.g., book-adjusted carrying value and uncalled commitment) from the annual report using insurer-fund-year as matching keys. These values provide an anchor for inferring missing quarterly observations.
3. **Merge quarterly transactions from quarterly reports.** I then left join quarterly transaction data, such as capital calls, distributions, and disposal, from the quarterly reports using insurer-fund-year-quarter as matching keys.
4. **Infer quarterly values.** With the annual totals and Q1–Q3 transaction data, I back out the Q4 transaction values and estimate quarterly positions. The detailed methods are as follows:
   - **Capital calls and distributions:** The Q4 value equals the residual between the year-end total and the sum of the reported Q1–Q3 values:

$$\text{Q4 Call} = \text{Annual Call} - (\text{Q1 Call} + \text{Q2 Call} + \text{Q3 Call})$$

   - **Uncalled commitment:** For quarters prior to Q4, I infer the uncalled commitment by working backward from the year-end value and subtracting the cumulative capital calls made after each quarter. For example:

$$\text{Q1 Uncalled} = \text{Year-End Uncalled} + (\text{Q1 Call} + \text{Q2 Call} + \text{Q3 Call})$$

   - **Book value (BACV):** I first estimate quarterly BACV using the year-end value and the cumulative capital calls and distributions. I then account for fair value adjustments such as unrealized gains/losses by assuming these are evenly distributed across quarters. That is, the quarterly fair value adjustment is set to one-fourth of the total annual adjustment. For example

$$\begin{aligned}\text{Q1 BACV} = \text{Year-End BACV} &- (\text{Q1 Call} + \text{Q2 Call} + \text{Q3 Call}) \\ &- (\text{Q1 Dist} + \text{Q2 Dist} + \text{Q3 Dist}) \\ &- 0.25 \times \text{Annual Adjustment}\end{aligned}$$

5. **Handle fully exited holdings.** For fund positions that are no longer listed in the year-end annual report (due to full liquidation or sale), I reconstruct quarterly values using the previous year-end value as the starting point. In such cases, I apply capital calls, distributions, and estimated fair value adjustments to the full exit periods, where all level variables are set to zero.

Filtering Abnormal Values To ensure data quality and improve the reliability of the capital call forecasts, I apply several filtering steps to address reporting inconsistencies and eliminate implausible values. These steps are necessary because the reconstructed quarterly panel may contain mechanical or reporting-induced anomalies. Specifically, I proceed as follows:

1. By definition, uncalled commitments should only decline over time as capital is called. In cases when uncalled commitment is larger than the previous period-end value, I set the current period's uncalled commitment equal to the previous period's value. I also set the capital call for the current period to zero.
2. I set capital call to zero if it is negative. Begenau et al. (2020) point out that negative capital calls could be attributed to fee offsets. But it does not affect my analysis.
3. If a capital call exceeds the uncalled commitment from the previous period, I set that capital call value equal to the uncalled commitment from the previous period. Note that I do not impose any restriction based on the cumulative capital call. As pointed out by Begenau et al. (2020), cumulative capital call could exceed the initial commitment due to recycled capital.
4. To simplify the forecasting task later, I assume capital calls equal to zero after their tenth year. Accordingly, for any fund with age greater than 10 years, I set both capital call and uncalled commitment to zero. This step does not affect the results.
5. In principle, capital calls and uncalled commitments should evolve consistently over time. I manually inspect cases where the two series exhibit significant misalignment and attempt to reconcile them. If reconciliation is not possible, I drop the affected observations from the sample.
6. For funds held by multiple insurers at the same period, I compare the capital call rates and distribution rates across insurers. Although small differences are normal, large discrepancies likely indicate potential errors. I manually inspect all such suspicious cases and attempt to reconcile them. If reconciliation is not possible, I replace the outlier observation with the median capital call (or distribution) rate reported by other insurers holding the same fund in the same period.

Identify Fund Type I use the following steps to identify fund types.

1. For funds that can be merged with the PitchBook data, I use the fund type classification from PitchBook. Specifically, I group PitchBook fund types into the following six categories: Private Equity, Venture Capital, Real Estate, Private Debt, Infrastructure, and Others.

2. For the remaining funds, I use fund names to perform further classification. Specifically,
   - Funds with names including words such as `Buyout`, `Equity`, `Balance`, `Growth`, or `Stock` are classified as Private Equity Funds.
   - Funds with names including words such as `Venture`, `Early`, `Seed`, or `Start Up` are classified as Venture Capital Funds.
   - Funds with names including words such as `Real Estate`, `Housing`, `Residential`, or `Mortgage` are classified as Real Estate Funds.
   - Funds with names including words such as `Debt`, `Credit`, `Mezzanine`, `Direct Lending`, or `Distressed Debt` are classified as Private Debt Funds.
   - Funds with names including the word `Infrastructure` are classified as Infrastructure Funds.
3. Finally, I use ChatGPT to further classify funds into the above six categories using the following prompt.

Prompt for Fund Type Classification (reformatted for readability)

I have a list of private fund names. Please help classify each fund into one of the following six categories: (1) Private Equity, (2) Venture Capital, (3) Real Estate, (4) Private Debt, (5) Infrastructure, (6) Others.

Use your broader understanding of private market terminology to make informed judgments. If a fund name does not fit into any category, classify it as `Others`.

Return your output in CSV format with two columns:
- `FundName`: the original fund name.
- `FundType`: one of the six categories.

IA.2.3 Data Comparison

Table IA.1 compares my dataset, based on Schedule BA statutory filings, with commonly used data sources in the literature such as Preqin and MSCI Burgiss. Below, I summarize the key similarities and differences:

- **Data Source and Coverage**: The Schedule BA data is derived from mandatory statutory filings submitted by U.S. insurance companies. In contrast, most traditional datasets, such as Preqin, primarily rely on Freedom of Information Act (FOIA) requests to U.S. public pension funds (Begenau et al., 2020). While some more proprietary datasets exist based on information collected by investment advisors or third-party providers, these are relatively uncommon. Due to the difference in source, my data covers U.S. insurers, whereas traditional datasets focus largely on U.S. public pensions. A further distinction is that Schedule BA filings provide a complete investor-level panel of holdings, while FOIA-based data is often insufficient to reconstruct a complete panel for each investor.
- **Capital Calls and Distributions**: Both my dataset and traditional sources report after-fee cash flows—that is, the actual cash flows experienced by the investor, net of fees.
- **Sample Period and Frequency**: My dataset includes annual holdings starting in 2005 and quarterly transaction-level data beginning in 2008. Traditional datasets, such as Preqin and Burgiss, typically start in the 1990s. Both my data and traditional sources provide quarterly frequency for cash flow and valuation information.
- **Secondary Market Sales**: Although secondary sales of private fund stakes remain relatively limited, they do affect investor-level holdings. My data captures all secondary market sales, whereas traditional datasets generally do not track these transactions.
- **Fund Characteristics**: Key fund-level attributes, such as vintage year, fund age, size, general partner identity, and fund type, are available in both my data and in traditional sources. However, in my data, extracting these fund characteristics requires additional processing.
- **Rest of portfolio**: My data can link investors' private fund holdings with the rest of their portfolio, which is not possible in traditional data sources.

It is possible to merge the Schedule BA data with traditional datasets. To do this, I apply the same fund name standardization algorithm used in the first step of creating fund identifiers (as discussed earlier) to the fund names in the other data sources. The standardized fund names then serve as a common key for merging both datasets.

Table IA.1: Data Comparison

This table compares the Schedule BA data with the other data commonly used in the PE literature.

	Schedule BA Data	**Other Data Used in the Literature**
Data Source	Mandatory Statutory Filings	(1) FOIA request (2) Voluntary disclosure from GP (3) Third party data
Fund Type Coverage	All private funds	Depends on your subscription
Investor Type Coverage	Insurance companies	Mostly public pension funds
Investor-level Completeness	Complete	Not complete
Sample Period	Since 2008	Since 1990s
Frequency	Quarterly	Quarterly
Easy to use	No	Yes
Key Variables		
Fund Information	Name, Vintage, Age, Size, GP, Type (needs some work)	Available and easy to use
Initial Commitment Amount	Yes	Depends
Capital Call	Yes (include fee)	Yes (include fee)
Distribution	Yes	Yes
Uncalled Commitment	Yes	Depends
Secondary Market Sale	Yes	No
Performance Measures	Need to calculate yourself	Yes
Rest of Portfolio	Yes	No
Investor Financial	Yes	No
Deals/Portfolio Companies	No	Yes

IA.2.4 Variable Definitions

Table IA.2: Variable Definitions

Variable	Definition
Capital Call	Amount of capital call an insurer received during a quarter, scaled by the lagged total portfolio size.
Expected Capital Call	Expected amount of capital call an insurer received during a quarter, defined as in Section 4, scaled by the last period total portfolio size.
Unexpected Capital Call	Unexpected amount of capital call an insurer received during a quarter, defined as in Section 4, scaled by the last period total portfolio size.
Capital Call Rate	Amount of capital call scaled by the lagged uncalled commitment. Same for expected and unexpected capital call rate.
Distribution	Amount of distribution an insurer received during a quarter, scaled by the lagged total portfolio size.
Uncalled Commit	The total amount of uncalled commitment an insurer has, scaled by the lagged total portfolio size.
New Commit	The total amount of new commitment an insurer made during a quarter, scaled by the lagged total portfolio size.
Private Fund	Percentage holdings of private funds based on the book value (BACV).
Bond	Percentage holdings of all long-term bonds, reported in Schedule D Part 1.
Treasury	Percentage holdings of all treasury bonds.
Industrial	Percentage holdings of all industrial bonds, based on the definition of NAIC.
Corporate Bond	Percentage holdings of all corporate bonds.
Other-Industrial Bond	Percentage holdings of all non-corporate industrial bonds.
Govt Agent	Percentage holdings of all government-related, non-Treasury bonds.
Other Bond	Percentage holdings of other long-term bonds.
Mortgage	Percentage holdings of all mortgage loans, reported in Schedule B.
Stock	Percentage holdings of stocks (both common and preferred stocks), reported in Schedule D Part 2.
Rest	All remaining holdings.
NAIC	A numerical number for the NAIC designations, range from 1 to 6.
RBC Ratio	Risk-Based Capital Ratio.
Unrealized G&L	Unrealized gains and losses computed as the difference between book value (BACV) and fair value, scaled by the book value.
Exposure	Bond-level capital call shock exposure measure, defined as in equation (7)
Yield Spread	Corporate bond yield spread defined as yield minus the maturity-match treasury yield.
Ownership	The percentage bond share owned by each insurer.
Insurer Ownership	The percentage bond share owned by all insurers.
Insurer Sell	The par amount of bond sold by all insurers, scaled by bond size. Only active sales are considered.
Bid-Ask Spread	Corporate bond bid-ask spread.
Bond Ratings	Numerical number of corporate bond ratings.
Trading Volume	Log of bond trading volume based on par value.
Bond Size	Log of bond outstanding amount
Time-to-Maturity	The number of years before the stated maturity date.

IA.3 Forecasting Capital Calls

IA.3.1 Forecasting Models

LASSO LASSO (Least Absolute Shrinkage and Selection Operator) is a type of linear regression model designed to identify the most important predictors. Specifically, it models the outcome variable as a linear function of the predictor vector $X_{j,t}$, but with a penalty on complexity. Formally, it estimates coefficients β by solving:

$$\min_{\beta} \sum_{j,t} \left(RC_{j,t+1} - \mathbf{X}'_{j,t}\beta\right)^2 + \lambda \sum_{k} |\beta_k|$$

The second term is a penalty on the absolute values of the coefficients, controlled by the hyperparameter $\lambda \geq 0$. When λ is large, the model shrinks more coefficients toward zero, effectively performing variable selection by excluding weak predictors. When $\lambda = 0$, LASSO reduces to ordinary least squares. The key advantage of LASSO is the interpretability. However, LASSO cannot capture nonlinear interactions or complex functional forms.

Decision Tree A decision tree is a flexible, non-parametric model that predicts the outcome variable by recursively splitting the data based on values of the predictors. The model creates a tree-like structure where each internal node represents a rule, and each terminal leaf node assigns a predicted value based on the average of the outcome variable in that subgroup. Formally, a decision tree partitions the feature space $\mathbf{X}_{j,t}$ into regions $\{R_1, R_2, \ldots, R_M\}$, and predicts the outcome variable as the average in the corresponding region:

$$\widehat{RC}_{j,t+1} = \sum_{m=1}^{M} \bar{RC}_m \cdot 1\left\{\mathbf{X}_{j,t} \in R_m\right\}$$

where $\bar{RC}_m$ is the average capital call ratio in region R_m. The key hyperparameters include: (1) Maximum tree depth (limits the number of splits); (2) Minimum samples per leaf (prevents overfitting by requiring enough observations per group); (3) Split criterion (e.g., mean squared error)

Figure IA.7 illustrates a simple decision tree used to predict capital call outcomes. Each node represents a decision rule that splits the data based on a specific predictor, recursively dividing the sample into increasingly homogeneous subgroups. The top number in each node is the predicted outcome variable, and the bottom number shows the proportion of observations in that group. The tree starts with the full sample (100% in the root node) and a sample average capital call rate of 11%. The first split is based on whether the lagged capital call rate is below 25%. 10% of the sample has a lagged call rate above 25%, and has a predicted capital call rate of 18%. The remaining 90% is further split based on whether the uncalled commitment (as a percentage of the initial commitment) exceeds 66%. If it does, the predicted call rate is 6.4%; if not, the predicted call rate is 11%.

As the example shows, decision trees are highly interpretable and automatically capture nonlinearities and interactions. However, a single decision tree tends to overfit the data, which is why a single tree is rarely optimal. Instead, it serves as the building block for more powerful ensemble methods such as random forests and gradient boosting, which I describe next.

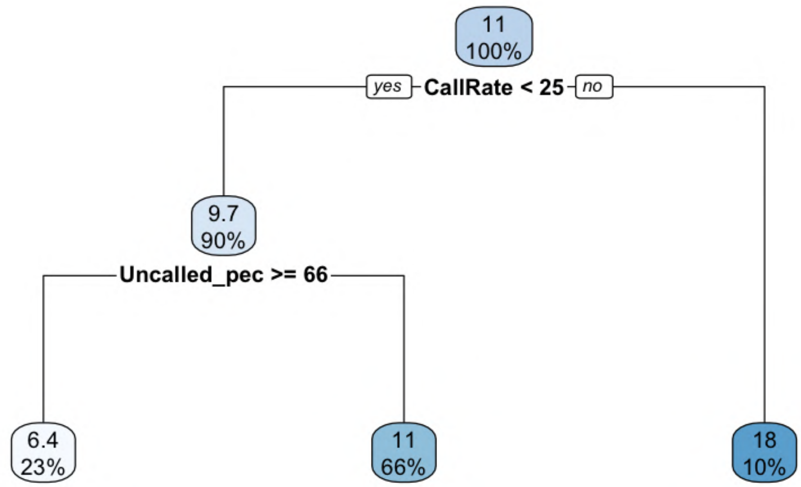


Figure IA.7: Illustration of Decision Tree

This figure illustrates the idea of a decision tree.

Random Forest Random Forest is an ensemble learning method that builds upon the decision tree model. Instead of relying on a single tree, it constructs many trees and averages their predictions to produce a more stable and accurate forecast. Each tree is trained on a different random subset of the data and, at each split, considers only a random subset of the predictors. This randomness helps reduce overfitting. Formally, the Random Forest prediction for the outcome variable is the average of predictions from B separate trees:

$$\widehat{RC}_{j,t+1} = \frac{1}{B} \sum_{b=1}^{B} \widehat{RC}_{j,t+1}^{(b)}$$

where each $\widehat{RC}_{j,t+1}^{(b)}$ is the prediction from tree b. Key hyperparameters include: (1) Number of trees (B): more trees usually improve performance up to a point; (2) Maximum tree depth: controls complexity of each tree; (3) Minimum samples per leaf: avoids splitting into overly small regions; (4) Number of predictors considered at each split: adds randomness and reduces correlation among trees.

Advantages of Random Forest include its ability to capture complex nonlinear interactions without much tuning, its robustness to overfitting, and its built-in measure of variable importance. The main drawback is that the model loses interpretability compared to a single decision tree and LASSO.

LightGBM LightGBM (Light Gradient Boosting Machine) is a fast and efficient implementation of gradient boosting, a technique that builds a sequence of decision trees, where each tree tries to improve on the errors made by the previous ones. Unlike Random Forest, which averages predictions from many independent trees, LightGBM builds trees sequentially in a boosting framework to correct past mistakes.

Formally, at each stage, LightGBM minimizes a loss function (such as squared error) by fitting a new tree to the residuals of the current model. The updated prediction becomes:

$$\widehat{RC}_{j,t+1}^{(m)} = \widehat{RC}_{j,t+1}^{(m-1)} + \eta \cdot h_m\left(\mathbf{X}_{j,t}\right)$$

where $h_m(\cdot)$ is the new tree added at stage m, and η is a learning rate controlling how much weight is given to new trees. Key hyperparameters include: (1) Learning rate (η): smaller values slow learning but improve stability; (2) Number of boosting rounds; (3) Maximum depth or number of leaves: controls complexity of individual trees; (4) Minimum data in a leaf and feature fraction: regularization parameters to prevent overfitting.

LightGBM is highly efficient and well-suited for large structured datasets. It often achieves state-of-the-art accuracy with relatively fast training time. The disadvantage is that it reduces transparency and requires more careful tuning.

XGBoost XGBoost (Extreme Gradient Boosting) is another popular and powerful implementation of gradient boosting. Like LightGBM, XGBoost constructs trees sequentially to minimize prediction error, improving upon prior trees by fitting to residuals. Formally, XGBoost solves the following penalized objective:

$$\text{Objective } = \sum_{j,t} \ell\left(RC_{j,t+1}, \widehat{RC}_{j,t+1}\right) + \sum_{m} \Omega\left(h_m\right)$$

where $\ell(\cdot)$ is the loss function, and $\Omega\left(h_m\right)$ penalizes model complexity to prevent overfitting. Key hyperparameters include: (1) Learning rate (η) and number of boosting rounds; (2) Maximum depth, minimum child weight, subsample ratio, and colsample by tree (fraction of features randomly sampled per tree); (3) Gamma (minimum loss reduction required to make a split).

XGBoost is robust and flexible. In many settings, it delivers strong performance. Like LightGBM, its main limitation is interpretability.

Two-stage Hurdle Model One challenge in forecasting capital calls is the prevalence of zero observations: many fund-quarter observations have capital calls exactly equal to zero. This feature creates what is known as zero-inflated data, which violates standard model assumptions and can lead to biased or inefficient forecasts (Lambert, 1992). To overcome this challenge, I implement a two-stage hurdle model framework, a method commonly used in econometrics to model outcomes with excess zeros (Cragg, 1971; Mullahy, 1986). The core idea is to treat the zero and non-zero outcomes separately: the first-stage is a classification task to forecast whether there is going to be any capital call (non-zero), and the second-stag is a regression task to forecast how magnitude of the capital call, conditional on having non-zero capital calls.

Specifically, in the first stage, the binary classification task is to estimate the probability that a capital call is non-zero:

$$\Pr\left(RC_{j,t+1} > 0 \mid \mathbf{X}_{j,t}\right) = g_1\left(\mathbf{X}_{j,t}\right) = \hat{p}_{j,t+1}$$

In the second stage, a regression model is fit to the subsample of non-zero capital calls to estimate the expected magnitude, conditional on a call occurring:

$$\mathbb{E}\left(RC_{j,t+1} \mid RC_{j,t+1} > 0, \mathbf{X}_{j,t}\right) = g_2\left(\mathbf{X}_{j,t}\right) = \hat{\mu}_{j,t+1}$$

The final forecast is computed as the product of the two components:

$$\widehat{RC}_{j,t+1} = \hat{p}_{j,t+1} \cdot \hat{\mu}_{j,t+1}$$

This two-stage approach is especially beneficial in my setting, where a large portion of the observations are zeros but the positive realizations display significant heterogeneity. I implement this two-stage framework across all above machine learning models discussed earlier: LASSO, decision tree, random forest, LightGBM, and XGBoost. Hence, there are ten machine learning models in total.

IA.3.2 Implementation

Predictors Predictors $\mathbf{X}_{jt}$ includes

- Macro variables: GDP, CPI, industrial production, unemployment,
- Public market indicators: S&P 500 returns, Price-Dividend ratio, Price-Earnings ratio, credit spread index, fed fund rate, Treasury yield curve, VIX
- Private market: PE fundraising, PE deal volume, PE rolling IRR.
- Fund-level variables: vintage year, fund age, fund type, fund size, three lagged capital call rates $(t, t-1, t-2)$, and lagged uncalled commitment (as the percentage of initial commitment). Note that some fund-level variables might be missing. I set the missing value to zero.

Sample All models are initially trained and tested using the Preqin fund cash flow data. Since the Preqin data spans a significantly longer period (starting in the 1990s), it enables me to perform hyperparameter tuning and out-of-sample model selection without reducing the size of the main sample.

Hyperparameter Selection When hyperparameter tuning is required, I perform cross-validation using data available up to 2003. Specifically, this pre-2003 data is split into two equal parts: a training set and a validation set. The model is trained on the training set across various combinations of hyperparameters, and performance is evaluated on the validation set. I then select the hyperparameter combination that yields the best out-of-sample performance on the validation set. This selected configuration is fixed and used for all subsequent forecasts across time, i.e., hyperparameters are are only choose once.

Rolling Window Forecast Evaluation To evaluate out-of-sample forecasting performance, I adopt a five-year rolling window approach. For each forecast year t, I train the model using data from the previous five calendar years, i.e., from year $t-4$ through $t-1$. For example, to forecast capital calls in 2019, the model is trained on data from 2014 Q1 to 2018 Q4. This procedure is repeated for each year in the evaluation period (2008 to 2023), and I compute the average out-of-sample R^2 across all test years. This method resembles standard cross-validation method but is tailored for time-series data, ensuring that future information is never used in model training.

Apply the Selected Model to Main Sample I then apply the selected forecasting model to the main sample. For each year t, I use the same model specification as in the out-of-sample rolling window evaluation, i.e., trained on data from year $t-4$ through $t-1$. For any predictor variables that are unavailable in the main sample, I either set them to zero or leave them as missing (most packages can handle the missing values automatically).

IA.3.3 Additional Forecasting Results

Figure IA.8 shows the average of the predicted capital call rate. Subfigure (a) shows the sample average and fitted value of the capital call rate over the life of the fund. Subfigure (b) shows the percentage amount of uncalled commitment over the life of the fund.

(a) Predicted Capital Call Rate (b) Predicted Cumulative Capital Call

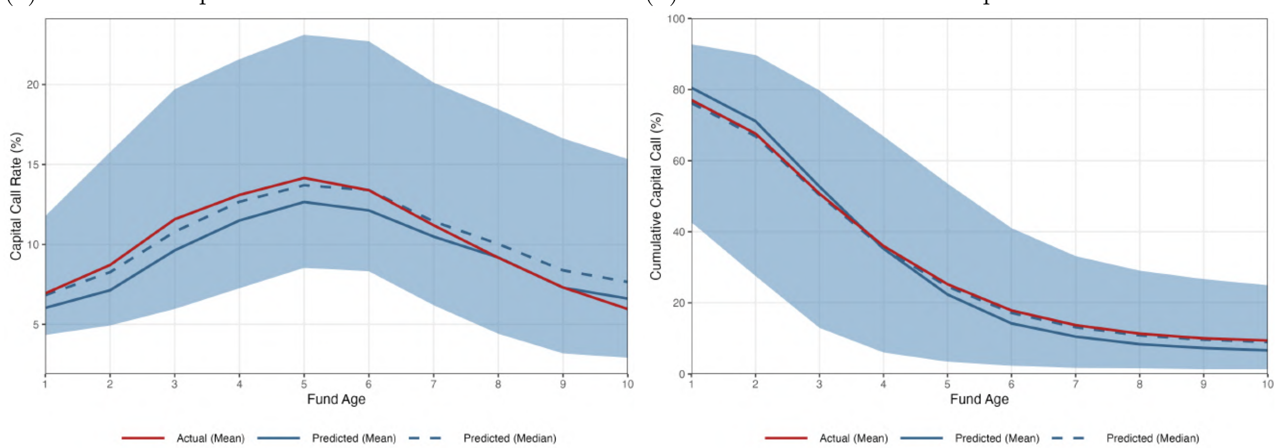


Figure IA.8: Predicted Capital Call Rates over Fund Ages

Subfigure (a) shows the sample average and fitted value of the capital call rate over the life of the fund. Subfigure (b) shows the percentage amount of uncalled commitment over the life of the fund.

IA.4 Additional Results

(a) Life Insurers (c) P&C Insurers

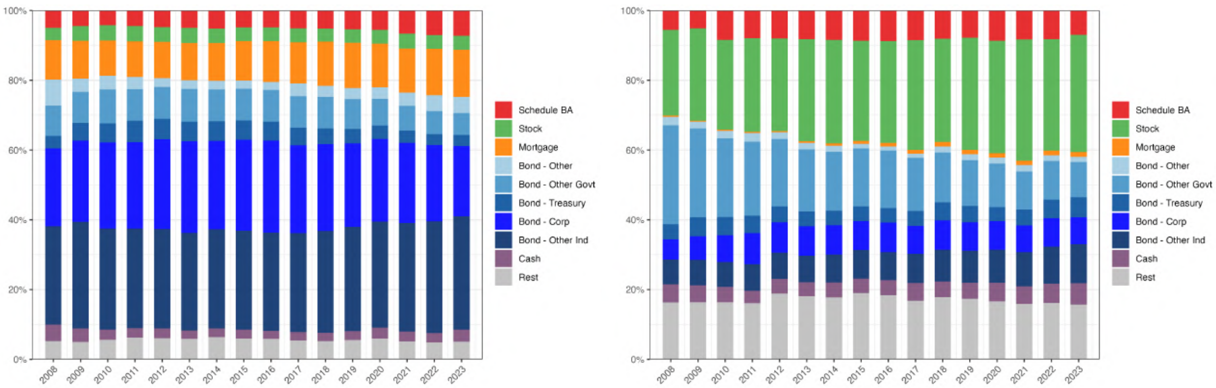


Figure IA.9: Insurers' Portfolio Allocation

This figure shows the aggregate allocation of insurance companies in the sample. Subfigure (a) is for Life insurers, and Subfigure (b) is for P&C insurers.

(a) By Fund Types (b) By Fund Ages

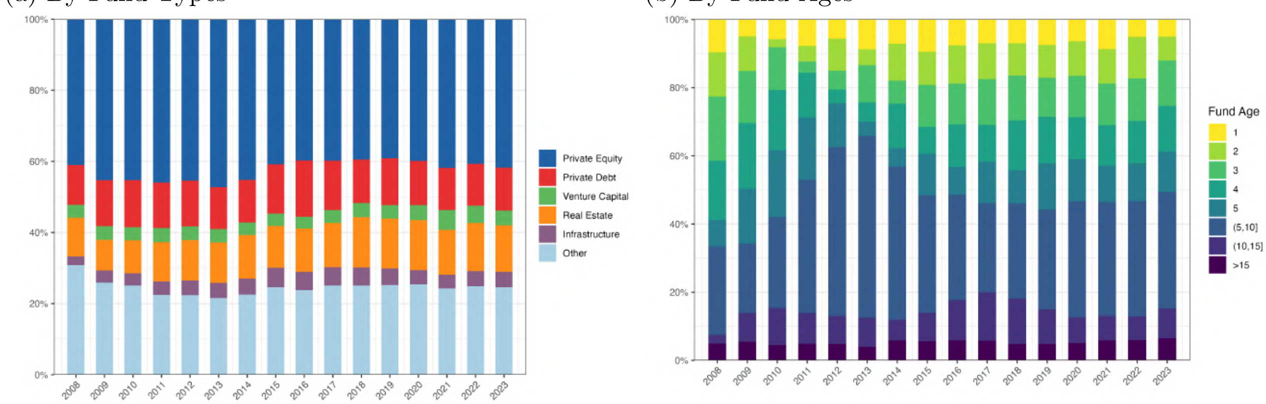


Figure IA.10: Private Fund Allocation

This figure shows insurers' private fund allocation over time: Subfigure (a) breaks allocation by fund types and Subfigure (b) breaks allocation by fund ages.

Table IA.3: Summary Statistics: Life vs. P&C Insurers

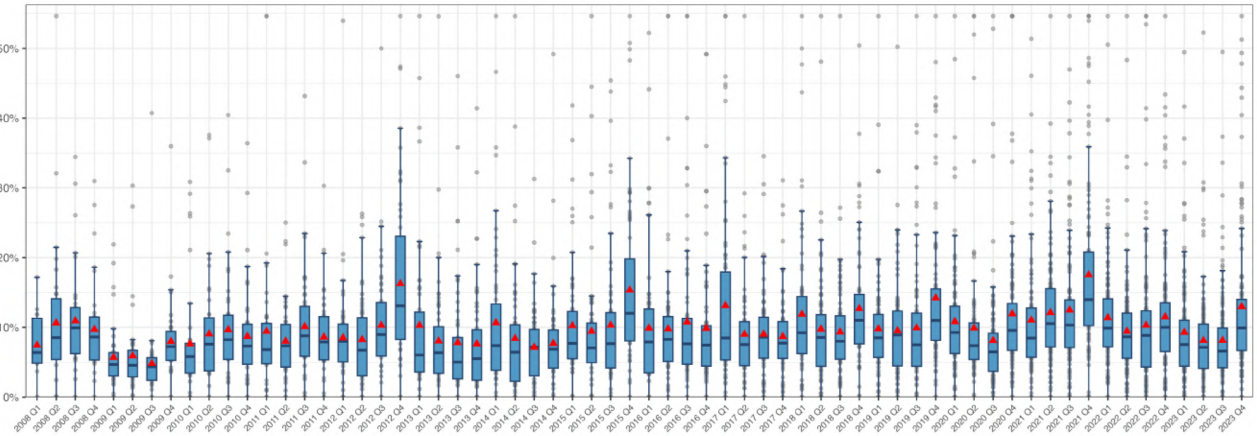
Panel A: Life Insurers								
Variable	N	Mean	SD	P1	P25	Med	P75	P99
Private Fund ($ M)	6977	867.59	2281.41	0.00	5.76	48.77	609.56	11926.60
Private Fund (%)	6977	2.01	12.46	0.00	0.22	1.06	2.60	10.46
Number Private Fund	6977	67.05	115.31	1.00	2.00	9.00	80.00	497.00
Uncalled Commit ($ M)	6977	381.29	910.88	0.00	0.00	15.62	299.54	4589.91
Distribution ($ M)	6977	38.44	144.03	0.00	0.00	0.76	16.36	672.85
Insurer Size ($ B)	6977	33.82	58.87	0.01	1.71	11.03	35.71	292.50
RBC Ratio (%)	6977	939.92	2764.92	291.48	732.86	900.74	1122.61	3544.55
Leverage	6977	12.95	9.16	1.55	6.16	10.50	16.94	43.28
Bond (%)	6977	73.64	14.23	15.98	67.72	74.73	83.44	94.81
NAIC 1 (%)	6977	46.82	62.26	5.10	37.98	44.35	53.78	83.59
NAIC 2 (%)	6977	26.46	72.74	0.47	19.03	24.84	31.01	56.64
NAIC 3 (%)	6977	2.64	8.92	0.00	1.31	2.30	3.39	8.68
NAIC 4 (%)	6977	0.87	1.08	0.00	0.22	0.64	1.27	3.65
NAIC 5 (%)	6977	0.34	0.82	0.00	0.02	0.13	0.37	4.04
NAIC 6 (%)	6977	0.09	0.19	0.00	0.00	0.02	0.10	0.82
Industrial (%)	6977	57.89	117.09	1.29	47.83	56.80	65.95	90.43
Corporate Bond (%)	6977	30.74	66.75	0.00	20.02	28.76	38.07	62.59
Other Industrial (%)	6977	27.15	52.10	0.13	18.18	26.98	33.12	57.09
Treasury (%)	6977	4.42	5.96	0.00	0.81	2.51	5.73	29.62
Other Govt Related (%)	6977	12.31	18.30	0.00	5.08	9.61	15.85	49.36
Other Bond (%)	6977	2.74	11.65	0.00	0.38	1.44	3.36	15.14
Cash (%)	6977	4.47	8.17	0.06	1.21	2.38	4.52	38.92
Mortage (%)	6977	7.93	7.19	0.00	0.70	7.43	12.87	32.47
Stock (%)	6977	4.77	5.92	0.00	0.94	2.98	6.13	30.46
Rest (%)	6977	7.19	13.91	-0.08	3.38	6.04	9.34	25.90
Panel B: P&C Insurers								
Private Fund ($ M)	8739	246.05	744.15	0.00	2.99	17.89	103.12	3895.42
Private Fund (%)	8739	2.03	2.62	0.00	0.22	1.02	2.85	11.84
Number Private Fund	8739	26.54	65.93	1.00	2.00	5.00	18.00	390.00
Uncalled Commit ($ M)	8739	104.31	283.17	0.00	0.00	4.66	53.52	1503.36
Distribution ($ M)	8739	9.22	53.34	0.00	0.00	0.14	2.39	140.14
Insurer Size ($ B)	8739	12.09	38.30	0.03	0.69	2.35	7.13	180.56
RBC Ratio (%)	8739	2157.50	44763.11	241.16	505.17	727.10	1046.96	3179.28
Leverage	8739	3.18	4.71	1.34	2.02	2.53	3.12	45.95
Bond (%)	8739	65.37	16.83	8.34	57.18	68.19	77.25	92.07
NAIC 1 (%)	8739	52.79	81.96	3.27	40.79	52.86	63.20	88.00
NAIC 2 (%)	8739	10.39	16.68	0.00	4.79	8.63	13.76	41.74
NAIC 3 (%)	8739	1.25	1.63	0.00	0.07	0.65	1.84	7.61
NAIC 4 (%)	8739	0.82	1.44	0.00	0.00	0.17	1.11	6.33
NAIC 5 (%)	8739	0.23	0.58	0.00	0.00	0.02	0.22	3.03
NAIC 6 (%)	8739	0.12	1.02	0.00	0.00	0.00	0.04	1.18
Industrial (%)	8739	30.05	47.98	0.00	16.32	27.88	39.86	73.51
Corporate Bond (%)	8739	15.79	27.08	0.00	7.27	13.43	21.31	52.64
Other Industrial (%)	8739	14.26	22.82	0.00	5.79	11.84	20.00	45.22
Treasury (%)	8739	8.21	21.64	0.01	2.23	5.20	10.29	41.08
Other Govt Related (%)	8739	25.69	33.99	0.07	12.46	22.83	36.14	67.64
Other Bond (%)	8739	1.76	3.38	0.00	0.00	0.59	2.24	14.66
Cash (%)	8739	6.64	8.14	-1.46	2.18	4.24	8.12	40.98
Mortage (%)	8739	0.66	1.84	0.00	0.00	0.00	0.06	10.10
Stock (%)	8739	20.00	14.25	0.00	9.73	17.81	26.86	70.57
Rest (%)	8739	5.30	5.48	-0.38	1.83	3.82	7.28	23.21

Table IA.4: Correlation with Other Data Source

This table shows the correlation between my data and Preqin. The first column shows the number of observations successfully merged. The second column shows the correlation for capital call rate, and the third column shows the correlation for uncalled commitment.

N	(1) Capital Call Rate	(2) Uncalled Commit
235,773	0.816	0.977

(c) Capital Call Rates



(c) Unexpected Capital Call Rates

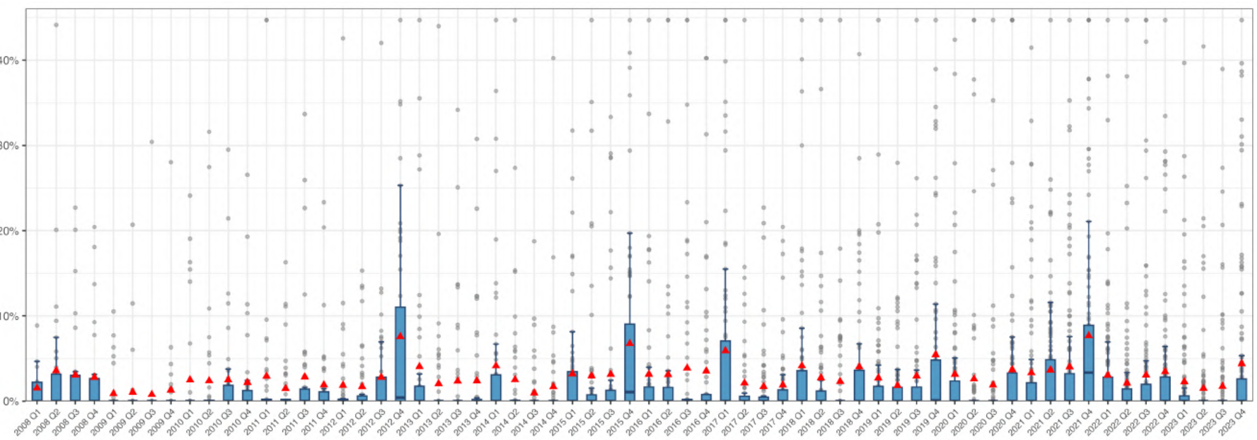


Figure IA.11: Investor-level Capital Call Rate Distribution over Time

This figure plots the distribution of investor-level capital call rates over time using boxplots, where Subfigure (a) is for the total capital call and Subfigure (b) is for the unexpected component. Capital calls are scaled by the previous period-end uncalled commitments. Each box represents the interquartile range (IQR), with the bottom and top edges corresponding to the first and third quartiles. The horizontal short dark blue line inside each box denotes the median, while the red triangle indicates the mean. The vertical lines extending from the boxes (whiskers) show the range of the data, excluding outliers. Individual observations beyond the whiskers (outliers) are plotted as light gray dots.

Table IA.5: Time Series Determinants of Capital Calls

This table shows the time series determinant of capital call. Panel A shows the results for capital call rate, and Panel B shows the results for unexpected capital call rate. Insurer fixed effects are included. Standard errors double clustered at the insurer and time level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Capital Call Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(P/D)	0.118***							0.063**
	(0.024)							(0.030)
log(Credit Spread)		−0.042***						0.028**
		(0.012)						(0.011)
log(Fund Raising)			0.050***					0.037***
			(0.005)					(0.007)
log(PE Deal Volume)				0.044***				0.013*
				(0.006)				(0.007)
log(PE IRR)					0.064***			0.002
					(0.023)			(0.030)
Treasury 1Y						0.002		0.001
						(0.006)		(0.004)
Treasury 5Y						0.047***		0.003
						(0.015)		(0.010)
Treasury 10Y						−0.055***		−0.002
						(0.012)		(0.009)
GDP Growth							0.001	−0.001
							(0.001)	(0.001)
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,498	11,498	11,498	11,498	11,498	11,498	11,498	11,498
Adjusted R^2	0.449	0.436	0.474	0.461	0.428	0.457	0.421	0.480

Panel B: Unexpected Capital Call Rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(P/D)	0.018**							0.006
	(0.009)							(0.014)
log(Credit Spread)		−0.006*						0.007*
		(0.004)						(0.004)
log(Fund Raising)			0.008***					0.011***
			(0.002)					(0.002)
log(PE Deal Volume)				0.008***				0.009***
				(0.002)				(0.003)
log(PE IRR)					0.019**			−0.010
					(0.008)			(0.016)
Treasury 1Y						−0.001		−0.002
						(0.002)		(0.002)
Treasury 5Y						0.008		−0.007*
						(0.006)		(0.004)
Treasury 10Y						−0.008*		0.009**
						(0.004)		(0.004)
GDP Growth							0.0001	−0.0003
							(0.001)	(0.0005)
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,498	11,498	11,498	11,498	11,498	11,498	11,498	11,498
Adjusted R^2	0.153	0.149	0.160	0.159	0.152	0.150	0.146	0.168

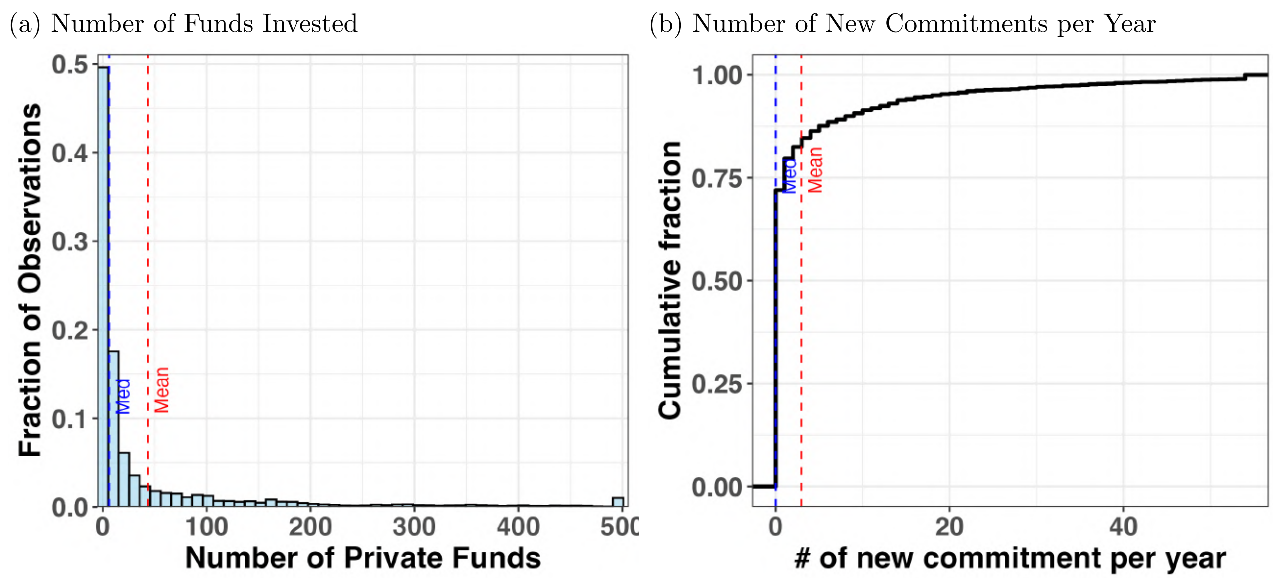


Figure IA.12: Distribution of Number of Private Funds Invested

Subfigure (a) shows the distribution of number of private funds held by one insurer. Subfigure (b) shows the cumulative distribution of number of new commitments made by each insurer every year.

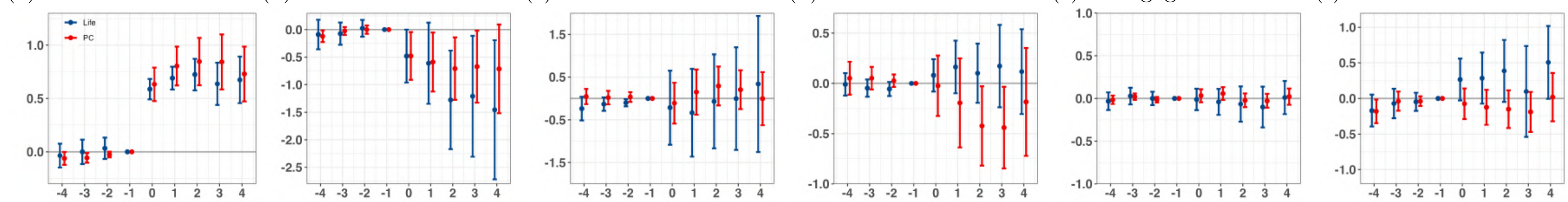
Table IA.6: Portfolio Rebalancing: Life vs. P&C Insurers

This table examines differences in portfolio adjustment decisions between Life and P&C insurers when facing capital calls. Panels A and C present results for Life insurers, while Panels B and D present results for P&C insurers. Panels A and B correspond to Panel A of Table 5, and Panels C and D correspond to Panel B of Table 5. All regression specifications are identical to those in Table 5.

Panel A: Life						
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Capital Call	0.629***	−0.577**	−0.243	0.071	0.021	0.135
	(0.049)	(0.281)	(0.385)	(0.120)	(0.036)	(0.166)
Distribution	−0.732***	0.784*	0.498	−0.152	0.018	−0.293
	(0.137)	(0.419)	(0.336)	(0.151)	(0.062)	(0.568)
Observations	6,050	6,050	6,050	6,050	6,050	6,050
Adjusted R^2	0.315	0.096	0.107	0.266	0.116	0.066
Panel B: P&C						
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Capital Call	0.624***	−0.502**	−0.124	−0.050	0.034	−0.080
	(0.078)	(0.235)	(0.235)	(0.141)	(0.026)	(0.112)
Distribution	−0.850***	0.245	0.155	0.156	0.017	0.362***
	(0.082)	(0.383)	(0.359)	(0.287)	(0.027)	(0.132)
Observations	6,078	6,078	6,078	6,078	6,078	6,078
Adjusted R^2	0.537	0.239	0.155	0.512	0.098	0.213
Panel C: Life – Unexpected vs. Expected						
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Unexpected Capital Call	0.616***	−0.632**	−0.059	0.030	0.018	0.128
	(0.055)	(0.300)	(0.396)	(0.134)	(0.041)	(0.182)
Expected Capital Call	0.315**	−0.048	−0.341	0.115	0.040	−0.165
	(0.151)	(0.369)	(0.732)	(0.141)	(0.091)	(0.278)
Observations	5,476	5,476	5,476	5,476	5,476	5,476
Adjusted R^2	0.218	0.082	0.144	0.119	0.106	0.081
Panel D: P&C – Unexpected vs. Expected						
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Unexpected Capital Call	0.659***	−0.573**	−0.233	0.070	0.046	−0.165
	(0.089)	(0.264)	(0.248)	(0.152)	(0.030)	(0.108)
Expected Capital Call	0.090	−0.133	−0.099	−0.112	0.039	−0.031
	(0.166)	(0.504)	(0.468)	(0.414)	(0.049)	(0.357)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,652	6,652	6,652	6,652	6,652	6,652
Adjusted R^2	0.535	0.206	0.124	0.447	0.204	0.179

Panel A: Life vs. P&C Insurers – Capital Calls and Distributions

(a) Private Fund (b) Bond (c) Cash (d) Stock (e) Mortgage (f) Rest



Panel B: Life vs. P&C Insurers – Expected and Unexpected Capital Calls

(a) Private Fund (b) Bond (c) Cash (d) Stock (e) Mortgage (f) Rest

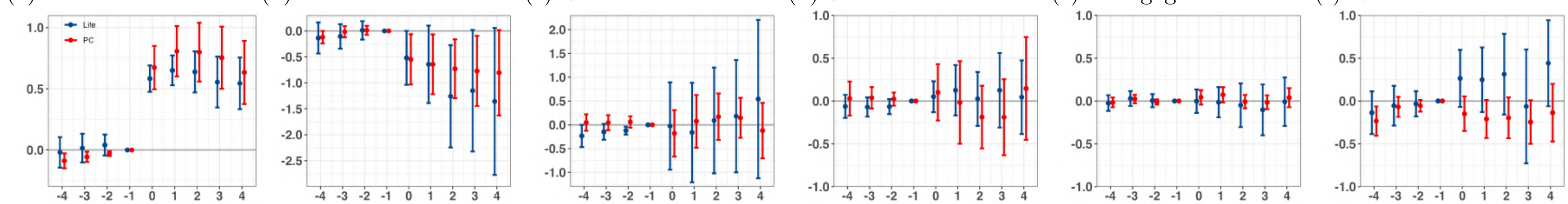


Figure IA.13: Dynamic Portfolio Effects: Life vs. P&C Insurers

This figure examines differences in dynamic portfolio adjustment decisions between Life and P&C insurers when facing capital calls. Panel A presents results for total capital calls, while Panel B presents results for unexpected capital calls. Panel A corresponds to Figure 10, and Panel B corresponds to Figure 11. All specifications are identical to those in Figures 10 and 11.

Table IA.7: Robustness: Net Cash Flow

This table examines portfolio effects using net private fund cash flow as the shock. Net cash flow is defined as the quarterly private fund distributions minus capital calls, with positive values indicating distributions exceed capital calls. Panel A reports portfolio effects by asset class, corresponding to Panel A of Table 5. Panel B reports bond holding adjustments by bond type, corresponding to Panel A of Table 6. Panel C reports bond holding adjustments by NAIC designation, corresponding to Panel B of Table 6. All specifications are identical to those in Tables 5 and 6.

Panel A: By Asset Class						
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Net Cash Flow	−0.641***	0.529***	0.190	0.024	−0.023	−0.008
	(0.049)	(0.179)	(0.194)	(0.090)	(0.022)	(0.085)
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.428	0.148	0.119	0.392	0.098	0.112
Panel B: By Bond Type						
	Treasury (1)	Industrial (2)	Govt Agent (3)	Other (4)	Corporate (5)	Non-Corporate (6)
Net Cash Flow	0.075	0.597***	−0.284**	−0.099	0.487***	0.133
	(0.082)	(0.202)	(0.134)	(0.464)	(0.141)	(0.123)
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.288	0.126	0.679	0.460	0.451	0.043
Panel C: By NAIC Designation						
	NAIC 1 (1)	NAIC 2 (2)	NAIC 3 (3)	NAIC 4 (4)	NAIC 5 (5)	NAIC 6 (6)
Net Cash Flow	−0.106	0.254**	0.080***	0.024	0.011	−0.017
	(0.260)	(0.117)	(0.025)	(0.015)	(0.008)	(0.017)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.334	0.091	0.001	0.158	0.057	0.172

Table IA.8: Robustness: Using Linear Model

This table examines the robustness of the portfolio effects of unexpected capital call shocks, using a linear model to estimate expected calls. Panel A reports portfolio effects by asset class, corresponding to Panel A of Table 5. Panel B reports bond holding adjustments by bond type, corresponding to Panel A of Table 6. Panel C reports bond holding adjustments by NAIC designation, corresponding to Panel B of Table 6. All specifications are identical to those in Tables 5 and 6.

Panel A: By Asset Class						
	Private Fund	Bond	Cash	Mortgage	Stock	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.618***	−0.656***	−0.123	0.053	0.039	−0.009
	(0.059)	(0.216)	(0.216)	(0.108)	(0.030)	(0.102)
Expected Capital Call	0.171	−0.118	−0.190	−0.051	0.022	−0.077
	(0.135)	(0.305)	(0.448)	(0.241)	(0.046)	(0.276)
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.425	0.149	0.119	0.392	0.098	0.117
Panel B: By Bond Type						
	Treasury	Industrial	Govt Agent	Other	Corporate	Non-Corporate
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	−0.007	−0.912***	0.250*	0.541	−0.748***	−0.204
	(0.101)	(0.228)	(0.142)	(0.662)	(0.146)	(0.175)
Expected Capital Call	0.017	−0.421	0.494	1.138	−0.082	−0.445
	(0.230)	(0.649)	(0.360)	(1.773)	(0.332)	(0.503)
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.288	0.126	0.680	0.460	0.452	0.043
Panel C: By NAIC Designation						
	NAIC 1	NAIC 2	NAIC 3	NAIC 4	NAIC 5	NAIC 6
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.023	−0.403***	−0.102***	−0.030**	−0.007	0.001
	(0.301)	(0.121)	(0.029)	(0.015)	(0.008)	(0.009)
Expected Capital Call	0.507	−0.024	−0.094	−0.010	−0.021	0.112
	(0.986)	(0.301)	(0.089)	(0.054)	(0.024)	(0.086)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.334	0.090	0.0004	0.159	0.057	0.172

Table IA.9: Robustness: Using Industrial Model

This table examines the robustness of the portfolio effects of unexpected capital call shocks, using a commonly used industrial model to estimate expected calls. The industrial model predict capital call rate as a stepwise function of fund age. Panel A reports portfolio effects by asset class, corresponding to Panel A of Table 5. Panel B reports bond holding adjustments by bond type, corresponding to Panel A of Table 6. Panel C reports bond holding adjustments by NAIC designation, corresponding to Panel B of Table 6. All specifications are identical to those in Tables 5 and 6.

Panel A: By Asset Class						
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Unexpected Capital Call	0.492***	−0.663***	0.029	−0.152	0.039	0.222**
	(0.053)	(0.209)	(0.195)	(0.105)	(0.030)	(0.103)
Expected Capital Call	0.202	0.202	−0.228	−0.117	−0.008	−0.317
	(0.290)	(0.615)	(0.722)	(0.517)	(0.085)	(0.585)
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.414	0.150	0.119	0.392	0.098	0.119
Panel B: By Bond Type						
	Treasury (1)	Industrial (2)	Govt Agent (3)	Other (4)	Corporate (5)	Non-Corporate (6)
Unexpected Capital Call	0.089	−1.046***	0.232*	1.567	−0.715***	−0.396*
	(0.095)	(0.264)	(0.128)	(1.498)	(0.157)	(0.198)
Expected Capital Call	0.222	0.042	0.740	5.472	0.005	−0.114
	(0.509)	(1.296)	(0.790)	(5.095)	(0.740)	(0.845)
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.288	0.126	0.680	0.461	0.452	0.043
Panel C: By NAIC Designation						
	NAIC 1 (1)	NAIC 2 (2)	NAIC 3 (3)	NAIC 4 (4)	NAIC 5 (5)	NAIC 6 (6)
Unexpected Capital Call	0.134	−0.506***	−0.194***	−0.054***	−0.013	−0.004
	(0.325)	(0.140)	(0.032)	(0.017)	(0.011)	(0.010)
Expected Capital Call	1.154	0.133	−0.113	0.127	−0.066	0.251
	(2.088)	(0.675)	(0.228)	(0.104)	(0.071)	(0.183)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,128	12,128	12,128	12,128	12,128	12,128
Adjusted R^2	0.334	0.090	0.001	0.161	0.057	0.172

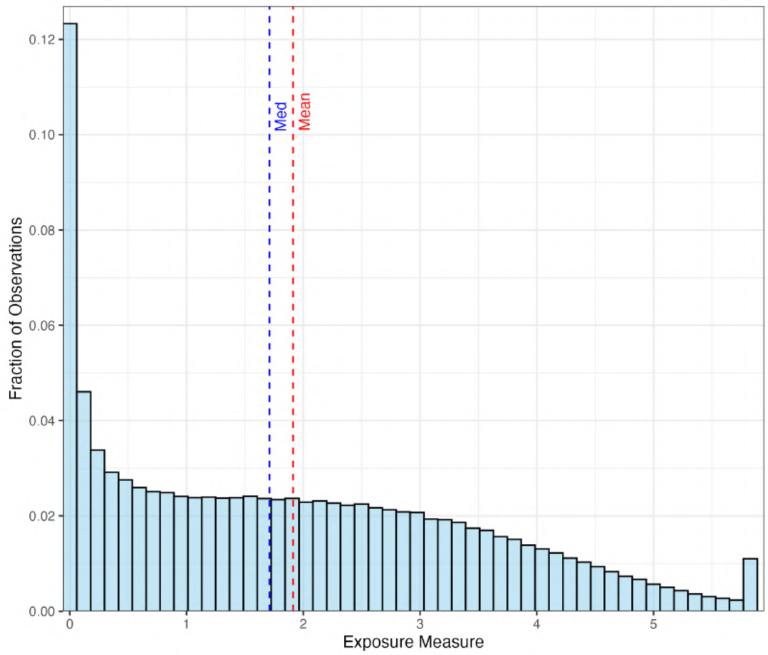


Figure IA.14: Distribution of Bond-level Exposure Measure

This figure shows the distribution of bond-level exposure measure.

Table IA.10: Spillover Heterogeneity: The First Stage

This table shows the first stage results for the 2SLS results in Table 11. Panel A corresponds to the first stage for Column (4) of Table 11, and Panel B corresponds to the first stage for Column (6) of Table 11. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: Bond Rating Test

	$\Delta Holdings \times NAIC1$ (1)	$\Delta Holdings \times NAIC2$ (2)	$\Delta Holdings \times NAIC3$ (3)
Exposure × $NAIC1$	−0.082*	−0.014	0.021***
	(0.042)	(0.020)	(0.006)
Exposure × $NAIC2$	0.031**	−0.363***	0.029***
	(0.014)	(0.034)	(0.005)
Exposure × $NAIC3$	0.030***	−0.025*	−0.137***
	(0.011)	(0.015)	(0.024)
Controls	Yes	Yes	Yes
Bond FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	355,626	355,626	355,626
Adjusted R^2	0.033	0.046	0.049
Kleibergen-Paap F-Statistic	5.3	38.3	20.7

Panel B: Covid Test

	$\Delta Holdings \times COVID$ (1)	$\Delta Holdings \times REST$ (2)
Exposure × $COVID$	−0.166***	−0.017
	(0.014)	(0.032)
Exposure × $REST$	−0.004	−0.197***
	(0.004)	(0.036)
Controls	Yes	Yes
Bond FE	Yes	Yes
Time FE	Yes	Yes
Observations	355,626	355,626
Adjusted R^2	0.008	0.085
Kleibergen-Paap F-Statistic	7.8	41.7

IA.5 Demand-System Counterfactual Stress Tests

In this section, I briefly explain the demand-system corporate bond pricing model proposed by Bretscher et al. (2024). I refer readers to the original paper for more details. Building on Koijen and Yogo (2019), the model uses a nested logit demand system to account for the segmentation across rating groups in the corporate bond market.

IA.5.1 Model Setup

Investors are indexed by $i = 1, \ldots, I$. Bonds are indexed by $n = 0, \ldots, N$, where $n = 0$ corresponds to the outside assets. Time is denoted by t. The yield of bond n at time t is $y_t(n)$. $\mathrm{x}_t(n)$ is a vector of bond characteristics, including time-to-maturity, ratings, size, and bid-ask spread. Investor total wealth is $A_{i,t}$. The model assumes that investors choose bonds only from their investment universe, denoted by $N_{i,t}$.

The portfolio weight can be decomposed into two parts: an across rating group allocation and a within rating group allocation.

$$w_{i,t}(n) = w_{i,t}(n, l) = w_{i,t}(n \mid l) w_{i,t}(l),$$

where $w_{i,t}(n \mid l)$ is the weight for bond n within rating group l and $w_{i,t}(l)$ is the weight for rating group l.[1] The within rating group portfolio weight is modeled as

$$w_{i,t}(n \mid l) = \frac{\delta_{i,t}(n, l)}{1 + \sum_{m=1}^{N} \delta_{i,t}(m, l)},$$

where

$$\delta_{i,t}(n, l) = \exp\left\{\beta_{0,i,l} y_t(n) + \beta'_{1,\mathrm{i},l} \mathbf{x}_t(n) + \epsilon_{i,t}(n)\right\}.$$

The portfolio weight in the outside asset equals

$$w_{i,t}(0 \mid l) = \frac{1}{1 + \sum_{m=1}^{N} \delta_{i,t}(m, l)}$$

We can rewrite the portfolio weight as a logit function of the yield and bond characteristics:

$$\log \frac{w_{i,t}(n \mid l)}{w_{i,t}(0 \mid l)} = \log \delta_{i,t}(n, l) = \beta_{0,i,l} y_t(n) + \beta'_{1,\mathrm{i},l} \mathrm{x}_t(n) + \epsilon_{i,t}(n),$$

where $\epsilon_{i,t}(n)$ is the latent demand for investor i.

Next, we can model the aggregate portfolio (i.e., incorporate the across-group allocation):

$$w_{i,t}(l) = \frac{\left(1 + \sum_{m=0}^{N} \delta_{i,t}(m, l)\right)^{\lambda_{i,l}} \exp\left\{\alpha_l + \xi_{i,t}(l)\right\}}{\sum_{k=1}^{2} \left(1 + \sum_{m=0}^{N} \delta_{i,t}(m, k)\right)^{\lambda_{i,k}} \exp\left\{\alpha_k + \xi_{i,t}(k)\right\}},$$

[1] Weights must sum to one: $\sum_{n=0}^{N} w_{i,t}(n \mid l) = 1$ and $w_{i,t}(1) + w_{i,t}(2) = 1$

where $\lambda_{i,l} \in [0,1]$ govern the substitution between IG and HY bonds.[2] We can also derive the corresponding logit function

$$\log\left(\frac{w_{i,t}(1)}{w_{i,t}(2)}\right) = \lambda_{i,1}\log\left(1+\sum_{m=1}^{N}\delta_{i,t}(m,1)\right) - \lambda_{i,2}\log\left(1+\sum_{m=1}^{N}\delta_{i,t}(m,2)\right) + \alpha_1 + \xi_{i,t}(1)$$
$$= -\lambda_{i,1}\log\left(w_{i,t}(0\mid 1)\right) + \lambda_{i,2}\log\left(w_{i,t}(0\mid 2)\right) + \alpha_1 + \xi_{i,t}(1)$$

Finally, we impose market clearing

$$M_t(n) = \sum_{i=1}^{I} A_{i,t} w_{i,t}(n),$$

where $M_t(n)$ is the market value of bond n.

IA.5.2 Estimation

For identification, Bretscher et al. (2024) instrument bond yields $y_t(n)$ in the same spirit as Koijen and Yogo (2019). The intuition is that investors have a persistent investment universe and can only invest in bonds within that universe. Specifically, Bretscher et al. (2024) define the investment universe as bonds either currently held or held within the past 11 quarters. Then, yields are instrumented as follows

$$\widehat{\mathrm{y}}_{i,t}(n) = \log\left(\sum_{j\neq i} A_{j,t}\frac{\mathbf{1}_{j,t}(n)}{1+\sum_{m=1}^{N}\mathbf{1}_{j,t}(m)}\right)$$

Using this instrument, Bretscher et al. (2024) estimate the demand functions for each investor and at each point of time (quarter). To save space, I refer readers to the original paper for more details about the estimation procedures and results.

IA.5.3 Counterfactual Stress Tests

In this demand system, bond prices are fully determined by bond supply $\mathbf{s}_t$, bond characteristics $\mathbf{x}_t$, investors' wealth $\mathbf{A}_t$, the latent demand ϵ_t, estimated coefficients β_t and λ. More formally, we have

$$\mathbf{p}_t = \mathbf{g}\left(\mathbf{s}_t, \mathbf{x}_t, \mathbf{A}_t, \beta_t, \lambda, \epsilon_t\right)$$

The goal of the counterfactual analysis is to examine how bond yield spread would change when some of the input elements change, i.e., $\Delta\mathbf{p}_t = \mathbf{p}_t^{\mathbf{CF}} - \mathbf{p}_t$.

To examine the impact of capital call shocks, I begin with the bond characteristics, holdings and coefficients estimated in 2019Q4. This is because the sample of Bretscher et al. (2024) ends in 2020Q3 and I want to avoid the COVID period. Because I focus just on one period, I drop the time subscript from now on. I first link all insurers (both life and P&C) to my dataset to obtain their actual uncalled private fund commitments as of 2019Q4. Next, for each insurer, I randomly draw a capital call rate

[2] When $\lambda_{i,1} = \lambda_{i,2} = 1$, the model simplifies to the original demand system in Koijen and Yogo (2019).

CC_i from the historical distribution. In the baseline simulations, these draws are independent across insurers. Effectively, I assume that all other investor types have no uncalled commitments to private funds. Because pension funds also allocate to both private funds and corporate bonds, my estimates should be viewed as a lower bound.

Capital call shocks affect insurers' corporate bond allocation. I model the shock by directly scaling portfolio weights rather than reducing investor wealth (A_i) or altering latent demand (ϵ_i). This approach allows me to precisely target the BBB/HY bonds, consistent with empirical findings.[3] Specifically, I first keep baseline wealth distribution unchanged and compute each investor's within-nest and across-nest choice weights at the current price guess, $w_i(n) = w_i(n|l)w_i(l)$. I then find the investor's total weight on BBB/HY bonds $W_i^{\mathrm{BBB/HY}} = \sum_{n \in \mathrm{BBB/HY}} w_i(n)$ and scale only those eligible weights by the scaling factor s_i, defined as

$$s_i = 1 - \frac{\mathrm{CC}_i}{A_i W_i^{\mathrm{BBB/HY}}}, \quad s_i \in [0, 1]$$

The scaled weights are

$$\tilde{w}_i(n) = \begin{cases} s_i w_i(n) & n \in \mathrm{BBB/HY} \\ w_i(n) & \text{otherwise} \end{cases}.$$

The missing weights represent the demand that leaves the risky-bond universe to meet the capital call shocks. I do not renormalize the remaining weights so the rest of investors endogenously absorb the demand shock. Then the market demand for each bond is

$$D(n) = \sum \mathrm{A}_i \tilde{w}_i(n).$$

I then iterate on price to clear markets using the same algorithm as in Bretscher et al. (2024). For each simulation, I then calculate the average change in yield spreads across bonds. The simulation is repeated 10,000 times, and I report the 1% Value-at-Risk (VaR).

In addition to the baseline, I consider two stress scenarios: (1) uncalled commitments are twice as large, and (2) capital-call shocks are concentrated. The first scenario is implemented by doubling each insurer's uncalled commitments. For the second scenario, in each simulation, I randomly select half of the insurers to experience capital call rates drawn from the top quartile of the historical distribution.

Figure IA.15 plots the histogram of all simulations. Under the baseline scenario, the 1% VaR is roughly 2 bps (i.e., 1% percentile average spread changes). Doubling insurers' uncalled commitments increases the 1% VaR to about 6 bps. The effect of concentrated shocks is even larger, with the 1% VaR reaching nearly 10 basis points. Based on a back-of-the-envelope calculation using the average duration and bond market size, it corresponds to an aggregate loss of roughly $8.7 billion. Admittedly, these hypothetical stress scenarios have not been observed historically. The goal is not to forecast precise outcomes, but rather to illustrate the underlying mechanism: capital-call-induced selling can amplify stress in credit markets and potentially contribute to financial fragility.

[3] Change A_i would imply a proportional selling of all bond holdings. It's not feasible to link latent demand directly with capital call shocks.

(a) Baseline (b) Double Commitment (c) Concentrated Shocks

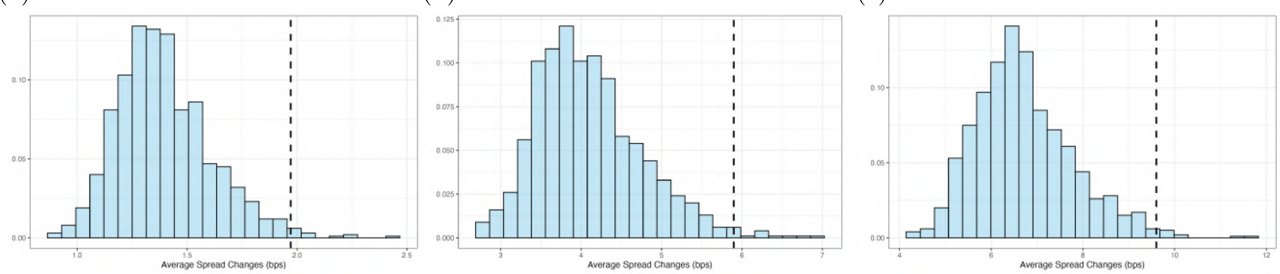


Figure IA.15: Counterfactual Stress Tests

This figure shows the results of counterfactual stress tests based on simulations using the demand-system asset pricing approach. Each panel plots the histogram of average bond spread changes. The vertical dashed line represents the 99th percentile of the spread changes (i.e., the 1% VaR). Panel (a) presents the baseline scenario, where capital calls are drawn independently from the historical distribution for each insurer. Panel (b) represents the scenario in which uncalled commitments are doubled. Panel (c) shows the scenario where capital call shocks are concentrated. Specifically, in each simulation, I randomly select half of the insurers to experience capital call rates drawn from the top quartile of the historical distribution.