Private Fund Capital Calls, Investor Portfolios, and Spillovers*

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July 2025

Abstract

Institutional investors commit trillions of dollars to private funds that give fund managers discretion to make capital calls on short notice. Using novel data on insurers' private fund investments, this paper examines the implications of unexpected capital calls for investor portfolios and financial markets. I first document that investor-level unexpected capital calls are substantial. Despite this, investors do not appear to manage capital calls by increasing cash buffers ex-ante. Instead, when faced with unexpected calls, insurers rebalance their portfolios primarily by selling corporate bonds with high risk weights and unrealized gains. I show that this seemingly counterintuitive behavior is likely driven by regulatory capital concerns. Moreover, these asset sales induced by unexpected calls spill over into the corporate bond market, leading to temporary price declines. The spillover effects are more pronounced when unexpected calls coincide with other adverse shocks. Overall, these findings suggest that unexpected capital calls pose significant challenges to investor portfolio management and may introduce new sources of financial fragility as private fund investments continue to grow.

Keywords: capital call, capital commitment, private fund, alternative investment, portfolio rebalance, insurers, risk-based capital, institutional investor, corporate bond.

JEL Classification: G11, G22, G23, G28, G32

^{*}I am deeply grateful to my committee Lukas Schmid (Chair), Erica Jiang, Mete Kilic, and Arthur Korteweg, for invaluable guidance and continuous support. I also thank Lorenzo Bretscher, AJ Yuan Chen, Spencer Couts, Ricardo Delao, Dardan Gashi, Kristy Jansen, Wenhao Li, John Matsusaka, Sangmin Oh, Rodney Ramcharan, Ishita Sen, Zhang Zhao, and participants at the European Summer Symposium in Financial Markets (ESSFM) Evening Session for valuable comments and suggestions. All errors are my own.

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1 Introduction

Institutional investors are rapidly expanding their allocation to private funds, such as private equity, private debt, real estate, and venture capital funds.¹ A distinctive feature of these investment is the *Capital Call* mechanism: investors make binding commitments upfront to contribute capital upon receiving a capital call request, which is at the full discretion of the fund manager. Similar to a bank credit line, capital call resembles a contingent liquidity obligation that is not controlled by the capital suppliers. As of 2024, the private fund market has grown to over \$9 trillion, with uncalled commitments estimated at nearly \$3 trillion, exceeding the size of unused corporate credit lines. Meanwhile, capital calls have drawn increasing concerns from policymakers. For example, Financial Stability Report 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), and International Monetary Fund also notes the possibility that significant capital calls in a downside scenario and the spillover to other markets and the broad economy (IMF, 2024).

However, no existing study has directly examine the validity and severity of above concerns because the lack of data linking investor portfolio holdings to their private fund investments. This paper helps fill that gap by leveraging a novel dataset on insurance companies private fund investment. Specifically, I address the following research questions: (1) What are the dynamics of investor-level unexpected capital calls? (2) How do investors manage their portfolio in response to unexpected capital call shocks? In particular, do they maintain sufficient buffers? How do they rebalance their portfolios when such shocks occur? (3) Do unexpected capital calls generate spillover effects in public asset markets through investor portfolio rebalancing?

The novel data introduced in this paper is based on Schedule BA from the statutory filings of U.S. insurance companies.² Schedule BA reports "Other Long-Term Invested Assets," which include alternative investments such as private funds. Crucially, this data offers complete coverage of each insurer's private fund holdings, as Schedule BA is a mandatory filing. Commonly used private fund datasets are largely (over 80%) based on Freedom of Information Act (FOIA) requests to public pension funds (Begenau et al., 2020a). While FOIA requests can provide detailed fund-level

¹Throughout this paper, I use the term "private fund" to refer exclusively to funds that use capital call.

²To my knowledge, the only existing study use Schedule BA data is Foley-Fisher et al. (2023), which studies insurers' CLO investment.

information, they are often insufficient for reconstructing the complete panel of each investor's private fund portfolio. In addition, insurers are required disclose detailed position-level holdings in all asset classes, such as bonds and equities, enabling a comprehensive analysis of how capital calls affect investors' portfolio allocation. To my knowledge, this is the first dataset that directly links private fund investments to the rest of an investor's portfolio.

Utilizing this novel dataset, I estimate the portion of capital calls that are unanticipated by investors. The focus on unexpected capital calls not expected ones is motivated by their economic implications: unlike expected calls, which can be planned for, unexpected calls require investors to adjust their portfolios on short notice. In addition, the unexpected component is more likely to resemble a random shock, given that it is outside of investor's control. I adopt a bottom-up approach to construct investor-level expected and unexpected components as it allows me to exploit granular fund-level information and yields better forecast. Specifically, I first forecast the expected capital calls for each fund in an investor's portfolio, then aggregate these fund-level estimates to the investor level.

To capture potential nonlinear predictive patterns in capital call dynamics, I consider a wide range of state-of-the-art machine learning methods, including LASSO, Decision Trees, Random Forest, LightGBM, and XGBoost. I also consider two-stage hurdle models to address the issue of zero-inflated capital call data. I employ predictors of four categories: (1) macroeconomic indicators such as GDP growth; (2) public market indicators such as S&P 500 returns; (3) private market indicators such as private equity deal volume; and (4) fund-specific characteristics. Model selection is based on out-of-sample (OOS) performance using rolling windows. The best-performing model is the two-stage LightGBM, with out-of-sample R^2 of 7.4%. This low OOS R^2 reflects the inherently unpredictable nature of capital calls. Additionally, despite the use of complex models, the performance gains over simple linear benchmarks are modest. This suggests that the capital call process exhibits a low signal-to-noise ratio, and any nonlinear patterns are either weak or unstable over time, limiting their usefulness for consistent out-of-sample prediction. I use the forecasts from the best model to construct expected capital calls at the fund level, which are then aggregated to the investor level. The unexpected capital call is defined as the positive component of the difference between actual and expected capital calls at investor level. The reason to only take the positive

part is because the paper focus on the results when realized calls exceed expectations.

I first present descriptive analysis on the dynamics of capital calls. As insurers' private fund investment grow from around \$100 billion in 2008 to roughly \$380 billion in 2023, the aggregate expected capital calls also increase from approximately \$3 billion to over \$10 billion per quarter. Aggregate capital calls exhibit significant fluctuations over time. During these high-capital-call quarters, aggregate unexpected capital call shocks amount to over \$5 billion. To further understand the sources of variation in investor-level capital calls, I perform a variance decomposition. Expected capital calls account for approximately 60% of the total variation, largely driven by cross-sectional differences in uncalled commitments. The remaining 40%, attributed to unexpected components, is further decomposed into investor-specific, time-specific, and idiosyncratic elements. About 78% of the variation in unexpected capital calls is idiosyncratic, while only 4.2% is time-specific, driven largely by private market indicators like aggregate PE deal volume. This suggests that, although aggregate capital calls exhibit some cyclicality, most of the variation at the investor level is still idiosyncratic, consistent with the inherently stochastic nature of unexpected capital calls.

To make cross-sectional compassion, I compute the investor-level capital call rate, which is defined as the total amount of capital calls divided by lagged uncalled commitment. The average quarterly capital call rate is round 10%. Conditional on experiencing a positive unexpected call (that is, when the realized call exceeds the expected amount), the average unexpected capital call rate is about 12% (i.e., total capital call rate of 22%). The distribution of capital call rates is highly right-skewed: the 90th, 95th, and 99th percentiles are approximately 20%, 30%, and 55%, respectively. A back-of-the-envelope calculation illustrates the potential magnitude of these shocks: assume the uncalled commitment is 30% of total private fund allocations, an investor with a 20% allocation to private funds could face a quarterly capital call shock of up to 1% (3%) of its total portfolio value in the 90th (99th) percentiles worst cases.³

Given that the unexpected capital call shocks are substantial, I then examine how investors manage their portfolios ex-ante in response to unexpected capital call shocks. A straightforward strategy is to maintain a buffer, such as cash or other liquid assets, to prepare for future unexpected capital calls. This allows investors to meet capital calls without having to sell illiquid assets on short notice. However, maintaining large buffers can be costly, especially when capital calls are

³This measure is similar to the Capital-Call-at-Risk (CCaR) discussed by PitchBook (see Link).

highly stochastic. Investors may need to hold large portion of low-yielding assets for extended periods. Whether investors actually hold such buffers is therefore an empirical question. Using various definitions of liquid assets, I find either no correlation or a slightly negative correlation between uncalled commitments and liquid asset holdings. Moreover, I find no evidence that investors increase liquid asset allocations following new private fund commitments. These findings suggest that investors generally do not rely on liquid asset buffers to manage unexpected capital calls.

Next, I examine how investors adjust their portfolios in response to unexpected capital calls. I find that investors predominantly sell long-term bonds: approximately 76% of the increase in private fund allocation is funded through reductions in long-term bond holdings, with the remainder mostly funded by decreases in cash. Interestedly, in the subsequent quarter, investors keep reducing their long-term bond holdings to revert the cash reserve back to the pre-shock level. Meanwhile, expected capital calls do not appear to affect investors' portfolio allocations, which supports the earlier discussion that expected calls can be managed ex-ante, through strategy such as internal cash flow netting. I further analyze which types of bonds investors choose to liquidate. Surprisingly, rather than selling the most liquid assets such as Treasury bonds, investors primarily reduce their holdings of corporate bonds. This pattern is consistent when analyzing bonds by NAIC designation, which reflects regulatory risk categories. Specifically, investors tend not to sell bonds with NAIC 1 designation, corresponding to A to AAA ratings. Instead, insurers mostly sell bonds with NAIC 2 designation or higher, which correspond to BBB and high-yield (HY) bonds.

These findings may seem puzzling at first. If investors were seeking to minimize transaction costs, they would want to sell Treasury securities or direct draw on cash reserves. One potential explanation is that insurers are instead focused on preserving their Risk-Based Capital (RBC), a key regulatory metric used to assess the financial health of insurance companies. Prior research has shown that the RBC ratio is critical for insurers (Koijen and Yogo, 2015). Under the current regulatory framework, the RBC ratio is calculated based on on-balance-sheet assets, and does not account for off-balance-sheet items such as uncalled commitments. As a result, an unexpected capital call will increase insurers' required capital, as private funds carry the highest risk weight. If

⁴Though 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). In extreme scenarios, regulatory pressure can even trigger fire sales (Ellul et al., 2011; Merrill et al., 2021).

insurers fund these calls using assets with low risk weights, such as Treasury securities or cash, they effectively replace "cheapest" assets with the most "expensive" ones. Such substitution would lead to a significant deterioration in RBC ratio, a key metric for rating agency and regulators.

I provide three pieces of evidence in support of this hypothesis. First, insurers facing tighter regulatory capital constraints are more likely to sell bonds with high risk weights. In contrast, less constrained insurers tend to fund capital calls using more cash and 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. This contrasts with typical behavior, as they tend to hold onto such bonds in normal periods. The reason for this behavior is that, most bonds on insurers' balance sheet are valued using historical cost rather than mark-to-market (Ellul et al., 2015). As a result, selling a bond with unrealized gains will increase insurers' book equity value and help improve the RBC ratio. This behavior is also more pronounced for constrained insurers. 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 offset the negative effects from capital calls.

Finally, I examine whether the documented asset sales induced by unexpected capital calls generate spillover effects in the public asset market. Given previous findings that suggest insurers primarily sell corporate bonds, I focus my analysis on the corporate bond market. I hypothesize that bonds more heavily held by investors facing larger unexpected capital calls are more likely to be sold. As a result, such bonds should experience negative price pressure. To test this, I construct a bond-level measure of exposure to unexpected calls, defined as the ownership-weighted average of unexpected calls across insurers. Consistent with the hypothesis, bonds with higher exposure to capital call shocks face greater selling pressure from insurers and exhibit a temporary price decline. The spillover effects are more pronounced for bonds with higher risk weights, consistent with the previous finding that these bonds are more likely to be sold. Moreover, the effects are amplified during periods of broader market stress, such as COVID-19. The average spillover effect is nearly three times larger during the first quarter of 2020 than during regular periods. Overall, the results highlight that portfolio rebalancing induced by capital calls serves as a distinct mechanism linking private funds to public asset markets. As private fund investments continue to grow, unexpected capital calls may introduce new sources of financial fragility.

Although this paper focuses on insurance companies due to data availability, the main findings are likely generalizable to other institutional investors, such as pension funds and sovereign wealth funds. These investors often have even higher allocations to private funds, which amplifies the portfolio management challenges posed by unexpected capital calls. Specifically, holding a liquid asset buffer remains costly for all investors, especially when private fund exposure is large. Additionally, while these investors may face lighter regulatory constraints, they might still avoid using cash or Treasury securities to fully fund capital calls for risk management reasons. That said, portfolio composition might influence the specific assets investors sell to fund capital calls. For instance, U.S. pension funds, with their larger equity allocations, may choose liquidate stocks in response to unexpected capital calls, potentially leading to spillovers into public equity markets.

Related Literature This paper contributes to several strands of literature. First, this paper significantly advances the understanding of private fund capital calls and their implications for investor portfolio management. Despite the well-recognized importance of capital call by practitioners, very few academic studies have systematically examined the implications of capital calls. Robinson and Sensoy (2016) investigate the cyclicality of capital calls and their relationship with fund performance. Consistent with the notion that cyclical capital calls impose greater costs on investors, their findings indicate that funds with more cyclical calls are associated with higher expected returns. Brown et al. (2021) find that timing exposure to private funds is difficult for investors due to uncertain capital calls and distributions. Li (2025) find that idiosyncratic liquidity shocks experienced by LPs cause GPs to slow down capital calls and subsequent investment, which in turn leads to lower productivity among portfolio companies. Leveraging granular portfolio holdings data from insurers, this paper is the first to study the portfolio implications of private fund capital calls. Moreover, this research demonstrates the differential portfolio impacts of expected versus unexpected capital calls.⁵

This research also aligns with the growing body of literature studying private fund investments from the investors' perspective⁶. For example, Sensoy et al. (2014) evaluate the performance of LPs' private equity investments over time, while Sorensen et al. (2014) examine whether PE performance

⁵Related work on predicting private fund cash flows includes Takahashi and Alexander (2002), Jeet (2020), Jeet (2024), Cao (2023), and Brown et al. (2023).

⁶Korteweg and Westerfield (2022) provides a detailed literature review with open questions.

sufficiently compensates for associated fees and illiquidity costs. Brown et al. (2020) study the performance impact of integrating private funds into diversified portfolios otherwise consisting solely of stocks and bonds. Relatedly, Focusing on specific investors, Korteweg et al. (2023) evaluate PE performance for public pension funds using investor-specific stochastic discount factors. On the theoretical side, Ang et al. (2014) and Giommetti and Sorensen (2024) solve for investors' optimal allocations to private funds, accounting for their illiquid nature. Gourier et al. (2024) model the exante capital commitments and find they significantly alter investors' optimal allocations. Chen et al. (2025) develop a state-of-the-art dynamic model for private fund allocation that incorporates realistic challenges investors face, such as illiquidity, ex-ante commitments, and regulatory constraints. This paper is the first to document investors' portfolio management challenge regarding unexpected capital calls. Its results highlight the challenges and costs private fund investors face due to the inherent uncertainty of capital calls.

Additionally, this paper contributes to the extensive body of literature studying the implications of RBC regulation for insurance companies. Ellul et al. (2011), Ellul et al. (2015), Merrill et al. (2021) and Becker et al. (2022) find that RBC requirement and mark-to-market accounting affect insurers' incentive 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 turns of real effects, Koijen and Yogo (2015) showed that statutory reserve levels led to extraordinary pricing behaviors for annuity and life insurance products during the financial crisis. This paper is the first to examine how RBC requirements and associated constraints affect insurers' portfolio rebalancing decisions in response to unexpected private fund capital calls. Furthermore, this research offers valuable policy insights regarding the RBC requirements for private fund investment by highlighting the importance of considering off-balance sheet investments such as uncalled commitment when assessing insurers' risk exposure.

Lastly, this paper belongs 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 documents a novel spillover channel connecting private assets and public markets: asset sales induced by unexpected private fund capital calls. This channel could be amplified during periods of market stress, as suggested by IMF (2024). Furthermore, the recent growth of private credit funds could increase the amount of counter-cyclical capital calls, potentially exacerbating systemic risk concerns. This paper serves as a first step toward understanding how capital calls affect the interconnectedness between private funds and the public market.

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. In Section 5, I document key stylized facts about unexpected capital calls. Section 6 presents results on the portfolio implications of unexpected calls, 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 reveals that the total AUM in private funds (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 very small share of the market. Some institutional investors have extremely high allocations to private funds. According to a report by Private Equity

⁷For example, see discussion from MSCI

International, as of the end of 2024, Temasek Holdings was the largest investor in the private fund space, with more than \$148 billion allocated, representing to 58% of its portfolio.

[Insert Figure 1]

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 operation of the fund. 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-Estanol et al. 2017, LPA template by ILPA). In addition to financial consequences, defaulting on a capital call can cause significant reputational damange, 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 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 (Greenwald et al., 2020).

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 about 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 roll 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 breakeven and eventually turns positive. This unique cash flow pattern is commonly referred to as the "J-curve."

Figure IA.13 provides a real fund example to illustrate 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 increase 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 challenges 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 second market for private fund are still limited, which make it hard to use secondary market price to infer the fair value of the fund (Jenkinson et al., 2013; Chakraborty and Ewens, 2018; Barber and Yasuda, 2017; Brown et al., 2019).

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. 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.

⁸This 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.

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 other investment schedules. Schedule BA is specifically designed to cover alternative investments such as private funds. Other typical investment 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 is 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.B 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,

⁹Other investments schedules include Schedule A for real estate, Schedule B for mortgages, and Schedule D for bonds and stocks.

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 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 obtained GP names and fund types by feeding the fund names to LLM. In their collect quarterly transaction data, including capital calls, distributions, and sales of fund stakes. Finally, I construct the quarterly fair value for each investment. Computing quarterly fair value 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.B 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.

¹⁰Specifically, I define six fund types: private equity, venture capital, private debt, real estate, infrastructure and others.

¹¹Insurers 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 remaining of the paper, I use fair value to refer to BACV

including private equity, venture capital, private debt, real estate, and infrastructure. Second, this novel data allow 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 a analysis of how insurers manage their overall portfolios in response to private fund investment, 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.

3.2 Other Data

Insurer Financial and Portfolio Data I obtain financial information of 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 Returns database. I calculate bond yield spreads by subtracting the maturity-matched Treasury yield from each bond's yield. Additionally, I obtain monthly bond-level return volatility measures from the "Open Source Bond Asset Pricing" dataset. All monthly variables are converted to 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 Data Most macroeconomic and public market data are obtained from the Federal Reserve Economic Database (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 have positive and non-missing asset and equity value (Capital & Surplus). I also require the annual RBC ratio not missing. The final sample includes 506 unique insurer groups (220 life insurers and 286 P&C insurers), and 6,501 unique private funds.

4 Empirical Methods

This section describes two key empirical methods of this paper: (1) estimation of investor-level unexpected capital call, and (2) main regression specifications.

4.1 Estimate Unexpected Capital Call

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 commitment. 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.¹² As a result, the expected and unexpected components of capital calls are likely to have distinct implications on investors' portfolio management.

I adopt a bottom-up approach to estimate investor-level expected capital calls. Specifically, I first estimate the expected capital calls for each individual fund in an investor's portfolio and then aggregate the fund-level estimates to the investor level. This approach takes advantage of more granular fund-level information and improves the predictive performance. I assume investors behave rationally and form expectations using the best available statistical forecasts.

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-art forecasting techniques. Let the j index fund and t index time.¹³ 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 previous period and $RC_{j,t+1}$ is the fundand time-specific capital call rate.¹⁴ Since $U_{j,t}$ is known, the expected capital call can be expressed

as

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

I use the statistical 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 follow:

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

¹²Internal cash flow netting 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. 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.

¹³Let 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 calender time t

¹⁴In the original TA model, $RC_{j,t}$ is simplified as a stepwise function of fund age: $RC_{j,t} \approx RC(Age)$.

where $f(\cdot)$ is the nonlinear function to be estimated and $X_{j,t}$ is the vector of predictors. $X_{j,t}$ 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 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. 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 the Appendix IA.C. Here, I provide a short introduction of 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, a 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, which allows for the model to learn complex patterns and often leads to state-of-the-art performance. I do not consider more complex methods like neural networks, as their "black box" nature. Furthermore, classical gradient-boosting methods are usually more effective and efficient for structured tabular data without the significant tuning and computational cost.

A key challenge in forecasting capital calls is the prevalence of zeros (Lambert, 1992). Such data is called zero-inflated. To address this issue, I adopt a two-stage hurdle model, which can improve performance for zero-inflated data (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: $\widehat{RC}_{j,t+1} = \hat{p}_{j,t+1} \cdot \hat{\mu}_{j,t+1}$

I also consider a simple linear model with five variables as the benchmark. The five variables are fund age, log fund size, fund type, the lagged capital call rate, and fraction of uncalled commitment as a fraction of total commitment. These five variables are selected because they are the five most important predictors from the best machine learning model.

4.1.2 Forecasting Outcomes

The models are trained annually using 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 observation in my main sample, all models are first trained and tested in the Preqin data, which also provide fund-level cash flow similar to my data. The advantage is that the Preqin data starts in 1990s, which allow me to have out-of-sample forecasting model ready at the beginning of my sample. For machine learning models that require tuning of hyper-parameters, I apply standard cross-validation procedures using the data before the first 5-year training sample (sample before 2003). All hyper-parameters are chosen once and remain the constant after. I delegate detailed description to the online Appendix IA.C.

To evaluate the 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 Two-stage LightGBM with average out-of-sample R^2 of 7.4%. As expected, the two-stage hurdle models have superior performance. 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 capital call process features low signal-to-noise ratio. While nonlinear interactions and patterns may exist, this modest improvement implies they are either weak or unstable over time, making them difficult for machine learning models to exploit consistently out-of-sample. This is consistent with the institutional knowledge that capital call is at GP's discretion and driven by idiosyncratic factors such as investment opportunities and strategy. From LPs' perspective, capital calls therefore

¹⁵The results are qualitatively similar if I directly estimate the model using my sample. But I have to start my main sample in 2013.

often resemble idiosyncratic shocks. Nonetheless, I use the best model (Two-Stage LightGBM) to predict the capital call rate in the subsequent analysis. ¹⁶

4.1.3 Construct Investor-level Measures

Using the best predicting 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

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

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 focus on the liquid shock impose by unexpected capital call, I only take the positive component of unexpected call. Formally, unexpected capital call, $UnexpCall_{it}$ is defined as in equation (3). Section 5 provides more descriptions about the unexpected capital call measures.

$$UnexpCall_{it} = \max\{Call_{it} - ExpCall_{it}, 0\}$$
(3)

Figure IA.7 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 is the 95% confidence interval of the predicted value. 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

 $^{^{16}}$ All results remain similar if I use linear benchmark model. Robustness of some key results are tabulated in the Appendix.

blue lines provide validation for the prediction model.

4.2 Main Regression Specification

The main regression model is at insurer-time level. Specification, the specification is as follow:

$$\Delta Y_{i,t} = \beta_1 U n exp Call_{it} + \beta_2 Exp Call_{it} + \beta_3 Dist_{it} + Controls + \gamma_i + \alpha_t + \epsilon_{it}$$
(4)

The main dependent variables are changes in portfolio allocations. The key explanatory variables is unexpected capital call, $UnexpCall_{it}$. I also include expected capital call, $ExpCall_{it}$, to examine how investor manage the capital calls that are anticipated. I also control for distribution, $Dist_{it}$, as distribution is a positive cash flow shock that will also affect portfolio allocation. 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 variable might bias the estimation as this empirical approach only relies on fixed effects and control variables.¹⁷ For an omitted factor to bias the estimation, it must satisfy two conditions: (1) correlated with both unexpected capital calls and changes in portfolio allocations, and (2) disproportionally affect some certain investors (not absorbed by time fixed effects).¹⁸ There are several reasons why I don't think omitted variable bias is a serious threat to the validity of my analysis. First, it is important to note that private fund managers, not investors, control the timing of capital calls, and commitments are made well in advance of when capital is called. As a result, it is unlikely that investors can influence capital calls in response to recent or contemporaneous shocks, such as changes in revenue or leverage. Second, the key explanatory variable is the unexpected capital call, which by construction captures the unpredictable component. Given the high degree of unpredictability documented in Tables 2, this component is

¹⁷Reverse causality is unlikely as capital calls are initialed by GP.

¹⁸For example, one scenario is that an sudden negative credit market shocks might simultaneously cause private credit funds to make more capital calls (due to credit line drawdowns) and investors to sell corporate bonds to reduce risk. The time fixed effects would not be enough if (1) the shock affect some insurers differently than others, and (2) the more vulnerable investors are invested more in private credit funds. However, as shown in Appendix IA.D, private credit funds only constitute a relative small part (around 15%) of insurers' PF investment. Untabulated tests show that removing private credit funds do not change key results materially. For private equity funds, I am not aware of theoretical or empirical evidence to support such arguments.

likely orthogonal to other variables. Third, investor-level capital calls represent the aggregation of many capital calls from individual investment. This aggregation makes the investor-level shock approximately random, as it is unlikely that any single fund or fund type drives the observed variation.¹⁹ Lastly, for most analysis I am primary interested in the direction of the treatment effects. In conclusion, I believe my empirical design is well suited to examine investors' portfolio adjustments in response to capital calls as there appears to be no clear confounders with a plausible economic rationale.²⁰

Lastly, to fully account for the dynamic effects of unexpected capital call, I estimate local projection as in Jordà (2005). Specifically, the model specification is as follow:

$$Y_{i,t+h} - Y_{i,t-1} = \beta_1^h UnexpCall_{it} + \beta_2^h ExpCall_{it} + \beta_3^h Dist_{it} + Controls + \gamma_i + \alpha_t + \epsilon_{it}$$
 (5)

5 Descriptive Statistics

5.1 Insurers' Portfolio Allocation

Table 1, Panel A, presents summary statistics on insurers' portfolio allocations, while Figure IA.8 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'. 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 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 portfolios by the end of the sample period.

¹⁹As shown in the next section, most variation of unexpected capital call is idiosyncratic.

²⁰It is theoretically possible to construct an instrumental variable based on some plausible exogenous shocks such as unexpected policy shock in certain industry that boost investment opportunity for certain fund types. However, estimating a Local Average Treatment Effect (LATE) would not be meaningful in this context. The objective is to understand how investors rebalance their portfolios in response to investor-level capital calls more broadly, not how they respond to small, random capital calls induced by specific exogenous shocks. In other words, a LATE estimate may capture behavior that differs significantly from the Average Treatment Effect (ATE).

[Insert Table 1]

5.2 Insurers Private Fund Investment

Figure 2 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 exceeds 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 commitment held by insurers is approximately 100 billion dollars. The orange line plots the ratio of uncalled commitment 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 percent.

[Insert Figure 2]

Figure 3 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 3]

5.3 Investor-level Capital Call Dynamics

Figure 5 Subfigure (a) plots the time series of aggregate amount 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 in private fund investment. 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 a almost a flat line around 10%, indicating about 10% of remaining commitments are called each quarter. On the contrary, the total capital call rate display substantial fluctuation overtime, 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 (3) are 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 portfolio. Within each panel, Subfigures (a) through (c) show total capital calls, 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 call is 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. As expected, private market variables, such as aggregate PE deal volume, explain for the majority of the time-specific variation. 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 Management

6.1 Ex-ante Buffer

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 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. For example, PitchBook provides clients with solutions for capita call forecasting and liquidity management (see Link.). 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 suggest no ex-ante liquid asset buffer in preparing for future capital call.

[Insert Figure 8]

Table 4 presents 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.

[Insert Table 4]

[Insert Figure 9]

[Need to add discussion for internal cash flow matching]

6.2 Ex-post Portfolio Rebalancing

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 intra-quarter 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 allocation, 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 IA.12 presents the dynamic effects using local projection.

[Insert Table 5]

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. It is consistent with the earlier discussion that expected calls are managed ex-ante, through strategy such as internal cash flow netting. Such approach eliminates the need for investor to adjust portfolio when expected calls are realized. As a result, expected capital calls generates little explanatory variation in portfolio shifts, leading to small and insignificant regression coefficients. The Appendix IA.A provides a simulation that illustrates how commitment strategies can mute the estimated effect of expected calls.

Additionally, Figure 10 presents the dynamic effects using local projection as in Equation (5). The results suggest that the effects of unexpected capital calls on portfolio allocations are persistent. Notably, while not statistically significant, investors continue reducing 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 10]

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 11 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 to 100% of total impact of capital call on long-term bond holdings. Additionally,

columns (5) and (6) further divide industrial bonds into corporate and non-corporate segments, revealing that nearly all of the reduction occurs in corporate bonds. These results together imply that investors predominantly liquidate corporate bonds to meet unexpected capital calls.

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 for NAIC 2 bonds, which correspond to BBB-rated corporate bonds. The impact on NAIC 3 through NAIC 6 bonds—primarily high-yield bonds—is also statistically significant but of smaller magnitude. 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 11]

6.3 Explanation

Why do insurers choose to sell BBB and HY 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 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 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 lowest-cost assets with highest-cost ones. This substitution leads to a significant increase in required capital and deterioration in 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, 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 9 presents the results. 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 9]

In addition to selling bonds with high risk weights, insurers may also preserve their RBC ratio 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 gain will increases equity and improves 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 for the low-RBC group, and Panel C for the high-RBC group. First, in line with earlier findings from 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 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 tend to also be less liquid. Importantly, both triple interaction terms are significantly negative. This suggests that, conditional on the same NAIC designation and unrealized gain, 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 effector to preserve the RBC ratio. Table 7 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 7]

7 Spillovers

7.1 Bond-level Capital Call Exposure Measure

In this section, I examine whether portfolio rebalancing induced by unexpected capital calls generates spillover effects to other part of the financial market. Particularly, as previous results show insurers mostly sell corporate bond, 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.

To test that hypothesis, I first construct a bond-level measure of exposure to insurers' unexpected capital calls, z_{it} , which is effective a ownership-weighted average of unexpected calls across insurers. The formal definition of z_{it} is provided in Equation (6). Ownership_{ij,t-1} insurer j's lagged ownership share of bond i and $UnexpCall_{jt}$ is the dollar amount of unexpected calls for insurer j at time t. This step assumes that non-insurance bondholders face no capital calls. Given that corporate bonds are predominantly held by insurance companies and mutual funds, this assumption is reasonable. I then scaled by this weighted average by the lagged amount outstanding for bond i to account for different bond size. Finally, I take the log as the distribution of the raw measure is very dispersed. Appendix shows the distribution of z_{it} .

$$z_{it} = \log\left(1 + \frac{\sum_{j} Ownership_{ij,t-1} \times UnexpCall_{jt}}{Outstanding_{i,t-1}}\right)$$
 (6)

The intuition behind z_{it} is similar to the shift-share instrumental variable (See Borusyak et al. (2025) for example). Insurers' unexpected capital calls are plausibly exogenous to bond fundamentals. Further, each bond's exposure to to the capital call shock is determined by the lag ownership. Hence, z_{it} should satisfy the exclusion restriction and can be used as an instrumental variable (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-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, z_{it} can serve as an instrument for the insurer sales variable. The corresponding two-stage least squares (2SLS) specification is shown in Equation (7).

$$\Delta YieldSpread_{it} = \beta \Delta Holdings_{it} + Controls_{it} + FEs + \epsilon_{it}$$

$$\Delta Holdings_{it} = \gamma z_{it} + Controls_{it} + FEs + u_{it}$$
(7)

7.2 Spillover Results

Table 10 presents the results of the spillover tests. Columns (1) to (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 z_{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 z_{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 z_{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 z_{it} is significantly positive, consistent with the hypothesis that bonds with higher exposure experience price declines. Economically, a one standard deviation increase in z_{it} is associated with a 0.85 basis point increase in yield spread. To further test this relationship, I use z_{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 5. Figure 12 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 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 12]

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)²¹. 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 a 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 to NAIC 2. Column (4) reports 2SLS estimates to directly compare price elasticities (first-stage results are in Appendix Tables).

²¹I 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).

Overall, these results align with the findings in Section 6.2, which show that insurers predominantly sell BBB-rated 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 investor 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 z_{it} . Columns (2) and (5) report OLS results, and Column (6) presents the 2SLS estimates. The coefficient on insurer holdings is slightly smaller during this period, possibly reflecting insurers' reluctance to sell corporate bonds in stressed markets. Despite that, 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 (Cite MSCI). As private fund investment continues to grow, the risk of such "inconvenient" capital calls may pose threats to financial stability.

8 Conclusion

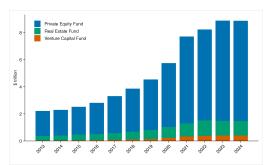
Capital calls are a binding obligation for private fund investors to contribute capital. Because fund managers retain full discretion over the timing and amount of capital calls, they are inherently difficult for investors to manage. In particular, an unanticipated large capital call represents a negative cash flow shock. Investors must either maintain costly cash buffers in advance or liquidate assets when such shocks occur. Leveraging novel data on insurers' private fund investments, this paper is the first to examine the how unexpected capital call affect investors portfolios and financial market.

I first document that unexpected capital calls are substantial and impose economically meaningful shocks to investor portfolios. The predictable component accounts for only 60% of the total variation in capital calls. Moreover, most of the variation in unexpected capital calls is idiosyncratic. Although aggregate cyclical patterns exist, time-specific factors explain only a small portion of the overall variation. Even during economic downturns, some investors continue to experience extremely large capital calls. Next, I examine how investors manage unexpected capital calls. Insurers appear not to rely on cash buffers. Instead, they primarily sell long-term bonds in response to unexpected capital calls. Interestingly, rather than liquidating the most liquid assets such as Treasury securities, they tend to sell corporate bonds with high risk weights and unrealized gains. I provide evidence that this seemingly counterintuitive behavior is likely driven by the desire to mitigate the impact of capital calls on their RBC ratios. Insurers facing tighter regulatory constraints are more likely to sell risky corporate bonds following capital call shocks. Moreoever, I find that bond sales triggered by unexpected capital calls have spillover effects on corporate bond prices. Bonds with greater exposure to capital call shocks face stronger selling pressure and temporary price declines. The effects are especially pronounced for bonds with high risk weights. These spillovers are further amplified when capital calls coincide with broader market disruptions.

Although this paper focuses on insurance companies due to data availability, the challenges posed by capital calls are likely generalizable to other institutional investors. As private markets continue to expand, capital calls could emerge as a new threat to financial stability. In addition, the rise of private debt may unintentionally amplify the spillover effects of capital call, as private

credit demand tends to be more countercyclical. This paper offers a important first step toward understanding how private fund capital calls affect the broader financial system. Further research is needed to assess their full implications for capital allocation and financial stability.

(a) Asset Under Management



(b) Ownership

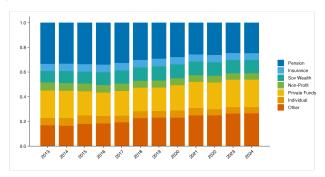


Figure 1: Aggregate Private Fund Investment

This figure plots the total asset under management for different private fund types (Private Fund Statistics Report Table 2.1) from the SEC private fund statistics. Subfigure (a) plots the total asset under management for different private fund types and Subfigure (b) plots the ownership by different investor types. Private fund types are defined by SEC according to instruction of Form ADV (Instruction Part 1A 6.e(2)).

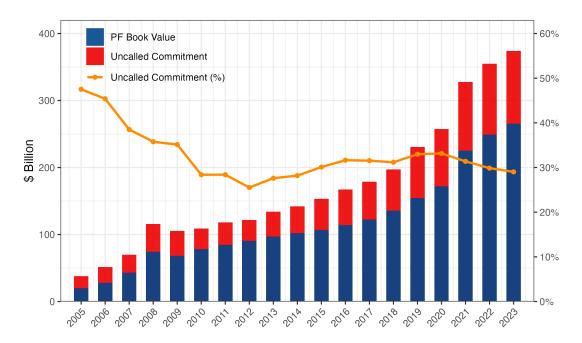
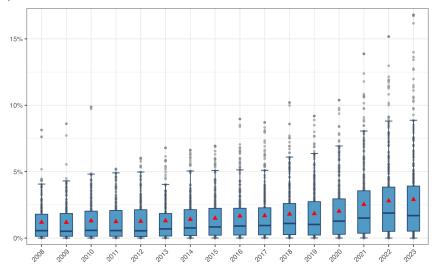


Figure 2: Insurers' Aggregate Private Fund Investment and Uncalled Commitment

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

(a) Distribution of PF Allocation



(b) Size vs PF Allocation

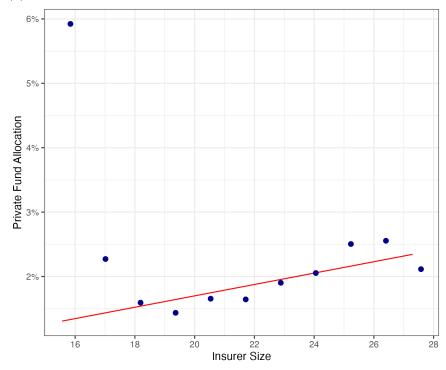
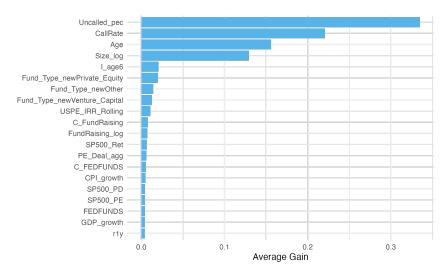


Figure 3: Distribution of Insurers' Private Fund Allocation

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 whisker range 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) First-stage Classification



(b) Second-stage Regression

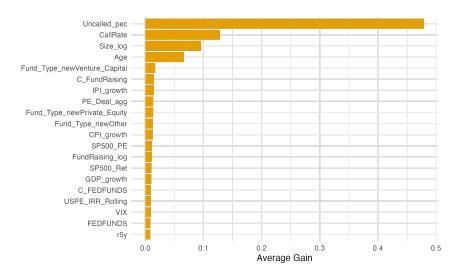
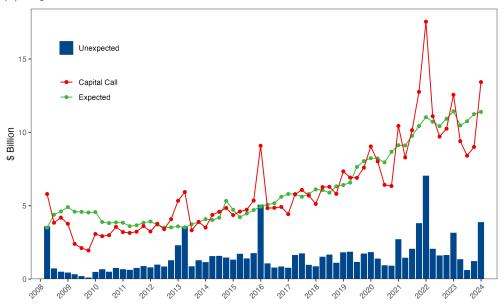


Figure 4: Predictor Importance

This figure shows the predictor (feature) importance of the best performing machine learning model (two-stage LightGBM). Subfigure (a) shows the first-stage classification task and Subfigure (b) shows the second-stage regression task.

(a) Capital Call



(b) Capital Call Rate

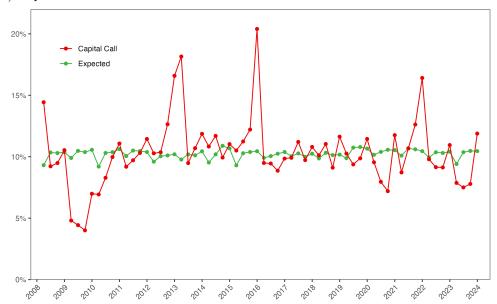
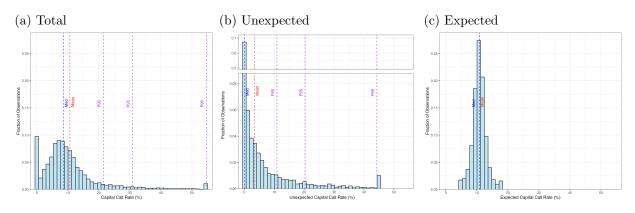


Figure 5: Time-series of Aggregate Capital Call

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

Panel A: Capital Call Rate



Panel B: Capital Call Amount

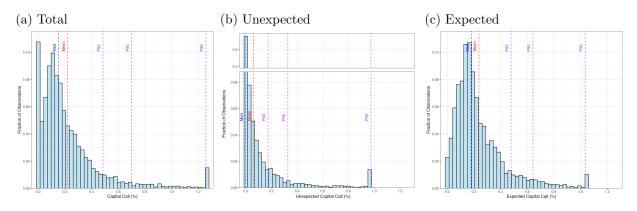
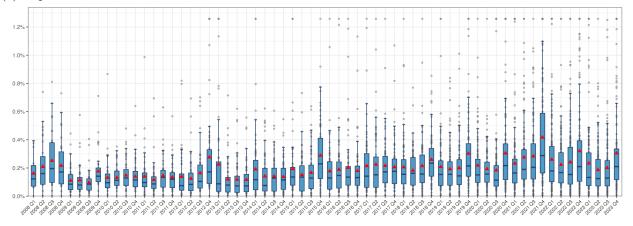


Figure 6: Distribution of Investor-level Capital Calls

This figure shows the distribution of investor-level capital calls. Panel A plots capital call rates (capital calls scaled by previous period-end uncalled commitments), while Panel B plots capital call amounts (scaled by 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 Call



(b) Unexpected Capital Call

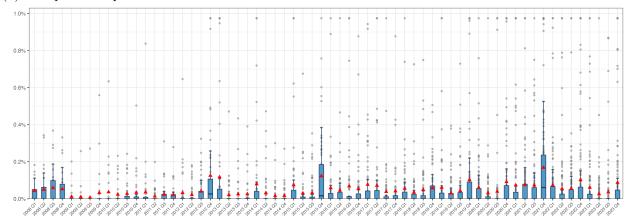


Figure 7: Investor-level Capital Call Distribution Over Time

This figure plots the distribution of investor-level capital call over time using boxplot, where Subfigure (a) is for the total capital call and Subfigure (b) is for the unexpected component. 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. Capital calls are scaled by previous period-end insurer portfolio size.

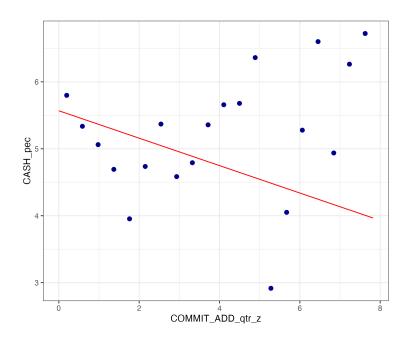


Figure 8: Insurers' Cash Buffer and Uncalled Commitment

This figure presents a bin-scatter plot of insurers' cash holdings against their uncalled commitments.

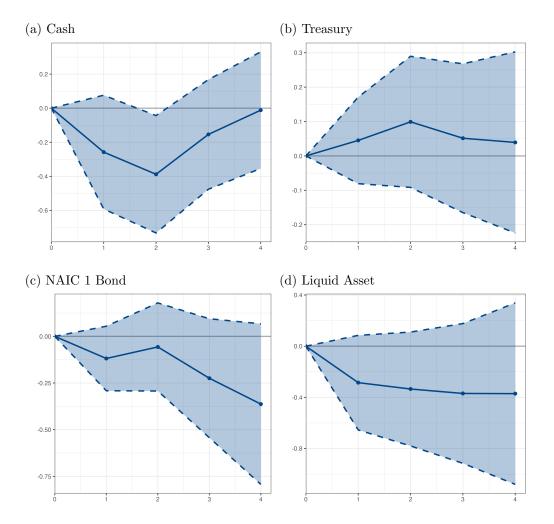


Figure 9: New Commitment and Liquid Asset Dynamic

This figure shows the dynamic effects of new commitment on investors' liquid asset holdings. Coefficients are estimated using local projection. Subfigure (a) plots results for cash and cash equivalent, Subfigure (b) plots results for Treasury securities, Subfigure (c) plots results for long-term bonds with NAIC designation of 1, Subfigure (d) plots results for the combination of all three liquid assets.

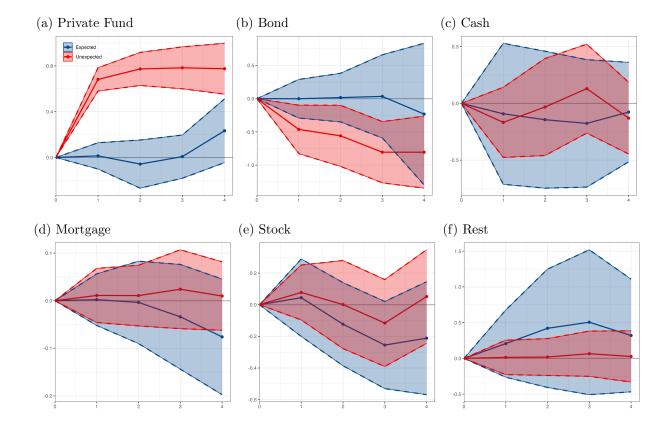


Figure 10: Dynamic Portfolio Impacts of Expected versus Unexpected Capital Calls

This figure plots the dynamic portfolio impacts of unexpected (red) and expected (blue) using local projection. The dependent variables are $\Delta Holdings_{i,t\to t+h}$, where $h\in[1,4]$. Subfigures (a) to (f) correspond to private funds, long-term bonds, cash and cash equivalents, stocks, and rest. Controls include lagged expected and unexpected capital call, lagged distribution, lagged private fund allocation, asset growth, return on assets, log asset size, log capital and surplus, leverage ratio, and previous year-end RBC ratio. Insurer and time (calendar year-quarter) fixed effects are included. Standard errors double clustered at the insurer and time level. The colored areas represent the 95% confidence interval.

Panel A: Break by Bond Types

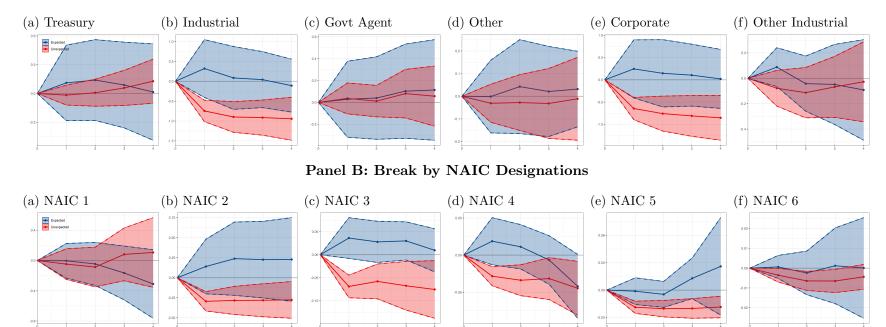
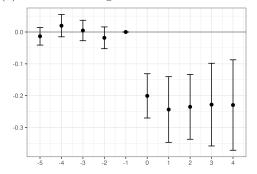


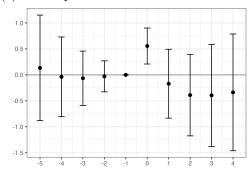
Figure 11: Dynamic Impacts of Capital Call on Bond Allocations

This figure plots the dynamic impacts of unexpected (red) and expected (blue) on different bond types using local projection. The dependent variables are Net Change $_{i,t\to t+h}$, where $h\in[1,4]$. Net change of bond allocations defined as buy minus sell, scaled by the lagged cash and invested assets. I only consider active sales, which exclude passive disposal such as redemption, scheduled paydown, maturing, etc. Panel A reports the results of different bond types. Bond sells Subfigures (a) to (d) correspond to treasury bonds, industrial bonds, other government-related bonds, and all other bonds. Subfigures (e) and (f) break industrial bonds into corporate bonds and other industrial bonds. Panel B reports the results for different NAIC designations. Subfigures (a) to (f) correspond to NAIC designations 1 to 6. Controls include lagged expected and unexpected capital call, lagged distribution, lagged private fund allocation, asset growth, return on assets, log asset size, log capital and surplus, leverage ratio, and previous year-end RBC ratio. Insurer and time (calendar year-quarter) fixed effects are included. Standard errors double clustered at the insurer and time level. The colored areas represent the 95% confidence interval.

(a) Insurer Holdings



(a) Yield Spread: OLS



(a) Yield Spread: 2SLS

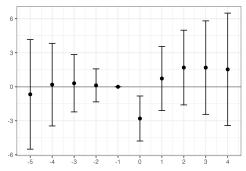


Figure 12: Dynamic spillover effect

This figure explore the dynamic spillover effects of assets sales induced by capital call. Subfigure (a) plots result for insurers holdings (corresponding to Column (3) of Table 10), Subfigure (b) plots the results for yield spread using OLS (corresponding to Column (4) of Table 10), Subfigure (c) plots the results for yield spread 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, where standard errors are double clustered at the bond and time levels.

Table 1: Summary Statistics (need update)

Variable	N	Mean	SD	P25	Median	P75
Total Assets	11049	35513.79	77228.88	601.98	2771.95	25402.51
Schedule BA Assets (%)	11049	3.20	3.57	0.50	1.97	4.70
Cash (%)	11049	5.87	7.81	1.41	2.91	6.46
Bonds (%)	11049	73.97	15.52	67.45	76.01	85.02
NAIC 1 (%)	11049	46.45	15.76	37.54	45.54	56.50
NAIC 2 (%)	11049	22.62	10.75	15.64	22.92	29.49
NAIC 3 (%)	11049	2.24	1.72	0.91	2.07	3.19
NAIC 4 (%)	11049	0.78	0.87	0.09	0.52	1.15
NAIC 5 (%)	11049	0.30	0.54	0.00	0.11	0.36
NAIC 6 (%)	11049	0.34	0.88	0.00	0.06	0.33
Industiral (%)	11049	51.80	17.05	42.31	54.25	63.58
Corporate Bond (%)	11049	28.72	14.23	18.62	28.16	37.98
Rating AA (%)	11049	2.38	2.05	1.00	1.93	3.19
Rating A (%)	11049	11.21	7.02	6.23	10.04	15.31
Rating BBB (%)	11049	13.39	8.32	7.46	12.33	18.33
Rating HY (%)	11049	1.21	1.39	0.24	0.84	1.68
Federal Govt (%)	11049	5.54	6.96	1.05	2.91	7.20
Other Govt (%)	11049	13.57	11.35	5.42	10.50	18.72
Bank Loan (%)	11049	0.12	0.42	0.00	0.00	0.00
Other (%)	11049	1.46	2.22	0.02	0.61	1.88
Mortgage Loans (%)	11049	6.67	7.08	0.00	4.92	11.55
Common Stock (%)	11049	5.00	6.35	0.69	2.76	6.40
Preferred Stock (%)	11049	0.84	1.87	0.00	0.17	0.76
Rest Invested Assets (%)	11049	3.97	4.87	0.76	2.30	5.40
Invested Assets Ratio (%)	11049	82.34	21.24	76.81	92.26	96.35
Total Liability	11049	33102.23	72862.54	479.31	2422.26	22591.69
Investment Income	11049	249.11	566.08	4.98	26.57	202.82
Net Operation Gain	11049	107.03	304.78	0.19	5.91	57.19
Total Income	11049	55.48	332.97	0.01	3.56	35.72
Investment ROA	11049	0.90	0.38	0.67	0.93	1.13
Operation ROA	11049	0.40	1.04	0.05	0.27	0.58
Total ROA	11049	0.28	0.92	0.00	0.17	0.44
Leverage	11049	0.84	0.16	0.81	0.90	0.94
Group	11049	0.80	0.40	1.00	1.00	1.00

Table 2: Capital Call Prediction Model Summary

This table reports the performance of forecasting models. Root Mean Squared Error (RMSE) is measured as percentage improvement relative to the linear benchmark model. Columns (1) and (2) reports the in-sample performance. Columns (3) and (4) reports 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 fraction of uncalled commitment as a fraction of total commitment. The detailed definition of other models are shown in Appendix.

	In-sample		Out-of-s	ample
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 do 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	Amou	$\overline{ m nt}$	
	Total	Expected	Unexpected
Share of Total Variance	100%	63.3%	20.7%
Firm-FE Share	44.1%	62.2%	16.8%
Time-FE Share Residual Share	$6.7\% \\ 49.1\%$	$5\% \\ 32.5\%$	4.2% $78.3%$
Panel B: Capital Call	Rate		
	Total	Expected	Unexpected
Share of Total Variance	100%	8.3%	48.2%
Firm-FE Share	27%	23.8%	23.5%
Time-FE Share Residual Share	$7.6\% \\ 64.8\%$	2.9% $73.1%$	5.8% $70.4%$

Table 4: New Commitment and Cash Buffer

This table studies whether insurers increase cash buffer when making new commitment. Standard errors double clustered at the insurer and time level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

Panel A: New Comr	nitment			
	Cash (1)	Treasury (2)	NAIC 1 Bond (3)	Liquid Asset (4)
New Commitment	-0.229 (0.180)	0.051 (0.070)	-0.107 (0.092)	-0.285 (0.202)
Controls Time FE	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Insurer FE Observations Adjusted R^2	Yes 14,351 0.002	Yes 14,351 0.085	Yes 14,351 0.233	Yes 14,351 0.153
Panel B: Uncalled C	ommitme	ent		
	Cash (1)	Treasury (2)	NAIC 1 Bond (3)	Liquid Asset (4)
Uncalled Commitment	-0.009 (0.029)	0.014 (0.020)	-0.024 (0.031)	-0.019 (0.046)
Controls Time FE	Yes Yes	Yes Yes	Yes Yes	Yes Yes
Insurer FE Observations Adjusted R ²	Yes 14,351 -0.009	Yes 14,351 0.085	Yes 14,351 0.223	Yes 14,351 0.128

Table 5: Portfolio Rebalance and Capital Call

This table studies the portfolio impacts of capital call. The dependent variables are the change of portfolio allocations to each asset type. Columns (1) to (6) correspond to private funds, long-term bonds, cash and cash equivalents, mortgage loans, stocks, and the rest. The key explanatory variables are capital call and distribution. Controls include lagged capital call, lagged distribution, lagged private fund allocation, asset growth, return on assets, log asset size, log capital and surplus, leverage ratio, and previous year-end RBC ratio. Insurer and time (calendar year-quarter) 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.

			$\Delta Holding$	s(%)		
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Capital Call	0.635***	-0.498***	-0.248	0.014	0.001	0.074
	(0.049)	(0.176)	(0.149)	(0.018)	(0.082)	(0.137)
Distribution	-0.918***	0.135	0.359	0.006	0.107	0.331
	(0.079)	(0.302)	(0.278)	(0.028)	(0.203)	(0.246)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,615	13,615	13,615	13,615	13,615	13,615
Adjusted \mathbb{R}^2	0.348	0.060	0.001	0.070	0.306	0.077
Panel B: Expected	vs Unexpected Capita	l Calls				
			A TT 11.	(04)		

			$\Delta Holding$	s(%)		
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Unexpected Capital Call	0.683*** (0.052)	-0.517*** (0.184)	-0.201 (0.155)	0.023 (0.019)	0.026 (0.081)	-0.018 (0.133)
Expected Capital Call	0.014 (0.059)	-0.042 (0.119)	-0.100 (0.323)	-0.008 (0.019)	-0.108 (0.096)	0.291 (0.305)
Distribution	-0.881^{***} (0.078)	0.105 (0.301)	0.341 (0.275)	0.006 (0.028)	0.111 (0.203)	0.330 (0.251)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,615	13,615	13,615	13,615	13,615	13,615
Adjusted R ²	0.349	0.060	0.001	0.070	0.306	0.078

Table 6: Capital Call and Bond Allocations

This table studies how insurers adjust bond allocations when facing unexpected capital calls. The dependent variable is the net change of bond allocations defined as buy minus sell, scaled by the lagged cash and invested assets. I only consider active sales, which exclude passive disposal such as redemption, scheduled paydown, maturing, etc. Panel A reports the results of different bond types. Bond sells Columns (1) to (4) correspond to treasury bonds, industrial bonds, other government-related bonds, and all other bonds. Columns (5) and (6) break industrial bonds into corporate bonds and other industrial bonds. Panel B reports the results for different NAIC designations. Columns (1) to (6) correspond to NAIC designations 1 to 6. Controls include lagged capital call, lagged distribution, lagged private fund allocation, asset growth, return on assets, log asset size, log capital and surplus, leverage ratio, and previous year-end RBC ratio. Insurer and time (calendar year-quarter) 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: Bond Sells b	y Bond Ty	pes					
	Net Change (%)						
	Treasury	Industrial	Govt Agent	Other	Corporate	Non-Corporate	
	(1)	(2)	(3)	(4)	(5)	(6)	
Unexpected Capital Call	-0.022	-0.745***	0.032	-0.028	-0.646***	-0.076	
	(0.052)	(0.135)	(0.072)	(0.043)	(0.127)	(0.075)	
Expected Capital Call	0.088	0.314	-0.0005	0.010	0.233	0.090	
	(0.212)	(0.351)	(0.152)	(0.089)	(0.309)	(0.077)	
Distribution	0.082	0.421**	-0.187^*	0.049	0.110	0.379**	
	(0.129)	(0.183)	(0.101)	(0.045)	(0.125)	(0.157)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	13,615	13,615	13,615	13,615	13,615	13,615	
Adjusted R ²	0.087	0.207	0.168	0.108	0.109	0.315	
Panel B: Bond Sells b	y NAIC D	esignations					
			Net C	Change (%)			
	NAIC 1	NAIC 2	NAIC 3	NAIC 4	NAIC 5	NAIC 6	
	(1)	(2)	(3)	(4)	(5)	(6)	
Unexpected Capital Call	-0.053	-0.290***	-0.069***	-0.029***	-0.018***	-0.004**	
	(0.103)	(0.060)	(0.012)	(0.007)	(0.003)	(0.002)	
Expected Capital Call	-0.037	0.150	0.036	0.017	0.001	0.0004	
	(0.102)	(0.173)	(0.022)	(0.015)	(0.008)	(0.003)	
Distribution	0.116	0.091	0.001	0.018	0.003	-0.007	
	(0.199)	(0.069)	(0.014)	(0.014)	(0.004)	(0.004)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	13,615	13,615	13,615	13,615	13,615	13,615	
Adjusted R ²	0.240	0.283	0.136	0.196	0.136	0.112	

Table 7: Regulatory Constraints and Portfolio Impacts of Capital Call

This table studies how regulatory constraints affect insurers' portfolio adjustment when facing capital calls. The sample is split equally based on insurers' previous year-end RBC Ratio. Panel A reports the results for the low RBC ratio group, and panel B reports the results for the high RBC ratio group. Panels C and D repeat the same exercise with capital calls decomposed into expected and unexpected components. The dependent variables are the change of portfolio allocations to each asset type. Columns (1) to (6) correspond to private funds, long-term bonds, cash and cash equivalents, mortgage loans, stocks, and the rest. Controls include lagged capital call (or lagged expected and unexpected capital calls), lagged distribution, lagged private fund allocation, asset growth, return on assets, log asset size, log capital and surplus, leverage ratio, and previous year-end RBC ratio. Insurer and time (calendar year-quarter) 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: Low RBC R	atio					
	Private Fund (1)	Bond (2)	Cash (3)	Mortgage (4)	Stock (5)	Rest (6)
Capital Call	0.694***	-0.592**	-0.209	0.006	-0.036	0.129
	(0.074)	(0.264)	(0.221)	(0.024)	(0.141)	(0.215)
Distribution	-0.882^{***}	-0.173	0.591^{*}	-0.057^{*}	0.283	-0.032
	(0.080)	(0.408)	(0.340)	(0.029)	(0.296)	(0.298)
Observations	6,938	6,938	6,938	6,938	6,938	6,938
Adjusted R ²	0.327	0.021	-0.004	0.099	0.229	0.047
Panel B: High RBC F	Ratio					
	Private Fund	Bond	Cash	Mortgage	Stock	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Call	0.537***	-0.292	-0.452**	0.033	0.059	0.055
•	(0.053)	(0.234)	(0.190)	(0.028)	(0.092)	(0.128)
Distribution	-1.055^{***}	$0.471^{'}$	0.011	0.088*	-0.116	0.954***
	(0.167)	(0.309)	(0.337)	(0.047)	(0.234)	(0.355)
Observations	6,677	6,677	6,677	6,677	6,677	6,677
Adjusted R ²	0.367	0.117	-0.004	0.066	0.392	0.132
Panel C: Low RBC R	atio – Unexpec	ted vs Exp	ected			
	Private Fund	Bond	Cash	Mortgage	Stock	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.742***	-0.621**	-0.111	0.019	-0.039	0.010
	(0.078)	(0.272)	(0.228)	(0.025)	(0.149)	(0.216)
Expected Capital Call	0.041	-0.060	0.035	-0.031	-0.107	0.174
	(0.037)	(0.096)	(0.258)	(0.022)	(0.095)	(0.264)
Distribution	-0.851^{***}	-0.199	0.557	-0.057^{*}	0.288	-0.013
	(0.080)	(0.409)	(0.335)	(0.030)	(0.299)	(0.305)
Observations	6,938	6,938	6,938	6,938	6,938	6,938
Adjusted R ²	0.327	0.021	-0.004	0.099	0.230	0.047
Panel D: High RBC I	Ratio – Unexpe	cted vs Ex	pected			
	Private Fund	Bond	Cash	Mortgage	Stock	Rest
	(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call	0.574***	-0.271	-0.494**	0.041	0.100	0.022
	(0.057)	(0.257)	(0.208)	(0.031)	(0.092)	(0.128)
Expected Capital Call	-0.340	-0.332	-0.339	0.136	-0.172	0.896
	(0.329)	(0.425)	(0.437)	(0.105)	(0.322)	(0.593)
Distribution	-0.998***	0.462	0.008	0.080*	-0.105	0.906**
	(0.158)	(0.304)	(0.335)	(0.047)	(0.229)	(0.350)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,677	6,677	6,677	6,677	6,677	6,677
Adjusted R ²	0.373	0.117	-0.004	0.067	0.392	0.134

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 variable equal to one if a bond is sold partially or fully at quarter t. I only consider active sales, which exclude passive disposal such as redemption, scheduled paydown, maturing, etc. Panel A reports the results of different bond types. NAIC is 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 book-adjusted carrying value at the previous year-end, scaled by the book-adjusted carrying value. Illiqudity 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 low RBC ratio indicator, bond size, time-to-maturity, lagged bond trading volume, and lagged bond bid-ask spread. Columns (1) to (3) include bond, insurer, and time (calendar year-quarter) fixed effects. Columns (4) to (6) include bond-by-time and insurer-by-time fixed effects. Standard errors clustered at the bond-by-time levels are presented in parentheses. ***, ***, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(1)	(2)	(3)	(4)	(5)	(6)
Unexpected Capital Call × NAIC	Unexpected Capital Call	0.054***	0.037***	0.031***			
Unexpected Capital Call × Unrealized G&L		(0.005)					
Unexpected Capital Call × Unrealized G&L (0.006) (0.007) (0.005) (0.007) (0.005) (0.007) (0.005) (0.007) (0.005) (0.007) (0.007) (0.005) (0.007) (0.00	Unexpected Capital Call \times NAIC	0.008***	0.008***	0.006**	0.034***	0.036***	0.049***
Unexpected Capital Call × Illiquidity Unexpected Capital Call × NAIC × Illiquidity Unexpected Capital Call × NAIC × Illiquidity Unexpected Capital Call × NAIC × Illiquidity Unexpected Capital Call × Unrealized G&L × Illiquidity Unexpected Capital Call × Unrealized G&L × Illiquidity NAIC (0.0007) Unexpected Capital Call × Unrealized G&L × Illiquidity (0.0007) Unexpected Capital Call × Unrealized G&L × Illiquidity NAIC (0.0007) Unexpected Capital Call × Unrealized G&L × Illiquidity (0.0007) Unexpected Capital Call × Unrealized G&L × Illiquidity (0.0007) Unexpected Capital Call × Unrealized G&L × Illiquidity (0.0007) Unexpected Capital Call × Unrealized G&L × Illiquidity (0.0007) Unexpected Capital Call × NAIC × Illiquidity (0.0001) Unexpected Capital Call × NAIC × Illiquidity (0.0001) Unexpected Capital Call × NAIC × Illiquidity (0.0007) Unexpected Capital Call × NAIC × Illiquidity (0.0007) Unexpected Capital Call × NAIC × Illiquidity (0.0007) Unexpected Capital Call × NAIC × Illiquidity (0.0008) (0.0007) Unexpected Capital Call × NAIC × Illiquidity (0.0001) Unexpected Capital Call × Unrealized G&L × Illiquidity (0.0001) Unexpected Capital Call × Unrealized G&L × Illiquidity (0.0001) Unexpected Capital Call × Unrealized G&L × Illiquidity (0.0001) Unexpected Capital Call × Ves Ves No		(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Unexpected Capital Call \times Unrealized G&L	, ,	0.033***	0.041***	, ,	0.061***	0.108***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$			(0.006)	(0.007)		(0.005)	(0.007)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Unexpected Capital Call \times Illiquidity			0.022***			0.146***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(0.008)			(0.015)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Unexpected Capital Call \times NAIC \times Illiquidity			0.002			-0.038***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(0.002)			(0.007)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Unexpected Capital Call \times Unrealized G&L \times Illiquidity			-0.021**			-0.126***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$				(0.009)			(0.011)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	NAIC	0.005***	0.005***	0.004***			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0007)	(0.0007)	(0.0008)			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Unrealized G&L	-0.016***	-0.018***	-0.022***	-0.010***	-0.014***	-0.016***
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0010)	(0.0010)	(0.001)	(0.0009)	(0.0009)	(0.001)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Low RBC Ratio	0.006***	0.006***	0.006***			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0006)	(0.0006)	(0.0006)			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Trading Volume	0.005***	0.005***	0.005***			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0002)	(0.0002)	(0.0002)			
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Illiquidity	-0.002***	-0.002***	-0.006***			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		(0.0003)	(0.0003)	(0.0008)			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Bond Size	-0.011***	-0.011***	-0.011***			
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		(0.001)	(0.001)	(0.001)			
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	Time-to-Maturity	0.085	0.085	0.085			
		(0.065)	(0.065)	(0.065)			
Unrealized G&L × Illiquidity	$NAIC \times Illiquidity$			0.0004			
Bond FE Yes Yes Yes No No No No Insurer FE Yes Yes Yes Yes No No No No No				(0.0003)			
Bond FE Yes Yes Yes No No No Insurer FE Yes Yes Yes Yes No No No	Unrealized G&L \times Illiquidity			0.007^{***}			0.005***
Insurer FE Yes Yes Yes No No No				(0.0008)			(0.001)
Insurer FE Yes Yes Yes No No No	Bond FE	Yes	Yes	Yes	No	No	No
Time FE Yes Yes Yes No No No	Insurer FE			Yes			
		Yes					
Bond-by-Time FE No No No Yes Yes Yes	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	Observations	8,851,969	8,851,969	8,851,969	8,851,969	8,851,969	8,851,969
Adjusted \mathbb{R}^2 0.106 0.106 0.3352 0.335 0.336	Adjusted R^2		, ,	, ,	, ,	, ,	, ,

Table 9: Capital Calls and Risk-Based Capital Ratio

This table studies how capital calls affect insurers Risk-Based Capital (RBC) ratio. The dependent variable is the percentage changes of insurers' RBC ratio. The key explanatory variables are changes in insurers allocation to private funds, capital call, unexpected and expected capital calls. Column (1) to (3) report the results for the full sample. I then split the full sample into half based on the lagged RBC ratio. Column (4) and (5) report the results for the low RBC ratio sample and columns (6) and (7) report the results for the high RBC sample. Controls include asset growth, return on assets, log asset size, log capital & surplus, leverage ratio, and percentage changes of capital & surplus. Insurer and year fixed effects are included. Standard errors double clustered at the insurer and year level. ***, ***, and * indicate statistical significance at the 1%, 5%, and 10%, respectively.

		$\Delta \mathrm{RBC}$ Ratio (%)						
	Full Sample			Low RE	BC Ratio	High RBC Ratio		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Δ Private Fund (%)	-1.085** (0.481)							
Capital Call		-1.542^{***} (0.428)		-0.869 (0.921)		-1.141^{**} (0.476)		
Unexpected Capital Call		, ,	-1.454^{***} (0.431)	,	-0.305 (1.007)	,	-1.457^{**} (0.491)	
Expected Capital Call			(0.431) -1.711 (1.135)		-1.400 (1.136)		-1.651 (1.138)	
Distribution		2.484** (1.128)	(1.133) $2.576*$ (1.208)	2.156* (1.221)	(1.130) (2.155) (1.225)	0.648 (1.479)	0.987 (1.534)	
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Insurer FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	3,773	3,773	3,773	1,886	1,886	1,887	1,887	
Adjusted \mathbb{R}^2	0.204	0.204	0.204	0.744	0.744	0.257	0.258	

Table 10: Spillover Effect

This table studies spillover effects of asset sales induced by unexpected capital calls using 2SLS methods. I built a shift-share instrument exploiting a bond's heterogeneous exposure to insurers' unexpected capital calls. Specifically, the instrument is defined as

$$z_{it} = \log \left(1 + \frac{\sum_{j} Ownership_{ij,t-1} \times UnexpCall_{jt}}{Outstanding_{i,t-1}} \right)$$

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 z_{it} using OLS. 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 $(\Delta Yield_Spread)$. In Column (5), z_{it} is used as instrument for $\Delta Insurer_Holdings$ in 2SLS model.

$$\Delta YieldSpread_{it} = \beta_h \Delta Holdings_{it} + Controls_{it} + FEs + \epsilon_{it}$$
$$\Delta Holdings_{it} = \gamma_h z_{it} + Controls_{it} + FEs + u_{it}$$

Other controls include bond size, time-to-maturity, credit ratings, 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.

	$In surer_Sell$	$1(Insurer_Sell)$	$\Delta In surer_Holdings$	$\Delta Yield$	$_Spread$
	(1)	(2)	(3)	(4)	(5)
z_{it}	0.967***	0.026***	-0.201***	0.555**	
	(0.131)	(0.003)	(0.035)	(0.211)	
$\Delta Insur\widehat{er}$ _Holdings					-2.798**
Ü					(1.210)
Bond_size	0.903***	0.158***	-0.898***	1.221***	-1.323
	(0.155)	(0.007)	(0.187)	(0.434)	(1.485)
TMT	0.469	0.149	-84.049***	-61.767^{***}	-280.084**
	(3.899)	(0.199)	(10.768)	(14.268)	(109.353)
RATING_NUM	0.067	-0.001	-0.195***	0.313***	-0.219
	(0.046)	(0.002)	(0.020)	(0.099)	(0.284)
TVolume_log_l1	0.688***	0.029***	-0.092***	-0.318**	-0.732***
	(0.052)	(0.002)	(0.022)	(0.138)	(0.206)
T_Spread_ew_l1	0.173	-0.006	-0.041	-0.093	-0.206
	(0.194)	(0.004)	(0.038)	(0.404)	(0.450)
Insurer_Ownership_l1	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 studies spillover effects of asset sales induced by unexpected capital calls using 2SLS methods. I built a shift-share instrument exploiting a bond's heterogeneous exposure to insurers' unexpected capital calls. Specifically, the instrument is defined as

$$z_{it} = \log \left(1 + \frac{\sum_{j} Ownership_{ij,t-1} \times UnexpCall_{jt}}{Outstanding_{i,t-1}} \right)$$

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 z_{it} using OLS. 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 $(\Delta Yield_Spread)$. In Column (5), z_{it} is used as instrument for $\Delta Insurer_Holdings$ in 2SLS model.

$$\Delta YieldSpread_{it} = \beta_h \Delta Holdings_{it} + Controls_{it} + FEs + \epsilon_{it}$$
$$\Delta Holdings_{it} = \gamma_h z_{it} + Controls_{it} + FEs + u_{it}$$

Other controls include bond size, time-to-maturity, credit ratings, 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.

	$\Delta Insurer$	$_Holdings$		$\Delta Yield$	d_Spread	
	(1)	(2)	(3)	(4)	(5)	(6)
$\overline{z_{it} \times NAIC1}$	-0.074^*		0.062			
	(0.044)		(0.303)			
$z_{it} \times NAIC2$	-0.303***		0.853***			
	(0.038)		(0.267)			
$z_{it} \times NAIC3$	-0.132****		0.668**			
	(0.032)		(0.288)			
$z_{it} \times COVID$,	-0.182***	,		1.480***	
		(0.034)			(0.303)	
$z_{it} \times REST$		-0.201***			0.546***	
		(0.036)			(0.219)	
$\Delta Holdings \times NAIC1$, ,		0.914	,	
3				(1.919)		
$\Delta Holdings \times NAIC2$				-2.953**		
				(1.249)		
$\Delta Holdin\widehat{gs imes NAIC3}$				-1.875		
ΔHoldings ∧ WHC5				(1.738)		
A II II: COULD				(1.756)		0.010***
$\Delta Holdings \times COVID$						-8.913***
						(2.014)
$\Delta Holdings \times REST$						-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 \mathbb{R}^2	0.088	0.085	0.869	0.787	0.869	0.799

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Internet Appendix for

"Private Fund Capital Calls, Investor Portfolios, and Spillovers"

Tiange Ye

IA.A Conc	eptual Framework
IA.A.1	Illustrative Example
IA.B Data	
IA.B.1	Raw Schedule BA Data
IA.B.2	Schedule BA Cleaning Procedure
IA.B.3	Data Comparison
IA.B.4	Variable Definition
IA.C Fored	east Capital Call
IA.C.1	Forecasting Models
IA.C.2	Implementation
IA.C.3	Additional Forecasting results
IA.D Addi	tional Results
IA.D.1	Additional Descriptive Results

IA.A Conceptual Framework

IA.A.1 Illustrative Example

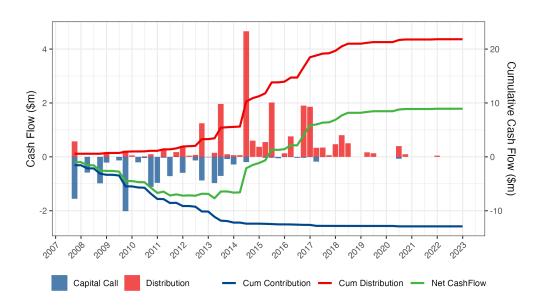
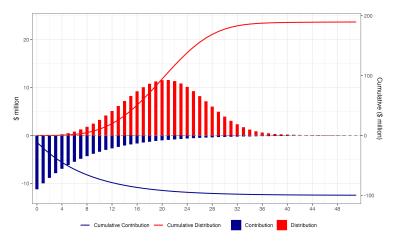


Figure IA.1: Example of Private Fund Cash Flow

This figure shows the cash flow from a real private fund.

Panel A: Single fund cash flow and NAV



Panel B: Portfolio of private funds

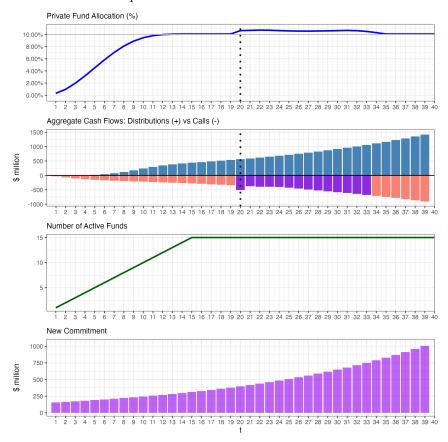


Figure IA.2: A Illustrative Example

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.B Data

IA.B.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 include 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.3 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.4 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 fund, it can be interpreted as the contribution at the time of initial commitment.
- Column (10): Additional Investment Made After Acquisition. For private fund, 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.5

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 distribution, partial disposal, full disposal, secondary market sales, and liquidation/termination. For most of time, partial disposal also represents distribution.
- Column (7): Disposal Date. Blank for distribution.
- Column (8): Book value from part 1 of last year.
- Column (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 it as the amount from distribution.
- 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-Ter		Accete OWA			Current Ve												
1	2	3	Location		Showing Other Long-Ten	10	18	19	20													
'	2	"	"	3	3	4	5	ď	NAIC	l °	9	'0	11	12	13	nge in Bool	15	Jarrying vai	ue 17	10	19	20
			4	5		Designation.						13	14	Current	16	17						
						NAIC								Year's		Total						
											DIII		Current	Other-								
						Designation					Book/		Year's		0	Foreign		0				
						Modifier					Adjusted		(Depre-	Than-	Capital-	Exchange		Commit-				
						and					Carrying	l	ciation)	Temporary	ized	Change in		ment	_			
						svo		_			Value	Unrealized	or	Impair-	Deferred	Book/	l	for	Percen			
CUSIP						Admini-	Date	Type			Less	Valuation	(Amorti-	ment	Interest	Adjusted	Invest-	Additional	tage of			
Identi-					Name of Vendor	strative	Originally	and	Actual	Fair	Encum-	Increase/	zation)/	Recog-	and	Carrying	ment	Invest-	Owner-			
fication	Name or Description	Code	City	State	or General Partner	Symbol	Acquired	Strategy	Cost	Value	brances	(Decrease)	Accretion	nized	Other	Value	Income	ment	ship			
	BUILDERS FACILITY			US	BUILDERS FACILITY		02/01/2021		2,552,614	2,467,536	2,552,617		(128)				438,543		0.000			
BGAOXA-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			
	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			
	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. N	Ion-Registered Private Funds - Mortga	age Loar	ns - Unaffiliated						489,567,790	443,784,665	489,626,407		296,063				23, 187, 591		XXX			
	ERESI WAREHOUSE - ABS			us	ERESI WAREHOUSE - ABS		01/07/2022		218,501	143,489	143,489		(12)				75,047		0.000			
	ERESI WAREHOUSE LINE - ABS			US	ERESI WAREHOUSE LINE - ABS	L	09/01/2023	L	67,276,199	43, 172, 182	44, 152, 706	L	(47,867)		L	L	8,388		0.000			
	Ion-Registered Private Funds - Mortga		ns - Affiliated		100				67,494,700	43.315.671	44,296,195		(47.879)				83.435		XXX			
	TOAMS 2017-1 LLC		7 timatou	DE	TOAMS 2017-1 LLC		03/01/2019		9,000,000	126 . 454 . 039	126,454,039	(487,771)	(41,010)				00,400		0.000			
	BDC EQUITY INVESTMENT			NY	BC Partners Lending Corporation		10/16/2019	·····	9.963.858	10,602,358	10,602,358						451.205		18.450			
	Landis - Equity			US	Landis - Equity	l	12/29/2021	·····		4, 163,442	2,504,154	030,499							0.000			
	FIDUCIARY EXCHANGE LLC			US	FIDUCIARY EXCHANGE LLC		11/04/2022		8.000.000	7.523.845	7.523.845	(476. 155)							4.990			
	TOW/ORESCENT MEZZANINE PARTNER			0S	TCW/Crescent Mezzanine V. LLC		06/24/2010		8,000,000			(4/6, 100)							0.298			
	GLOBAL ENERGY CAPITAL			US			12/08/2011	·····		75.400		(14,954)						004.040				
BHSUHV-FZ-Z	GLUBAL ENERGY CAPITAL				GEC Capital Group LP PineBridge Structured Capital General Pa		12/08/2011	·····	/5, 160	75, 160	/5, 160	(14,954)						264,218	1.300			
BRSFMM-GE-7	PINEBRIDGE STRUCTURED CAPITAL			DC	Finebiloge Structured Capital General Fa	1	08/02/2012	١.	376,217	157 . 142	157 . 142	(375,319)						27.790	1.100			
	OLYMPUS CAP ASIA III LP			DE	Olympus Capital Asia III GP. L.P		04/01/2013		2.473.347	297 .008	137 , 142						989	433.350				
	KRG CAPITAL FUND IV			DE	KRG Capital Management, L.P.		04/01/2013	·····			416.365						989	205.510				
	BRENTWOOD IV			DE	Brentwood Private Equity IV. L.P		04/04/2013	······		416,365	416,365	(1, 104)						1.574				
	Panamint Power			IIS	Panamint Power		08/21/2023	·····	97,956,428		99,200,296							1,0/4				
							05/21/2023			99,200,296		1,243,868							0.000			
	Panamint Capital			US	Panamint Capital		05/2//2022		3,609,600	970,847	970,847	(2,638,753)							47.000			
	oint Venture Interests - Common Stoc		filiated						134,971,211	250,253,879	248,594,591	(2,404,569)					452, 194	932,442				
	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			
	oint Venture Interests - Common Stoc		ated						973,890	991,375	991,375	203					54,535		XXX			
	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. S	urplus 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			
BGAOA1-8X-9 .	GOODGREEN HOLDINGS 2016-A	l	l	us	GOODGREEN HOLDINGS 2016-A	L	10/25/2016		740.431	740.431		L	l	l	l	L	255.283	l	0.000			
	AREVIA DEVELOPMENT LOAN FACILITY - ABS			US	AREVIA DEVELOPMENT LOAN FACILITY - ABS	L	06/03/2022	ļ	38,017,299	38,566,882	38,451,441		284,414				2,376,403		0.000			
		"			BIRCH CREEK DEVELOPMENT LOAN FACILITY -	1	1															
GA2309-98-3	BIRCH CREEK DEVELOPMENT LOAN FACILITY - ABS .		l	US			09/28/2023		36, 148, 041	36,148,041	36, 153, 797		5,755						0.000			
2999999. C	Collateral Loans - Unaffiliated		•						77,718,935	78,268,518	78,158,833		290, 169				3,333,023		XXX			
					STELLAR DEVELOPMENT LOAN FACILITY - ABS																	
BGA10S-7B-8 .	STELLAR DEVELOPMENT LOAN FACILITY - ABS		l	US			01/27/2022	ļ	54,473,139	53,324,443	54,473,139						3,769,718		0.000			
3099999. C	Collateral Loans - Affiliated		•						54,473,139	53,324,443	54,473,139						3,769,718		XXX			
					Central Valley Coalition for Affordable						,,						.,,					
BRS7KV-H9-7	LEMOORE PACIFIC ASSOCIATES LP		Eagle	ID			06/24/2010	t	309, 100	309, 100	309, 100		(13,428)		ļ				28.010			
BRS80C-SM-8	WP KEARNEY PALMS II SR APT LP		Westlake Village	CA	WP Kearney Court Phase II, LLC	L	06/24/2010	L 1	155 ,552	155,552	155,552	L	(20,088)	L	L	L	L	L	99.990			
BRSCSR-71-5	RED STONE 2011 NATIONAL FD LP	l	Cleveland	OH	RSEP MM, LLC	L	08/05/2011	1	248,748	248,748	248 748	L	(63,648)	L				L	0.000			
	ALLIANT TAX CREDIT PARTNERSHIP		Palm Beach	FL	Alliant Real Estate Investment, LLC	L	12/22/2011	L 1				L	(90,636)		L	L			4.000			
	GREAT LAKES CAPITAL FUNDING	1	Lansing		GLCFH-XXVI Inc	L	05/14/2012	L 1	284.927	284.927	284.927	L	(248,736)	l	L	L	L	l	3.866			
	NATIONAL EQUITY FUND 2012 LP	l	Chicago	IL	NEF 2012 Fund Manager LLC	L	01/16/2013	L 1	329.549	329,549		L	(324, 120)	l	L	L		L	4.950			
	Ion-Guaranteed State Low Income Ho	using T		p					1.417.012	1,417,012	1.417.012		(760,656)						XXX			
	GSHLT TRUST 2021-A Class F - ABS		Trialillated	us	GSHLT TRUST 2021-A Class F - ABS		12/12/2023		4.408.643	2.929.636	2.929.636	(1,479,007)	(700,000)						0.000			
	GSHLT TRUST 2021-B Class F - ABS			US			12/12/2023	ļ		2,929,636		(1,4/8,00/)						····	0.000			
	MOST TRUST 2020-1 F			US	MOST TRUST 2020-1 F	ļ	08/29/2023	l	16.997.424		16,997,424	····							0.000			
ל-AH-טו/פוסן	MUSI IMUSI ZUZU-I F			JUS		ļ	J08/29/2023	ļ	10,997,424	J 24,237,609 J.	10,997,424	ļ				ļ			J0.000			

Figure IA.3: Example – Schedule BA Part 1

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

SCHEDULE BA - PART 2

		Showing Other	r Long-Tern	n Invested Assets ACQUIRED AND ADD	ITIONS MAD	E During th		t Quarter				
1	2	Location		5	6	7	8	9	10	11	12	13
		3	4		NAIC							
					Designation, NAIC							
					Designation							
					Modifier							
					and							
					svo						Commitment	
					Admini-	Date	Type	Actual Cost	Additional		for	
CUSIP				Name of Vendor	strative	Originally	and	at Time of	Investment Made	Amount of	Additional	Percentage of
Identification	Name or Description	City	State	or General Partner	Symbol	Acquired	Strategy	Acquisition	After Acquisition	Encumbrances	Investment	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	
	770729 COURT SQUARE CAP PARTNERS III	NEW YORK	NY	COURT SQUARE CAPITAL GP III LLC		10/02/2012	3		14,091		559,142	
	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&P ASSOCIATES IX LP		11/21/2013	3					0.550
	77089 CENTRE CAPITAL INVESTORS VI LP	WILMINGTON	DE	CENTRE PARTNERS VI IP		01/03/2014	3		217,356			
	770897 PAINE & PARTNERS CAPITAL FD IV	GEORGE TOWN	CYM	PAINE & PARTNERS CAPITAL FUND IV GP LP		05/30/2014	3		4,636,671		5.577.393	
	770904 BLUE POINT CAPITAL PERS III LP	CLEVELAND	OH	BLUE POINT CAPITAL PTRS MONT III LP		08/18/2014	3		342.467		2,147,050	7.500
	770948 HARVEST PARTNERS STRUCTURED	NEW YORK	NY	HARVEST ASSOCIATES SOF LP		12/31/2014	3				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	
	770980 BAIN CAPITAL EUROPE IV LP	GEORGE TOWN	CYM	BAIN CAPITAL PARTNERS EUROPE IV LP		05/12/2015	3		56,010			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			4.790
	771119 AURORA EQUITY PARTNERS V LP	DOVER	DE	AURORA CAPITAL PARTNERS V LP		06/10/2016	3				8,233,372	5.340
	771129 KKR AMERICAS FUND XII LP	GEORGE TOWN	CYM	KKR ASSOCIATES AMERICAS XII LP		10/31/2016	3		62,700		2,493,123	
	771141 HAMILTON LANE NM FUND I LP	WILMINGTON	DE	HAMILTON LANE NM FUND I GP LLC		06/28/2016	3		1.203.572			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 VILIA LP	CHICAGO	II.	WIND POINT INVESTORS VIII LP		06/07/2016	3				26,868,024	5.240
	771153 JLL PARTNERS FUND VII LP	WILMINGTON	DE	JLL ASSOCIATES VII LP		04/19/2016	3		60.402			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	
	771240 ABRY SENIOR EQUITY V LP	DOVER	DE	ABRY SENIOR EQUITY INVESTORS V LP		11/21/2016	3		168,542		255,643	
	771246 LEEDS EQUITY PARTNERS VI LP	WILMINGTON	DE	LEEDS EQUITY ASSOCIATES VI LP		06/02/2017	3		617,770		3,023,600	
	771266 BAIRD CAPITAL GLOBAL FUND I LP	GRAND CAYMAN	CYM	BAIRD CAPITAL GLOBAL FUND MANAGEMENT I		07/11/2017	J 3		818,916		1,064,076	8.730
	1771289 VANCE STREET CAPITAL II LP	DOVER	DE	GENSTAR CAPITAL VIII LP		04/03/2017	3		90,243			8.170
	771309 WHITEHORSE LIQUIDITY PTR LP	WILMINGTON	DE	WHITEHORSE ASSOCIATES LLP		04/28/2017	J		116,341			
	771323 GENSTAR VIII COINVT DAGE FUND	WILMINGTON	DE	GENSTAR CAPITAL VIII LP		10/05/2017	3					2.450
	771348 VINTAGE VII LP	WILMINGTON	DE	VF VII ADVISORS LLC		08/28/2017			1.096.879			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 GTOR FUND XII LP	DOVER	DE	GTOR PARTNERS XII LP		05/04/2018	3		312,130		5,492,116	0.740
	771414 KKR NIM 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 SOF 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			3.620
	771464 VESTAR CAPITAL PARTNERS VII LP	GRAND CAYNAN	CYM	PPC FUND GP II LP		04/02/2018	3		749,215		6,826,276	
	// 14/0 PTV FUND LP	T WILMINGTON	j l/E	procrumo ur ii LP	ļ	04/26/2018	J 3		121,284		4,315,185	4.090

Figure IA.4: Example – Schedule BA Part 2

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

SCHEDULE BA - PART 3

			St	nowing Other Long-Term Inve	ested Assets	DISPOSED), Transfe	rred or Re											
1	2	Location	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						
							Book/			Current				Book/					
							Adjusted			Year's		Total	Total	Adjusted					
							Carrying		Current	Other		Change in	Foreign	Carrying					
							Value		Year's	Than	Capital-	Book/	Exchange	Value		Foreign			
							Less	Unrealized	(Depre-	Temporary	ized	Adjusted	Change in	Less		Exchange			
							Encum-	Valuation	ciation) or	Impair-	Deferred	Carrying	Book/	Encum-		Gain	Realized	Total	
					Date		brances,	Increase	(Amorti-	ment	Interest	Value	Adjusted	brances		(Loss)	Gain	Gain	Invest-
CUSIP				Name of Purchaser or	Originally	Disposal	Prior	(De-	zation)/	Recog-	and	(9+10-	Carrying	on	Consid-	on	(Loss) on	(Loss) on	ment
Identification	Name or Description	City	State	Nature of Disposal	Acquired	Date	Year	crease)	Accretion	nized	Other	11+12)	Value	Disposal	eration	Disposal	Disposal	Disposal	Income
	771317 FRONTENAC XI PRIVATE CAP LP	CHI CAGO	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			ļ							3,566,773	(241,506)		(241,506)	
	771414 KKR NWM PARTNERSHIP LP	GRAND CAYMAN	CYM	DISTRIBUTION	06/25/2018										134,287	[]			
	771422 LINDEN CAPITAL PARTNERS IV LP	DOVER	DE	DISTRIBUTION	09/25/2018			ļ							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			ļ							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			ļ l							2,426,944				
	771478 PPC FUND II LP	WILMINGTON	DE	DISTRIBUTION	04/26/2018			ļ l							121,284				121, 284
l	771480 PROVIDENCE EQUITY PTR VIII LP	GEORGE TOWN	CYM	DISTRIBUTION	07/17/2019		L	L	l	L	L	L		l	222, 112	l			13,286
l l	771501 DATUM ONE LP	GEORGE TOWN	CYM	DISTRIBUTION	07/26/2018		L	L	l	L	L	L		l	222,207	l			222, 207
l	771503 INSIGHT VENTURE PARTNERS X LP	GEORGE TOWN	CYM	DISTRIBUTION	08/02/2018		L	L	l	L	L	L			366, 453	l			366, 453
	771519 COURT SOUR 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 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 SCHIIARTZ 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	VILMINGTON	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 HOLDOO 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		[l	l	[l			510,494	l			318.537
	771668 BLACKSTONE TAC OPP FUND III LP	WILMINGTON	DE	DISTRIBUTION	09/03/2019										853,481	l			
	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	[2,011,410
	771710 NEW MTN STRATEGIC EQ FUND I LP	WILMINGTON	DE	DISTRIBUTION	03/26/2021		l					l			156,390	[l
	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	[144,32
	771743 GREEN EQUITY INVESTORS VIII LP	DOVER	DE	DISTRIBUTION	10/21/2020					l		l			128.829	[177,02
	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	(14,091)		(17,001)	716.75
	771778 INSIGHT PARTNERS XI LP	GEORGE TOWN	CYM	DISTRIBUTION	03/25/2020										47,292				10,73
	771780 IVY HILL REVOLVER FUNDING LP	WILL MINGTON	DE	DISTRIBUTION	05/19/2020										157,546	l			157,546
	771781 GIP SPECTRUM FUND LP	WILMINGTON	DE	DISTRIBUTION	06/12/2020							l			278,566	l			278.56
	771803 GRYPHON HERITAGE PARTNERS LP	WILMINGTON	DE	DISTRIBUTION	12/15/2020										367,711				210,000
	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
		WILMINGTON	DE	DISTRIBUTION	12/18/2020										490,697				9/2,/18
	// 1042 THINKEST PHIN STRUCT CAP FO TT	WILMINGTON	j Ut	Not in tout 10N	J (2/ 18/2020										490,697				<u> </u>

Figure IA.5: Example – Schedule BA Part 3

IA.B.2 Schedule BA Cleaning Procedure

Create Fund ID I create fund identifier (ID) using 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, ptr, etc (more than 100 variations).
 - Phrases such as American, United States, US, USA, are standardized to America.
 - Phrases such as Euro, Europe, 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 score.
- 5. I repeat step 2 to 4 multiple times to ensure consistent and accurate name match.
- 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, considering following rules:

- Name variations caused by typos and abbreviations.
- Name variations caused 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 an 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.
- 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 to the residual between the year-end total and the sum of the reported Q1–Q3 values:

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

• 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:

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

• 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

Q1 BACV = Year-End BACV
$$-$$
 (Q1 Call + Q Call + Q3 Call)
$$-$$
 (Q1 Dist + Q Dist + Q3 Dist)
$$-$$
 0.25 \times Annual Adjustment

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. (2020b) points out negative capital call could be attribute to fee offsets. But it does not affect my analysis.
- 3. If capital call exceeds the uncalled commitment from the previous period, I set the capital call equals to the uncalled commitment from the previous period. Note that I do not impose restriction based on the cumulative capital call. As pointed out by Begenau et al. (2020b), 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 difference is 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.B.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., 2020b). 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 (1) FOIA request (2) Voluntary disclosure from GP (3) Third party data			
Data Source	Mandatory Statutory Filings				
Fund Type Coverage	All private funds	Depend 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			
Easyness to use	Not easy	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.B.4 Variable Definition

Table IA.2: Variable Definition

Variable	Definition			
Capital Call	Amount of capital call a insurer received during a quarter, scaled by the lagged total portfolio size.			
Expected Capital Call	Expected amount of capital call a 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 a 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 the lagged uncalled commitment. Same for expected and unexpected capital call rate.			
Distribution	Amount of distribution a insurer received during a quarter, scaled by the lagged total portfolio size.			
Uncalled Commit	The total amount of uncalled commitment a insurer has, scaled by the lagged total portfolio size.			
New Commit	The total amount of new commitment a 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 (6)			
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 bond trading volume based on par value.			
Bond Size	Log bond outstanding amount			
Time-to-Maturity	The number of years before the stated maturity date.			

IA.C Forecast Capital Call

IA.C.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 $\{R_1, R_2, \dots, R_M\}$, 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 \overline{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.6 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 an 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 non-

linearities and interactions. However, single decision tree tend 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.

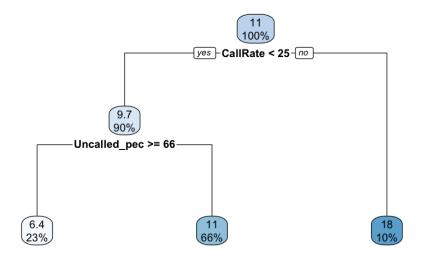


Figure IA.6: Illustration of Decision Tree

This figure illustrates the idea of 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 reduces 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. A main drawback is that the model loses interpretability compared to 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 reduced 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:

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 $\Omega(h_m)$ 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 call exactly equals 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 call.

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.C.2 Implementation

Predictors Predictors X_{it} 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 \mathbb{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.C.3 Additional Forecasting results

Figure IA.7 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.

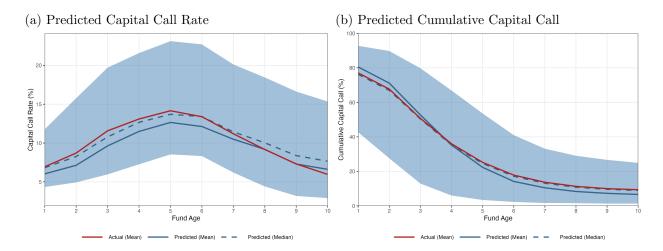


Figure IA.7: Predicted Capital Call

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.D Additional Results

IA.D.1 Additional Descriptive Results

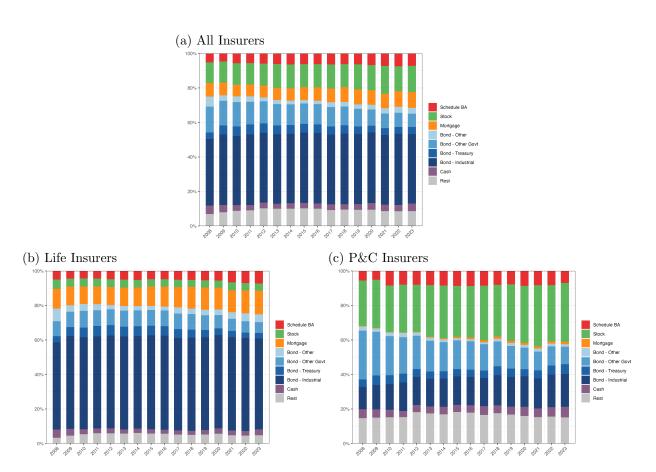


Figure IA.8: Insurers' Portfolio Allocation

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

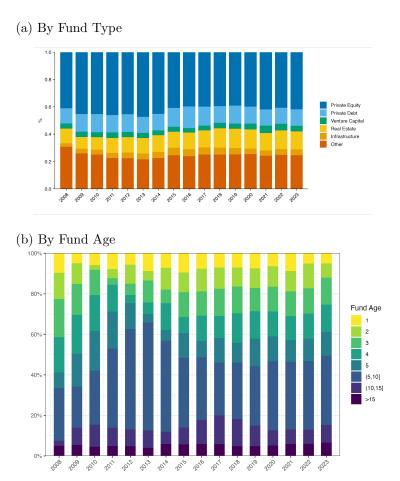


Figure IA.9: Private Fund Allocation

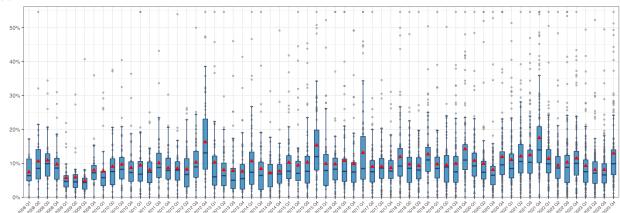
This figure shows the predictor (feature) importance of the best performing machine learning model (two-stage LightGBM). Subfigure (a) shows the first-stage classification task and Subfigure (b) shows the second-stage regression task.

Table IA.3: Capital Call Correlation with Other Data

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.

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

(c) Capital Call Rate



(c) Unexpected Capital Call Rate

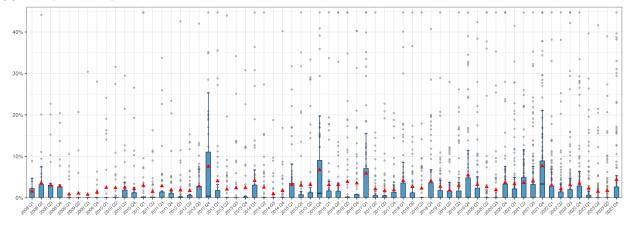


Figure IA.10: Investor-level Capital Call Rate Distribution Over time

This figure plots the distribution of investor-level capital call over time using boxplot, where Subfigure (a) is for the total capital call and Subfigure (b) is for the unexpected component. 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. Capital calls are scaled by previous period-end insurer portfolio size.

Table IA.4: Determinant of Capital Call

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 Rate	;						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SP500_PD_log	0.118***							0.063**
	(0.024)							(0.030)
CreditSpread_log	,	-0.042***						0.028**
		(0.012)						(0.011)
FundRaising_log			0.050***					0.037***
			(0.005)					(0.007)
PE_Deal_log			,	0.044***				0.013*
<u> </u>				(0.006)				(0.007)
USPE_IRR_Rolling				,	0.064***			0.002
9					(0.023)			(0.030)
r1y					()	0.002		0.001
J						(0.006)		(0.004)
r5y						0.047***		0.003
103						(0.015)		(0.010)
r10y						-0.055***		-0.002
1103						(0.012)		(0.009)
GDP_growth						(0.012)	0.001	-0.001
GD1 -810Wth							(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: Unexpe								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SP500_PD_log	0.018**	(-)	(9)	(-)	(*)	(*)	(*)	0.006
31 300 L D 10g	(0.009)							(0.014)
CreditSpread_log	(0.009)	-0.006*						0.007*
CreditSpread_log		-0.000 (0.004)						
E JD .:.: 1		(0.004)	0.008***					(0.004) $0.011***$
FundRaising_log								
DE D. 11			(0.002)	0.008***				(0.002)
PE_Deal_log								0.009***
HCDE IDD D II.				(0.002)	0.019**			(0.003)
USPE_IRR_Rolling								-0.010
					(0.008)	0.004		(0.016)
r1y						-0.001		-0.002
r5y						(0.002)		(0.002)
						0.008		-0.007*
						(0.006)		(0.004)
r10y						-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
		11 100	11 100	11 100	11 400	11 400	11 400	11 100
Observations Adjusted R ²	11,498 0.153	11,498 0.149	11,498 0.160	11,498 0.159	11,498 0.152	11,498 0.150	11,498 0.146	11,498 0.168

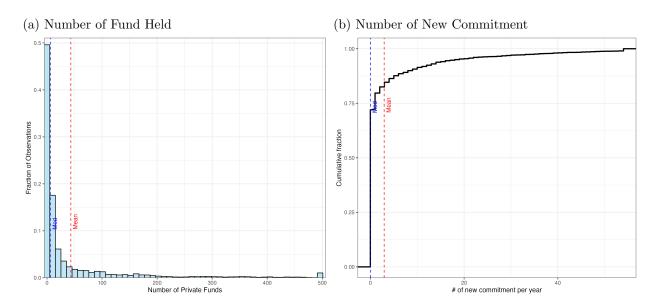


Figure IA.11: Distribution of Number of Private Fund Invested

Subfigure (a) shows the distribution of number of Private Fund held by one insurer. Subfigure (b) shows the cumulative distribution of number of new commitment made by each insurer every year.

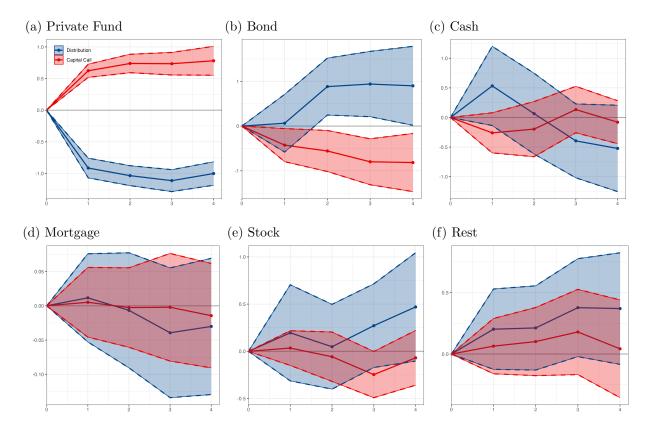
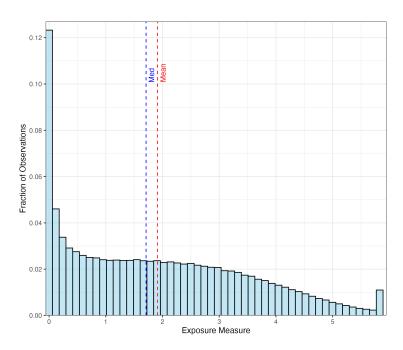


Figure IA.12: Dynamic Portfolio Impacts of Capital Call and Distribution

This figure plots the dynamic portfolio impacts of capital call (red) and distribution (blue) using local projection. The dependent variables are $\Delta Holdings_{i,t\to t+h}$, where $h\in[1,4]$. Subfigures (a) to (f) correspond to private funds, long-term bonds, cash and cash equivalents, stocks, and rest. Controls include lagged capital call, lagged distribution, lagged private fund allocation, asset growth, return on assets, log asset size, log capital and surplus, leverage ratio, and previous year-end RBC ratio. Insurer and time (calendar year-quarter) fixed effects are included. Standard errors double clustered at the insurer and time level. The colored areas represent the 95% confidence interval.



 ${\bf Figure~IA.13:~Distribution~of~Bond-level~Exposure~Measure}$

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

Table IA.5: Spillover Heterogeneity: 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			
	$\Delta Holdings \times NAIC1$	$\Delta Holdings \times NAIC2$	$\Delta Holdings \times NAIC3$
	(1)	(2)	(3)
$\overline{z_{it} \times NAIC1}$	-0.082*	-0.014	0.021***
	(0.042)	(0.020)	(0.006)
$z_{it} \times NAIC1$	0.031**	-0.363***	0.029***
	(0.014)	(0.034)	(0.005)
$z_{it} \times NAIC1$	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			
	$\Delta Holdings \times COVID$	$\Delta Holdings imes REST$	
	(1)	(2)	
$\overline{z_{it} \times COVID}$	-0.166***	-0.017	
	(0.014)	(0.032)	
$z_{it} \times REST$	-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 \mathbb{R}^2	0.008	0.085	
Kleibergen-Paap F-Statistic	7.8	41.7	