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# Insurers' Investments and Insurance Prices

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**Abstract**

We develop a theory that connects insurance prices, insurance companies' investment behavior, and equilibrium asset prices. Consistent with the model's predictions, we show empirically that (1) insurers with more stable insurance funding take more investment risk and, therefore, earn higher average investment returns; (2) insurers set lower prices on policies when expected investment returns are higher, both in the cross-section of insurance companies and in the time series. Our results hold for both life insurance and property and casualty insurance companies. The findings show that insurers' asset allocation and product pricing decisions are more connected than previously thought.

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# 1 Introduction

Insurance companies serve two important functions in the U.S. economy. First, they facilitate risk-sharing for 95% of U.S. households, and, second, they are the major investors in financial markets with assets worth $11.8 trillion at the end of 2022.[1] The traditional view of insurers is that their main business — and therefore their main source of risk and return — is insurance underwriting. This view assumes that insurers' asset allocation is independent of their underwriting business and does not provide a rationale for insurers' strikingly large allocations to illiquid credit assets.[2] However, as has been recently documented, insurers are different from other investors, as they act as *"safe hands"* (Coppola, 2022) who *"insulate"* assets from market fluctuations (Chodorow-Reich et al., 2021). This ability to buy and hold assets for the long term and the potential synergies this ability has with the insurer's liabilities motivates our two main research questions. Is an insurer's investment strategy related to the stability of an insurer's underwriting funding? If so, do insurance prices reflect insurers' expected investment returns?

To answer these questions, this paper proposes and tests a new theoretical model of insurance pricing that connects the two main decisions facing insurers – namely, how to price their insurance products and how to invest their assets. In our model, insurers invest in illiquid assets because insurance underwriting is a stable source of funding that allows insurers to hold assets for the long term and extract excess returns. These excess returns lower the costs of supplying insurance, and thus, insurers pass back part of the returns to policyholders through lower insurance prices. We present the following empirical evidence consistent with the model's predictions using data from both the life insurance industry and the property and casualty (P&C) insurance industry: (1) in the time series, average insurance prices are lower when expected investment returns are higher; (2) in the cross-section, insurers with more stable insurance funding take more investment risk and therefore earn higher average investment returns; and (3) in the cross-section, insurers with higher expected returns set lower insurance prices relative to competitors. Our results highlight the interdependency between insurers' funding, investments, and pricing decision.

Our model features three periods, two types of agents (investors and insurance com-

[1]Data sources: Insurance Information Institute, Federal Reserve Board: Financial Accounts of the United States.

[2]Insurers are the largest investors in the U.S. Corporate Bond market, holding $3.4 trillion of the $9.9 trillion market at the end of 2022 (SIFMA Fact Book, 2022).

panies), and two financial assets (one liquid and one illiquid). The liquid asset can be sold at any point at zero cost, while the illiquid asset incurs an exogenous cost if sold before maturity. In the spirit of Diamond and Dybvig (1983), investors are *ex-ante* uncertain whether they are early or late consumers, which generates an endogenous liquidity premium on the illiquid asset. Insurance companies underwrite insurance contracts and invest the insurance premiums into the financial assets before paying claims. Like the model's other investors, insurers face cash flow uncertainty, as claims can arrive either early or late. However, insurers enjoy relatively more certainty on the timing of their cash flows due to the diversification benefit of underwriting many homogeneous insurance policies. This diversification creates stable insurance funding, which provides insurers with a competitive advantage relative to other investors in the illiquid asset market. Insurers are also not all equal, enjoying varying degrees of insurance funding stability and producing products that are imperfect substitutes.

Our model delivers an expression of equilibrium insurance prices that is a product of four components:

$$\text{Price} = \underbrace{\frac{E\left[Claim\right]}{1+R^F}}_{\substack{\text{Actuarial price:}\\ \text{(Hill (1979),}\\ \text{Kraus and Ross (1982))}}} \times \underbrace{\text{Markup}}_{\substack{\text{Imperfect competition}\\ \text{(Mitchell et al., 1999)}}} \times \underbrace{\text{Shadow Cost}}_{\substack{\text{Capital constraints}\\ \text{(Gron (1994a),}\\ \text{(Froot and O'Connell (1999),}\\ \text{Koijen and Yogo (2015),}\\ \text{Ge (2022),Verani and Yu (2023))}}} \times \underbrace{\frac{1}{1+R^P}}_{\substack{\text{Investment pass-through}\\ \text{(This paper)}}}$$

The first term is the expected claim discounted at the risk-free rate, which is typically considered to be an insurer's frictionless marginal cost of underwriting an insurance policy (Hill, 1979; Kraus and Ross, 1982). The second term stems from imperfect competition, which allows insurers to set prices above the marginal cost of providing insurance (Mitchell et al., 1999). The third term is a shadow cost that arises if insurers are constrained by capital requirements. Given that such capital constraints are a well-known factor in insurance pricing (Gron, 1994a; Froot and O'Connell, 1999; Koijen and Yogo, 2015; Ge, 2022; Verani and Yu, 2023), we subject insurers in our model to regulatory capital requirements, which, if binding, means insurers deviate from their optimal unconstrained price.

The fourth term is the key contribution of our paper. We challenge whether the risk-free rate is the appropriate discount rate for an insurer's expected claims, as the actuarial price suggests. Instead, insurers use a discount rate, $R^P$, in addition to the risk-free rate, because insurers can extract a higher return on their illiquid investments due to the stable funding that policyholders provide. Insurers thus pass back part of their expected investment return to policyholders through lower insurance prices. The model's predictions rest on a violation of the Modigliani and Miller (1958) capital structure irrelevance theorem. The excess return an insurer expects to make on an illiquid asset is increasing with the insurer's funding stability, which means the value of the illiquid asset depends on the funding structure of the asset holder.

The model delivers three key propositions that we test empirically. First, we show that insurers charge low prices when the expected investment returns are high in the time series (Proposition 1). We measure the expected excess return on illiquid assets using the credit spread between seasoned BAA-rated corporate bonds and the 10-year Treasury yield. We use the BAA credit spread as our baseline measure of expected excess returns, as it most closely matches the credit spread of the average insurer's investment portfolio. In the life insurance industry, we measure insurance prices as annuity markups as in Koijen and Yogo (2015). Using data from 1989 to 2011, we find that a 1 percent increase in credit spreads is associated with annualized markups being between 0.4 and 0.8 percent lower across products. In the P&C industry, we develop a novel approach to infer insurance prices from the insurers' realized underwriting profitability. Underwriting profitability measures difference between the premiums an insurer receives and the claims they pay on their insurance contracts relative to the insurer's underwriting liabilities, so that lower underwriting profitability implies that insurers charge lower prices. Using data from 2001 to 2022, we find that the average underwriting profitability falls 0.36 percent when credit spreads increase by 1 percent.

Thus, we find an economically significant pass-through of investment yields to insurance prices in both the life and P&C insurance markets, suggesting that policyholders receive a meaningful share of the value they provide to insurers through stable funding. Consistent findings across two these distinct markets allow us to control for alternative channels of insurance price variation, as the P&C industry faces different consumer markets and operates in a different regulatory framework relative to the life insurance industry. Further, we show that our results are robust to using a variety of other measures of the insurers' expected investment return as well as controlling for the Global Financial Crisis of 2008-09 (GFC) and a vector of other time series controls.

Second, we show that insurance companies with more stable insurance funding allocate a greater fraction of their investments to illiquid assets (Proposition 2). We document the interaction between insurance funding stability and investment allocations in the market for P&C insurance by utilizing the rich heterogeneity across the 871 P&C insurance groups in our sample. We measure the stability of an insurer's underwriting as the volatility of the insurer's underwriting profitability. We find that P&C insurers with more stable funding (lower volatility of underwriting profitability) have lower allocations to cash, higher allocations to credit, and especially higher allocations to risky credit. The result is robust to controlling for both the size and rating of the insurer, which are known determinants of insurers' investment choice (Ge and Weisbach, 2021).

Third, we find that insurers with higher expected investment returns set lower insurance prices in the cross-section of insurers (Proposition 3). We measure an insurer's expected return at a given point as the value-weighted net yield on the insurer's invested assets. The net yield is the return an insurer's investment portfolio delivers if held to maturity and therefore captures the insurer's expected return at a given point, as insurers are typically buy-and-hold investors (Coppola, 2022). Analyzing the cross-section of insurers allows us to absorb unobserved time variant factors that are potentially confounding our time series analysis. Further, we show that our results are robust to the inclusion of a range of controls capturing the strength of insurers' balance sheets as well as fixed effects that capture variation in insurance prices across states and insurance lines.

Proposition 3 predicts that insurers pass expected investment returns through to policyholders because of the funding stability that insurance underwriting provides. In fact, it is only the *excess* return that insurers earn due to stable underwriting funding that passes through to insurance prices, as opposed to all expected returns. We test this prediction by implementing a two-step empirical estimation of our model. In the first step, we regress the insurers' expected returns (net yields) on the insurers' funding stability and find that the cross-section of insurers' expected returns is strongly predicted by the stability of their funding. We then take the two orthogonal components from the first step regression (i.e., the expected returns related to stable funding and the expected returns unrelated to stable funding) and regress insurance prices on these two components. Consistent with the model, we find that it is the part of expected returns correlated with stable funding that passes through to insurance prices, with a 1 percent higher expected return due to stable funding, resulting in 0.6 to 0.8 percent lower underwriting profitability and indicating a much larger pass-through than when looking at the correlation between raw net yields and underwriting profitability alone. Further, the component of net yields unrelated to stable funding – the residual of the first step regression – does not transfer through to insurance prices.

In the final section of the paper, we consider alternative mechanisms of insurance pricing, starting with regulatory capital constraints and the shadow cost of capital.[3] To mitigate concerns this channel may be driving our empirical results, we emphasize three observations regarding the correlation between expected returns and insurance prices: (1) it holds for both life and P&C insurers, who are subject to very different economic and regulatory constraints; (2) it is present both in and out of the GFC, where insurers were most likely capital constrained;[4] and (3) the cross-sectional correlation between insurance prices and expected returns is strongest for the highest-rated insurers, which are least likely to be capital constrained.

We also control for other potentially confounding factors such as variation in demand for insurance, reinsurance activity, and state-level regulation. Oh, Sen, and Tenekedjieva (2023) show that state-level regulation of P&C insurers causes insurers to cross-subsidize pricing across states. Relative to this paper, we focus on insurance price variation across insurers and across time, rather than within insurers, and show that the cross-sectional relationship between expected returns and insurance prices is present after absorbing all variation across states, years, and P&C insurance categories.

**Related literature.** Beyond the papers on insurance pricing mentioned above, our paper is related to the literature that shows how insurers' portfolio choice is influenced by regulatory incentives (Ellul et al., 2011; Becker and Ivashina, 2015; Ellul et al., 2015; Sen, 2023; Becker et al., 2022; Sen and Sharma, 2020; Ellul et al., 2022), financial constraints (Chen et al., 2020; Ge and Weisbach, 2021), international portfolio frictions (Du et al., 2023), diversification needs (Damast, 2023), and loose leverage constraints compared with other investors (Koijen and Yogo, 2023). We add to this strand of papers by showing that, even when controlling for these alternative channels, insurers with more stable funding take more investment risk.

Our departure from the conventional wisdom in the insurance literature has clear links to the synergies between deposit funding and asset holdings studied in the banking literature (Cooper and Ross, 1998; Stein, 1998; Kashyap, Rajan, and Stein, 2002; Ennis

[3]Regulation also affects insurers beyond pricing. For life insurers, increased market and regulatory constraints following the GFC have led insurers to increase the use of off-balance-sheet reinsurance(Koijen and Yogo, 2016), charge higher fees (Koijen and Yogo, 2022), and push through policy exchanges with consumers (Barbu, 2022).

[4]In fact, it holds strongest *outside* of the GFC, which is consistent with the intuition that it is in good times that insurers are particularly well-positioned to act as patient investors and extract value from illiquid asset markets (Chodorow-Reich, Ghent, and Haddad, 2021).

and Keister, 2006; Drechsler, Savov, and Schnabl, 2021; Choudhary and Limodio, 2021). While the link to the banking literature makes our results all the more credible, our paper distinguishes itself by applying similar high-level ideas to the specifics of the insurance industry, which is different from banking on several important dimensions.[5]

Our paper is more related to a newer literature that argues that the long-term stable funding of banks (Stein, 2012; Hanson, Shleifer, Stein, and Vishny, 2015), insurers (Chodorow-Reich, Ghent, and Haddad, 2021; Coppola, 2022), and hedge funds (Aragon, 2007; Hombert and Thesmar, 2014) make them well-suited to invest in illiquid assets. Our main theoretical innovation relative to these papers is to consider how this comparative advantage in asset markets influences the intermediaries product pricing that ultimately funds their investments. Our paper further relates to recent empirical papers documenting that insurance companies act as liquidity providers in the U.S. corporate bond market (Bretscher, Schmid, Sen, and Sharma, 2022; O'Hara, Rapp, and Zhou, 2022) and debt markets more broadly (Timmer, 2018), which is consistent with our model's prediction that insurers act as counter-cyclical investors in illiquid credit markets.

Finally, our paper relates to work on a broader range of financial intermediaries that face similar asset and liability management problems. For example, U.S. public pensions, for accounting purposes, erroneously discount the value of their liabilities with the expected return on pension plan assets (Brown and Wilcox, 2009; Novy-Marx and Rauh, 2011; Rauh, 2016), which can lead pension funds to increase investment risk in order to bring down the accounting value of liabilities (Andonov, Bauer, and Cremers, 2017). We find that in the insurance sector, it is only a fraction of excess returns – those returns that are due to stable funding – that impact the discounting of liabilities. This discounting is not motivated by regulatory concerns as in the public pensions system but by the marginal value of stable funding.

# 2 Model of Insurance Prices and Illiquid Asset Prices

We consider an economy with three periods ($t = 0$, 1, and 2), two types of agents (investors and insurance companies), and two tradeable assets (a liquid and an illiquid asset).

[5]For example, run risk is not a concern for insurers given that future payments are contracted *ex-ante*. Lapse risk is a related issue in some types of life insurance products (Koijen et al., 2023), but it is not present in annuity insurance and P&C insurance, which are the two markets we study empirically.

**Assets.** There is a liquid asset with exogenous return $R^F$ and an illiquid asset with fixed supply $S$. The return on the liquid asset accrues entirely over the model's first period. The illiquid asset pays one unit of wealth at maturity $t = 2$, and the price at $t = 0$ is determined endogenously. The defining characteristic of the illiquid asset is that it incurs a cost if sold before maturity (i.e., sold at $t = 1$). The cost of selling $x$ dollars of the illiquid asset at time 1 is $\frac{1}{2}\lambda x^2$, where the parameter $\lambda$ captures liquidity conditions in the secondary market for this asset.

**Investors.** Our model features a continuum of risk-neutral investors with mass 1, each endowed with $e$, who are identical at $t = 0$. In the spirit of Diamond and Dybvig (1983), each investor learns at $t = 1$ if she is an early or a late consumer. Early consumers only care about consumption at $t = 1$, while late consumers only care about consumption at $t = 2$. Each investor knows at $t = 0$ the probability $\omega$ of being an early consumer.

Given that each investor buys dollar amount $\theta$ of the illiquid asset, their consumption is

$$c = \begin{cases} e\left(1 + R^F\right) - \frac{1}{2}\lambda\theta^2\left(1 + R^F\right)^2 & \text{with probability } \omega \quad \text{(early consumer)} \\ e\left(1 + R^F\right) + \theta R^A & \text{with probability } 1 - \omega \quad \text{(late consumer)} \end{cases} \tag{1}$$

where $R^A$ is the equilibrium excess return on the illiquid asset.[6] In the first case of equation (1), the investor learns she is an early consumer and sells all of her assets at time 1, paying the associated transaction costs on her illiquid asset holdings that have dollar value $\theta\left(1 + R^F\right)$ at $t = 1$. In the second case, the investor learns she is a late consumer and holds all assets to maturity, earning the excess return on her illiquid asset holdings.

The problem facing investors is to choose $\theta$ to maximize expected consumption

$$\max_{\theta} \ \mathbb{E}\left[c\right] = e\left(1 + R^F\right) + \left(1 - \omega\right)\theta R^A - \frac{1}{2}\omega\lambda\theta^2\left(1 + R^F\right)^2. \tag{2}$$

We think of the investors as mutual funds, which are the other main investors in the corporate bond market besides insurance companies, which we introduce next.

[6]Specifically, the equilibrium excess return on the illiquid asset is:

$$R^A = \frac{1}{\text{Price of the illiquid asset}} - \left(1 + R^F\right)$$

**Insurance companies.** The economy's other agents are a continuum of risk-neutral insurance companies indexed by $i \in [0,1]$. Each insurer $i$ sets a price, $P_i$, to underwrite $I_i$ insurance contracts. The amount of insurance contracts that the insurer underwrites, $I_i$, is determined by a downward-sloping demand curve, which we specify later when we discuss the insurance market equilibrium. Further, each insurer $i$ is endowed with equity capital $E_i$. Total liabilities at $t = 0$ for an insurer are therefore the sum of equity funding and the funding generated from insurance underwriting:

$$L_i = E_i + I_i P_i. \tag{3}$$

Insurance policy claims are paid at either $t = 1$ or $t = 2$. The total future claims underwritten by insurer $i$ are defined as

$$C_i = I_i \bar{C}. \tag{4}$$

where $\bar{C}$ is the expected policy claim on each individual contract. We assume that the insurance businesses are sufficiently diversified that we can think of the expected policy claim, $\bar{C}$, on each insurance contract as being a known constant. Insurance companies in our model are thus not worried about the size of the claims to be paid but instead face liquidity risk, as claims can arrive at either $t = 1$ or $t = 2$. We define the fraction of total claims arriving at time 1 for insurer $i$ as $\tau_i \in \{\bar{\tau} - \sigma_i, \bar{\tau} + \sigma_i\}$ and assume that each outcome (i.e. $\tau_i = \bar{\tau} - \sigma_i$ and $\tau_i = \bar{\tau} + \sigma_i$) is equally likely. The remaining fraction of claims, $(1 - \tau_i)$, arrive at time 2.

To summarize, we think of the insurance product as car or property insurance, which is held by a representative household outside of the model, and which has claims that are uncorrelated with the investors' consumption risk. We assume the claim is the same on all insurance contracts, $\bar{C}$, and that the expected fraction of total claims arriving early, $\bar{\tau}$, is the same for all insurers. Insurers differ in their funding stability, $\sigma_i$, in the sense that the fraction of total claims arriving early may be more or less volatile.

Given this liability profile, insurer $i$ buys dollar amount $\Theta_i \geq 0$ of the illiquid asset and puts remaining wealth $L_i - \Theta_i \geq 0$ in the liquid asset. We assume both allocations are greater than or equal to zero, so the insurer's only source of balance sheet leverage is the funds generated from insurance underwriting. Insurer $i$'s final wealth depends on the dollar amount $\tau_i C_i$ of claims to be paid at $t = 1$ relative to the dollar amount $(L_i - \Theta_i)\left(1 + R^F\right)$ of liquid assets held at $t = 1$. If the insurer holds more liquid assets than early claims, there is no sale of illiquid assets at $t = 1$. However, if early claims exceed liquid asset holdings, the insureris forced to sell a fraction of illiquid assets before maturity. If the insurer only invests in the liquid asset, the insurer's final wealth is $\overline{W}_i = L_i \left(1 + R^F\right) - C_i$. If instead the insurer invests in both the liquid and the illiquid asset, the insurer's final wealth is expressed with two cases

$$W_i = \begin{cases} \overline{W}_i + \Theta_i R^A & \text{if } \tau_i C_i \leq (L_i - \Theta_i)\left(1 + R^F\right) \\ \overline{W}_i + \left(L_i - \frac{\tau_i C_i}{(1+R^F)}\right) R^A - \frac{1}{2}\lambda \left(\tau_i C_i - (L_i - \Theta_i)\left(1 + R^F\right)\right)^2 & \text{if } \tau_i C_i > (L_i - \Theta_i)\left(1 + R^F\right). \end{cases} \tag{5}$$

The first case shows the simple outcome in which the insurer holds enough liquid assets to cover early claims, and all illiquid asset holdings therefore earn the liquidity premium $R^A$. In the second case, at time 1 the insurer sells all their liquid assets plus a portion of their illiquid asset portfolio to cover the claims arriving early. This means that $\tau_i C_i - (L_i - \Theta_i)\left(1 + R^F\right)$ of illiquid assets are sold before maturity and incur the associated sale cost. The remaining illiquid assets are held to maturity and earn the liquidity premium $R^A$.

We also consider the impact of regulatory capital constraints on insurance companies. The statutory value of each insurance policy is

$$\bar{V} = \frac{\bar{C}}{1 + R^S} \tag{6}$$

where $R^S$ is the statutory discount rate for claims. In the spirit of Koijen and Yogo (2015), insurers face a leverage constraint

$$\frac{I_i \bar{V}}{E + I_i P_i} \leq \phi \tag{7}$$

where $\phi \leq 1$ is the maximum leverage ratio of statutory liabilities to total assets.

The insurer's objective function is to set the price of the insurance contract, $P_i$, and the level of investment in the illiquid asset, $\Theta_i$, to maximize their expected final wealth

$$\max_{P_i,\, \Theta_i} \; \mathbb{E}\left[W_i\right] \tag{8}$$

subject to the capital constraint in equation (7) where wealth $W_i$ is defined in equation (5). Following Stein (2012), we assume that the insurer treats the excess return on the illiquid asset $R^A$ as given — that is, they do not internalize the impact of their investment choices on the excess return of the illiquid asset.

**Insurance market.** In the insurance market, we assume monopolistic competition (Stiglitz and Dixit, 1977) with insurers producing insurance products that are imperfect substitutes. A representative household derives utility by consuming an index of insurance contracts given by a standard CES aggregator:

$$I = \left( \int_0^1 I_i^{\frac{\varepsilon-1}{\varepsilon}} \, di \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{9}$$

where $1 < \varepsilon < \infty$ is the elasticity of substitution across insurers.[7] From equation (9), it can be shown that the elasticity of demand facing each insurer is identical and given by:

$$\varepsilon = -\frac{\partial I_i}{\partial P_i} \frac{P_i}{I_i}. \tag{10}$$

Given that the representative household is outside our model, we do not address the origin of insurers' market power. However, segmented consumer markets across geographies (as documented in the bank deposit market; Drechsler et al. (2017)), consumer inattention (as documented in the life insurance market; Barbu (2022)), or imperfect consumer information and search costs are all plausible explanations for why price variation may persist across insurers. In Section A.3 of the Internet Appendix, we present a more detailed discussion of the insurance market equilibrium.

**Equilibrium.** We conclude this section by defining the equilibrium in the economy. The competitive equilibrium in the illiquid asset market is given by the market clearing condition

$$\theta + \Theta = S \tag{11}$$

where $\theta$ is the aggregate demand from investors and $\Theta = \int_0^1 \Theta_i \, di$ is the aggregate demand from insurers. The supply $S$ of the illiquid asset is exogenously given. Equilibrium in the insurance market is where demand equals supply, with supply determined by each insurer's profit- maximization function in equation (8) and demand determined by the exogenous demand curve of the representative household (10).

# 3 Theoretical Results

We begin by considering the asset allocation of the insurance companies in the model. All proofs are in Appendix A.

[7] Drechsler, Savov, and Schnabl (2017) model a similar intermediary market structure in the banking sector, with a cross-section of banks producing deposits for a representative household.

**Theorem 1 (illiquid asset allocation).** *Insurer i's equilibrium dollar investment in the illiquid asset is*

$$\Theta_i^* = \underline{\Theta}_i + \alpha \frac{R^A}{\lambda} \tag{12}$$

*where*

$$\underline{\Theta}_i = L_i - \frac{(\bar{\tau} + \sigma_i)\, C_i}{1 + R^F} \tag{13}$$

*is a lower bound on insurer i's illiquid asset holdings and* $\alpha = \frac{1}{(1+R^F)^2}$ *is a constant.*

The first component of an insurer's illiquid asset allocation is a minimum asset holding, $\underline{\Theta}_i$, that results from the fact that the maximum dollar amount of claims an insurer will be required to pay at $t = 1$ is $(\bar{\tau} + \sigma_i)\, C_i$.[8] Importantly, this quantity is known at $t = 0$ and therefore investing less than $\underline{\Theta}_i$ in the illiquid asset would mean that insurer $i$ is forgoing a risk-free excess return. The second component of an insurer's optimal illiquid asset allocation is a constant $\alpha$ multiplied by a ratio, $R^A/\lambda$, that represents the cost-benefit trade-off for an illiquid asset investment. The ratio, which applies to all insurance companies equally, is the hold-to-maturity expected excess return per unit of transaction cost for early sales.

We next consider insurers' pricing decisions on insurance policies. First-order conditions of equation (8) with respect to $P_i$ subject to the capital constraint in equation (7) yields the following theorem for the insurance price.

**Theorem 2 (insurance pricing).** *The equilibrium insurance price* $P_i^*$ *set by insurer i for a policy with claim* $\bar{C}$ *is*

$$P_i^* = \frac{\bar{C}}{1 + R^F} \frac{\varepsilon}{\varepsilon - 1} \Gamma_i(\phi) \frac{1}{1 + R_i^P} \tag{14}$$

*where* $\Gamma_i(\phi)$ *is the insurer's shadow cost of capital and*

$$R_i^P(\sigma_i) = \frac{1 + R^F + R^A}{1 + R^F + (\bar{\tau} + \sigma_i)\, R^A} - 1 \geq 0 \tag{15}$$

*is part of insurer i's expected excess return on the illiquid asset that passes through to policy holders.*

The insurance price is the product of four components. The first component is the actuarial price, $\frac{\bar{C}}{1+R^F}$, and is the claim discounted by the risk-free rate. The second

[8] Recall that the fraction of claims arriving at $t = 1$ is $\tau_i \in \{\bar{\tau} - \sigma_i, \bar{\tau} + \sigma_i\}$.

component, $\frac{\varepsilon}{\varepsilon-1} > 1$, is the markup the insurer can charge due to imperfect competition. The third component is the shadow cost of capital that arises if the leverage constraint in equation (7) is binding. We explore this channel of insurance pricing in detail in Section 6. The final component discounts the expected claim by $1 + R_i^P$, where $R_i^P$ is insurer $i$'s marginal value of stable insurance funding that results from illiquid asset investments. Given that the fraction of claims $\tau_i \in \{\bar{\tau} - \sigma_i, \bar{\tau} + \sigma_i\}$ arriving at $t = 1$ cannot exceed one, $R_i^P = 0$ only if $\bar{\tau} + \sigma_i = 1$. In all other cases, $R_i^P > 0$ and thus insurer $i$ sets lowers prices due to the expected returns on their investments in illiquid assets.

Theorems 1 and 2 violate the Modigliani and Miller (1958) proposition of capital structure irrelevance and highlight the interdependencies between an insurer's assets and liabilities in the model. An insurer's asset allocation depends on the stability of the insurance policies underwritten, and prices of the insurance policies themselves depend on the excess return that insurers can expect to make on their asset allocations as a consequence of their stable funding. These results arise because a fraction $(1 - \bar{\tau} - \sigma_i)$ of insurer $i$'s policy claims, $C_i$, will be paid at $t = 2$ with certainty, and therefore the premiums received for this fraction of claims can be held to maturity without risk of early liquidation. Since the insurer earns a risk-free excess investment return $R^A$ on this fraction of premiums, this investment return reduces the insurer's marginal cost of supplying insurance. The equilibrium insurance price is thus found by discounting expected claims by the discount rate $(1 + R^F)(1 + R_i^P) \approx 1 + R^F + (1 - \bar{\tau} - \sigma_i)R^A$, which captures the time-value of money for insurer $i$. The higher the excess return on the illiquid asset, $R^A$, the higher the time-value of money for an insurer with stable funding and the lower the marginal cost of underwriting each insurance contract.[9]

Two special cases illuminate the point. First, consider the case where $\bar{\tau} = 0$ and there is an insurer $s$ with fully stable funding $\sigma_s = 0$. Insurer $s$ knows with certainty that all insurance claims arrive at $t = 2$ and thus all insurance premiums can be invested in the illiquid asset without a risk of early liquidation costs. In this case, insurer $s$'s time value of money on insurance underwriting is $(1 + R^F)(1 + R_s^*) = 1 + R^F + R^A$ and fully reflects the expected return on the illiquid asset. Second, consider an insurer $u$ with unstable funding, where $\bar{\tau} + \sigma_u = 1$. Insurer $u$ faces the risk that all claims could possibly arrive at $t = 1$, and thus has no competitive advantage in the illiquid asset market relative to other investors in the model. The expected excess investment return net of early liquidation

[9] Unlike U.S. public pensions, where discount rates move one-to-one with the expected return on risky asset holdings (Novy-Marx and Rauh, 2011), only a fraction, ca. $1 - \bar{\tau} - \sigma_i$, of the excess return on illiquid asset holdings, $R^A$, is reflected in the insurer's discount rate.

costs on the asset holdings funded by premiums for insurer $u$ is $R_u^* = 0$, and the time-value of money on insurance premium funding is simply $1 + R^F$. In this latter case, our model nests Modigliani and Miller (1958) propositions of capital structure irrelevance. The equilibrium insurance price $P_u$ is no longer dependent on the insurer's illiquid asset allocation $\Theta_u$ or the equilibrium excess return $R^A$ on the illiquid asset.

**Comparative statics.** We now consider the model's key testable predictions. We begin with the average insurance price, $\bar{P} = \int_i^1 P_i \, di$, and how it depends on liquidity conditions and the expected return in the illiquid asset market.[10]

**Proposition 1 (time series of insurance prices).** *Insurance companies set lower insurance prices in response to an exogenous increase in early liquidation costs in the illiquid asset market*

$$\frac{\partial \bar{P}}{\partial \lambda} < 0, \tag{16}$$

*because an increase in liquidation costs increases the equilibrium expected excess return on the illiquid asset,* $\frac{\partial R^A}{\partial \lambda} > 0$*, and thereby reduces the marginal cost of writing insurance contracts for insurers with stable funding.*

Proposition 1 shows that the average insurance price across insurers fluctuates over time in response to expected return on the illiquid asset. Insurance companies face a downward sloping demand curve for their insurance products. When the expected return on the illiquid asset increases due to an exogenous shock to liquidity conditions in the illiquid asset market, insurers optimally reduce insurance prices in order to increase the size of their balance sheet and take advantage of the improved investment opportunity in their asset portfolios. Consistent with recent empirical evidence (Bretscher et al., 2022; O'Hara et al., 2022), insurers in the model therefore act as countercyclical liquidity providers to the illiquid asset market. When liquidity conditions deteriorate, insurers increase their illiquid asset holdings, dampening the impact of negative liquidity shocks on equilibrium expected returns.[11]

[10] While we focus on shocks to liquidity, $\lambda$, the model has similar predictions for the equilibrium illiquid asset return and insurance prices in response to shocks in the demand for liquidity from other investors $\omega$.

[11] Bretscher et al. (2022) find that mutual funds, with short investment horizons and high demand elasticities, increasingly seek liquidity in corporate bond markets, and that this liquidity is provided by insurance companies with long investment horizons and inelastic demand. O'Hara et al. (2022) focus on the COVID-19 liquidity crisis and find that insurers acted as "buyers of last resort" in this

The key assumption underpinning Proposition 1 is that insurers have a competitive advantage when investing in the illiquid asset because of the stable funding generated by insurance underwriting. While the other investors in the economy face the risk of selling all assets holdings at $t = 1$, insurers can hold a portion of assets to maturity with certainty. Insurance companies therefore benefit from exogenous increases in expected illiquid asset returns and set their policy prices accordingly. This pass-through of excess returns is how exogenous variation in asset markets directly affects insurance prices in the model.

The insurer's competitive advantage in the asset market is fundamentally tied to the stability of insurance funding, but this stability varies across insurers. We consider the model implications for the cross-section of insurers next.

**Proposition 2 (the insurer's illiquid asset allocation).** *The more volatile an insurer's underwriting, the fewer illiquid assets the insurer holds in equilibrium*

$$\frac{\partial \Theta_i^*}{\partial \sigma_i} < 0, \tag{17}$$

*where $\sigma_i$ measures the volatility of insurer i's underwriting.*

Proposition 2 allows us to make predictions about the asset allocation in the cross-section of insurance companies. A lower (higher) $\sigma_i$ implies insurer $i$ has more (less) stable insurance funding which is a comparative advantage when investing in illiquid assets. Thus, insurers with the most stable funding allocate the largest quantity of assets to the illiquid asset market.

The model's final prediction is about the cross-section of insurance prices and the role of expected investment returns and stable insurance funding.

**Proposition 3 (cross-section of insurance prices).** *For insurance company i, the insurance price is a decreasing function of the insurer's expected excess return*

$$\frac{\partial P_i}{\partial R_i^P} < 0 \tag{18}$$

*where the variation in expected excess returns across insurers is decreasing in the volatility of insurance funding with*

$$\frac{\partial R_i^P}{\partial \sigma_i} < 0. \tag{19}$$

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period. Insurance companies increased their corporate bond positions, particularly in bonds suffering from mutual fund fire sales. Consistent with the model predictions, it was the insurance companies with the most stable funding that purchased the largest fraction of bonds.

Proposition 3 shows that prices vary with insurers' relative expected investment returns compared to their competitors and predicts that the expected returns themselves are tied to the variation in funding stability across competitors. Combining Propositions 2 and 3, we predict that the insurance companies with the most stable funding take the most investment risk, earn the highest investment returns and ultimately set the lowest insurance prices relative to other insurers.

We conclude this section with the observation that equity is also a potential source of long-term funding. In the model, the insurers cannot issue any additional equity to supplement the initially endowed equity, which is consistent with the idea that equity issuances are costly for intermediaries (Brunnermeier and Pedersen, 2009; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014). If risk-neutral insurers could issue equity without costs, then they would do so when $R^A > 0$, investing the proceeds into the illiquid asset until the excess return is zero. In the absence of equity funding, insurers instead reduce prices when $R^A > 0$ in order to increase insurance funding and allocate more capital to the profitable investment opportunity. Costly equity is therefore an important feature for the model predictions. Stable funding is valuable to asset holders (Stein, 2012; Hanson et al., 2015; Chodorow-Reich et al., 2021; Coppola, 2022) only if stable funding is in short supply in the economy more broadly.

# 4 Data and Methodology

## 4.1 Measuring Insurance Prices

**P&C insurance.** Data on P&C insurance markups are sparse in the literature, as neither actual contract prices nor actuarially fair prices (the frictionless marginal cost) are readily available. However, P&C insurers do provide detailed financial reporting on their underwriting businesses at a quarterly frequency, and we use this reporting to generate a novel measure of P&C insurance prices. Specifically we define and study insurance underwriting profitability:

$$\text{Underwriting Profitability}_{i,t+1} = \frac{\text{Premium Earned}_{i,t+1} - \text{Losses}_{i,t+1} - \text{Expenses}_{i,t+1}}{\text{Insurance Liabilities}_{i,t}} \tag{20}$$

where Premium $\text{Earned}_{i,t+1}$ is the insurance premium earned across all insurance contracts by insurer $i$ in quarter $t+1$, $\text{Losses}_{i,t+1}$ are the claims paid out on policies by insurer $i$ in quarter $t+1$ (plus any significant revisions to the insurer's expectation of claims in future quarters), $\text{Expenses}_{i,t+1}$ are the operating expenses of running the underwriting business for insurer $i$ in quarter $t+1$, and $\text{Insurance Liabilities}_{i,t}$ is the sum of "management's best estimate" of future losses and reinsurance payables (Odomirok et al., 2014). We use the insurance liabilities reported by insurer $i$ as of the end of quarter $t$. The insurance underwriting profitability measure is therefore the insurer's quarterly underwriting profit normalized by the size of the insurance underwriting business, and higher underwriting profitability at time $t+1$ is on average the result of higher insurance pricing at time $t$.

The definition of *Premium Earned* is important for understanding how underwriting profitability captures price variation. Suppose insurer $i$ receives a premium $P^{(j)}_{i,t,n}$ at time $t$ for an insurance contract $j$ that is written at the end of quarter $t$ and expires in $n$ quarters from time $t$. The insurer's reported premium earned on this contract in reporting quarter $t'$ is the initial premium received divided by the number of periods the contract covers:

$$Premium\,Earned^{(j)}_{i,t'} = \begin{cases} \frac{P^{(j)}_{i,t,n}}{n}, & \text{if } t < t' \leq t+n. \\ 0, & \text{otherwise.} \end{cases} \tag{21}$$

The total premium earned on contract $j$ across all reporting quarters is therefore equal to the dollar premium received on the contract at the time of underwriting. However, the premium income is not recognized when the premium is received but is evenly spread over the life of the contract, which is also the period where a claim could occur and the insurer is required to payout (i.e., when the premium is "earned").[12]

Crucially, the use of the variable *Premium Earned* (rather than *Premium Received*) in the definition of underwriting profitability ensures that the measure is not biased by changes in an insurer's underwriting volume. For example, suppose an insurer keeps insurance prices unchanged but suddenly doubles the quantity of insurance contracts underwritten in one quarter relative to the quantity written in normal quarters. Premiums received doubles while claims, for now, are unaffected (claims are expected to increase over future quarters as the claim risk from the additional contracts are realized). Calculating the underwriting profitability with premiums received would therefore suggest a sudden improvement in underwriting profitability (high inflows relative to outflows) even though the insurance pricing and profitability of the underwriting business is unchanged. Premiums earned, on the other hand, increase in future periods at the same time that

[12]Premium earned at the insurer level, $i$, is the sum of premiums earned across all insurance contracts, $j$, in a given quarter: $Premium\,Earned_{i,t} = \sum_j Premium\,Earned^{(j)}_{i,t}$.

claims are increasing due to the increased number of insurance contracts. So long as the profitability of the business has not changed with the change in volume, our underwriting profitability measure will remain unchanged, and we correctly infer no change in insurance pricing.[13]

**Life insurance.** To measure the price of life and term annuities we use the markups, which are defined as the percent deviation of the quoted price to the actuarial price. The actuarial price is defined as the expected claims discounted at the risk-free rate. To make the markups comparable across different products, we annualize the markups by dividing the absolute markup by the duration of the insurance contract. In order to compute the duration of life insurance contracts, we follow Koijen and Yogo (2015) and calculate expected cash flows and present values based on the appropriate mortality table from the American Society of Actuaries and the zero-coupon Treasury curve (Gürkaynak et al., 2007).

## 4.2 Measuring Insurer Expected Investment Returns

**Industry-wide expected investment returns.** For our time series analysis, we use credit spreads on investment-grade corporate bonds to measure the average insurer's expected investment return. This approach reflects that the asset side of insurers' balance sheets are predominately made up of illiquid credit investments with an investment- grade credit rating. Specifically, our main measure is the spread between BAA-rated corporate bonds and the 10-year Treasury yield, which reflects the bond portfolio characteristics of the average life insurance company. Section C.1 of the Internet Appendix provides further details on balance sheets and bond portfolio characteristics in the life insurance and P&C insurance sectors. Further, in Section B of the Internet Appendix we use several other measures of credit market expected returns in a series of robustness exercises. Finally, to control for the default risk embedded in credit spreads, we use the excess bond premium of Gilchrist and Zakrajšek (2012) while controlling for expected default losses.

**Insurer-level expected investment returns.** For our cross-sectional analysis, we use

[13] Insurers report a related measure of their underwriting performance called *combined ratio* that is well-known in the industry. This ratio is defined as losses and expenses over premiums earned, where premium earned is once again used to make sure that volume does not distort the performance measure.

insurers' *Net Yield on Invested Assets* to measure expected returns:

$$Net\ yield_{it} = \sum_{k=1}^{N} \frac{B_{ikt}}{B_{it}} Net\ yield_{ikt} \tag{22}$$

where $Net\ yield_{ikt}$ is the net yield on insurer $i$'s investment in asset $k$ at time $t$, $B_{ikt}$ is the book value of insurer $i$'s investment in asset $k$ at time $t$, and $B_{it} = \sum_{k=1}^{N} B_{ikt}$ is the total value of insurer $i$'s investment portfolio at time $t$, where $N$ is the number of assets in the insurer's investment portfolio. $Net\ yield_{it}$ is therefore the (book value) weighted average net yield in insurer $i$'s investment portfolio at time $t$.

The net yield and book value of investments are both accounting identities. For bonds, which constitute the largest asset class in insurers' investment portfolios, the net yield for insurer $i$ on asset $k$ is the yield-to-maturity at purchase and is therefore time invariant over the insurer's holding period. The book value for insurer $i$ at time $t$ is the purchase value amortized by the net yield accrued since purchase. By construction, our net yield measure therefore reflects the expected return to an insurer's buy-and-hold investment strategy, with mark-to-market volatility partially smoothed in the short term.

For our implementation purposes, it is crucial that the net yield is a holistic measure of an insurer's investment return on their total portfolio and includes their exposures to all asset classes. We present two empirical findings consistent with our interpretation that the measure captures variation in investment returns that different insurers expect to earn going forward. First, insurance companies that take more credit risk earn higher investment net yields. Second, net yields strongly predict future net yields at a firm level. Section C.2 of the Internet Appendix provides more detail on both the construction and economic interpretation of $Net\ yield_{it}$.

## 4.3 Measuring the Stability of Insurance Underwriting Funding

To measure the stability of insurance underwriting funding, we use the historical volatility of an insurer's underwriting profits:

$$\text{Volatility}_{it} = \sigma_{it-1}\,(\text{Underwriting Profitability}) \tag{23}$$

where higher volatility implies less stable funding. In our baseline measure, we calculate the four-year rolling volatility of insurance underwriting profitability for each insurer $i$ at each date $t$ using data up to, and including, date $t-1$ to ensure that the insurer's current pricing decision does not affect our measure of funding volatility. We use the four-year rolling window to ensure that our measure of funding volatility captures funding volatility of an insurer's current underwriting business while not being overly sensitive to any individual realization of underwriting profitability. In Table B.1 of the Internet Appendix, we show that our empirical results are robust to alternative lengths of the rolling window. We study the volatility of the insurer's underwriting profitability, as opposed to the volatility of claims paid alone, as it more directly captures the volatility of the insurer's funding (i.e., the premiums they can charge over claims).

## 4.4 Data

**P&C insurer financial statements.** Insurance entities are required to report detailed financial statements to regulatory authorities on a quarterly basis. We collect these data from S&P Global: Market Intelligence using an FTP feed to access the full back-end of their SNL database. Section C.3 of the Internet Appendix provides a detailed description of the database and the aggregation of individual insurers to the group level (large insurance groups often have many separately regulated insurance entities within their group umbrella that report separately).

Our final P&C sample consists of 871 insurance groups running P&C businesses over 85 quarters from March 2001 through March 2022.[14] In total we have 47,125 firm quarter observations, with a minimum of 153 insurance groups available in any given quarter and a maximum of 635. To get to this final sample, we have excluded insurance companies with less than four years of data and companies who never exceed $10 million in net total assets. We do this to ensure that the companies we are looking at are relatively large and active. Further, we try to mitigate erroneous data entries by eliminating company-quarter observations where either firm total assets, direct premiums written, or net yield on invested assets were negative, or extreme observations where a firm's underwriting profitability exceeds 10% (positive or negative) of the firm's insurance liabilities. All financial statement variables are winsorized at the 1st and 99th percentiles in each quarterly reporting period.

Beyond the investment net yield described in the previous section, our cross-sectional analysis of P&C insurers also uses the insurer's asset allocations, the average credit ratings of the insurer's investment portfolios[15], and various measures of balance sheet

[14]The insurance groups are aggregated from 4,038 insurance entities.

[15]The insurance regulator NAIC assigns bonds into six broad categories (categories 1 through 6) based on their credit ratings, with higher categories reflecting higher credit risk. Level 1 is credit AAA-A, level

strength: risk-based capital ratio, the unearned premium ratio[16], and reinsurance activity (net premiums reinsured / net premiums received). We further supplement the P&C Insurer Financial Statement data with the A.M. Best Financial Strength Ratings data. A.M. Best is an independent provider of ratings for insurance companies in the U.S.

**Life annuity data.** For prices on life annuities we use the Koijen and Yogo (2015) database. Koijen and Yogo (2015) collate prices on annuity products from WebAnnuities Insurance Agency over the period 1989 to 2011. Prices are available for three types of annuities: term annuities (products that provide guaranteed income for a fixed term), life annuities (products that provide guaranteed income for an unfixed term that is dependent on survival), and guarantee annuities (products that provide guaranteed income for fixed term and then for future dates dependent on survival). The maturity of term annuities ranges from 5 to 30 years, while guarantees are of terms of 10 or 20 years. Further, for life and guarantee annuities, pricing is distinguished for males and females, and for ages 50 to 85 (with every five years in between). The time series consists of roughly semiannual observations, except for the life annuities (with and without guarantees), which are also semiannual but with monthly observations during the years around the GFC, which is the focus of Koijen and Yogo (2015). To summarize we have 96 insurers quoting prices on at least 1 of 54 different annuity products at one or more of 73 different dates.

**Financial market and macroeconomic variables.** We retrieve Moody's Seasoned Baa corporate bond yield relative to the 10-year Treasury from the St. Louis Fed's website (fred.stlouisfed.org). We also use the excess bond risk premium as provided in (Gilchrist and Zakrajšek (2012)). To proxy for general funding costs and financial constraints we include the 6-month to 10-year Treasury Constant Maturity Rates and TED spread (downloaded from the St. Louis Fed's website), respectively. The TED spread is the difference between the three-month Treasury bill and the three-month LIBOR based in US dollars.

2 is BBB, level 3 is BB, level 4 is B, level 5 is CCC, and level 6 is all other credit.

[16]The unearned premium ratio is the ratio of unearned to earned premium and gives an indication of the remaining unpaid liabilities relative to the current volume of business. It is therefore a proxy for the average duration of an insurance contract that the insurer underwrites.

## 4.5 Summary Statistics

Table 1 presents summary statistics for the key variables in our empirical analysis. The average annualized life annuity markups are 1.0%, 0.5%, and 1.1% for life annuities, guaranteed annuities, and fixed-term annuities, respectively. Our main dependent variable in P&C markets is underwriting profitability, which across our sample has a mean of 0.3%. The average insurer-level four-year rolling standard deviation of underwriting profitability is 1.8%. In our cross-sectional analysis, the main independent variable is insurance companies' investment returns measured via net yields. This averages 3.1% in the P&C industry.

# 5 Empirical Results

## 5.1 Expected Investment Returns and the Time Series of Prices

We first test Proposition 1's prediction that insurance prices and expected returns on illiquid assets are correlated in the time series with insurance prices being low when expected returns are high. We are able to test the proposition using prices on both life insurance contracts and P&C insurance contracts given the long time series available for both products. P&C insurance companies face different consumer markets and operate under different regulatory frameworks than life insurance companies, which allows us to rule out alternative channels of insurance price variation. We discuss these alternative channels in detail in Section 6.

**Life insurance.** We first test Proposition 1 in the market for life insurance annuities by using the credit spread between Moody's BAA-rated corporate bonds and the 10-year Treasury yield to measure the expected return on the insurers' illiquid assets. As outlined in Section C.1 of the Internet Appendix, we use this spread in our main specification to match the investment portfolio of the average life insurer. However, as we show in Appendix Table B.3, our results are robust to using a variety of other measures capturing expected excess returns in the bond market.

Figure 1 illustrates our central time series finding using the insurance product with the longest available sample: 10-year fixed-term annuities. The figure presents the industry average markup on 10-year fixed term annuities against the 10-year BAA credit spread from 1989 to 2011, where markups are defined as the quoted price relative to the actuarially fair price. The negative correlation between the markup and credit spreads is evident from both the simple time series plot (panel A; note that the right-hand side axis is inverted) and the scatter plot of changes in markups and changes in credit spreads (panel B). In fact, the $R^2$ from the single variable regression of markups on credit spreads is a noticeable 73%. The $R^2$ remains high at 39% when regressing changes in markups on changes in credit spreads.

We formally document the robust negative relationship between annuity markups and credit spreads across different life insurance products by estimating the following regression model:

$$\bar{m}_t = \beta_c \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot CS_t \cdot \mathbb{1}_{GFC} + \gamma^T X_t + \epsilon_t \tag{24}$$

where $\bar{m}_t$ is the average (annualized) markup across insurers and subproducts at time $t$. The two main explanatory variables are (1) the credit spread of Moody's BAA corporate bonds over the 10-year Treasury yield, $CS_t$, and (2) an indicator variable equal to one over the GFC (September 2008 through December 2009), $\mathbb{1}_{GFC}$. $X_t$ is a vector of time series control variables that includes the 10-year constant maturity Treasury yield (to proxy for the risk-free rate), the difference between the 10-year and 2-year Treasury yield (capturing the slope of the yield curve), the US unemployment rate (to capture time variation in the demand for insurance), and the TED spread.[17]

Table 2 presents the results for three different life insurance products, with panel A showing results for life annuities, panel B showing results for guaranteed annuities, and panel C showing results for fixed-term annuities. In each panel, columns (1) through (3) present the results from the collapsed time series, while columns (4) and (5) present the results from the full panel estimation. Across specifications, we see that a 1 percent increase in credit spreads significantly lowers annualized markups by between 0.4 and 0.8 percent. Further, the explanatory power is very large, with an average $R^2$ of 0.71 across the three life insurance products in the simple time series specification. Taking life annuities in panel A as an example, a 1 percentage point increase in credit spreads lowers (annualized) markups by 0.53 percentage point on average, with an $R^2$ of 0.72 in the univariate time series regression shown in column (1). As seen in column (2) (panel A), the result is robust to the inclusion of our time series controls – namely, the level and

[17] While we present the results from a "levels on levels" regression, Table B.5 in the appendix presents results from identical specifications as Table 2, but with dependent and explanatory variables in changes rather than levels. Our results are robust to this specification with statistical significance and economic magnitudes remaining intact.

slope of the Treasury rate, the U.S. unemployment rate, and the TED spread.[18]

A natural question is whether the effect shown above is driven by the financial crisis. In particular, Koijen and Yogo (2015) document that the financial crisis saw a dramatic fall in markups for life insurers at the same time as credit spreads ballooned. In column (3) we interact the credit spread with an indicator variable, $\mathbb{1}_{GFC}$, which takes the value of one during the GFC, and find no change in the effect of credit spreads on markups outside the GFC. If anything, the effect becomes slightly stronger outside the GFC, as the effect of credit spreads on markups during the GFC is dampened.[19] This is after accounting for the fact that average markups were lower and credit spreads higher during the GFC, $\beta_{GFC} = -0.843$; however, our main insight from this regression is that the pass-through of expected returns to insurance prices is not just a GFC phenomenon, but is present throughout our sample period.[20]

Finally, to ensure that our results in the collapsed time series are not a consequence of the aggregation across products and firms, we re-estimate the regression in a full panel with firm and subproduct fixed effects, where subproducts vary depending on age, sex, and maturity of the annuities. The results are reported in columns (4) and (5) and do not differ from the simple time series specification.

**P&C insurance.** In Table 3 we repeat the analysis of Table 2 but now use prices on P&C insurance contracts instead of markups on life insurance products. As discussed in Section 4.1, we do not observe prices on P&C contracts directly but infer them from underwriting profitability as defined in equation (20). Underwriting profitability measures the ratio of an insurer's underwriting profit relative to insurance liabilities, meaning that when an insurer sets low prices (relative to expected claims) it will report lower underwriting profitability going forward. Given that underwriting profitability reflects insurance prices over the previous year, we regress underwriting profitability on lagged credit spreads averaged over the previous year to reflect the expected return on investments at the time of underwriting.

Table 3 has the same column specifications as the previously discussed Table 2. We

[18]We report estimates for all variables in vector $X_t$ in Appendix Table B.6, but leave them out of the main table for brevity.

[19]Outside of the GFC the sensitivity of markups to credit spreads is $\beta_c = -0.657$. During the GFC the effect of credit spreads on life insurance markups is $\beta_c + \beta_{cGFC} = -0.657 + 0.293 = -0.364$

[20]This finding is consistent with the results of Chodorow-Reich et al. (2021) who find that life insurers are able to insulate their investment portfolios from market fluctuations outside of the GFC.

find a statistically significant impact of credit spreads on underwriting profitability with a 1 percent increase in credit spreads lowering underwriting profitability by 0.36 percent in the simple time series specification. The result is robust to the inclusion of the same vector of time series controls as in Table 2 and we see again that the result seems to be even stronger outside the GFC period. Further, the result does not change when we estimate the model in a full panel with firm fixed effects.

**Robustness.** In Appendix Table B.3, we show that the time series correlation between insurance prices and credit spreads is not sensitive to the choice of credit spread for either life insurance or P&C insurance prices. The correlation between insurance prices and credit spreads remains economically and statistically significant when we replace our benchmark credit spread, BAA-rated corporate bonds and the 10-year Treasury, with alternative credit spreads. Further, credit spreads consist of both a compensation for expected default losses and a premium on top of this, which is the expected excess return. Our model predicts that it is the latter component, the expected excess return, that drives the correlation between credit spreads and insurance prices. We test this prediction in Appendix Table B.4 using the Gilchrist and Zakrajšek (2012) decomposition of the credit spread. We find that both life and P&C insurance prices are correlated to the part of the credit spread that reflects the expected excess return (the excess bond premium) as opposed to the part that reflects the underlying default risk (the default spread).

In summary, in this subsection we document an economically and statistically significant negative relationship between insurance prices and insurers' expected investment returns in the time series. We have documented the relationship in two separate insurance markets and shown that it is robust to the inclusion of a series of controls.

## 5.2 Stable Insurance Funding and Illiquid Asset Allocations

We next turn to the cross-section of insurers and utilize the large number of P&C insurers in our sample to test Proposition 2: insurers with more stable funding hold more illiquid assets.[21] We take this prediction to the data by using P&C insurers' historical volatility

[21] Our sample contains 871 individual P&C groups with more than 4,000 different insurance entities, and we have between 153 and 635 insurance groups present at any date. Our matched sample of life insurers – where we have both net yields and markups – contains only 43 individual insurers, with each date having only between 6 and 19 insurers. The number of life insurers at a given date is thus

of insurance underwriting as a measure of the insurer's funding stability. That is, for each insurer at each date we calculate the four-year rolling volatility of their insurance underwriting profitability. To test if funding stability predicts insurer's portfolio choices we regress the insurers' investments, $y_{it}$, in three asset classes on rolling estimates of underwriting volatility, $Volatility_{i,t-1}$, lagged by one quarter:

$$y_{it} = \beta_{vol} \cdot Volatility_{i,t-1} + \delta^T Z_{i,t-1} + FE_{Rating_i} + FE_t + \epsilon_{it}. \tag{25}$$

The three asset classes are (1) cash, (2) non-government bonds, and (3) risk-weighted bonds, where the risk-weighted bond allocation is the insurer's bond allocation times the average credit rating of the insurer's credit portfolio. The credit rating is given by the National Association of Insurance Commissioners, NAIC, which assigns a numeric rating from 1 to 6 to each credit asset in an insurer's portfolio.[22] We observe the value-weighted average credit rating of each insurer's portfolio, normalize this measure to a $z$-score across all insurers, and multiply each insurers bond allocation by their $z$-score to obtain their risk-weighted bond allocation. $Z_{i,t-1}$ is a vector of control variables described below. $FE_{Rating_i}$ and $FE_t$ absorb rating and time fixed effects, respectively, where the rating is the financial strength rating provided by AM Best.

Table 4 presents the results of the regressions, and we see that stable funding predicts low allocations to cash and high allocations to credit, especially risky credit, in the cross-section of P&C insurers. Specifically, a one standard deviation higher volatility of underwriting profitability increases an insurer's cash allocation by 1.2 percentage points in the cross-section and decreases an insurer's allocation to non-government bonds by a similar amount.[23] The result is even stronger, both statistically and economically, when we look at the risk-weighted bond allocations – that is, the insurer's bond allocation multiplied by a standardized numeric measure of the insurer's portfolio's credit rating. Specifically, the effect of funding stability on risk-weighted bond allocation is roughly twice that of the effect of funding stability on pure bond allocation.[24] This indicates that

too narrow to conduct reliable cross-sectional analysis. However, in Appendix Table B.7 we repeat the analysis presented in this subsection using life insurers and find evidence, albeit statistically insignificant, consistent with the results for P&C insurers.

[22]Corporate and municipal bonds with rating AAA-A are assigned as 1, BBB as 2, BB as 3, B as 4, CCC as 5, and CC and below as 6 (Becker and Ivashina, 2015; Becker et al., 2022; Ge and Weisbach, 2021)

[23]Our measure of underwriting volatility has been normalized to have a standard deviation of one for the full sample.

[24]Note that the standard deviations of raw bond allocation and risk-weighted bond allocation are

insurers with stable funding are not only buying more bonds, but importantly, also riskier bonds. Our results are robust to the inclusion of a vector of control variables including the insurer's risk based capital ratio (capturing the insurer's financial constraints), *Unearned Premium Ratio* (capturing the duration of the insurer's insurance underwriting portfolio), *Reinsurance Ratio* (capturing the fraction of written premiums that the insurer actually underwrites), and financial strength rating.[25]

We perform several robustness tests to support our result. First, we demonstrate that our results are not sensitive to the specification of funding stability. Table B.1 of the Internet Appendix repeats the exercise of Table 4 but replaces the four-year rolling volatility as explanatory variable with (1) the two-year rolling volatility of underwriting profitability, (2) the eight-year rolling volatility of underwriting profitability, and (3) the full sample volatility of funding stability. The alternative measures of funding stability prove that our results are unaffected by changing the window in which we estimate funding stability, consistent with the idea that funding stability is a persistent feature of an insurer's underwriting business.

Second, our paper is not the first to empirically explore the cross-sectional determinants of insurance companies' portfolio allocations. Notably, Ge and Weisbach (2021) find that larger (and better-rated) insurers take more investment risk. Given that an insurer's size and funding stability are naturally correlated as larger insurers can write more contracts, we separate the effects of size and funding stability by splitting our sample into three groups based on size of the insurance companies. For each size group we then predict the cross-sectional variation in insurers' risk-weighted bond allocation with funding stability (as in columns (5) and (6) of Table 4), controlling for both size and rating of the insurance company. Consistent with Ge and Weisbach (2021), in Table B.2 of the Internet Appendix we find that larger firms take more investment risk but also that funding stability remains a strong predictor of an insurer's investment risk for both large and medium-sized insurance companies even after the inclusion of size and rating as control variables. It is only for small insurers that we do not find a statistically significant relationship between underwriting stability (or size), which may be caused by the limited flexibility that these smaller insurers have in their investment portfolios.[26] That is, hold-

almost exactly the same, allowing us to compare the coefficients across the regressions.

[25]As mentioned in the data section, the insurer's *Unearned Premium Ratio* is the ratio of unearned premiums to net premiums earned while the *Reinsurance Ratio* is the ratio of net reinsurance premiums to direct premiums written.

[26]Damast (2023) shows that small insurers are typically limited to holding a few large bond positions.

ing fixed the size and rating of an insurance company, funding stability still significantly predicts higher allocation to riskier credit. Section B.1 of the Internet Appendix provides more details of the robustness test.

In summary, consistent with our model, we see that insurers with more stable funding hold less cash and take more credit risk in their investment decisions. We find that this effect is driven in large part by the behavior of large, financially unconstrained insurance companies.

### 5.3 Expected Investment Returns and the Cross-Section of Prices

Having documented the cross-sectional relationship between funding stability and asset allocation, we now test if insurers' asset allocations explain insurance prices in the cross-section by testing Proposition 3: insurers with higher expected investment returns set lower prices.[27] Analyzing the cross-section of insurers allows us to absorb unobserved time-variant factors that are potentially confounding our time series analysis in Section 5.1. To measure an insurer's expected return we use the *net yield* reported by insurers in their quarterly accounts.[28] Insurance prices are measured as underwriting profitability as in Section 5.1.

Figure 2 illustrates our main result by plotting the average underwriting profitability (demeaned by date) for 20 portfolios based on the insurer's net yields. That is, at each date we divide the insurance companies in the sample into 20 portfolios based on their reported net yield and measure the average net yield and underwriting profitability over the following quarter for each portfolio relative to the average net yield and underwriting profitability at that date. Figure 2 plots the average net yield and underwriting profitability of each portfolio over time. The figure displays a clear negative correlation between net yields and underwriting profitability, where a 1 percent increase in portfolio net yield is associated with a fall in portfolio underwriting profitability of 0.08% on average.

[27]While the low number of life insurers in our sample deters us from running cross-sectional regressions, we repeat the analysis presented in this subsection using life insurers and find evidence, albeit statistically insignificant, consistent with the results for P&C insurers. The results are reported in Appendix Table B.7.

[28]See Section 4.2 and Section C of the Internet Appendix for discussions on the construction and interpretation of this variable as a measure of cross-sectional variation in expected investment returns.

We perform a formal test of Proposition 3 by estimating the regression equation

$$\begin{aligned} u_{it+1} = &\beta_{ny} \cdot \textit{Net yield}_{it} + \delta^T Z_{it} + \beta_{nyGFC} \cdot \textit{Net yield}_{it} \cdot \mathbb{1}_{GFC} + \\ &\delta^T_{zGFC} Z_{it} \cdot \mathbb{1}_{GFC} + FE_{Rating_i} + FE_t + \epsilon_{it} \end{aligned} \tag{26}$$

where $u_{it}$ is the underwriting profitability for insurer $i$ at time $t$ and $\textit{Net yield}_{it}$ is the insurer's net yield at time $t$. $\mathbb{1}_{GFC}$ is an indicator variable set to one over the GFC (September 2008 through December 2009) and $Z_{it}$ is a vector of controls containing the insurer's *Capital Ratio* which is the risk-based capital ratio, the insurer's *Unearned Premium Ratio*, which is the ratio of unearned premiums to net premiums earned and measures the average duration of an insurer's contracts, and the insurer's *Reinsurance Ratio*, which is the ratio of net reinsurance premiums to direct premiums written. $FE_{Rating_i}$ is a fixed effect for the insurer's AM Best financial strength rating, and $FE_t$ captures time fixed effects.

Table 5 reports the results of the estimation of (26). Column (1) shows the simplest specification with no controls beyond date fixed effects and reiterates the result of Figure 2: a 1 percent higher net yield decreases underwriting profitability by 8 basis points. In column (2) we control for the strength of the insurer's balance sheet by including as controls the insurer's capital ratio, unearned premium ratio, and reinsurance ratio. We see that the inclusion of these controls only slightly reduces the cross-sectional correlation between net yields and underwriting profitability, which remains significant. Next, we test if the results are driven by the GFC by interacting our explanatory variables with an indicator variable that turns on during the GFC from September 2008 to December 2009. However, there is no significant difference between the explanatory variables' correlation inside and outside the GFC. In column (4) we further show that our result is not driven by differences in the credit rating of insurance companies by adding rating fixed effects.

Given that we are measuring underwriting returns at the insurance group level, one concern is that the cross-sectional variation in prices is driven by variation in the type of insurance written or in the geographic location of the customers. To control for this alternative narrative, we collect the underwriting returns at the state-business line level of each of the P&C insurers in our sample. We look at the six largest categories of P&C insurance: private auto insurance, private multiple peril insurance, fire and allied insurance, commercial auto insurance, commercial multiple peril insurance, and workers' compensation. These six business lines make up 76% of all P&C insurance in terms of direct premiums written in 2022 according to S&P Global. Geographically, the sample covers all 50 U.S. states, five U.S. territories[29], and the District of Columbia. The sample still covers the period 2001 to 2021, though observations are now only available at the annual level. Column (5) of Table 5 presents the results of our main cross-sectional regression with this decomposed data:

$$\begin{aligned} u_{ibst+1} =& \beta_{ny} \cdot \textit{Net yield}_{it} + \delta^T Z_{it} + \beta_{nyGFC} \cdot \textit{Net yield}_{it} \cdot \mathbb{1}_{GFC} + \\ & \delta^T_{zGFC} Z_{it} \cdot \mathbb{1}_{GFC} + FE_{Rating_i} + FE_t \cdot FE_s \cdot FE_b + \epsilon_{ibst} \end{aligned} \tag{27}$$

where $u_{ibst}$ measures insurer $i$'s underwriting profitability at time $t$ for business lines $b$ in state $s$. The important difference to our main regression specification in equation (26) is the triple-interacted fixed effects, which absorb all variation stemming from differences in state-business line-year effects. That is, we are now measuring the sensitivity of insurance prices to expected returns within a business line, within a state, within a year. As we see from column (5), our main result is robust to the inclusion of these controls, with a 1 percent higher net yield corresponding to a 6 basis point lower underwriting profitability. In Table B.8 of the Internet Appendix we present more regression specifications with this data, and show that our results hold also within each individual insurance line.

**Decomposing the cross-section of expected returns.** While Table 5 documents that insurers with higher expected returns (as measured by net yields) set lower insurance prices on average, the economic effect is smaller than what we documented in the time series. One reason for this may be that net yields fluctuate for reasons unrelated to insurers stable funding. As stated in Proposition 3, these fluctuations should not affect insurance prices. Instead, it is only the part of the insurer's expected returns related to stable funding that should cause the insurer to set lower prices. We test this second part of Proposition 3 by running a two-step estimation of our model of insurance prices. First, we regress expected investment returns, measured by net yields, on underwriting stability, measured as the four-year rolling standard deviation of underwriting profitability. We use the estimated results to decompose the cross-sectional variation in net yields into a part driven by stable funding and a residual that captures other factors such as risk. We then regress underwriting profitability on to the decomposed net yield – i.e., the predicted net yield and the residual from our first step regression – to see what part of the net yield

[29]Guam, Puerto Rico, United States Virgin Islands, Northern Mariana Islands, and American Samoa.

predicts underwriting profitability. Formally our setup consists of the two regressions:

$$\text{First step:} \quad Net\ yield_{it} = \kappa \cdot Volatility_{i,t-1} + \delta_1^T Z_{it} + FE_{Rating_i} + FE_t + \xi_{it}$$

$$\text{Second step:} \quad u_{it+1} = \beta_{\widehat{ny}} \cdot \widehat{Net\ yield}_{it} + \beta_{res} \cdot \xi_{it} + \delta_2^T Z_{it} + FE_{Rating_i} + FE_t + \epsilon_{it}$$

where $Volatility_{i,t-1}$ is the four-year rolling standard deviation of insurer $i$'s underwriting profitability up to, and including, time $t-1$, $\widehat{Net\ yield}_{it}$ is the estimated net yield from the first step regression, and $\xi_{it}$ is the residual from the first step regression (i.e., the cross-sectional variation in net yields not explained by underwriting stability).[30]

Table 6 presents the results. Column (1) presents the result of the first step regression and we see that underwriting stability is a significant predictor of expected returns with a one standard deviation lower volatility of underwriting profitability corresponding to a 0.2 percent higher net yield in the cross-section. Although this first step result is not surprising in light of the portfolio allocation results presented in Table 4, it is an important validation of our methodology; insurers that have more stable funding invest less in cash, take more credit risk in their bond portfolios, and ultimately earn higher investment returns as compared to their competitors. Column (2) of Table 6 then presents the results of the second step estimation, and we see that the estimated (stable) net yield strongly predicts underwriting profitability, whereas the residual net yield does not have much explanatory power. In other words, it is the part of expected returns driven by funding stability that transfers through to insurance prices. The magnitude of the relationship is notably in the ball park of our time series estimates, with a 1 percent increase in net yield driven by stable funding corresponding to a 0.6 to 0.8 percent lower underwriting profitability in the cross-section. In columns (3) and (4), we re-estimate both the first and second steps but add the same controls as in Table 5 (the insurer's capital ratio, unearned premium ratio, reinsurance ratio, and rating) in both steps. While the residual does become significant, the economic effect is an order of magnitude lower than that of the estimated net yield.

In summary, we have shown that higher expected investment returns are associated with lower insurance prices in the time series of both life and P&C insurance. Further, we have shown that insurers with more stable funding take more investment risk and make higher investment returns, which causes them to set lower insurance prices in the cross-section of P&C insurers.

[30] Despite our setup's resemblance to an instrumental variables approach, in this exercise we are merely decomposing the insurer's expected returns into two components, and include *both* of these components as a structural test of our model.

# 6 Discussion of Alternative Mechanisms

## 6.1 Insurer capital constraints

It is a well-documented fact that capital constraints affect insurance prices (Gron (1994b), Froot and O'Connell (1999), Koijen and Yogo (2015), and Ge (2022)). To distinguish the pass-through of expected investment returns on insurance prices from the effect of capital constraints on insurance prices, we introduced the statutory leverage constraint in equation (7) of the model setup. In this subsection we now consider the implications for insurance pricing when this constraint is binding. The model delivers the following predictions:

**Proposition 4 (Shadow cost of capital).** *When the insurer is capital constrained and equation (7) is binding, the impact of the shadow cost of capital on optimal insurance price depends on the relationship between the insurer's time value of money,* $\left(1+R^F\right)\left(1+R_i^P\right)$*, the statutory discounting rate,* $1+R^S$*, and the maximum statutory leverage ratio,* $\phi \leq 1$*. In particular:*

*(i) If* $\left(1+R^F\right)\left(1+R_i^P\right) > \phi\left(1+R^S\right)$ *then* $\Gamma_i > 1$

*(ii) If* $\left(1+R^F\right)\left(1+R_i^P\right) < \phi\left(1+R^S\right)$ *then* $\Gamma_i < 1$

The impact of capital constraints on insurance prices shown in Proposition 4 depends on whether an additional insurance contract increases or decreases the statutory capital ratio shown in equation (7). If the statutory discount rate, $R^S$, is sufficiently low (scenario (i)), binding capital constraints force the insurer to raise prices and write fewer contracts, as the insurer uses more regulatory capital than it receives when writing an additional contract. Froot and O'Connell (1999) document an empirical example of scenario (i), showing that the supply of catastrophe insurance fell following a negative shock to insurers' capital. On the other hand, if the statutory discount rate, $R^S$, is sufficiently high (scenario (ii)), binding capital constraints encourage the insurer to lower prices and write more insurance contracts, as the statutory value of an insurance contract is so low that the insurer replenishes more capital than it uses when writing an additional insurance contract. Koijen and Yogo (2015) find evidence consistent with scenario (ii) in the financial crisis when $R^S$ was particularly high for life insurers and constrained life insurers reduced annuity markups significantly.

Empirically, capital constraints may confound our empirical results if episodes of binding capital constraints correlate with episodes of high expected returns (i.e. high credit spreads).[31] The pass-through of expected returns to insurance prices (Proposition 1) predicts that high expected returns lead to lower insurance prices, but Proposition 4 generates the same prediction in scenario (ii) if the high expected returns coincide with binding capital constraints, even in the absence of a pass-trough of expected returns. To see this, eliminate the insurer's funding advantage, $\bar{\tau} + \sigma_i = 1 \Rightarrow R_i^P = 0$, and note how binding capital constraints, $\eta_i > 0$, lead to lower insurance prices in scenario (ii) where $\left(1 + R^F\right) < \phi\left(1 + R^S\right)$.

To mitigate concerns that capital constraints may be driving our empirical results we emphasize three empirical findings about the pass-through of expected investment returns to insurance prices: (1) it is present for P&C insurers who, as opposed to life insurers, cannot discount their statutory liabilities; (2) it is present both in and out of the GFC where insurers were most likely capital constrained; and (3) it is strongest for the highest-rated insurers, who are least likely to be capital constrained. Below we discuss each of these results in detail.

First, P&C insurers are not allowed to discount the statutory value of their liabilities ($R^S = 0$) for typical products such as car insurance as the regulator makes no adjustment for time value of money (NAIC (2018)). This regulatory feature of the P&C industry means that case (i) of Proposition 4 always applies in this market. This means that, given that expected returns (measured via credit spreads) and capital constraints are positively correlated, the pass-through of expected returns and capital constraints generate opposite predictions, with the pass-through of expected returns predicting that high credit spreads are associated with low insurance prices, while capital constraints predict that high credit spreads are associated with high insurance prices. Documenting the negative time series correlation between P&C insurance prices and credit spreads in Table 3 therefore helps to identify the pass-through of expected returns while controlling for the potential impact of capital constraints. Further, from columns (3) and (5) of Table 3 we see that the sensitivity of insurance prices to credit spreads is much lower during the financial crisis of 2008-09 as opposed to outside, indicating that P&C insurers were constrained during this period and, consistent with Life industry evidence in Chodorow-Reich et al. (2021), therefore less capable of holding assets for the long-term and monetizing excess returns

[31]Theoretically, capital constraints can also confound our results if episodes of binding capital constraints correlate with *low* expected returns, but we focus on the more plausible scenario of binding capital constraints and high expected returns.

on illiquid assets.

Second, while life insurers are allowed to discount their liabilities, they only lower their markups (scenario (ii)) in the special situation where the insurer is both capital constrained and the statutory discount rate, $R^S$, is sufficiently high. In columns (3) and (5) of Table 2 (panels A, B, and C), we document that the negative correlation between credit spreads and life insurance markups is at least as strong outside the GFC as it is during the crisis, where insurers were most likely to be constrained, $\eta > 0$. Outside of the crisis, life insurers are more likely to be unconstrained, $\eta = 0$, and lowering markups would thus hurt insurer profits in the absence of higher expected investment returns. Further, looking at the interaction between credit spreads and the crisis indicator variable, we see that the sensitivity of insurance prices to credit spreads is actually lower inside the GFC than it is outside, while insurance prices, on average, are lower. For example, column (3) of Table 2 - panel A shows the sensitivity of insurance markups to credit spreads is lower by 0.293% inside the crisis, while insurance prices were (insignificantly) lower by 0.843%.

Finally, in Figure 3 we rerun the cross-sectional regression of underwriting profitability on net yields presented in Table 5 but split the sample in three based on the rating of the insurer. Echoing the results of Table 6, we find that the pass-through of expected returns to insurance prices is most present for highly rated insurers (A++ to A-), who are less likely to be financially constrained. This is consistent with our expectations for P&C insurers who cannot discount statutory liabilities. It is therefore only the high-rated, unconstrained insurers who are able to harvest the excess return on illiquid assets by lowering insurance prices. We show in Figure 3 that the result is robust to the same series of control variables applied in Table 5.

In summary, capital constraints are very important determinants of insurance prices, especially in periods of market turmoil, where insurers scramble to obtain capital. However, they do not explain the empirical results presented in Section 5. The pass-through of expected returns on insurance prices as such provides an additional mechanism that must be included in order to understand insurance prices and the societal value of insurance underwriting.

## 6.2 Demand for insurance

In this subsection we consider potential variation in the demand for insurance and discuss how we control for these potentially confounding factors in our empirical setting. First, insurer default risk might affect the demand for insurance and thus the price of insurance contracts. If insurer default risk also correlates with the level of investment risk in insurers' asset portfolios, this could bias our results. In particular, when credit spreads increase due to higher credit risk in asset markets, insurers' assets are more likely to suffer, and the probability that insurers default on insurance contracts thus increases. Insurance prices would therefore fall as credit spreads increase due to consumers reducing demand in reaction to a perceived increase in insurer default risk. However, as documented in Table B.4, we find that the time series relation between insurance prices and credit spreads are driven by the excess bond risk premium (Gilchrist and Zakrajšek, 2012) rather than the expected default component of credit spreads. Further, the insurer default risk channel predicts the credit spread and insurance price correlation should hold strongest in the GFC, where default risk in credit markets was most elevated. We find the opposite, with the pass-through of expected returns to insurance prices holding strongest outside of the GFC.

In the cross-section, the insurer default risk channel predicts that insurers taking more credit risk in asset portfolios are more likely to default on insurance contracts and thus face less demand from consumers and set lower insurance prices in equilibrium. However, as shown in Tables 4 and 5, our cross-sectional results for both asset allocation and the pass-through of expected returns to insurance prices are robust to the inclusion of a vector of control variables capturing the balance sheet strength of insurers as well as the insurer's A.M. Best financial strength rating, which plausibly captures cross-sectional variation in insurer default risk. In summary, the empirical evidence does not support the insurer default risk channel of insurance demand as a driving force behind our findings.

A second potential source of insurance demand variation is product substitutability. In particular, life insurance annuities are savings products and demand may fall when the opportunities in alternative saving strategies improve. When expected investment returns are higher, consumers could choose to invest their savings in alternative assets rather than purchasing annuities, thereby reducing demand for annuities when credit spreads are higher. However, we also document our time series results in the P&C markets, where the decision to purchase car and household insurance is less likely to be viewed as a savings alternative. This potentially confounding source of demand variation is thus much less likely to hold for the P&C specifications.

Beyond the investment opportunities, there could be other latent sources of demand variation correlated with the business cycle and credit spreads.[32] While the cross-sectional

[32]For example, Corbae and D'Erasmo (2021) show that competition in the banking sector decreases in

results naturally absorb any aggregate demand variation with time fixed effects, the time series specification estimates could be biased by these channels. For this reason, we also include the unemployment rate in the time-series regressions to absorb some of the latent demand variation correlated with the business cycle. We find the results are consistent with this macroeconomic control in both the life and P&C insurance specifications.

### 6.3 Reinsurance activity

A final alternative mechanism to consider is the potential impact of reinsurance in our cross-sectional P&C results. Reinsurance is a major part of the P&C insurance business model, with insurers offloading some of the risk they initially underwrite to third parties. In 2021, the aggregated market of U.S. P&C insurers retained 80 percent of premiums written on their own balance sheet. We can therefore see that, on average, approximately 20 percent of underwriting contracts are re-insured, which is a sizable fraction. Importantly, our underwriting profitability measure, as defined in Section 4.1, is net of gains/losses from reinsurance. Therefore, we are capturing the true profitability of the underwriting business after reinsurance considerations. However, the level of reinsurance activity an insurer engages in could impact the insurance pricing and could also be correlated to the portfolio choice decision and the level of investment risk the insurer takes. We therefore include the level of an insurer's reinsurance activity – net premiums reinsured over net premiums received – in the control vector in the cross-sectional regressions. The results presented in Table 5 show that our main findings hold while including this potentially confounding factor in the regression specification.

## 7 Conclusion

The pass-through of expected investment returns is a new channel of insurance pricing, which shows that stable funding from underwriting allows insurers to earn higher expected investment returns in illiquid asset markets and thus set lower insurance prices. In a violation of the Modigliani and Miller (1958) capital irrelevance theorem, the pricing of insurer liabilities thus depends on the expected returns on their asset portfolios. Our theory suggests that the insurance industry increases economic welfare in two distinct, but

bad times and markups increase as lower quality firms exit the market. Assuming bad times are correlated with higher credit spreads, this confounding factor would push markups in the opposite direction of our main time series results.

interdependent, ways. First, insurers act as stable, counter-cyclical investors, increasing asset allocations to illiquid investments when the liquidity premium is higher, dampening asset market volatility, and spurring investments and economic activity (Aslan and Kumar, 2018; Coppola, 2022; Kubitza, 2023). Second, insurers allow households to not only share risk and avoid financial ruin, but also to benefit, through lower insurance prices, from the stable funding they collectively provide.

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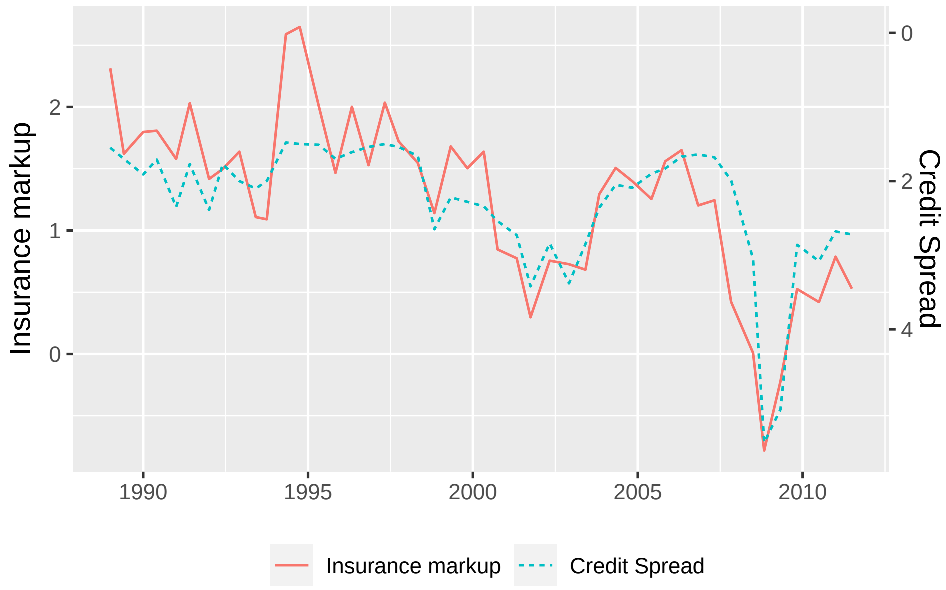
**Figure 1: Expected investment returns and the time series of insurance prices.** This figure shows the relation between insurance prices and insurer expected investment returns as proxied by credit spreads. Panel A plots the two time series in levels. Panel B plots a scatter plot of the two time series in changes. Insurance prices are measured as the percent deviation of the quoted price from actuarially fair value. We use the industry average 10-year fixed-term annuity markup of Koijen and Yogo (2015). The credit spread variable is Moody's BAA 10-year corporate bonds yield over 10-year Treasury yield (fred.stlouisfed.org).

**(a) Time-Series Graph (Levels)**




**(b) Scatter Plot (Changes)**

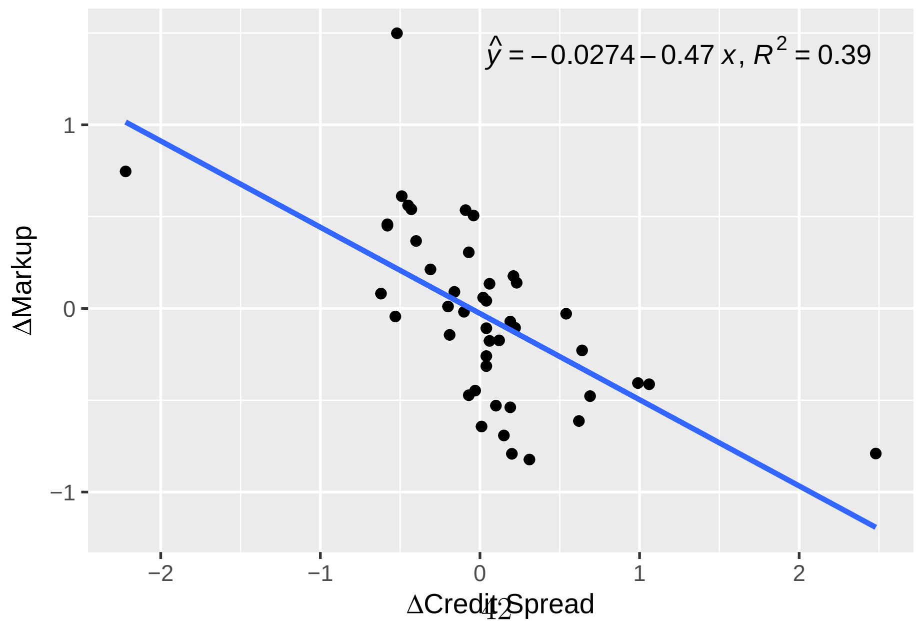


**Figure 2: Expected investment returns and the cross-section of insurance prices.** This figure presents a binned scatter plot of insurance prices against insurers' expected investment returns. Insurance companies are grouped into 20 equal sized portfolios at each date based on their expected investment returns. The figure plots each portfolio's average insurance price against its average investment return demeaned by the date average. Insurance prices are measured as underwriting profitability: the ratio of an insurer company's insurance underwriting profit to their insurance liabilities. The sample includes firm-level data for 3311 Property & Casualty (P&C) insurers over the period Q1 2001 to Q1 2022, with a total of 47,125 observations.

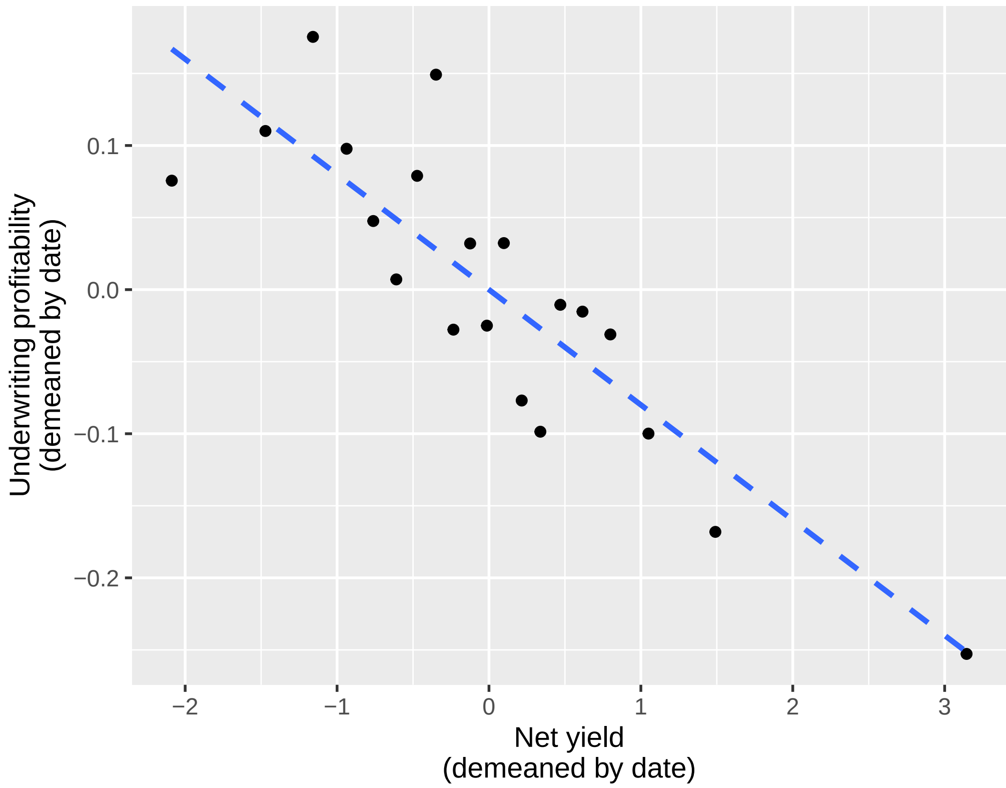


**Figure 3: The cross-sectional relationship between expected investment returns and insurance prices for different rating groups.** This figure displays the estimated $\beta_{j,ny}$-coefficients from two different specifications for the regression equation:

$$u_{it+1} = \sum_j \beta_{j,ny} \cdot \textit{Net yield}_{it} \cdot \mathbb{1}_{i \in \textit{Rating Group } j} + \sum_j \delta_j^T \cdot Z_{it} \cdot \mathbb{1}_{i \in \textit{Rating Group } j} + FE_t + FE_{\textit{Rating Group } j} + \epsilon_{it}$$

corresponding to the first two columns of Table 5. $u_{it}$ is the underwriting profitability for insurer $i$ at time $t$, $\textit{Net yield}_{it}$ is the insurer's net yield, $\mathbb{1}_{i \in \textit{Rating Group } j}$ is an indicator variable that is equal to one if insurer $i$ is in rating group $j \in \{$"A++ to A+", "A to A-", "B++ to B-", "C++ to D"$\}$, and $Z_{it}$ is a vector of controls for insurer $i$'s balance sheet strength and reinsurance activity at time $t$ (*Capital Ratio*, *Unearned Premium Ratio*, and *Reinsurance Ratio*). Confidence intervals are calculated using standard errors clustered by date and firm.

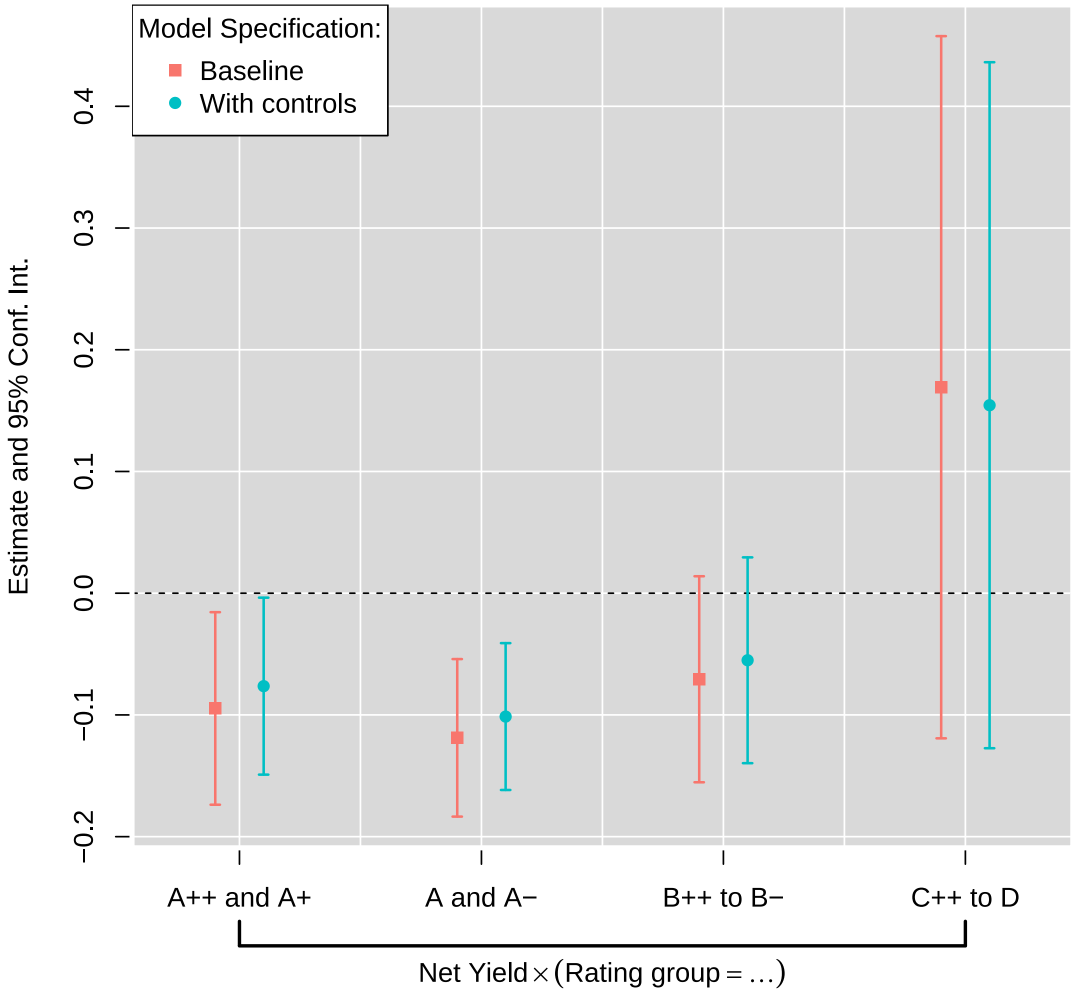


**Table 1: Summary statistics**

This table presents summary statistics of the variables used in the empirical analysis. The life insurance data covers 96 insurers with biannual observations from 1989 through 2011 (Koijen and Yogo (2015)) and the data on P&C insurance data covers 871 insurance groups with quarterly observations from March 2001 through March 2022. The financial market and macroeconomic variables are available at monthly frequencies. Variables are reported in percent with the exception of the balance sheet ratios and size, which is the log of total assets.

| | | | | Percentile | | | | |
|---|---|---|---|---|---|---|---|---|
| | N | Mean | SD | 5th | 25th | 50th | 75th | 95th |
| *Life Insurer Prices* | | | | | | | | |
| Life Annuities Markups | 13,675 | 1.0 | 1.1 | −0.5 | 0.4 | 1.0 | 1.6 | 2.9 |
| Guarantee Annuity Markups | 16,469 | 0.5 | 0.7 | −0.6 | 0.0 | 0.5 | 0.9 | 1.7 |
| Fixed Term Annuity Markups | 2,927 | 1.1 | 1.2 | −0.4 | 0.4 | 1.0 | 1.8 | 3.1 |
| *P&C Insurer Prices* | | | | | | | | |
| Underwriting Profitability | 47,125 | 0.3 | 3.0 | −4.9 | −1.1 | 0.2 | 1.7 | 5.7 |
| Volatility of Underwriting Prof. | 20,889 | 1.8 | 1.0 | 0.5 | 1.0 | 1.7 | 2.4 | 3.7 |
| *P&C Balance Sheet Variables* | | | | | | | | |
| Net Yield | 47,125 | 3.1 | 1.4 | 1.1 | 2.1 | 2.9 | 3.9 | 5.4 |
| Unearned Premium Ratio | 47,125 | 2.1 | 1.4 | 0.5 | 1.6 | 2.0 | 2.3 | 3.8 |
| Reinsurance Ratio | 47,125 | −1.1 | 9.9 | −2.7 | 0.0 | 0.1 | 0.3 | 0.8 |
| Capital Ratio | 47,125 | 10.9 | 9.3 | 3.3 | 5.7 | 8.5 | 12.7 | 26.2 |
| Size | 47,125 | 19.2 | 2.0 | 16.4 | 17.7 | 19.0 | 20.4 | 22.7 |
| *P&C Investment Allocation* | | | | | | | | |
| Cash Allocation | 20,313 | 7.0 | 8.3 | 0.8 | 2.4 | 4.5 | 8.4 | 22.1 |
| Bond Allocation (Non-gvt.) | 20,877 | 47.9 | 18.6 | 11.7 | 36.0 | 50.4 | 61.1 | 75.1 |
| Risk Weighted Bond Allocation | 20,365 | 0.9 | 20.2 | −21.7 | −12.2 | −3.7 | 8.5 | 39.6 |
| *Financial Market and Macroeconomic Variables* | | | | | | | | |
| Credit Spread (Moody's BAA) | 270 | 2.2 | 0.8 | 1.5 | 1.7 | 2.0 | 2.6 | 3.4 |
| Treasury Yield (10 year) | 270 | 5.5 | 1.6 | 3.2 | 4.2 | 5.4 | 6.7 | 8.4 |
| Slope (10 year - 2 year) | 270 | 1.1 | 1.0 | −0.2 | 0.2 | 0.9 | 2.0 | 2.6 |
| US Unemployment Rate | 270 | 5.9 | 1.5 | 4.1 | 4.7 | 5.5 | 6.6 | 9.5 |
| TED Spread | 270 | 0.6 | 0.4 | 0.2 | 0.3 | 0.5 | 0.7 | 1.3 |
| Excess Bond Premium | 270 | 0.1 | 0.7 | −0.6 | −0.3 | 0.0 | 0.4 | 1.4 |
| Default Spread | 270 | 2.0 | 0.7 | 1.1 | 1.5 | 2.0 | 2.4 | 3.1 |

## Table 2: Investment returns and the time series of prices: life insurance

This table presents the time series relation between life insurance prices, as measured by the annualized markups, and expected returns as measured by credit spreads. Columns 1, 2, and 3 report the parameter estimates from the following regression:

$$\bar{m}_t = \beta_c \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot CS_t \cdot \mathbb{1}_{GFC} + \delta^T X_t + \epsilon_t$$

where $\bar{m}_t$ is the average (annualised) markup across insurers and subproducts at time $t$. $CS_t$ is Moody's credit spread of BAA-rated corporate bonds yields over 10-year Treasuries, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (September 2008 through December 2009). $X_t$ is a vector of time series controls: the 10-year Treasury rate, the slope of the Treasury yield curve (10-year - 2-year Treasury yields), the TED spread, and the US unemployment rate. Columns 4 and 5 present the results of estimating the model in a full panel with fixed effects:

$$m_{ikt} = \beta_{CS} \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{csGFC} \cdot CS_t \cdot \mathbb{1}_{GFC} + \delta^T X_t + FE_i + FE_k + \epsilon_{ikt}$$

where $m_{ikt}$ is the annualised markup set by insurer $i$ at time $t$ for an annuity which is in sub-product $k$. Sub-products vary depending on age, sex, and maturity of the annuities. Panel A, B and C show the results for markups on life, guarantee and fixed-term annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. The t-statistics in columns 1-3 are calculated using Newey and West (1987) standard errors with 4 lags. The t-statistics in columns 4 and 5 are calculated standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

**Panel A: Life Annuity Markups and Credit Spreads**

| Dependent Variable: | Markup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Credit Spread (Moody's BAA) | -0.525*** | -0.444*** | -0.657*** | -0.467*** | -0.700*** |
| | (-9.75) | (-8.21) | (-4.91) | (-8.85) | (-8.49) |
| $\mathbb{1}_{GFC}$ | | | -0.843 | | -1.06*** |
| | | | (-1.32) | | (-2.91) |
| $\mathbb{1}_{GFC}$ × Credit Spread (Moody's BAA) | | | 0.293* | | 0.349*** |
| | | | (1.93) | | (3.54) |
| *Controls:* | | | | | |
| Time series controls | | Yes | Yes | Yes | Yes |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 73 | 73 | 73 | 13,675 | 13,675 |
| $R^2$ | 0.720 | 0.847 | 0.862 | 0.746 | 0.754 |
| Within $R^2$ | | | | 0.412 | 0.429 |

*[table continued on next page...]*

**Panel B: Guarantee Annuity Markups and Credit Spreads**

| Dependent Variable: | Markup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Credit Spread (Moody's BAA) | -0.449*** | -0.370*** | -0.589*** | -0.433*** | -0.700*** |
| | (-8.80) | (-7.32) | (-6.63) | (-7.40) | (-9.41) |
| $\mathbb{1}_{GFC}$ | | | -0.889** | | -1.26*** |
| | | | (-2.04) | | (-4.42) |
| $\mathbb{1}_{GFC}$ × Credit Spread (Moody's BAA) | | | 0.292** | | 0.401*** |
| | | | (2.64) | | (4.74) |
| *Controls:* | | | | | |
| Time series controls | | Yes | Yes | Yes | Yes |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 54 | 54 | 54 | 16,469 | 16,469 |
| $R^2$ | 0.768 | 0.859 | 0.879 | 0.729 | 0.750 |
| Within $R^2$ | | | | 0.524 | 0.560 |

**Panel C: Fixed-Term Annuity Markups and Credit Spreads**

| Dependent Variable: | Markup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Credit Spread (Moody's BAA) | -0.808*** | -0.632*** | -0.854*** | -0.460*** | -0.619*** |
| | (-5.76) | (-2.93) | (-4.29) | (-3.77) | (-5.78) |
| $\mathbb{1}_{GFC}$ | | | -1.72** | | -1.14** |
| | | | (-2.54) | | (-2.50) |
| $\mathbb{1}_{GFC}$ × Credit Spread (Moody's BAA) | | | 0.604*** | | 0.389** |
| | | | (2.70) | | (2.62) |
| *Controls:* | | | | | |
| Time series controls | | Yes | Yes | Yes | Yes |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 46 | 46 | 46 | 2,927 | 2,927 |
| $R^2$ | 0.642 | 0.792 | 0.823 | 0.736 | 0.742 |
| Within $R^2$ | | | | 0.285 | 0.300 |

## Table 3: Investment returns and the time series of prices: P&C Insurance

This table presents the time series relation between P&C insurance prices, as measured by underwriting profitability, and expected returns as measured by credit spreads. Columns 1, 2, and 3 report the parameter estimates from the following regression:

$$\bar{u}_{t+1} = \beta_c \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot CS_t \cdot \mathbb{1}_{GFC} + \delta^T X_t + \epsilon_{t+1}$$

where $\bar{u}_t$ is the average underwriting profitability across insurers and subproducts at time $t$. $CS_t$ is Moody's credit spread of BAA-rated corporate bonds yields over 10-year Treasuries averaged over the previous four quarters from $t-3$ to $t$. $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (September 2008 through December 2009). $X_t$ is a vector of time series controls: the 10-year Treasury rate, the slope of the Treasury yield curve (10-year - 2-year Treasury yields), the TED spread, and the US unemployment rate, all of which are measured as one-year rolling averages. Columns 4 and 5 present the results of estimating the model in a full panel with fixed effects:

$$u_{it+1} = \beta_{CS} \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{csGFC} \cdot CS_t \cdot \mathbb{1}_{GFC} + \delta^T X_t + FE_i + FE_k + \epsilon_{ikt}$$

where $u_{it}$ is the underwriting profitability of insurer $i$ at time $t$. The sample consists of quarterly observations from March 2001 through March 2022. The t-statistics in columns 1-3 are calculated using Newey and West (1987) standard errors with 4 lags. The t-statistics in columns 4 and 5 are calculated standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

| Dependent Variable: | Underwriting Profitability | | | | |
|---|---|---|---|---|---|
| | $\bar{u}_{t+1}$ | | | $u_{it+1}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Credit Spread (Moody's BAA) | -0.364*** | -0.619*** | -0.803*** | -0.616*** | -0.829*** |
| | (-2.74) | (-2.89) | (-3.45) | (-4.05) | (-5.52) |
| Treasury Yield (10 year) | | -0.194** | -0.167** | -0.125* | -0.101 |
| | | (-2.02) | (-2.02) | (-1.88) | (-1.65) |
| US Unemployment Rate | | -0.048 | -0.034 | -0.060 | -0.044 |
| | | (-0.775) | (-0.550) | (-1.21) | (-0.881) |
| TED Spread | | 0.690*** | -0.024 | 0.647*** | -0.141 |
| | | (2.87) | (-0.074) | (2.93) | (-0.483) |
| Slope (10 year - 2 year) | | 0.222 | 0.168 | 0.248** | 0.192* |
| | | (1.24) | (1.18) | (1.99) | (1.76) |
| $\mathbb{1}_{GFC}$ | | | -0.880 | | -0.907 |
| | | | (-1.36) | | (-1.09) |
| $\mathbb{1}_{GFC}$ × Credit Spread (Moody's BAA) | | | 0.528*** | | 0.567** |
| | | | (2.71) | | (2.63) |
| Constant | 1.25*** | 2.25*** | 2.83*** | | |
| | (3.71) | (3.86) | (4.30) | | |
| *Controls:* | | | | | |
| Time series controls | | Yes | Yes | Yes | Yes |
| Entity FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 85 | 85 | 85 | 47,125 | 47,125 |
| $R^2$ | 0.142 | 0.282 | 0.349 | 0.208 | 0.211 |
| Within $R^2$ | | | | 0.013 | 0.017 |

**Table 4: Funding stability and investment risk: P&C Insurance**

This table presents results of the following panel regression:

$$y_{it} = \beta_{vol} \cdot Volatility_{i,t-1} + \delta^T Z_{i,t-1} + FE_{Rating_i} + FE_t + \epsilon_{it}$$

where $y_{it}$ is either insurer $i$'s cash allocation at time $t$ (columns 1-2), insurer $i$'s bond allocation (non-government) at time $t$ (columns 3-4), or insurer $i$'s risk-weighted bond allocation at time $t$ (columns 5-6), all measured percent. $Volatility_{i,t-1}$ denotes the 4-year rolling volatility of insurer $i$'s underwriting profitability up to, and including, time $t-1$. $Z_{it}$ is vector of controls designed to capture the strength of insurer $i$'s balance sheet: the capital ratio, the ratio of unearned premia, and the reinsurance ratio. $FE_t$ and $FE_{Rating_i}$ capture time and rating fixed effects, respectively. *Risk* is the normalized credit rating of the insurer's credit portfolio as assigned by the insurance regulator, NAIC. $t$-statistics are reported in the brackets and are calculated using standard errors clustered by date and firm. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

| Dependent Variables: | Cash Allocation | | Bond Allocation | | Bond Allocation × Risk | |
|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) |
| *Variables* | | | | | | |
| Volatility of Underwriting Prof. | 1.19*** | 0.731*** | -1.18* | -1.58** | -3.13*** | -2.82*** |
| | (4.88) | (3.04) | (-1.77) | (-2.29) | (-5.55) | (-5.10) |
| Capital Ratio | | 0.0009 | | 0.003*** | | -0.001 |
| | | (1.66) | | (2.84) | | (-1.66) |
| Unearned Premium | | 0.074 | | 0.636 | | 0.581 |
| | | (0.524) | | (1.63) | | (0.941) |
| Reinsurance Ratio | | 0.004 | | 0.103* | | -0.020 |
| | | (0.311) | | (1.77) | | (-0.646) |
| *Controls:* | | | | | | |
| Date FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | | Yes | | Yes | | Yes |
| *Fit statistics* | | | | | | |
| Observations | 20,313 | 20,313 | 20,877 | 20,877 | 20,365 | 20,365 |
| $R^2$ | 0.028 | 0.070 | 0.020 | 0.056 | 0.116 | 0.127 |
| Within $R^2$ | 0.020 | 0.018 | 0.004 | 0.022 | 0.026 | 0.028 |

## Table 5: Investment returns and the cross-section of prices: P&C Insurance

This table presents the cross-sectional relationship between P&C insurance prices, measured by underwriting profitability, and firm-specific expected investment returns, measured by net yields. It reports the parameter estimate from the following panel regression:

$$u_{it+1} = \beta_{ny} \cdot Net\ yield_{it} + \delta^T Z_{it} + \beta_{nyGFC} \cdot Net\ yield_{it} \cdot \mathbb{1}_{GFC} + \delta^T_{zGFC} Z_{it} \cdot \mathbb{1}_{GFC} + FE_{Rating_i} + FE_t + \epsilon_{it}$$

where $u_{it}$ is the underwriting profitability for insurer $i$ at time $t$ and $Net\ yield_{it}$ is the insurer's net yield. $\mathbb{1}_{GFC}$ is an indicator variable set to one over the Global Financial Crisis (September 2008 through December 2009). $Z_{it}$ is a vector of controls for insurer $i$'s balance sheet strength and reinsurance activity at time $t$: *Capital Ratio* is the risk based capital ratio reported by the insurers themselves, *Unearned Premium Ratio* is the ratio of unearned premiums to net premiums earned, and *Reinsurance Ratio* is the ratio of net reinsurance premiums to direct premiums written. In column 5, we rerun the regression in a sample with underwriting returns measured at the state-insurance line level. The data for this regression is described in the main text. The insurer level sample consists of quarterly observations from Q1 2001 through Q1 of 2022. The state/insurance line sample consists of annual observations over the same period. $t$-statistics are reported in bracket and calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

| Dependent Variable: | Underwriting Profitability | | | | |
|---|---|---|---|---|---|
| Sample: | Insurer level | | | | State-Line |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Net Yield | -0.082*** | -0.067*** | -0.065** | -0.081*** | -0.056*** |
| | (-3.01) | (-2.66) | (-2.57) | (-3.24) | (-3.57) |
| Capital Ratio | | 0.0006*** | 0.0006*** | 0.0005*** | 0.0002*** |
| | | (10.9) | (10.8) | (9.76) | (4.31) |
| Unearned Premium | | -0.013 | -0.016 | -0.022 | $-7.13 \times 10^{-6}$*** |
| | | (-0.385) | (-0.465) | (-0.611) | (-5.64) |
| Reinsurance Ratio | | $-7.75 \times 10^{-5}$ | $1.3 \times 10^{-5}$ | 0.001 | $6.24 \times 10^{-9}$*** |
| | | (-0.038) | (0.006) | (0.498) | (20.2) |
| $\mathbb{1}_{GFC}$ × Net Yield | | | -0.026 | -0.034 | 0.002 |
| | | | (-0.809) | (-1.11) | (0.100) |
| $\mathbb{1}_{GFC}$ × Capital Ratio | | | $-8.84 \times 10^{-5}$ | $-9.57 \times 10^{-5}$ | $-6.98 \times 10^{-5}$ |
| | | | (-0.924) | (-1.05) | (-0.974) |
| $\mathbb{1}_{GFC}$ × Unearned Premium | | | 0.034 | 0.030 | -0.030 |
| | | | (0.593) | (0.532) | (-0.829) |
| $\mathbb{1}_{GFC}$ × Reinsurance Ratio | | | -0.002 | -0.002 | $-4.09 \times 10^{-5}$*** |
| | | | (-0.396) | (-0.362) | (-9.62) |
| *Controls:* | | | | | |
| Date FE | Yes | Yes | Yes | Yes | |
| Rating FE | | | | Yes | Yes |
| Date×State×Insurance Line FE | | | | | Yes |
| *Fit statistics* | | | | | |
| Observations | 47,125 | 47,125 | 47,125 | 47,125 | 831,077 |
| $R^2$ | 0.043 | 0.074 | 0.074 | 0.084 | 0.065 |
| Within $R^2$ | 0.001 | 0.033 | 0.033 | 0.026 | 0.014 |

**Table 6: Funding stability, investment returns, and insurance prices: A two-step estimation**

This table presents the cross-sectional relationship between P&C insurance prices and the part of insurers' expected returns driven by stable funding. Columns 1 and 3 decomposes the net yield by regressing it on the stability on insurance underwriting:

$$Net\ yield_{it} = \kappa \cdot Volatility_{i,t-1} + \delta_1^T Z_{it} + FE_{Rating_i} + FE_t + \xi_{it} \qquad \text{(first step)}$$

where $Net\ yield_{it}$ is the net yield of insurer $i$ at time $t$ and $Volatility_{i,t-1}$ is the 4-year rolling standard deviation of insurer $i$'s underwriting profitability up to, and including, time $t-1$. Columns 2 and 4 present the results of the regression:

$$u_{it+1} = \beta_{\widehat{ny}} \cdot \widehat{Net\ yield}_{it} + \beta_{res} \cdot \xi_{it} + \delta_2^T Z_{it} + FE_{Rating_i} + FE_t + \epsilon_{it} \qquad \text{(second step)}$$

where $u_{it}$ is the underwriting profitability for insurer $i$ at time $t$, $\widehat{Net\ yield}_{it}$ is the estimated net yield from the first step regression, and $\xi_{it}$ is the residual from the first step regression. $t$-statistics are reported in bracket and calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

| | Baseline specification | | With controls | |
|---|---|---|---|---|
| Estimation: | First step | Second step | First step | Second step |
| Dependent Variables: | Net Yield | Underwriting Prof. | Net Yield | Underwriting Prof. |
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Volatility of Underwriting Prof. | -0.196*** | | -0.169*** | |
| | (-6.76) | | (-6.17) | |
| $\widehat{Net\ Yield}_{it}$ | | -0.677** | | -0.686** |
| | | (-2.58) | | (-2.29) |
| $Residual_{it}$ | | -0.048 | | -0.057** |
| | | (-1.52) | | (-2.01) |
| Capital Ratio | | | $-3.89 \times 10^{-5}$ | 0.0005*** |
| | | | (-1.08) | (5.07) |
| Unearned Premium | | | -0.007 | 0.005 |
| | | | (-0.301) | (0.125) |
| Reinsurance Ratio | | | -0.007** | -0.004 |
| | | | (-2.15) | (-1.31) |
| *Controls:* | | | | |
| Date FE | Yes | Yes | Yes | Yes |
| Rating FE | | | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 20,889 | 20,889 | 20,889 | 20,889 |
| $R^2$ | 0.263 | 0.047 | 0.272 | 0.097 |
| Within $R^2$ | 0.030 | 0.003 | 0.028 | 0.028 |

# Internet Appendix for "Insurers' Investments and Insurance Prices"

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This Internet Appendix is organized as follows:

# A Proofs of Theoretical Results

## A.1 Proofs of Theorems

### Proof of Theorem 1

We have defined the lower bound on insurer $i$'s optimal asset allocation in equation (13). By a similar logic we can also define an upper bound. To see this, note that $\tau_i = \bar{\tau} - \sigma_i$ is the minimum fraction of claims that will arrive early. Each insurer therefore knows they will be forced to sell at least $(\bar{\tau} - \sigma_i) C_i$ of assets at time 1. They optimally hold at least this amount in liquid assets, which leads to the following definition

$$\overline{\Theta}_i = L_i - \frac{(\bar{\tau} - \sigma_i) C_i}{1 + R^F} \tag{28}$$

Investing $\Theta_i > \overline{\Theta}_i$ would mean insurer $i$ pays sales costs on illiquid assets of amount $\Theta_i - \overline{\Theta}_i$ with no expectation of earning the liquidity premia $R^A$. The key implication of the upper bound $\overline{\Theta}_i$ is that each insurer does not sell illiquid assets when $\tau = \bar{\tau} - \sigma$ realizes. We can therefore restate insurer $i$'s wealth in two cases depending on the fraction $\tau_i$ of claims arriving early

$$W_i = \begin{cases} L_i \left(1 + R^F\right) - C_i + \Theta_i R^A & \text{if } \tau_i = \bar{\tau} - \sigma_i \\ L_i \left(1 + R^F\right) - C_i + \underline{\Theta}_i R^A - \frac{1}{2}\lambda \left(\Theta_i - \underline{\Theta}_i\right)^2 \left(1 + R^F\right)^2 & \text{if } \tau_i = \bar{\tau} + \sigma_i \end{cases} \tag{29}$$

with both cases occurring with equal probability. The first case shows the simple outcome where insurer $i$ holds enough liquid assets to cover early claims. In the second case, insurer $i$ sells all liquid asset holdings, worth $(L_i - \Theta_i)\left(1 + R^F\right)$ at $t = 1$, plus a portion of their illiquid asset portfolio to cover remaining $t = 1$ claims. Specifically, dollar amount $(\bar{\tau} + \sigma_i) C_i - (L_i - \Theta_i)\left(1 + R^F\right)$ of illiquid assets are sold early. Substituting the lower bound of insurer $i$'s illiquid asset allocation in equation (13) the sold illiquid assets can be restated $(\Theta_i - \underline{\Theta}_i)\left(1 + R^F\right)$. The present ($t = 0$) residual value of this is, $\underline{\Theta}_i$, with these illiquid assets held to maturity and earning insurer $i$ the liquidity premia $R^A$.

Each insurers objective function, as described in equation (8), can therefore be restated

$$\max_{P_i,\, \Theta_i} \; L_i \left(1 + R^F\right) - C_i + \frac{1}{2}\left(\Theta_i + \underline{\Theta}_i\right) R^A - \frac{1}{4}\lambda \left(\Theta_i - \underline{\Theta}_i\right)^2 \left(1 + R^F\right)^2 \tag{30}$$

subject to the capital constraint in equation (7).

Assuming each insurer takes the illiquid asset return $R^A$ as fixed, the first-order condition for the illiquid asset dollar investment is

$$0 = \frac{1}{2}R^A - \frac{1}{2}\lambda \left(\Theta_i - \underline{\Theta}_i\right)\left(1 + R^F\right)^2 \tag{31}$$

and thus the optimal solution $\Theta_i^*$ in equation (12) follows.[33] ■

**Proof of Theorem 2**

The proof is shown with each insurer facing a generalised convex cost function of selling illiquid assets where each insurer pays $\lambda f(x)$ dollar for every $x$ dollar sold of the illiquid asset, where $f'(x) > 0$ and $f''(x) > 0$. The generalised version of the insurer's objective function (30) is thus

$$\max_{P_i,\, \Theta_i} \; L_i \left(1 + R^F\right) - C_i + \frac{1}{2}\left(\Theta_i + \underline{\Theta}_i\right) R^A - \frac{1}{2}\lambda f\left(x_i\right) \tag{32}$$

subject to the capital constraint in equation (7) where $x_i = \left(\Theta_i - \underline{\Theta}_i\right)\left(1 + R^F\right)$ is the dollar amount of illiquid assets sold.

For intuition, we begin the proof assuming the capital constraint is non-binding. The first-order condition with respect the illiquid asset allocation $\Theta_i$ is

$$0 = \frac{1}{2}R^A - \frac{1}{2}\lambda f'\left(x_i\right)\left(1 + R^F\right) \quad \Leftrightarrow \quad R^A = \lambda f'\left(x_i\right)\left(1 + R^F\right), \tag{33}$$

where we have used the chain rule and assumed each insurer $i$ treats the illiquid asset return $R^A$ as independent to their investment choice (Stein, 2012). The right hand side condition in equation (33) shows that in equilibrium the marginal benefit $R^A$ of an extra dollar of illiquid investment is equal to the marginal cost $\lambda f'\left(x_i\right)\left(1 + R^F\right)$ of an extra dollar of illiquid investment.

Meanwhile, for a fixed illiquid asset allocation, the first-order condition for the objective function in equation (32) with respect to the insurance price, $P_i$, is

$$0 = \frac{\partial L_i}{\partial P_i}\left(1 + R^F\right) - \frac{\partial C_i}{\partial P_i} + \frac{1}{2}\frac{\partial \underline{\Theta}_i}{\partial P_i}R^A + \frac{1}{2}\lambda f'\left(x_i\right)\left(1 + R^F\right)\frac{\partial \underline{\Theta}_i}{\partial P_i}. \tag{34}$$

Using the envelope theorem, we now substitute in condition (33) from insurer $i$'s optimal illiquid asset decision and simplify to

$$0 = \frac{\partial L_i}{\partial P_i}\left(1 + R^F\right) - \frac{\partial C_i}{\partial P_i} + \frac{\partial \underline{\Theta}_i}{\partial P_i}R^A. \tag{35}$$

This equation shows the key theoretical insight that the only impact of the illiquid asset excess return $R^A$ on the optimal insurance price comes via the last term, which is the

[33] The solution holds for any required return on insurer equity providing that the required return is independent of the insurer's asset allocation decision. We have this in this model due to risk neutral investors. However, it would hold in any model with a flat security market line.

return earned on the lower bound of the investment in the illiquid asset $\underline{\Theta}_i$. Recall, these are the assets insurer $i$ knows with certainty it will not be forced to sell at $t = 1$.

Substitute the lower bound of the illiquid asset allocation, equation (13), into equation (35) to show

$$0 = \frac{\partial L_i}{\partial P_i}\left(1 + R^F + R^A\right) - \frac{\partial C_i}{\partial P_i}\frac{\left(1 + R^F + (\bar{\tau} + \sigma_i) R^A\right)}{1 + R^F} \tag{36}$$

and rearrange to solve the equilibrium insurance price without capital constraints

$$P_i^* = \frac{\bar{C}}{1 + R^F}\frac{\varepsilon}{\varepsilon - 1}\frac{1}{1 + R_i^P} \tag{37}$$

using the elasticity of demand for insurance as defined in equation (10).

We now introduce the capital constraint in equation (7). The Lagrangian for insurer $i$'s optimisation problem subject to this constraint is

$$\mathcal{L}\left(P_i, \Theta_i, \eta_i\right) = W_i + \eta_i\left(L_i - \frac{C_i}{1 + R^S}\phi^{-1}\right) \tag{38}$$

where $C_i = I_i\bar{C}$. The first order condition with respect to the insurance price is

$$0 = \frac{\partial L_i}{\partial P_i}\left(1 + R^F + R^A + \eta_i\right) - \frac{\partial C_i}{\partial P_i}\frac{\left(1 + R^F + (\bar{\tau} + \sigma_i) R^A + \eta_i\frac{1+R^F}{\phi(1+R^S)}\right)}{1 + R^F} \tag{39}$$

which can be written

$$0 = -(\epsilon - 1)I_i\left(1 + R^F + R^A + \eta_i\right) + \epsilon\frac{I_i}{P_i}\frac{\bar{C}}{1 + R^F}\left(1 + R^F + (\bar{\tau} + \sigma_i) R^A + \eta_i\frac{1 + R^F}{\phi(1 + R^S)}\right) \tag{40}$$

and further rearranged to

$$P_i = \frac{\bar{C}}{1 + R^F}\left(\frac{\varepsilon}{\varepsilon - 1}\right)\frac{1 + R^F + (\bar{\tau} + \sigma_i) R^A + \frac{\eta_i(1+R^F)}{\phi(1+R^S)}}{1 + R^F + R^A + \eta_i} \tag{41}$$

$$= \frac{\bar{C}}{1 + R^F}\left(\frac{\varepsilon}{\varepsilon - 1}\right)\frac{1}{1 + R_i^P}\frac{1 + R^F + (\bar{\tau} + \sigma_i) R^A + \frac{\eta_i(1+R^F)}{\phi(1+R^S)}}{\left(\frac{1+R^F+R^A}{1+R_i^P} + \frac{\eta_i}{1+R_i^P}\right)} \tag{42}$$

and substitute in $1 + R_i^I$, as defined in equation (15), to the left hand side of the denominator in the final term to arrive at the formula show in equation (14) where

$$\Gamma_i(\phi) = \frac{1 + R^F + (\bar{\tau} + \sigma_i) R^A + \frac{\eta_i(1+R^F)}{\phi(1+R^S)}}{1 + R^F + (\bar{\tau} + \sigma_i) R^A + \frac{\eta_i}{(1+R_i^P)}} \tag{43}$$

is the shadow cost of capital. Note that when the insurer is unconstrained with $\eta_i = 0$ then $\Gamma_i(\phi) = 1$ and the insurance price is as set out in equation (37). ■

## A.2 Proofs of Propositions

Before proving the propositions, we first establish equilibrium conditions in the asset market.

### Asset market equilibrium

As all investors are *ex-ante* identical at time $t = 0$, we consider a representative investor with mass one optimising the objective function in equation (2). The first-order condition with respect to the investor's illiquid asset allocation is

$$0 = (1 - \omega) R^A - \omega\lambda\theta \left(1 + R^F\right)^2 \tag{44}$$

from which the equilibrium optimal allocation

$$\theta^* = \frac{(1 - \omega)}{\omega} \frac{R^A}{\lambda} \alpha \tag{45}$$

follows. Now insert the investors' optimal asset demand and the total optimal demand from insurers, $\Theta^* = \int_0^1 \Theta_i^*$, with $\Theta_i^*$ defined in equation (12), into the market clearing condition for the illiquid asset defined in equation (11):

$$S = \frac{(1 - \omega)}{\omega} \frac{R^A}{\lambda} \alpha + \underline{\Theta} + \frac{R^A}{\lambda} \alpha \tag{46}$$

and rearrange to define the equilibrium illiquid asset excess return as

$$R^A = \frac{\omega\lambda}{\alpha} S^* \tag{47}$$

where $S^* = S - \underline{\Theta}$ is the total supply of the illiquid asset adjusted for the minimum illiquid asset allocation from the insurance industry, $\underline{\Theta} = \int_0^1 \underline{\Theta}_i \, di$.

Intuitively, the excess return on the illiquid asset is increasing in the demand for liquidity from investors, $\omega$, the cost of selling the illiquidvasset in secondary markets, $\lambda$, and the supply of the asset, $S$. The insurance market affects the illiquid asset return via the minimum illiquid asset allocation aggregated across all insurers, $\underline{\Theta}$, which is an endogenous function of insurance prices that are determined in equilibrium and, as shown below, depend on the excess return itself. Because of the minimum allocation, the insurance market absorbs at least $\underline{\Theta}$ of the total supply of the illiquid asset, which reduces the supply for other investors and therefore reduces the excess return.

**Proof of Proposition 1**

For ease of notation, define the actuarial price as $C^A = \bar{C}/(1 + R^F)$, the markup $M = \varepsilon/(\varepsilon - 1)$, and the maximum fraction of insurer $i$'s claims arriving early $a_i = \bar{\tau} + \sigma_i$. The equilibrium insurance price is thus:

$$P_i = C^A M \frac{1 + R^F + a_i R^A}{1 + R^F + R^A} \tag{48}$$

and we see that insurer $i$'s price is decreasing in expected return on the illiquid asset:

$$\frac{\partial P_i}{\partial R^A} = C^A M \frac{\left(1 + R^F + R^A\right) a_i - \left(1 + R^F + a_i R^A\right)}{\left(1 + R^F + R^A\right)^2} \tag{49}$$

$$= C^A M \frac{\left(1 + R^F\right)(a_i - 1)}{\left(1 + R^F + R^A\right)^2} < 0 \tag{50}$$

if $a_i < 1$, i.e. if the insurer has some degree of stable funding. If the insurer does not have stable funding, $a_i = 1$, the price of insurance becomes independent of the expected excess return on the illiquid asset. From the definition of the average insurance price, $\bar{P} = \int_{i=0}^{1} P_i \, di$, it follows that $\frac{\partial \bar{P}}{\partial R^A} < 0$.

To prove proposition 1, we therefore need to show that the expected excess return on the illiquid asset is increasing in the transaction cost of selling the asset early (i.e. $\frac{\partial R^A}{\partial \lambda} > 0$).[34] From the asset market equilibrium defined in equation (47), the first derivative of the equilibrium return with respect to $\lambda$ is:

$$\frac{\partial R^A}{\partial \lambda} = \omega \left( S - \underline{\Theta} - \lambda \frac{\partial \underline{\Theta}}{\partial R^A} \frac{\partial R^A}{\partial \lambda} \right)$$

$$= \frac{\omega \left(S - \underline{\Theta}\right)}{1 + \lambda \omega \frac{\partial \underline{\Theta}}{\partial R^A}}. \tag{51}$$

Sufficient conditions for $\frac{\partial R^A}{\partial \lambda} > 0$ to hold are that both $S > \underline{\Theta}$ and $\frac{\partial \underline{\Theta}}{\partial R^A} > -\frac{1}{\omega \lambda}$. We focus on the model's interior solution ($S > \underline{\Theta}$), and therefore need to show latter condition: $\frac{\partial \underline{\Theta}}{\partial R^A} > -\frac{1}{\omega \lambda}$.[35]

[34] The proof can be applied interchangeably for shocks to either transaction costs in the illiquid asset market, $\lambda$, or to the demand for liquidity from other investors, $\omega$. We focus on $\lambda$ in our empirical setting and so use this variable in the proof below.

[35] The model has a corner solution where $S = \underline{\Theta}$. The insurance industry will not hold more illiquid assets than the total size of the illiquid asset market, otherwise the other investors in the model would be required to short the illiquid asset and thus the excess return would turn negative. However, a negative excess return means the risk-free asset dominates the illiquid asset, and thus insurers would fully allocate premiums to the risk-free asset in all cases where $R^A < 0$.

The partial derivative of the insurer $i$'s minimum illiquid allocation with respect to the excess return is

$$\frac{\partial \underline{\Theta}_i}{\partial R^A} = \frac{\partial I_i P_i}{\partial R^A} - a_i C^A \frac{\partial I_i}{\partial R^A}. \tag{52}$$

Next, note that $\frac{\partial I_i}{\partial R^A} = -\varepsilon \frac{I_i}{P_i} \frac{\partial P_i}{\partial R^A}$ and $\frac{\partial I_i P_i}{\partial R^A} = -(\epsilon - 1) I_i \frac{\partial P_i}{\partial R^A}$, and substitute in:

$$\frac{\partial \underline{\Theta}_i}{\partial R^A} = -(\varepsilon - 1) I_i \frac{\partial P_i}{\partial R^A} + a_i C^A \varepsilon \frac{I_i}{P_i} \frac{\partial P_i}{\partial R^A} \tag{53}$$

$$= \frac{I_i}{P_i} \frac{\partial P_i}{\partial R^A} \left( -(\varepsilon - 1) P_i + \varepsilon a_i C^A \right) \tag{54}$$

$$= (\varepsilon - 1) \frac{I_i}{P_i} \frac{\partial P_i}{\partial R^A} \left( -P_i + a_i C^A \frac{\varepsilon}{\varepsilon - 1} \right). \tag{55}$$

Given $\partial P_i / \partial R^A < 0$ and $\varepsilon - 1 > 0$, to show $\partial \underline{\Theta}_i / \partial R^A > -\frac{1}{\omega \lambda}$ it suffices to show that

$$P_i > \frac{\varepsilon}{\varepsilon - 1} a_i C^A \tag{56}$$

since we then have $\partial \underline{\Theta}_i / \partial R^A > 0 > -\frac{1}{\omega \lambda}$. This is easily shown by substituting $P_i$ into (56):

$$\frac{1 + R^F + a_i R^A}{1 + R^F + R^A} > a_i \Leftrightarrow 1 > a_i$$

which is true, except for the special case where the insurer has no funding advantage $a_i = 1$. As the condition holds for all individual insurers, then the minimum allocation to the illiquid asset from the insurance sector is also increasing in $R^A$, with $\partial \underline{\Theta} / \partial R^A > 0$, and thus we have shown $\frac{\partial R^A}{\partial \lambda} > 0$. We therefore have $\frac{\partial \bar{P}}{\partial \lambda} = \frac{\partial \bar{P}}{\partial R^A} \frac{\partial R^A}{\partial \lambda} < 0$ as required. ■

**Proof of Proposition 2 and Proposition 3**

Proposition 2 and 3 follow directly from Theorem 1 and Theorem 2 respectively. Differentiating equation (12) and equation (14) with respect to insurer $i$'s funding stability, $\sigma_i$, we immediately obtain the comparative statics shown in the propositions.

**Proof of Proposition 4**

This result follows straight from the insurer's shadow cost of capital $\Gamma_i$ defined in equation (43). The cases depend on whether

$$1 + (\bar{\tau} + \sigma_i) R^A + \frac{\eta_i (1 + R^F)}{\phi (1 + R^S)} > 1 + (\bar{\tau} + \sigma_i) R^A + \frac{\eta_i}{(1 + R_i^P)}$$

which simplifies to

$$\frac{1+R^F}{\phi(1+R^S)} > \frac{1}{1+R_i^P}$$

and thus to the cases set out in . ■

## A.3 Insurance Market Equilibrium.

Recall that our model has a continuum of risk-neutral insurance companies indexed by $i \in [0,1]$, where each insurer $i$ sets a price, $P_i$, to underwrite $I_i$ insurance contracts. A representative household seeks to maximise expected utility by consuming the insurance contracts as a composite good

$$I = \left(\int_0^1 I_i^{\frac{\varepsilon-1}{\varepsilon}}\, di\right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{57}$$

subject to a budget constraint. That is, the representative household maximises the insurance index, $I$, by deciding how to allocate total insurance expenditure, $\int_0^1 P_i I_i\, di$, across the different insurers. It can be shown (see Galí (2008)) that this maximisation problem results in the following demand equations:

$$\frac{I_i}{I} = \left(\frac{P_i}{P}\right)^{-\varepsilon} \tag{58}$$

for all $i \in [0,1]$, where $P = \left(\int_0^1 P_i^{1-\varepsilon}\, di\right)^{\frac{1}{1-\varepsilon}}$ is an aggregate insurance price index. Equation (58) shows that as insurer $i$ increases its price relative to other insurers, the household reduces its insurance contracts at insurer $i$ at the rate $\varepsilon$, the elasticity of substitution across insurers. The elasticity of demand facing each insurer, as presented in equation (10), is then derived from the partial derivative of equation (58) with respect to $P_i$.

# B Robustness Checks and Additional Empirical Results

## B.1 Robustness Checks for Table 4: *Asset Allocation Results*

This section provides two dimensions of robustness for Table 4. In Table B.1 we show that the results are robust to a variety of specifications for funding stability.

In Table B.2 we show that funding stability predicts asset allocations even after controlling for the size and rating of insurance companies. Specifically, at each date split the sample into three groups based on insurer size. For each size group we then predict the cross-sectional variation in insurers' risk-weighted bond allocation with underwriting stability (as in columns 5 and 6 of Table 4). As controls we include both insurer size, rating fixed effects, and the same vector of balance sheet variables as in Table 4. Columns 1 to 4 presents the results for small insurers, Columns 5 to 8 presents the results for medium-sized insurers, and columns 9 to 12 presents the results for large insurers. Comparing columns 1, 5, and 9, we find that the sensitivity of insurers' risk-weighted bond allocation to underwriting stability is strongest for the large and medium sized insurers. In fact, an increase in the standard deviation of underwriting volatility lowers risk-weighted bond allocation by more than twice as much for the largest insurers relative to smallest (for which the effect is statistically insignificant). In columns 2, 6, and 10, we include size as a control variable, and consistent with Ge and Weisbach (2021), see that larger firms tend to take more investment risk. This effect is however, only present among the largest insurers (column 10). Further, the effect of underwriting volatility on investment risk remains significant after the inclusion of size as a control variable. Finally, we see that our results are robust to the inclusion of the same vector of control variables as in Table 4, and that the effect is present when controlling rating fixed effects.

## Table B.1: Asset allocation and alternative measures of funding stability

This table reestimates the relationship between asset allocation and the stability of insurance underwriting estimated in Table 4 using alternative measures of funding stability. Specifically, we estimate the regression:

$$y_{it} = \beta_{vol} \cdot Volatility_{i,t-1} + FE_t + \epsilon_{it}$$

where $y_{it}$ is either insurer $i$'s cash allocation at time $t$ (columns 1-3), insurer $i$'s bond allocation (non-government) at time $t$ (columns 4-6), or insurer $i$'s risk-weighted bond allocation at time $t$ (columns 7-9), all measured percent. $Volatility_{i,t-1}$ denotes either the 2-year rolling volatility of insurer $i$'s underwriting profitability up to, and including, time $t-1$ (row 1), the 8-year rolling volatility of insurer $i$'s underwriting profitability up to, and including, time $t-1$ (row 2), or the full sample volatility of insurer $i$'s underwriting profitability (row 3). All specifications include time fixed effects $FE_t$ and controls for the insurers capital ratio, unearned premium ratio, and the reinsurance ratio. *Risk* is a normalized measure of the average credit rating of the insurer's credit portfolio as assigned by the insurance regulator, NAIC. $t$-statistics are reported in the brackets and are calculated using standard errors clustered by date and firm. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.



| Dependent Variables: | Cash Allocation | | | Bond Allocation | | | Bond Allocation × Risk | | |
|---|---|---|---|---|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| *Variables* | | | | | | | | | |
| Volatility of Underwriting Prof. (2 years) | 1.54*** | | | -2.05*** | | | -2.25*** | | |
| | (7.33) | | | (-3.91) | | | (-4.81) | | |
| Volatility of Underwriting Prof. (8 years) | | 0.956*** | | | -1.46 | | | -3.45*** | |
| | | (3.52) | | | (-1.58) | | | (-4.50) | |
| Volatility of Underwriting Prof. (Full sample) | | | 2.80*** | | | -2.86*** | | | -2.49*** |
| | | | (8.85) | | | (-4.80) | | | (-4.55) |
| *Controls:* | | | | | | | | | |
| Balance Sheet Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Date FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | | | |
| Observations | 29,607 | 9,828 | 46,074 | 30,307 | 10,163 | 45,343 | 29,383 | 9,985 | 43,265 |
| $R^2$ | 0.040 | 0.027 | 0.072 | 0.050 | 0.040 | 0.060 | 0.104 | 0.094 | 0.094 |
| Within $R^2$ | 0.032 | 0.020 | 0.064 | 0.026 | 0.034 | 0.030 | 0.020 | 0.045 | 0.021 |

## Table B.2: Sensitivity of investment risk to funding stability controlling for size

This table presents results of the following panel regression:

$$y_{it} = \beta_{vol} \cdot \mathit{Volatility}_{i,t-1} + \delta^T Z_{i,t-1} + \gamma \cdot \mathit{Size}_{i,t-1} + FE_t + FE_{\mathit{Rating}} + \epsilon_{it}$$

on three different subsamples based on the size of the insurance companies. $y_{it}$ is insurer $i$'s risk-weighted bond allocation at time $t$: *Bond Allocation*$\times$*Risk*, where *Risk* is a normalized measure of the average credit rating of the insurer's credit portfolio as assigned by the insurance regulator, NAIC. $\mathit{Volatility}_{i,t-1}$ denotes the 4-year rolling volatility of insurer $i$'s underwriting profitability up to, and including, time $t-1$. $Z_{it}$ is vector of controls designed to capture the strength of insurer $i$'s balance sheet: the capital ratio, the ratio of unearned premia, and the reinsurance ratio, $\mathit{Size}_{i,t}$ is the log of insurer $i$'s total assets at time $t$, $FE_t$ captures time fixed effects, and $FE_{\mathit{Rating}}$ captures fixed effects for the rating groups. $t$-statistics are reported in the brackets and are calculated using standard errors clustered by date and firm. *, **, and *** denote statistical significance at the 10%, 5% and 1% level, respectively.

| Dependent Variable: | Bond Allocation × Risk | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Size group: | *Small* | | | | *Medium* | | | | *Large* | | | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
| *Variables* | | | | | | | | | | | | |
| Volatility of Underwriting Prof. | -1.48 | -1.11 | -0.977 | -0.886 | -2.36** | -2.35** | -2.13** | -2.21** | -3.41** | -2.29** | -2.14* | -2.26** |
| | (-1.53) | (-1.19) | (-1.02) | (-0.905) | (-2.58) | (-2.41) | (-2.23) | (-2.21) | (-2.64) | (-2.04) | (-1.99) | (-2.10) |
| Size | | 1.71 | 1.41 | 1.70 | | 0.074 | -0.034 | 1.60 | | 4.66*** | 4.71*** | 6.28*** |
| | | (1.51) | (1.24) | (1.48) | | (0.026) | (-0.012) | (0.550) | | (3.36) | (3.35) | (4.41) |
| Capital Ratio | | | -0.002 | -0.001 | | | -0.0002 | 0.001 | | | -0.0005 | 0.0009 |
| | | | (-1.67) | (-1.19) | | | (-0.153) | (0.759) | | | (-0.382) | (0.686) |
| Unearned Premium | | | -0.477 | -0.280 | | | 1.30 | 1.15 | | | 0.641 | 0.219 |
| | | | (-1.02) | (-0.617) | | | (1.47) | (1.31) | | | (0.464) | (0.177) |
| Reinsurance Ratio | | | 0.020 | 0.036 | | | -0.028 | -0.011 | | | 0.052 | 0.049 |
| | | | (0.265) | (0.424) | | | (-0.367) | (-0.126) | | | (1.06) | (1.07) |
| *Controls:* | | | | | | | | | | | | |
| Date FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Rating FE | | | | Yes | | | | Yes | | | | Yes |
| *Fit statistics* | | | | | | | | | | | | |
| Observations | 6,814 | 6,814 | 6,814 | 6,814 | 6,788 | 6,788 | 6,788 | 6,788 | 6,763 | 6,763 | 6,763 | 6,763 |
| $R^2$ | 0.059 | 0.063 | 0.071 | 0.089 | 0.105 | 0.105 | 0.114 | 0.145 | 0.168 | 0.232 | 0.234 | 0.256 |
| Within $R^2$ | 0.007 | 0.012 | 0.020 | 0.016 | 0.011 | 0.011 | 0.021 | 0.026 | 0.017 | 0.093 | 0.095 | 0.119 |

## B.2 Robustness Checks for Table 2 and 3: *Time series results*

**Table B.3: Time series results with alternative measures of expected excess returns**

This table reestimates the time series regressions of Tables 2 and 3 with alternative measures of the expected excess return in the bond market. That is, we estimate the regression

$$y_t = \beta_c \cdot \textit{Exp. Ret.}_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot \textit{Exp. Ret.}_t \times \mathbb{1}_{GFC} + \delta^T X_t + \epsilon_t$$

where $y_t$ is either the average (annualised) markup across insurers and subproducts at time $t$ for Life insurance products or the average underwriting profitability across insurers and subproducts at time $t+1$ for P&C insurance. *Exp. Ret.*$_t$ captures different measures of the expected excess return in the corporate bonds market: 1. the spread of Moody's Seasoned AAA corporate bonds yields over 10-year constant maturity Treasuries, 2. the Option-Adjusted Spread of the ICE BofA Single-A US Corporate Index over Treasuries, 3. the spread of Moody's Seasoned BAA corporate bonds yields over 10-year constant maturity Treasuries (base line), 4. the Option-Adjusted Spread of the ICE BofA BBB US Corporate Index over Treasuries, 5. the Option-Adjusted Spread of the ICE BofA US Corporate Index (all IG bonds) over Treasuries, 6. the Gilchrist and Zakrajšek (2012) credit spread, 7. the Sørensen (2022) Yield-for-Risk, $\mathbb{1}_{GFC}$ is an indicator variable set to one during the global financial crisis (September 2008 through December 2009). $X_t$ is a vector of time series controls: the 10-year Treasury rate, the slope of the Treasury yield curve (10-year - 2-year Treasury yields), the TED spread, and the US unemployment rate, all of which are measured as one-year rolling averages. For regressions with Property and Casualty insurance the expected excess return and controls are averaged over the previous four quarters from $t-3$ to $t$. The sample of Life insurers consists of biannual observations from January 1989 through July 2011, and the sample of Property and Casualty insurers consists of quarterly observations from March 2001 through March 2022. The standard errors are reported in the parentheses and calculated using Newey and West (1987) standard errors with 4 lags. *, **, and *** indicate statistical significance at the 10%, 5% and 1%, respectively.
The first three columns provides the independent variable (the measure of expected excess return), the insurance sector, and the dependent variable for each specification. The next two columns provide the number of observations and the $R^2$. The last three columns provide the coefficient estimates.

| Illiquidity measure | Insurance type | Dependent variables | $N$ | $R^2$ | $Liq.\ Prem._t$ | $\mathbb{1}_{GFC}$ | $Liq.\ Prem._t \times \mathbb{1}_{GFC}$ |
|---|---|---|---|---|---|---|---|
| Credit Spread (Moody's AAA) | Fixed Term Annuity | Markup (annualized) | 46 | 0.75 | -0.714** (0.231) | -0.371 (1.47) | 0.192 (0.811) |
| Credit Spread (Moody's AAA) | Guarantee Annuity | Markup (annualized) | 54 | 0.83 | -0.576*** (0.119) | 0.134 (0.689) | -0.169 (0.308) |
| Credit Spread (Moody's AAA) | Life Insurance | Markup (annualized) | 73 | 0.80 | -0.559** (0.203) | 0.451 (0.888) | -0.337 (0.378) |
| Credit Spread (Moody's AAA) | Property and Casualty | Underwriting Profitability | 85 | 0.44 | -1.31*** (0.223) | -0.369 (0.679) | 0.517 (0.352) |
| OAS (ICE BofA Single-A US Corporate Index) | Fixed Term Annuity | Markup (annualized) | 29 | 0.91 | -0.785*** (0.196) | -1.19*** (0.261) | 0.541*** (0.146) |
| OAS (ICE BofA Single-A US Corporate Index) | Guarantee Annuity | Markup (annualized) | 54 | 0.90 | -0.506*** (0.054) | -0.260 (0.215) | 0.161* (0.064) |
| OAS (ICE BofA Single-A US Corporate Index) | Life Insurance | Markup (annualized) | 56 | 0.91 | -0.573*** (0.056) | -0.768** (0.256) | 0.261*** (0.066) |
| OAS (ICE BofA Single-A US Corporate Index) | Property and Casualty | Underwriting Profitability | 85 | 0.37 | -1.05** (0.340) | -0.895 (0.679) | 0.738* (0.281) |
| Moody's Baa - 10y Treas. | Fixed Term Annuity | Markup (annualized) | 46 | 0.82 | -0.854*** (0.199) | -1.72* (0.679) | 0.604** (0.224) |
| Moody's Baa - 10y Treas. | Guarantee Annuity | Markup (annualized) | 54 | 0.88 | -0.589*** (0.089) | -0.889* (0.435) | 0.292* (0.111) |
| Moody's Baa - 10y Treas. | Life Insurance | Markup (annualized) | 73 | 0.86 | -0.657*** (0.134) | -0.843 (0.637) | 0.293. (0.152) |
| Moody's Baa - 10y Treas. | Property and Casualty | Underwriting Profitability | 85 | 0.35 | -0.803*** (0.233) | -0.880 (0.645) | 0.528** (0.195) |
| OAS (ICE BofA BBB US Corporate Index) | Fixed Term Annuity | Markup (annualized) | 29 | 0.91 | -0.611*** (0.072) | -1.51*** (0.258) | 0.525*** (0.070) |
| OAS (ICE BofA BBB US Corporate Index) | Guarantee Annuity | Markup (annualized) | 54 | 0.91 | -0.476*** (0.047) | -0.552* (0.252) | 0.248*** (0.064) |
| OAS (ICE BofA BBB US Corporate Index) | Life Insurance | Markup (annualized) | 56 | 0.91 | -0.522*** (0.070) | -0.852* (0.371) | 0.292*** (0.083) |
| OAS (ICE BofA BBB US Corporate Index) | Property and Casualty | Underwriting Profitability | 85 | 0.32 | -0.619** (0.216) | -0.697 (0.565) | 0.471** (0.172) |
| OAS (ICE BofA US Corporate Index) | Fixed Term Annuity | Markup (annualized) | 29 | 0.91 | -0.773*** (0.129) | -1.39*** (0.235) | 0.603*** (0.102) |
| OAS (ICE BofA US Corporate Index) | Guarantee Annuity | Markup (annualized) | 54 | 0.91 | -0.549*** (0.051) | -0.386 (0.251) | 0.229** (0.071) |
| OAS (ICE BofA US Corporate Index) | Life Insurance | Markup (annualized) | 56 | 0.91 | -0.615*** (0.061) | -0.817* (0.321) | 0.313*** (0.077) |
| OAS (ICE BofA US Corporate Index) | Property and Casualty | Underwriting Profitability | 85 | 0.35 | -0.882** (0.297) | -0.816 (0.612) | 0.647** (0.240) |
| Credit Spread (GZ2012) | Fixed Term Annuity | Markup (annualized) | 46 | 0.82 | -0.585*** (0.103) | -0.813. (0.429) | 0.388** (0.132) |
| Credit Spread (GZ2012) | Guarantee Annuity | Markup (annualized) | 54 | 0.92 | -0.450*** (0.043) | -0.243 (0.239) | 0.168** (0.053) |
| Credit Spread (GZ2012) | Life Insurance | Markup (annualized) | 73 | 0.88 | -0.478*** (0.075) | -0.166 (0.421) | 0.156. (0.082) |
| Credit Spread (GZ2012) | Property and Casualty | Underwriting Profitability | 85 | 0.34 | -0.595** (0.177) | -0.656 (0.627) | 0.442** (0.159) |
| Yield-for-Risk | Fixed Term Annuity | Markup (annualized) | 46 | 0.76 | -0.066** (0.020) | -0.570. (0.283) | 0.054* (0.022) |
| Yield-for-Risk | Guarantee Annuity | Markup (annualized) | 54 | 0.81 | -0.060*** (0.011) | -0.651 (0.508) | 0.045* (0.022) |
| Yield-for-Risk | Life Insurance | Markup (annualized) | 73 | 0.78 | -0.042*** (0.010) | -0.028 (0.600) | -0.0010 (0.026) |
| Yield-for-Risk | Property and Casualty | Underwriting Profitability | 79 | 0.42 | -0.096*** (0.024) | 0.036 (0.431) | 0.089*** (0.023) |

## Table B.4: Time series results with Gilchrist and Zakrajšek (2012) decomposed credit spread.

This table reports the coefficients from the following time series regression:

$$\bar{y}_t = \beta_{ebp} \cdot EBP_t + \beta_{ds} \cdot \textit{Default spread}_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{ebpGFC} \cdot EBP_t \times \mathbb{1}_{GFC} + \beta_{dsGFC} \cdot \textit{Default spread}_t \times \mathbb{1}_{GFC} + \delta^T X_t + \epsilon_t$$

where $\bar{y}_t$ is either the average (annualised) markup across insurers and subproducts at time $t$ (columns 1-6) or the average underwriting profitability across insurers and subproducts at time $t$ (columns 7 and 8). $EBP_t$ is Gilchrist and Zakrajšek (2012) excess bond premium and $\textit{Default spread}_t$ is the difference between the Gilchrist and Zakrajšek (2012) credit spread and the excess bond premium. $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (September 2008 through December 2009). $X_t$ is a vector of time series controls: the 10-year Treasury rate, the slope of the Treasury yield curve (10-year - 2-year Treasury yields), the TED spread, and the US unemployment rate. For columns 7 and 8 all right-hand side variables are measured as one-year rolling averages. The t-statistics are calculated using Newey and West (1987) standard errors with 4 lags. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

| Dependent Variables: | Markup (annualised) | | | | | | Underwriting Profitability | |
|---|---|---|---|---|---|---|---|---|
| Type: | FixedTerm | | Guarantees | | Life | | P&C | |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables* | | | | | | | | |
| Excess Bond Premium | -0.364*** | -0.779*** | -0.370*** | -0.487*** | -0.384*** | -0.611*** | -0.467** | -0.820*** |
| | (-3.06) | (-4.52) | (-8.60) | (-13.0) | (-7.81) | (-6.46) | (-2.03) | (-4.61) |
| Default Spread | -0.852*** | 0.010 | -0.288*** | -0.202 | -0.408*** | 0.069 | 0.047 | -0.232 |
| | (-7.82) | (0.052) | (-2.95) | (-1.53) | (-7.11) | (0.379) | (0.191) | (-1.28) |
| $\mathbb{1}_{GFC}$ | | 2.22 | | 0.628 | | 1.40*** | | -3.05*** |
| | | (0.979) | | (1.60) | | (2.88) | | (-2.85) |
| $\mathbb{1}_{GFC}$ × Excess Bond Premium | | 0.670*** | | 0.250*** | | 0.389*** | | -0.318 |
| | | (3.53) | | (4.43) | | (3.15) | | (-0.897) |
| $\mathbb{1}_{GFC}$ × Default Spread | | -0.739 | | -0.173 | | -0.521*** | | 1.62*** |
| | | (-1.02) | | (-1.20) | | (-2.76) | | (3.38) |
| *Controls:* | | | | | | | | |
| Time series controls | | Yes | | Yes | | Yes | | |
| *Fit statistics* | | | | | | | | |
| Observations | 46 | 46 | 54 | 54 | 73 | 73 | 85 | 85 |
| $R^2$ | 0.697 | 0.850 | 0.833 | 0.923 | 0.798 | 0.904 | 0.200 | 0.391 |
| Adjusted $R^2$ | 0.683 | 0.812 | 0.827 | 0.908 | 0.792 | 0.890 | 0.181 | 0.352 |

**Table B.5: Life Insurance Time Series - Estimates in Changes**

Columns (1), (2), and (3) of this table presents the time series relation between insurance prices, as measured by the annualized markups on annuities issued by life insurers, and expected returns as measured by credit spreads. It reports the parameter estimates from the following regression:

$$\Delta\bar{m}_t = \beta_c \cdot \Delta CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot \Delta CS_t \times \mathbb{1}_{GFC} + \gamma^T \Delta X_t + \epsilon_t$$

where $\Delta\bar{m}_t$ is the change in the annualised markup across averaged across insurers and sub-products at time $t$. $\Delta CS_t$ is the change in the Moody's credit spread of BAA-rated corporate bonds yields over 10-year Treasuries, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through December 2009). $\Delta X_t$ contains a vector of time series controls: the change in the 10-year Treasury rate, the change in the slope of the Treasury yield curve (10-year - 2-year Treasury yields), the change in the TED spread, and the change in the US unemployment rate. Columns (4) and (5) present the results of estimating the model in a full panel with fixed effects:

$$\Delta m_{ikt} = \beta_{CS} \cdot \Delta CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{csGFC} \cdot \Delta CS_t \times \mathbb{1}_{GFC} + \delta^T \cdot \Delta X_t + FE_i + FE_k + \epsilon_{ikt}$$

where $\Delta m_{ikt}$ is the change in the annualised markup set by insurer $i$ at time $t$ for an annuity which is in sub-product $k$. Sub-products vary depending on age, sex and maturity of the annuities. Panel A, B and C show the results for markups on life, guarantee and fixed-term annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. The t-statistics in columns (1)-(3) are calculated using Newey and West (1987) standard errors with 4 lags. The t-statistics in columns (4) and (5) are calculated standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

**Panel A: Life Annuities**

| Dependent Variable: | ΔMarkup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| ΔCredit Spread (Moody's BAA) | -0.451*** | -0.296*** | -0.388*** | -0.320*** | -0.284*** |
| | (-4.90) | (-3.98) | (-4.04) | (-6.30) | (-2.84) |
| Δ Treasury Yield (10 year) | | 0.321*** | 0.289*** | 0.352*** | 0.362*** |
| | | (3.85) | (3.08) | (4.91) | (4.84) |
| ΔUS Unemployment Rate | | 0.040 | -0.032 | 0.050 | 0.024 |
| | | (0.356) | (-0.276) | (0.587) | (0.275) |
| ΔTED Spread | | 0.013 | 0.009 | -0.021 | -0.026 |
| | | (0.248) | (0.172) | (-0.269) | (-0.348) |
| ΔSlope (10 year - 2 year) | | 0.265*** | 0.314*** | 0.193* | 0.198** |
| | | (3.11) | (3.66) | (1.98) | (2.03) |
| $\mathbb{1}_{GFC}$ | | | 0.106 | | 0.096 |
| | | | (1.58) | | (1.17) |
| $\mathbb{1}_{GFC}$ × ΔCredit Spread (Moody's BAA) | | | 0.141 | | -0.049 |
| | | | (0.892) | | (-0.431) |
| Constant | 0.002 | 0.014 | -0.002 | | |
| | (0.108) | (0.575) | (-0.070) | | |
| *Controls:* | | | | | |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 72 | 72 | 72 | 12,278 | 12,278 |
| $R^2$ | 0.233 | 0.481 | 0.494 | 0.315 | 0.318 |
| Within $R^2$ | | | | 0.281 | 0.284 |

*[table continued on next page...]*

### Panel B: Guarantee Annuities

| Dependent Variable: | ΔMarkup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| ΔCredit Spread (Moody's BAA) | -0.374*** | -0.356*** | -0.394*** | -0.284*** | -0.343*** |
| | (-5.86) | (-5.30) | (-3.74) | (-6.25) | (-3.72) |
| Δ Treasury Yield (10 year) | | 0.169** | 0.151* | 0.213*** | 0.178** |
| | | (2.18) | (1.75) | (3.07) | (2.40) |
| ΔUS Unemployment Rate | | 0.073 | 0.002 | 0.057 | -0.002 |
| | | (0.612) | (0.014) | (0.751) | (-0.025) |
| ΔTED Spread | | 0.108 | 0.098 | -0.082 | -0.103 |
| | | (1.46) | (1.30) | (-0.988) | (-1.27) |
| ΔSlope (10 year - 2 year) | | 0.192** | 0.220*** | 0.121 | 0.151* |
| | | (2.59) | (3.24) | (1.53) | (1.99) |
| $\mathbb{1}_{GFC}$ | | | 0.084 | | 0.135 |
| | | | (1.13) | | (1.61) |
| $\mathbb{1}_{GFC}$ × ΔCredit Spread (Moody's BAA) | | | 0.054 | | 0.071 |
| | | | (0.348) | | (0.718) |
| Constant | -0.003 | -0.011 | -0.024 | | |
| | (-0.142) | (-0.464) | (-0.966) | | |
| *Controls:* | | | | | |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 53 | 53 | 53 | 14,391 | 14,391 |
| $R^2$ | 0.241 | 0.375 | 0.385 | 0.368 | 0.376 |
| Within $R^2$ | | | | 0.278 | 0.286 |

*[table continued on next page...]*

**Panel C: Fixed-Term Annuities**

| Dependent Variable: | ΔMarkup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| ΔCredit Spread (Moody's BAA) | -0.443*** | -0.184** | -0.218* | -0.196** | -0.252** |
| | (-5.05) | (-2.53) | (-1.96) | (-2.46) | (-2.03) |
| Δ Treasury Yield (10 year) | | 0.444*** | 0.435*** | 0.431*** | 0.408*** |
| | | (3.66) | (3.20) | (5.00) | (4.53) |
| ΔUS Unemployment Rate | | 0.193*** | 0.235* | 0.105* | 0.042 |
| | | (3.28) | (1.99) | (1.85) | (0.474) |
| ΔTED Spread | | -0.198 | -0.182 | -0.257* | -0.306** |
| | | (-1.50) | (-1.23) | (-1.88) | (-2.04) |
| ΔSlope (10 year - 2 year) | | -0.038 | -0.048 | -0.023 | 0.015 |
| | | (-0.556) | (-0.605) | (-0.270) | (0.202) |
| $\mathbb{1}_{GFC}$ | | | -0.104 | | 0.167 |
| | | | (-0.707) | | (1.10) |
| $\mathbb{1}_{GFC}$ × ΔCredit Spread (Moody's BAA) | | | 0.038 | | 0.090 |
| | | | (0.286) | | (0.638) |
| Constant | -0.029 | 0.004 | 0.009 | | |
| | (-0.749) | (0.084) | (0.154) | | |
| *Controls:* | | | | | |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 45 | 45 | 45 | 2,512 | 2,512 |
| $R^2$ | 0.331 | 0.594 | 0.596 | 0.385 | 0.388 |
| Within $R^2$ | | | | 0.329 | 0.332 |

*[table continued on next page...]*

## Table B.6: Life Insurance Time Series - Full Specification Estimates

Columns (1), (2), and (3) of this table presents the time series relation between insurance prices, as measured by the annualized markups on annuities issued by life insurers, and expected returns as measured by credit spreads. It reports the parameter estimates from the following regression:

$$\bar{m}_t = \beta_c \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot CS_t \times \mathbb{1}_{GFC} + \gamma^T X_t + \epsilon_t$$

where $\bar{m}_t$ is the average (annualised) markup across insurers and subproducts at time $t$. $CS_t$ is Moody's credit spread of BAA-rated corporate bonds yields over 10-year Treasuries, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through December 2009). $X_t$ contains a vector of time series controls: the 10-year Treasury rate, the slope of the Treasury yield curve (10-year - 2-year Treasury yields), the TED spread, and the US unemployment rate. Columns (4) and (5) present the results of estimating the model in a full panel with fixed effects:

$$m_{ikt} = \beta_{CS} \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{csGFC} \cdot CS_t \times \mathbb{1}_{GFC} + \delta^T \cdot X_t + FE_i + FE_k + \epsilon_{ikt}$$

where $m_{ikt}$ is the annualised markup set by insurer $i$ at time $t$ for an annuity which is in sub-product $k$. Sub-products vary depending on age, sex and maturity of the annuities. Panel A, B and C show the results for markups on life, guarantee and fixed-term annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. The t-statistics in columns (1)-(3) are calculated using Newey and West (1987) standard errors with 4 lags. The t-statistics in columns (4) and (5) are calculated standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

**Panel A: Life Term Annuities**

| Dependent Variable: | Markup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Credit Spread (Moody's BAA) | -0.525*** | -0.444*** | -0.657*** | -0.467*** | -0.700*** |
| | (-9.75) | (-8.21) | (-4.91) | (-8.85) | (-8.49) |
| Treasury Yield (10 year) | | 0.129*** | 0.112*** | 0.147*** | 0.109*** |
| | | (3.72) | (3.20) | (3.31) | (2.75) |
| US Unemployment Rate | | 0.064 | 0.017 | 0.150*** | 0.106*** |
| | | (1.66) | (0.239) | (4.49) | (3.10) |
| TED Spread | | -0.248*** | -0.266*** | -0.054 | -0.076 |
| | | (-3.53) | (-4.23) | (-0.836) | (-1.22) |
| Slope (10 year - 2 year) | | 0.084 | 0.202* | 0.002 | 0.115** |
| | | (1.14) | (1.88) | (0.042) | (2.25) |
| $\mathbb{1}_{GFC}$ | | | -0.843 | | -1.06*** |
| | | | (-1.32) | | (-2.91) |
| $\mathbb{1}_{GFC}$ × Credit Spread (Moody's BAA) | | | 0.293* | | 0.349*** |
| | | | (1.93) | | (3.54) |
| Constant | 2.30*** | 1.17*** | 1.88*** | | |
| | (14.9) | (3.69) | (4.72) | | |
| *Controls:* | | | | | |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 73 | 73 | 73 | 13,675 | 13,675 |
| $R^2$ | 0.720 | 0.847 | 0.862 | 0.746 | 0.754 |
| Within $R^2$ | | | | 0.412 | 0.429 |

*[table continued on next page...]*

**Panel B: Guarantee Annuities**

| Dependent Variable: | Markup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Credit Spread (Moody's BAA) | -0.449*** | -0.370*** | -0.589*** | -0.433*** | -0.700*** |
| | (-8.80) | (-7.32) | (-6.63) | (-7.40) | (-9.41) |
| Treasury Yield (10 year) | | 0.269*** | 0.284*** | 0.189** | 0.160* |
| | | (4.04) | (3.99) | (2.34) | (1.97) |
| US Unemployment Rate | | 0.098** | 0.068 | 0.132*** | 0.104*** |
| | | (2.61) | (1.66) | (3.53) | (3.07) |
| TED Spread | | -0.155*** | -0.160*** | -0.075 | -0.109 |
| | | (-2.95) | (-4.16) | (-1.02) | (-1.64) |
| Slope (10 year - 2 year) | | 0.006 | 0.143** | 0.033 | 0.151*** |
| | | (0.096) | (2.43) | (0.550) | (3.45) |
| $\mathbb{1}_{GFC}$ | | | -0.889** | | -1.26*** |
| | | | (-2.04) | | (-4.42) |
| $\mathbb{1}_{GFC}$ × Credit Spread (Moody's BAA) | | | 0.292** | | 0.401*** |
| | | | (2.64) | | (4.74) |
| Constant | 1.65*** | -0.162 | 0.313 | | |
| | (11.3) | (-0.367) | (0.554) | | |
| *Controls:* | | | | | |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 54 | 54 | 54 | 16,469 | 16,469 |
| $R^2$ | 0.768 | 0.859 | 0.879 | 0.729 | 0.750 |
| Within $R^2$ | | | | 0.524 | 0.560 |

*[table continued on next page...]*

## Panel C: Term Annuities

| Dependent Variable: | Markup (annualised) | | | | |
|---|---|---|---|---|---|
| | $\bar{m}_t$ | | | $m_{it}$ | |
| Model: | (1) | (2) | (3) | (4) | (5) |
| *Variables* | | | | | |
| Credit Spread (Moody's BAA) | -0.808*** | -0.632*** | -0.854*** | -0.460*** | -0.619*** |
| | (-5.76) | (-2.93) | (-4.29) | (-3.77) | (-5.78) |
| Treasury Yield (10 year) | | 0.243** | 0.244*** | 0.113* | 0.095 |
| | | (2.69) | (2.86) | (1.95) | (1.67) |
| US Unemployment Rate | | 0.034 | -0.007 | 0.058 | 0.038 |
| | | (0.700) | (-0.152) | (1.32) | (0.888) |
| TED Spread | | 0.011 | -0.305 | -0.020 | -0.203 |
| | | (0.047) | (-1.17) | (-0.116) | (-1.00) |
| Slope (10 year - 2 year) | | 0.108 | 0.143 | -0.043 | -0.018 |
| | | (0.891) | (1.22) | (-0.462) | (-0.243) |
| $\mathbb{1}_{GFC}$ | | | -1.72** | | -1.14** |
| | | | (-2.54) | | (-2.50) |
| $\mathbb{1}_{GFC}$ × Credit Spread (Moody's BAA) | | | 0.604*** | | 0.389** |
| | | | (2.70) | | (2.62) |
| Constant | 3.12*** | 1.03 | 1.87** | | |
| | (7.55) | (1.14) | (2.35) | | |
| *Controls:* | | | | | |
| Entity FE | | | | Yes | Yes |
| Product FE | | | | Yes | Yes |
| *Fit statistics* | | | | | |
| Observations | 46 | 46 | 46 | 2,927 | 2,927 |
| $R^2$ | 0.642 | 0.792 | 0.823 | 0.736 | 0.742 |
| Within $R^2$ | | | | 0.285 | 0.300 |

## B.3 Extension and Robustness for Table 5: *Cross-sectional results*

**Table B.7: Investment returns and the cross-section of life insurance prices**

This table presents the cross-sectional relationship between life insurance prices, measured by underwriting profitability, and firm-specific expected investment returns, measured by net yields. It reports the parameter estimate from the following panel regression:

$$m_{ikt} = \beta_{ny} \cdot Net\ yield_{it} + \delta^T \cdot Z_{it} + \beta_{nyGFC} \cdot Net\ yield_{it} \times \mathbb{1}_{GFC} + \delta^T_{GFZ} \cdot Z_{it} \times \mathbb{1}_{GFC} + FE_t + FE_k + \epsilon_{ikt}$$

where $m_{ikt}$ is the markup for insurer $i$ and product $k$ at time $t$ and $Net\ yield_{it}$ is the insurer's net yield. $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through December 2009). $Z_{it}$ is a vector of controls for insurer $i$'s balance sheet strength at time $t$: deferred annuity liabilities, risk-based capital relative to guideline, and the insurer's leverage ratio. Note that we cannot apply the same balance sheet controls as we did with P&C insurers due to different reporting requirements between life and P&C insurers. All control variables and markups are retrieved from Koijen and Yogo (2015). $t$-statistics are reported in bracket and calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

| Dependent Variable: | Markup (annualised) | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| Net Yield | -0.003 | -0.0005 | -0.0002 |
| | (-0.147) | (-0.027) | (-0.010) |
| Deferred annuity liabilities | | -0.004 | -0.005* |
| | | (-1.45) | (-1.74) |
| Risk-based capital | | -0.0009 | -0.0010 |
| | | (-1.01) | (-0.923) |
| Leverage ratio | | 0.014* | 0.016** |
| | | (1.70) | (2.08) |
| $\mathbb{1}_{GFC}$ × Net Yield | | | 0.020 |
| | | | (0.221) |
| $\mathbb{1}_{GFC}$ × Deferred annuity liabilities | | | 0.007** |
| | | | (2.52) |
| $\mathbb{1}_{GFC}$ × Risk-based capital | | | 0.0006 |
| | | | (0.488) |
| $\mathbb{1}_{GFC}$ × Leverage ratio | | | -0.013 |
| | | | (-1.25) |
| *Controls:* | | | |
| Date FE | Yes | Yes | Yes |
| Product FE | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 2,661 | 2,661 | 2,661 |
| $R^2$ | 0.686 | 0.694 | 0.696 |
| Within $R^2$ | 0.000 | 0.027 | 0.032 |

## Table B.8: Investment returns and the cross-section of prices: individual P&C insurance business lines

This table presents the cross-sectional relationship between P&C insurance prices, measured by underwriting profitability, and firm-specific expected investment returns, measured by net yields within the six largest insurance lines of US P&C insurers: Auto insurance (private and commercial), Multiple Peril (private and commercial), Fire and Allied, and Workers Compensation. It reports the parameter estimate from the following panel regression:

$$u_{isbt+1} = \beta_{ny} \cdot Net\ yield_{it} + \delta^T \cdot Z_{it} + FE_{sbt} + \epsilon_{isbt+1}$$

where $u_{isbt}$ is the underwriting profitability for insurer $i$'s business line $b$ in state $s$ at time $t$ and $Net\ yield_{it}$ is the insurer's net yield. $Z_{it}$ is a vector of controls for insurer $i$'s balance sheet strength and reinsurance activity at time $t$: *Capital Ratio* is the risk based capital ratio reported by the insurers themselves, *Unearned Premium Ratio* is the ratio of unearned premiums to net premiums earned, *Reinsurance Ratio* is the ratio of net reinsurance premiums to direct premiums written. $FE_{sbt}$ is a state-business line-year fixed effect. The sample consists of annual observations from 2001 through 2021 and covers all fifty US states, the five US territories, and the District of Columbia. $t$-statistics are reported in bracket and calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

| Dependent Variable: | Underwriting Profitability | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Insurance Line | All lines | | Auto (Private) | Mult. Peril (Private) | Fire and Allied | Auto (Com.) | Mult. Peril (Com.) | Workers' Comp. |
| Model: | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| *Variables* | | | | | | | | |
| Net Yield | -0.059*** | -0.056*** | -0.060*** | -0.050** | -0.064*** | -0.079*** | -0.043* | -0.050*** |
| | (-3.80) | (-3.70) | (-2.98) | (-2.12) | (-3.03) | (-5.70) | (-2.04) | (-3.78) |
| Capital Ratio | | 0.0002*** | 0.0004*** | 0.0004*** | 0.0002** | 0.0002*** | 0.0003** | 0.0001** |
| | | (4.52) | (4.68) | (3.80) | (2.15) | (3.35) | (2.59) | (2.26) |
| Unearned Premium | | $-5.98 \times 10^{-6}$*** | $-4.64 \times 10^{-6}$*** | 0.151* | -0.003 | -0.002 | -0.035 | 0.021 |
| | | (-4.94) | (-4.48) | (2.01) | (-0.036) | (-0.072) | (-0.476) | (0.429) |
| Reinsurance Ratio | | $6.2 \times 10^{-9}$*** | $9.67 \times 10^{-6}$ | $-1.16 \times 10^{-5}$*** | 0.0002** | $4.74 \times 10^{-5}$ | $-3.14 \times 10^{-6}$ | $5.99 \times 10^{-9}$*** |
| | | (38.4) | (1.25) | (-3.51) | (2.54) | (1.46) | (-1.01) | (32.7) |
| *Fixed-effects* | | | | | | | | |
| State×Year×Insurance Line | Yes | Yes | | | | | | |
| State×Year | | | Yes | Yes | Yes | Yes | Yes | Yes |
| *Fit statistics* | | | | | | | | |
| Observations | 831,482 | 831,482 | 92,839 | 80,838 | 182,931 | 179,479 | 155,044 | 140,351 |
| $R^2$ | 0.056 | 0.064 | 0.053 | 0.138 | 0.039 | 0.029 | 0.043 | 0.028 |
| Within $R^2$ | 0.006 | 0.014 | 0.036 | 0.022 | 0.013 | 0.015 | 0.018 | 0.006 |

# C Methodology and data

In this section of the appendix we provide additional details and motivation for how we measure expected returns in the time series and cross-section of insurers, as well as details on our work with the SNL database.

## C.1 Measuring the average insurers' investment opportunity

Panel A of Table C.1 presents the aggregated industry balance sheets for the Life Insurance industry and the P&C Insurance industry. Looking at the asset-side of the balance sheet, we see that insurance companies take a lot of of investment risk in their investment portfolios. Risk-free assets (cash and Treasuries) are only 7% for the Life Insurance industry and 14% for the P&C industry. Instead, insurers invest in risky and often illiquid assets. Corporate bonds, mortgage loans, and other credit (such as MBS, RMBS, and municipal bonds) make up 75% and 42% of the balance sheets for the Life and P&C industries respectively. Other investments, which includes real estate derivatives and contract loans, make up small fraction of the investment portfolios.

Panel B of Table C.1 presents distributional information on insurance industries' aggregated bond portfolios across the maturity and rating characteristics. The average bond maturity is 12.2 years (assuming an average maturity of 30 years in the great than 20 years bucket) in the life industry and 6.1 years in the P&C industry. The longer maturity holdings in life insurers assets likely reflects the longer duration of their liabilities. Looking at the average credit rating, we see that over 95% of insurers bond portfolios are in the credit rating range of AAA-BBB (which corresponds to NAIC bond portfolio ratings of 1 and 2), which is motivated by the high regulatory capital charges for holding non-investment grade credit Becker and Ivashina (2015).

In summary, we see from Table C.1 that the insurance industry invests predominantly in investment grade credit assets with an average duration of roughly 10-years. For a broad measure of the investment opportunities facing the average insurance company, we therefore use the credit spread between seasoned Moody's BAA-rated corporate bonds and the 10-year Treasury yield as our main proxy for the average insurer's expected return, though we also show that our results are robust to other measures of expected returns on illiquid credit assets.

## C.2 Measuring and interpreting insurer net yields in the cross-section of insurers

To measure cross-sectional variation in insurers' expected investment returns, we use insurers' *Net Yield on Invested Assets* as defined in equation (22). Net yield is an accounting return on assets, and is defined as dollar net income from investments over the dollar book value of invested assets. Anecdotally, we know from market participants that it is the key metric from which insurance companies assess their investment portfolio performance.

The accounting rules are designed so that the total net yield on each invested asset for an insurer must exactly equal the insurer's total economic return over the insurer's investment holding period for that investment. However, on a quarter-by-quarter basis, the economic return and accounting net yield may differ as the assets are not marked-to-market. For fixed income assets, the reported net yield on an asset is the amortisation of the purchase yield each quarter, i.e. bond values are on the balance sheet at *"historical cost"*. This accounting treatment reflects that insurers are buy and hold investors and can weather market fluctuations. If the insurer does sell a bond before maturity, the realised gain/loss is included in the reported net yield in the reporting period of the sale. This ensures the accounting return equals the economic return over the insurer's investment period for that asset.[36] For equity investments, the net yield is the dividend rate, with market fluctuations once again realised at the point of sale.

Figure C.1 presents boxplots of insurers' net yield on investments in each reporting quarter of our sample. It illustrates the time series trends in insurer investment returns. Note that the accounting treatment of net yields, which shields insurers from some mark-to-market volatility in the investment portfolio, kept net yields positive during the financial crisis. This was despite some large negative economic returns in that period. Turning to the cross-section, Figure C.1 highlights rich heterogeneity in net yields across insurers at any given point in time. In all quarters of our sample, the range between the 25th and 75th percentiles of investment returns is in excess of 150 bps. It is this variation in net yields across insurers that our empirical method utilizes.

Crucially, so long an insurer does not sell an asset (and the issuer default risk does not increase materially), the net yield methodology protects the insurer from mark-to-market volatility on their investments. This treatment reflects insurers' long-term buy and hold

[36] If there are significant revisions to the outlook for a bond (i.e. a permanent change in credit risk or a change in expected recovery rates), then adjustments may also be made in reported investment income. In this case, the bonds are "impaired" with book-value adjustments.

approach to investing,[37] and is consistent with the view of insurers as *"asset insulators"* (Chodorow-Reich et al., 2021) or *"safe hands"* (Coppola, 2022), holding bonds for the long-term and riding out transitory dislocations in market prices.

Table C.2 Panel A shows how variation in insurers' asset allocations explain cross-sectional variation in insurer investment returns. We regress investment net yields (in bps) on asset allocations (in percent) with controls for time fixed effects. We omit insurers allocation to Treasury bonds in the explanatory variable list but include all other asset allocations (split by cash, non-Treasury bonds, and all other asset). This regression specification means that the point estimate on any asset allocation variable can be interpreted as the effect on net yield that is generated from an increase in the allocation to that asset that is funded by a sale in Treasury bonds. In other words, the estimates capture the *excess* net yield an average insurer earns on the asset class relative to the Treasury yield. We see that, intuitively, insurers with large credit allocations earn higher investment returns, while large allocations to cash result in lower investment returns. For example, column 1 shows that a 1 percentage point increase in credit and cash allocations from Treasuries results in a 1.15 bps increase and 1.94 bps decrease in investment returns respectively. In column 2 of Table C.2 we include the credit risk taken within the credit portfolio, and in column 3 we interact this variable with the credit allocation. We see that the riskier an insurer's credit portfolio is, the higher the insurer's net yield.

Table C.2 Panel B explains the time series variation in individual insurance company's investment returns. Columns 1-2 show that there is a high degree of persistence in insurers' investment returns. The large r-squared shows that an insurer's accounting investment return in the current quarter explains 43% of the insurer's accounting investment return in the next quarter. Given that insurers' accounting returns predict next periods accounting returns, we interpret cross-sectional variation in net-yield as cross-sectional variation in insurers' *expected* investment opportunities going forward. An insurer with a relatively high net yield today as compared to competitors expects the net yield to be higher in future quarters.

Columns 3-4 of Table C.2 Panel B show the macro-level time series drivers of investment returns. We find that, consistent with the large fixed income allocations in insurers'

[37] Schultz (2001) and Campbell and Taksler (2003) estimate that insurers hold between 30% and 40% of corporate bonds and yet account for only about 12% of trading volume. In more recent evidence, Coppola (2022) documents the persistence of corporate bond holdings over time for insurance companies and mutual funds at a bond-issue level. The holdings of insurance companies are remarkably persistent over time, and much more so than mutual funds. Coppola (2022) finds that insurers typically buy bonds directly at issuance in the primary market and hold for multiple years or until maturity.

asset portfolios, the levels of interest rates and credit spreads are significant drivers of net yields on average. Notably, accounting investment returns must equal economic investment returns in the long-run. Therefore, if credit spreads only reflected default losses, then credit spreads would have no predictability for insurer investment returns on average. Our finding that credit spreads predict insurer net yields is consistent with evidence that corporate bonds deliver excess returns over Treasuries over the long-term (Krishnamurthy and Vissing-Jorgensen, 2012; Gilchrist and Zakrajšek, 2012). It is also consistent with our interpretation of net yield variation in the cross-section: insurers that take more credit risk in their investments earn higher net yields and expect to earn higher investment returns relative to their competitors going forward.

## C.3 Working with the SNL database and aggregating insurer entities at the group level

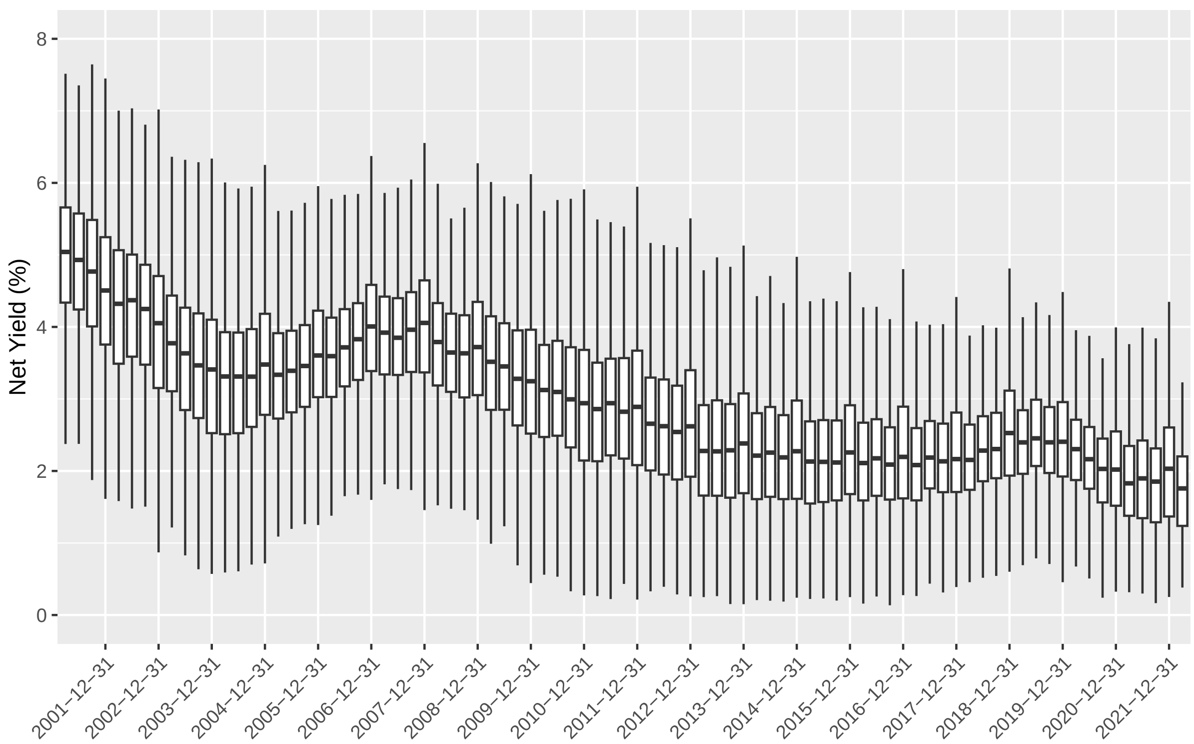
We collect data from S&P Global: Market Intelligence using a FTP feed to access the full back-end of their SNL database. Our main data sources are taken from the file group P&C Core Financials, and in particular we use variables from the Financial Highlights Table (File Name: $PC\_CoreFinl\_[year]\_CF0001$ for each reporting year) and the Capital Adequacy and Liquidity Analysis Table (File Name: $PC\_CoreFinl\_[year]\_CF0015$ for each reporting year).

A difficulty with working on insurance companies empirically is that there is often quite complex corporate structures, with large insurance groups consisting of many separate insurance entities, each of which files separately with the regulator and therefore has a unique company code with the NAIC (the National Association of Insurance Commissioners). There is also fairly frequent M&A activity across insurance groups with the underlying insurance entities. The SNL database provides several different reporting levels, including an SNL defined insurance group level, but the financial variables on these lines are reported on an *'as-is'* basis. An *'as-is'* basis means historical records of merged or acquired insurance entities are reported as if they have always been held within the current ownership group, which is problematic for empirical analysis.

To generate correct historical records of insurance groups, we first use the online screener on the S&P Global: Market Intelligence website to pull the historical 'NAIC combined company code' (which identifies the insurance group) for each individually filing insurance entity. This provides an accurate history of which NAIC insurance group the insurance entities were a member of in a given reporting period. We merge this table by ‘insurance entity NAIC code’ with the main datatables in the SNL database and drop the SNL group-level reporting lines. We then aggregate insurance entities to their historical NAIC group level in each reporting period, summing across entities for dollar financial variables, and using asset-value weighted averages to aggregate percentage and ratio variables. This gives the historical record of the insurance groups, i.e. Berkshire Hathaway, AllState, State Farm, Liberty Mutual...etc., which are entities we wish to study empirically.

In further analysis, we utilize more granular insurance underwriting reporting by insurers that is at a state and business line level (on an annual frequency). This data is stored in the StatePage files and we specifically use variables in the filename $PC\_Geographic\_GE0001$.

**Figure C.1: Variation in the expected investment returns of insurance companies.** This figure illustrates variation in the expected investment returns of insurance companies in both the time series and cross-section. In each reporting quarter of our sample, the figure presents a boxplot of expected investment returns. Our sample includes firm-level data for 871 P&C insurance groups. Expected investment returns are measured as the net yield on invested assets, as reported in insurance company financial accounts. The data comes from US insurance company statutory filings and is provided by SNL Global.



### Table C.1: Insurer financial reports aggregated to the industry level

This table shows the aggregated balance sheets and bond portfolio characteristics for the Life Insurance industry and the P&C Insurance Industry as of December 2022. In Panel A, the assets are split by the largest investment allocations, and the liabilities are split into insurance liabilities and other liabilities. In Panel B, the industry-wide bond portfolios are split by maturity and credit rating. The NAIC bond rating groups 1 and 2 includes all bonds rated in the range AAA-BBB by traditional credit ratings. Data for the table comes from US insurance company statutory filings and is provided by SNL Global. Individual insurer filings have been aggregated to present industry-wide balance sheets and bond portfolio information.

**Panel A: Balance sheets**

| | Life Industry ($bn) | P&C Industry ($bn) | Life Industry (%) | P&C Industry (%) |
|---|---|---|---|---|
| Cash & Short Term Investments | 152 | 164 | 3% | 6% |
| Bonds - US Government | 194 | 227 | 4% | 8% |
| Bonds - Industrial | 2794 | 582 | 51% | 21% |
| Bonds - Other | 573 | 417 | 10% | 15% |
| Mortgage Loans | 690 | 30 | 13% | 1% |
| Stocks | 118 | 649 | 2% | 23% |
| Other Investments | 596 | 214 | 11% | 8% |
| Non-Financial Assets | 370 | 506 | 7% | 18% |
| **Total Assets** | **5507** | **2789** | **100%** | **100%** |
| Insurance Liabilities | 3602 | 1458 | 65% | 52% |
| Other Liabilities | 693 | 293 | 13% | 10% |
| Capital And Surplus (Equity) | 1213 | 1039 | 22% | 37% |
| **Total Liabilities** | **5507** | **2789** | **100%** | **100%** |

**Panel B: Bond portfolio distributions**

| | Life Industry | P&C Industry |
|---|---|---|
| **Maturity Distribution (%)** | | |
| < 1 Year | 6.5 | 14.7 |
| 1 - 5 Years | 26.0 | 42.0 |
| 5 - 10 Years | 26.3 | 28.8 |
| 10 - 20 Years | 19.2 | 9.5 |
| > 20 Years | 21.9 | 4.6 |
| **Total Bond Portfolio** | **100** | **100** |
| **NAIC Credit Rating Distribution (%)** | | |
| 1-2 Rating | 94.6 | 95.6 |
| > 2 Rating | 5.4 | 4.4 |
| **Total Bond Portfolio** | **100** | **100** |

**Table C.2: Understanding the investment returns of insurance companies**

This table explains variation in the investment returns of insurance companies. Panel A reports the parameter estimate from the following panel regression:

$$\begin{aligned} Net\ Yield_{it} =& \beta_{Cash} \cdot Cash\ All._{it-1} + \beta_{Bond} \cdot Bond\ All._{it-1} + \beta_{Risk} \cdot Risk_{it-1} + \\ & \beta_{BondRisk} \cdot Bond\ All._{it-1} \times Risk_{it-1} + \beta_{Other.} \cdot Other\ Assets\ All._{it-1} + FE_t + \epsilon_{it} \end{aligned}$$

where $Net\ Yield_{it}$ is insurer $i$'s net yield (in basis points) at time $t$ and the explanatory variables are insurer $i$'s investment allocations (in pct.) to cash, non-government bonds, and other (non-Treasury) assets. In addition we include the risk-weighted bond allocation which is insurer $i$'s bond allocation interacted with a (normalized) measure of the average credit rating of the insurer's credit portfolio as in Table 4. All specifications in Panel A include time fixed effects $FE_t$.
Panel B reports the parameter estimate from the following panel regression:

$$Net\ Yield_{it} = \beta_{ny1} \cdot Net\ Yield_{it-1} + \beta_{ny5} \cdot Net\ Yield_{it-5} + \delta^T X_{t-1} + FE_i + \epsilon_{it}$$

where $X_t$ is a vector of time series variables that capture insurer investment opportunities (Moody's credit spread of BAA-rated corporate bonds yields over 10-year Treasuries, the 10-year Treasury rate, the slope of the Treasury yield curve (10-year - 2-year Treasury yields), the TED spread), and $FE_i$ captures firm fixed effects. All variables in panel B are measured in percent. $t$-statistics are reported in the brackets and are calculated using standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

**Panel A: Investment Returns and Asset Allocation**

| Dependent Variable: | Net Yield (bp.) | | |
|---|---|---|---|
| Model: | (1) | (2) | (3) |
| *Variables* | | | |
| Cash Allocation | -1.94*** | -2.14*** | -2.11*** |
| | (-7.99) | (-9.04) | (-9.02) |
| Bond Allocation | 1.15*** | 1.27*** | 1.31*** |
| | (6.54) | (6.92) | (7.57) |
| Allocation to Other Assets | -0.063 | -0.170 | -0.186 |
| | (-0.261) | (-0.688) | (-0.753) |
| Risk | | 26.5*** | 2.25 |
| | | (3.68) | (1.02) |
| Bond Allocation × Risk | | | 1.31*** |
| | | | (11.1) |
| *Controls:* | | | |
| Date FE | Yes | Yes | Yes |
| *Fit statistics* | | | |
| Observations | 43,056 | 41,017 | 41,017 |
| $R^2$ | 0.334 | 0.357 | 0.378 |
| Within $R^2$ | 0.103 | 0.128 | 0.156 |

**Panel B: Investment Returns and Time Series Variation**

| Dependent Variable: | Net Yield | | | |
|---|---|---|---|---|
| Model: | (1) | (2) | (3) | (4) |
| *Variables* | | | | |
| Net Yield (*t*-1) | 0.641*** | 0.444*** | | |
| | (21.0) | (15.9) | | |
| Net Yield (*t*-5) | | 0.248*** | | |
| | | (15.6) | | |
| Credit Spread (Moody's BAA) | | | 0.309*** | 0.414*** |
| | | | (8.51) | (6.59) |
| Treasury Yield (10 year) | | | 0.558*** | 0.574*** |
| | | | (18.3) | (22.1) |
| Slope (10 year - 2 year) | | | | -0.196*** |
| | | | | (-5.39) |
| TED Spread | | | | -0.064 |
| | | | | (-0.991) |
| *Controls:* | | | | |
| Entity FE | | | Yes | Yes |
| *Fit statistics* | | | | |
| Observations | 46,204 | 43,764 | 47,125 | 47,125 |
| $R^2$ | 0.425 | 0.437 | 0.527 | 0.537 |
| Within $R^2$ | | | 0.282 | 0.297 |