Asset-Driven Insurance Pricing

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Abstract

We develop a theory that connects insurance premiums, insurance companies' investment behavior, and equilibrium asset prices. Consistent with the model's key predictions, we show empirically that (1) insurers with more stable insurance funding take more investment risk and, therefore, earn higher average investment returns; (2) insurance premiums are lower when expected investment returns are higher, both in the cross section of insurance companies and in the time series. We show our results hold for both life insurance companies and, using a novel approach, for property and casualty insurance companies. Consistent findings across different regulatory frameworks helps identify asset-driven insurance pricing while controlling for alternative explanations.

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1 Introduction

This paper proposes and tests a new theory of insurance pricing, which shows that insurance premiums are lower when insurance companies have higher expected investment returns. We call this way of setting premiums "asset-driven insurance pricing". Our theory and evidence connects two important functions of the insurance industry, namely the pricing of insurance products and the allocation of its assets. Insurance products facilitate risk-sharing for 95% of all US households, and the premiums fund large asset portfolios, with US insurers holding marketable asset worth \$11.2 trillion as of Q4 2019.[1] Hence, insurance companies are both economically important asset allocators and facilitators of risk sharing, and we show that these two functions are more connected than previously thought.

The traditional view of insurers is that their main business – and therefore their main source of risk and return - is insurance underwriting. Such a view has little consideration for insurer's asset allocation decisions in the context of insurance premium pricing. However, recent evidence shows that there is significant risk in the asset portfolios of insurers (Ellul et al. (2011), Becker and Ivashina (2015), Becker et al. (2020), Ge and Weisbach (2020), Ellul et al. (2020)). Indeed, contrary to the traditional view, risk-free assets make up only 10% of investment portfolios, with insurers instead investing heavily in illiquid credit markets. This behaviour in their investment portfolios motivates our two main research questions: (1) Why do insurers have such high exposure to credit and liquidity risk in their asset portfolios? (2) Do the expected investment returns on these portfolios affect how they set premiums?

We address these questions by considering a model of insurance premiums and illiquid asset prices and by presenting consistent empirical evidence. We show asset-driven insurance pricing holds in both the time series and the cross section of insurance companies, in good and bad times, and for both life insurance companies and the property and casualty (P&C) industry. The P&C results use a novel approach, which, due to the industry's distinct regulatory framework relative to the Life Insurance industry, helps us to identify asset-driven insurance pricing from alternative mechanisms of insurance pricing. We also present evidence of asset-driven insurance pricing following changes to investment returns

[1] For a sense of the order of magnitude, note that the total value of insurer marketable assets is in excess of 40% of the US Treasury and corporate bond markets combined. Data sources: Insurance Information Institute, Financial Accounts of the United States (Fed Reserve), SIFMA Fact Book.

due to mergers.

Our model features two types of agents, investors and insurance companies. There are also two assets, one liquid and one illiquid. All agents face an exogenous cost from selling the illiquid asset before maturity, and, in the spirit of Diamond and Dybvig (1983), investors are *ex-ante* uncertain whether they are early or late consumers. These assumptions combine to generate an endogenous liquidity risk premium. The key insight of the model is that insurers enjoy relatively more certainty on the timing of cash flows due to the diversification benefit of underwriting many homogeneous insurance policies. This diversification creates stable insurance funding, which is an advantage when investing in illiquid assets.

Insurance companies with more stable insurance funding are able to extract more value from illiquid assets and therefore allocate a greater fraction of assets to illiquid investments (Proposition 1). In the time series, when the excess return on the illiquid asset is higher, the marginal cost of supplying insurance is lower, insurers compete for funding, and insurance premiums are set lower in the aggregate (Proposition 2). In the cross section, insurance companies that take more investment risk and have higher expected returns are able to set lower premiums relative to competitors (Proposition 3). The model's predictions rest on a violation of the Modigliani and Miller (1958) capital irrelevance theorem. We argue that an investor's funding structure matters when a illiquidity return premium is available in asset markets, and insurers' funding choices determine their ability to earn the illiquidity return premium.

To test Proposition 1, we calculate rolling 5-year estimates of the standard deviation of insurer's underwriting profitability. Using data from 2001-2018, we find that insurers with more stable underwriting profitability have lower allocations to cash assets and higher allocations to credit assets (and take more credit risk within their credit portfolios). Our results extend on Ge and Weisbach (2020), who show that large insurers take more investment risk. Assuming large insurers have more diversification benefits in their underwriting businesses, this initial result is consistent with our model prediction. However, our findings take this a step further, showing that, even when comparing firms of equal size, the insurer with less volatile underwriting performance takes more investment risk. The finding provides evidence that insurer's asset allocation decision depends on firm-level characteristics, and specifically on the stability of cash flows in their underwriting business. According to our model, the explanation is that insurers use the stability of the insurance funding to earn liquidity premium on their assets.

To test Proposition 2 and the time series of premiums, we use credit spreads as a proxy for industry-wide expected investment returns. Figure 1 presents an illustrative example in the life insurance industry, plotting the industry average insurance premium against credit spreads (on an inverse axis scale). The figure shows that insurance premiums are lower when insurance companies have higher expected investment returns. Our main dependent variable in the Life Insurance industry are annuity markups as calculated in Koijen and Yogo (2015). Across products, we find a 100bp increase in credit spreads leads to a 50bp decrease in an annualised annuity markup on average, with a t-statistic of 4.03 controlling for other effects. The average markup is 1%, and hence the 50bps decrease mean insurers drop their markups by half when they can earn 100bp more buying corporate bonds. This sensitivity is an economically significant effect. In the P&C industry, we use insurers' reported underwriting profitability as the main dependent variable. This measure is the ratio of their insurance underwriting profit to their insurance underwriting liabilities. We interpret lower underwriting profit as evidence of lower premiums. We find that the industry average underwriting profitability ratio falls by 1.31 standard deviations (t-statistic of 4.68 with full controls) when lagged credit spreads increase by one standard deviation.

To test Proposition 3, we use insurer's reported accounting investment returns to measure cross sectional variation in investment opportunities. The analysis utilizes a rich heterogeneity in investment portfolios across insurers. At any point in time, we show that the level of credit risk in credit portfolios explains the majority of variation in accounting returns, and that this variation predicts future returns, consistent with our interpretation that accounting returns captures insurers' expected investment returns.[2] We consistently find that the insurers with higher expected investment returns set lower insurance prices. In the life insurance industry, an insurer with an expected investment return one standard deviation higher than competitors reduces their relative markup by 0.05 standard deviations (t-statistic 2.77). In the P&C industry, we find an insurer with a one standard deviation higher expected investment return has an underwriting profitability ratio 0.03 standard deviations lower than competitors (t-statistic 5.45). The magnitudes are not as large as in the time series, showing that investment returns have more affect on industry

[2] Anecdotal evidence from market participants also tells us that insurers consider accounting returns to reflect future expected investment returns.

average premium, rather than relative pricing in the cross section of premiums.

We provide further evidence of asset-driven insurance pricing with three extensions to our analysis. First, in the cross section of P&C insurers, we implement an instrumental variable estimation, using underwriting funding volatility and firm size (from the test of Proposition 1) as instruments for insurer's investment returns. We show that when instrumented investment returns are 100bps higher, insurance premiums are 0.3 percentage points lower. Second, in the cross section of life insurers, we use a series of shocks to investment return due to mergers. When insurer companies are purchased by other insurers, their investment returns change as their portfolios adapt to the investment strategy of their acquiring insurance company. Using a difference in difference analysis, we show how insurance premiums fall (rise) in response to increases (decreases) in investment returns that are driven specifically by merger events. Third, in the time series, we show that the sensitivity to credit spreads is driven by expected excess return on bonds, as proxied by the Gilchrist and Zakrajšek (2012) excess bond premium, rather than the component of credit spreads that reflects expected default risk.

To understand our contribution, it useful to think of insurance premiums as the product of:

$$\text{Premium} = \underbrace{\frac{E\left[Claim\right]}{1+R^F}}_{\substack{\text{Actuarial price:} \\ \text{(Hill, 1979)} \\ \text{(Kraus and Ross, 1982)}}} \times \underbrace{\text{Markup}}_{\substack{\text{Imperfect competition} \\ \text{(Mitchell et al., 1999)}}} \times \underbrace{\text{Shadow Cost}}_{\substack{\text{Regulatory capital constraints} \\ \text{(Froot and O'Connell, 1999)} \\ \text{(Koijen and Yogo, 2015)} \\ \text{(Ge, 2020)}}} \times \underbrace{\frac{1+R^F}{1+R^I}}_{\substack{\text{Asset-driven insurance pricing} \\ \text{(this paper)}}}$$

The first term is the expected claim discounted at the risk free rate. It is typically considered to be the insurers' marginal cost of underwriting a policy. The basic intuition is that an insurer can invest premiums received in a portfolio of Treasury bonds that replicate the expected liabilities. Due to the time value of money, the marginal cost is therefore lower than the expected claim. The second term results from imperfect competition, and the third term rests on theories of financial frictions. When insurers are capital constrained and their access to external finance is costly, they deviate from their optimal unconstrained premium price in order to improve their regulatory capital position. The contribution of this paper is to return to the fundamental question of what insurance companies consider to be their time value of money. We challenge whether it is the risk-free rate, as the actuarial price suggests, instead arguing that insurers' also use the liquidity premium in their expected investment return, R^I, such that the discount rate is higher than the risk-free rate. The rational is based on there being a liquidity friction in asset markets, with insurance companies able to take advantage of this due to their unique funding source.

We consider the other channels of insurance pricing in our analysis, with particular focus on capital constraints (Froot and O'Connell (1999), Koijen and Yogo (2015), Ge (2020)), which has previously been shown to drive insurance prices. To guide the empirical analysis, we first extend the model with a statutory capital constraint that, in the spirit of Koijen and Yogo (2015), shows how insurance premiums can change when the constraint is binding. To rule out this mechanism capital constraints as the driver of our empirical results, we show that asset driven insurance pricing is present in the P&C markets industry, where binding capital constraints should result in higher premiums, thus alleviating the confounding variable problem. We further show that our results hold in periods where insurance companies are unlikely to have been capital constrained. We therefore argue that while capital constraints play an important role in insurance pricing, they are not the only factor. Instead, insurance companies also account for expected returns when setting prices, and this mechanism is especially important when insurance companies are unconstrained by regulatory capital requirements.

Two other alternative mechanisms we consider empirically are differences in the demand for insurance and also reinsurance activity. A possible explanation of our cross sectional results is that the insurance companies which take more investment risk are more likely to default themselves. Lower insurance premiums could thus be driven by relatively lower demand for insurance relative to their competitors. To rule out this alternative mechanism, we use AM Best capital strength ratings, showing that our results hold for the subset of highly rated firms in the life industry. The results also hold after controlling for measures of balance sheet strength in the full sample of P&C insurers. Regarding reinsurance activity, a potential alternative hypothesis is that insurance companies that are better able to reinsure their liabilities are therefore able to set lower premiums.[3] We show our results are robust to controlling for the fraction of an insurer's underwriting premiums that are reinsured.

Our paper is also related to Stein (2012), Hanson, Shleifer, Stein, and Vishny (2015), and Chodorow-Reich, Ghent, and Haddad (2020) who also study the comparative advantage of intermediaries investing in illiquid assets. As in our paper, these theories rest on a violation of the Modigliani and Miller (1958) capital irrelevance theorem, with an asset's value dependent on the funding structure of the investor. In particular, intermediaries are

[3] We thank Stefano Rossi for this observation.

able to earn excess returns relative to other investors. However, in the referenced papers, the value generated flows to the equity holder of the intermediary by assumption. The key contribution of our paper is to document that the value from stable funding can flow to the insurer's policy holders, rather than just the equity holders. Our finding has potential welfare implications, with insurers offering cheaper insurance to households when financial markets are distressed.

Novy-Marx and Rauh (2011) and Rauh (2016) document how US pension funds increase the discount rate on their existing liabilities to reduce the present value of their reported liabilities. We instead study how insurance companies set the price on new liabilities, highlighting the interconnectedness of an insurer's assets and liabilities. In this sense, our paper relates to Kashyap, Rajan, and Stein (2002), who show study the synergies of banks assets and liabilities. While their paper focuses on how banks provide immediate liquidity on both liabilities and assets (i.e. credit lines), we argue insurer's stable liabilities mean they can take liquidity risk on their assets.

More broadly, our results relates to the intermediary asset pricing literature. Constraints on the liability side of intermediary's balance sheets affect their asset preferences (Brunnermeier and Pedersen (2009) He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014)) which ultimately ends up changing asset prices (Ellul et al. (2011), Adrian et al. (2014), He et al. (2017) and Greenwood and Vissing-Jorgensen (2018)) due to intermediary's position as marginal investors in segmented markets. We not only study how intermediaries affect asset prices, but also consider how asset markets affect intermediary liability prices. The findings of our paper therefore sheds further light on the interdependencies of intermediaries and asset markets that has been widely discussed post financial crisis.

In summary, we contribute to the literature by uncovering a new stylised fact and presenting theory that explains this fact: insurance premiums are asset driven.

2 Model of Insurance Premiums and Illiquid Asset Prices

The economy has three periods, $t = 0$, 1 and 2, two types of agents, investors and insurance companies, and two asset markets.

Assets. There is a liquid asset with exogenous return R^F, and an illiquid asset with fixed supply S. The illiquid asset pays one unit of wealth at maturity $t = 2$, and the price at $t = 0$ is determined endogenously. The defining characteristic is that the illiquid asset incurs a cost if sold before before maturity (i.e. sold at $t = 1$). The seller of the asset receives their initial investment less a cost of $\frac{1}{2}\lambda x^2$ dollar for every x dollar sold. The parameter λ therefore captures liquidity conditions in the secondary market of the illiquid asset.

Investors. A continuum of risk-neutral investors, each endowed e, are identical at $t = 0$. In the spirit of Diamond and Dybvig (1983), they learn at $t = 1$ if they are early or late consumers. 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 ω of being an early consumer.

If the investor chooses to a buy dollar amount θ of the illiquid asset their consumption is

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

where

$$R = \frac{1}{\text{Asset Price}} - \left(1 + R^F\right) \tag{2}$$

is the equilibrium excess return on the illiquid asset.

In the first case of equation (1), the investor learns they are an early consumer and sells all assets at time 1, paying the associated transaction costs on their illiquid asset holdings. In the second case, the investor learns they are a late consumer and holds all assets to maturity, earning the excess return on their illiquid asset holdings.

The problem facing the investor is to choose θ to maximise expected consumption

$$\max_{\theta} \ \mathbb{E}\left[c\right] = e\left(1 + R^F\right) + \left(1 - \omega\right)\theta R - \frac{1}{2}\omega\lambda\theta^2. \tag{3}$$

Insurance Companies. The economy's other agent is a representative insurance company. The risk-neutral insurer receives premiums on insurance policies at $t = 0$ and pays the policy claims at either $t = 1$ or 2. The premium P is set by the insurance company, and the number of policies sold is determined by the exogenously given downward sloping demand curve

$$Q(P) = kP^{-\epsilon} \tag{4}$$

where $\epsilon > 1$ is the elasticity of demand.

The insurer is endowed with equity capital E at $t = 0$ such that their total liabilities

$$L = E + QP \tag{5}$$

are the sum of equity and the funding generated from the insurance underwriting business. The total future claims underwritten are defined

$$C = Q\bar{C}. \tag{6}$$

where $\bar{C}$ is the policy claim on each individual contract.

We assume that the insurance business is sufficiently diversified that we can think of total claims, C, as being a known constant. Insurance companies 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 time 1 as $\tau \in \{\bar{\tau} - \sigma, \bar{\tau} + \sigma\}$ and assume that each state occurs with equal probability. The remaining fraction of claims, $(1 - \tau)$, arrive at time 2. Claims are on insurance products such as car or household insurance, which are not related to the investment liquidity risk, λ, and are held by households outside of the model.

The insurer buys dollar amount $\Theta \geq 0$ in the illiquid asset and puts remaining wealth $L - \Theta \geq 0$ 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.

The insurer's final wealth depends on the dollar amount τC of claims to be paid at $t = 1$ relative to the dollar amount $L - \Theta$ invested in the liquid asset. 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 insurer is forced to sell a fraction of illiquid assets before maturity. The final wealth is thus expressed with two cases

$$W = \begin{cases} L\left(1 + R^F\right) - C + \Theta R & \text{if } \tau C \leq L - \Theta \\ L\left(1 + R^F\right) - C + (L - \tau C) R - \frac{1}{2}\lambda\left(\tau C - (L - \Theta)\right)^2 & \text{if } \tau C > L - \Theta. \end{cases} \tag{7}$$

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.

In the second case, the insurer sells all their liquid assets plus a portion of their illiquid asset portfolio to cover remaining $t = 1$ claims. Dollar amount $\tau C - (L - \Theta)$ of illiquid assets are sold before maturity and incur the associated sale cost, which we assume is paid at $t = 2$. The dollar amount of unsold illiquid assets is the initial holdings minus the sold holdings: $\Theta - (\tau C - (L - \Theta)) = L - \tau C$. These illiquid assets still earn the liquidity premium.

The insurer's objective function is to choose P and Θ to maximise their expected final wealth

$$\max_{P,\,\Theta} \; \mathbb{E}\left[W\right] \tag{8}$$

where wealth W is defined in equation (7).[4]

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

$$\theta^* + \Theta^* = S \tag{9}$$

where investor demand θ^* and insurer demand Θ^* are given by the optimisation problems (3) and (8) respectively. Supply S of the illiquid asset is exogenously given. Equilibrium in the insurance market is also where demand equals supply, with supply given by the insurers profit maximisation (8) and demand exogenously given from demand curve (4).

3 Theoretical Results

We begin by considering the asset allocation decision of the two agents in the model. All proofs are in Appendix B.

Proposition 1 (illiquid asset allocations).

1. *The investor's equilibrium dollar investment in the illiquid asset is*

$$\theta^* = \frac{(1-\omega)}{\omega} \frac{R}{\lambda}. \tag{10}$$

[4]We could also have insurance equity bought by investors,and insurance companies maximising the present value of final wealth. As along as the discount rate is a fixed required return (for example, the liquid return R^F or the illiquid return $R^F + R$), it is therefore independent of the insurance company's asset allocation, and the qualitative results of the model are unchanged. A fixed required return results from the fact that agents are risk-neutral.

2. The insurer's equilibrium dollar investment in the illiquid asset is

$$\Theta^* = L - (\bar{\tau} + \sigma) C + \frac{R}{\lambda}. \tag{11}$$

The investor and insurer both increase their illiquid asset allocation in the illiquid asset excess return, R, and reduce their illiquid asset allocation in the cost λ of selling the illiquid asset in secondary markets. The investor and insurer also decrease their illiquid allocation in the probability of early consumption ω and the expected fraction of claims $\bar{\tau}$ to be paid early. These parameters increase the chance of costly $t = 1$ sales of the illiquid asset. For the insurer, the variance σ of claims arriving early also matters for the illiquid investment allocation. The more volatile an insurer's funding (i.e. higher σ), the less illiquid assets they hold.

We next consider the insurer's pricing decision on insurance policies. We assume that the insurer treats the excess return on the illiquid asset R as a fixed constant — that is, they do not internalize the incremental impact of their choices on the magnitude of the excess return. First-order conditions of equation (8) with respect to P therefore yields the following proposition.

Theorem 1 (**asset-driven insurance pricing**)**.** *The equilibrium insurance premium P of a policy with claim $\bar{C}$ is*

$$P = \frac{\bar{C}}{1 + R^F} \left(\frac{\varepsilon}{\varepsilon - 1} \right) \left(\frac{1 + R^F}{1 + R^I} \right) \tag{12}$$

where R^I is the insurer's expected investment return on their asset holdings that are funded by premiums

$$R^I = \frac{1 + R^F + R}{1 + (\bar{\tau} + \sigma) R} - 1 > 0. \tag{13}$$

We can see that the insurance premium is the product of three components. The first term, the actuarial price, is the claim discounted by the risk-free rate. The second term, $\frac{\varepsilon}{\varepsilon - 1} > 1$, is the markup the insurer can charge due to imperfect competition.[5] The final term, $\frac{1+R^F}{1+R^I} < 1$, is related to the insurer's expected excess return on their illiquid asset holdings. Given that the fraction of claims $\tau \in \{\bar{\tau} - \sigma, \bar{\tau} + \sigma\}$ arriving at $t = 1$ can not exceed one, we know that $R^I > 0$. This means that insurers set lower premiums when illiquid investment returns are higher. We call this *asset-driven insurance pricing.*

[5] As the elasticity of demand for insurance tends to infinity, the insurer has no market power and the markup tends to one.

Asset-driven insurance pricing means that the premium depends on the illiquid asset excess return R, and the funding characteristics ($\bar{\tau}$ and σ) of the insurer. The insurer's borrowing costs through insurance underwriting are now dependent on their asset allocation and funding decisions. This Modigliani and Miller (1958) violation occurs because insurance companies can earn a risk-free liquidity premium on illiquid investments due to their stable funding.

To understand the mechanism, note that the maximum amount of claims to be paid by the insurer at $t = 1$ is $(\bar{\tau} + \sigma) C$. This observation leads to the lower bound $\underline{\Theta}$ on the insurer's illiquid asset holdings

$$\underline{\Theta} = L - (\bar{\tau} + \sigma) C. \tag{14}$$

Investing less than this in illiquid assets would mean forgoing liquidity premium that is available to the insurer risk-free, so $\Theta^* \geq \underline{\Theta}$. Other investors in the economy, on the other hand, face the risk of selling all assets at $t = 1$. The $\underline{\Theta}$ component of the illiquid allocation is therefore the insurer's source of competitive advantage relative to other investors in the illiquid asset market. Indeed, as $\underline{\Theta}$ investments earn insurers R with zero risk, these investments lower the insurer's marginal cost of underwriting . Insurers therefore compete for funding and insurance premiums are set lower when R is higher.

The special case where $\bar{\tau} + \sigma = 1$ illuminates the point. In this case, the insurer faces the risk that all claims arrive at $t = 1$ and they thus have no competitive advantage. The expected investment return on the asset holdings funded by premiums is $R^I = R^F$, and our result nests Modigliani and Miller (1958). The insurance premium is priced by discounting the claim by the exogenously given liquid risk-free rate, and is no longer dependent on the insurer's illiquid asset allocation Θ or the equilibrium liquidity premium R.

The model's next prediction follows directly from the partial derivative of insurance premium with respect to illiquid asset returns. While insurance companies take the illiquid asset return as a fixed constant in their pricing decision, we also show how the illiquid asset return moves in equilibrium with respect to exogenous shocks to liquidity.

Proposition 2 (time series of insurance premiums and illiquid asset returns). *Insurance companies set lower premiums when the expected excess returns on illiquid asset are higher*

$$\frac{\partial P}{\partial R} < 0, \tag{15}$$

with increases in equilibrium illiquid asset returns resulting from

1. *an exogenous increase in transaction costs for the illiquid asset* $\frac{\partial R}{\partial \lambda} > 0$*; or*

2. *an exogenous increase in demand for liquidity from other investors* $\frac{\partial R}{\partial \omega} > 0$*.*

Proposition 2 allows us to make predictions for the average insurance premium price, which we expect to fluctuate over time in response to expected illiquid asset returns. When illiquid asset returns increase, either due to exogenous shocks to liquidity or exogenous shocks to liquidity demand from investors, insurers reduce premiums and increase funding. Note that this behaviour makes the insurer a counter-cyclical liquidity investor. When liquidity conditions deteriorate, insurers increase their balance sheet and illiquid asset holdings, dampening the impact of negative liquidity shocks on equilibrium returns.

We now consider the cross section of insurance premiums. We introduce a small insurer to the model, which we will denote with subscript i. We assume that they have mass zero, such that they do not affect equilibrium, and that the small insurer has less stable funding relative to competitors (i.e. $\sigma_i > \sigma$). We can see from equation (13) that this means $R_i^I < R^I$. The next proposition follows from this observation.

Proposition 3 (cross section of insurance premiums and illiquid asset returns). *For insurer i, with an expected investment return on illiquid investments lower than that of the industry average ($R_i^I < R^I$), the insurance premium will be set higher relative to competitors ($P_i > P$).*

Proposition 3 allows us to make predictions for the cross section of insurance premiums, which we expect to vary in relation to individual insurer expected investment returns relative to their competitors.

Numerical Example. We conclude the model by illustrating how insurers' stable funding, σ, and exogenous shocks to asset market liquidity, λ, affect insurance premiums by way of a numerical example. We choose parameters as follows: asset supply is $S = 1$, investors have $\omega = 0.2$ probability of being early consumers, insurance claims arrive at $t = 1$ with probability $\bar{\tau} = 0.5$, elasticity of insurance demand is $\epsilon = 15$, the fixed parameter in the demand function is $k = 1$, claims are $\bar{C} = 1$, and the insurer is endowed with equity capital $E = 0.25$.

In Figure 2, Panels A, we investigate how the expected return on the illiquid asset, R, depends on the transaction costs of selling the illiquid asset, λ. We show the solution for three choices of funding stability of the insurer: $\sigma = 0.1$, $\sigma = 0.3$ and $\sigma = 0.5$. A lower σ means the insurer has more stable insurance funding. We see that the illiquid asset return increases as transaction costs increase in the secondary market. However, the sensitivity is less steep when insurer's funding is more stable and σ is lower.

In Panel B, we see that insurer's illiquid asset allocation also increases in λ, as the higher expected return encourages them to increase their exposure to the asset. The effect is stronger the more stable the insurer's funding is. The insurer's stable funding therefore makes them a counter-cyclical investor, increasing allocations when expected returns are higher. This feedback affects the equilibrium return, explaining why the return on the illiquid asset is less sensitive to λ when the insurer has more stable funding. The insurer absorbs more of the illiquid asset when liquidity conditions deteriorate, dampening the effect of liquidity on the equilibrium illiquid asset return.

Panel C shows that the insurance premium markup falls as λ increases. The insurer is able to extract more illiquid investment returns on their assets, and thus the marginal cost of underwriting the claim $\tilde{C}$ falls. In the case $\sigma = 0.5$, the insurer has no funding advantage, with $\bar{\tau} + \sigma = 1$ meaning they face the risk that all claims arrive at $t = 1$. The premium markup and insurer asset allocation are no longer dependent on λ, with our model nesting Modigliani and Miller (1958). The equilibrium return R is also now a linear function of λ, with no dampening impact of a counter-cyclical insurer allocation to the asset.

4 Data and Methodology

4.1 Measuring Insurance Prices

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:

$$\text{Actuarial Price}_t = \sum_{k=1}^{T} \frac{E_t\left[C_{t+k}\right]}{\left(1 + R^f_{t+k}\right)^k} \tag{16}$$

where C_{t+k} is the policy's claim k periods from its inception t, and R^f_{t+k} is the k-period risk-free rate at time t.

In addition to absolute markups, we also use annualised markups in our study. These are the markup divided by the duration of the expected cash flows of the product. Following Koijen and Yogo (2015), we calculate expected cash flows and present values based on appropriate mortality table from the American Society of Actuaries and the zero-coupon Treasury curve Gürkaynak, Sack, and Wright (2007).

P&C Insurance. For most types of P&C contracts neither actual nor actuarially fair prices are readily available, making it impossible to calculate a markup. However, P&C insurers do track their pricing and underwriting performance through a measure called *combined ratio*, which is reported quarterly to the market. It is defined as:

$$\text{Combined Ratio} = \frac{\text{Losses} + \text{Expenses}}{\text{Premium Earned}} \tag{17}$$

where *losses* are the claims paid out on policies in the quarter (plus any significant revisions to future expected claims), *expenses* are the operating expenses of running the underwriting business and *premium earned* are the premium received on policies spread evenly over the life of the contracts. For example, if an insurer receives premium $P_{t,n}$ at time t on a policy that has a life of n quarterly reporting periods, then the reported *premium earned* on this contract in future reporting periods t' will be

$$\text{Premium Earned}_{t'} = \begin{cases} \frac{P_{t,n}}{n}, & \text{if } t < t' \leq t+n. \\ 0, & \text{otherwise.} \end{cases} \tag{18}$$

Premium earned is used in the *combined ratio* to ensure that realised claims are offset against the premiums that were received to cover their payment, and prevents the measure from being biased by changes in an insurers' underwriting volume. If an insurer doubles the size of their underwriting business, premiums received, $P_{t,n}$, double immediately while realised claims, at that time, are unaffected. Calculating the combined ratio with premiums received would therefore suggest a sudden improvement in underwriting (high inflows to outflows) even though the profitability of the underwriting business is unchanged. Premium earned, on other hand, increase in future periods, at the same time that claims are increasing due to the increased volume of business.

In our empirical analysis, we define underwriting profitability as:

$$\text{Underwriting Profitability}_t = \frac{\text{Premium Earned}_t - \text{Losses}_t - \text{Expenses}_t}{\text{Insurance Liabilities}_{t-1}} \tag{19}$$

which is the profit from underwriting divided by the size of the underwriting business. Insurance liabilities are reported by insurance companies and are the sum of "management's best estimate" of future losses and reinsurance payables (Odomirok et al., 2014).

An increase in an insurer's underwriting profit can either be created by higher premiums relative to expected claims, or realised claims that are lower than insurer expectations. The latter generates some noise in our measure of insurance premiums, but we assume the noise from claim risk is uncorrelated with investment returns for our empirical analysis.

Our theory states that the predictive variables for premiums should reflect expected investment returns at the time the policies are written, not when the earning from these policies are reported. In our regression analysis, we therefore use annual averages over the preceding 12 months, since the Property and Casualty insurance is usually short maturity contracts. For example, auto-mobile insurance policies (42% of the total P&C market) are typically standardised to have one year duration. We therefore only need expected returns over the previous four quarters for our regression analysis.

4.2 Data

Life Annuity Pricing. Koijen and Yogo (2015) collate data on annuity products prices from WebAnnuities Insurance Agency over the period 1989 to 2011. There is pricing for 3 types of annuities: term annuities (i.e. products that provide guaranteed income for a fixed term), life annuities (i.e. products that provide guaranteed income for an unfixed term that is dependent on survival) and guarantee annuities (i.e. products that provide guaranteed income for fixed term and then for future dates dependent on survival). The maturity of term annuities range from 5 to 30 years, whilst guarantees are of term 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 semi-annual observations, except for the life annuities (with and without guarantees) which is also semi-annual, but with monthly observations during the years around the financial crisis, 2007-2009, which is the focus of Koijen and Yogo (2015). To summarize we have 96 insurers quoting prices on 1, or more, of 54 different annuity products at 73 different dates, which gives us 1380 company-date observations.

P&C Insurer Financial Statements. Insurance entities are required to report financial statements to regulatory authorities on a quarterly basis. S&P Global: Market Intelligence collates and provides this data. Our sample period is 2001 to 2018 for both Life Insurance and P&C Insurance companies.

In total, there are 3,951 individual P&C insurance entities in our sample. Large insurance groups often have many separately regulated insurance entities under their overall company umbrella. We aggregate the entities up to their P&C insurance groups. For example, the two largest P&C insurance groups in our sample, State Farm and Berkshire Hathway, have been aggregated from 10 and 68 individual insurance entities respectively. To aggregate dollar financial variables we sum across entities. To aggregate percentages and ratios (such as investment yield) we use the asset-value weighted average.

Our final P&C sample consists of 1,070 insurance groups running P&C businesses over 68 quarters from March 2001 through to December 2017. In total we have 44,780 firm-quarter observations, with a minimum of 184 insurance groups available in any given quarter and a maximum of 735. To get to this final sample we have excluded insurance companies with less than 4 years of data, companies who never exceed $10 million in net total assets, company-year observations where the company has less than $1 million in earned premium over the year, and observations with non-positive net total assets and net premium earned. We do this to ensure that the companies we are looking at are relatively large and active. All financial statement variables are winsorized at the 5th and 95th percentiles in each quarterly reporting period.

The financial statements provides balance sheet and net income variables. For cross sectional analysis, our main variable is the accounting investment returns as described in Section 5. We also use their average credit portfolio rating[6], asset allocations and various measures of balance sheet strength: Size (log of total assets), Asset Growth (annual change in total assets), Leverage Ratio, Risk-Based Capital, Amount of Deferred Annuities (Life insurers only)[7], Unearned Premium to Earned Premium ratio[8] and reinsurance activity (net premiums reinsured / net premiums received). The last two are for P&C insurers only.

For cross sectional analysis on life insurance companies, we merge S&P Global financial statement data with the annuity markup data provided in Koijen and Yogo (2015). In the period 2000 to 2011, the intersection of our two datasets, we are able to merge both data with investment yields and annuity markups for 16 companies. Consistent with the P&C data construction, we have excluded insurance companies with less than 4 years of data.

[6]The insurance regulator 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 2 is BBB, level 3 BB, level 4 is B, level 5 CCC and level 6 is all other credit.

[7]these unprofitable products caused constraints in the financial crisis

[8]this gives an indication of the remaining unpaid liabilities relative to current volume of business

Financial Market and Macroeconomic Variables. To measure the credit spread we use Moody's Seasoned Baa corporate bond yield relative to 10-Year Treasury and retrieved from St. Louis Fed's website (fred.stlouisfed.org). We also use the excess bond risk premium portion of credit spreads as provided in (Gilchrist and Zakrajšek (2012)). Other right-hand side variables include the 6-Month to 10-Year Treasury Constant Maturity Rates and TED spread (downloaded from St. Louis Fed's website), to proxy for funding costs and the shadow cost of funding respectively. The TED spread is the difference between the three-month Treasury bill and the three-month LIBOR based in US dollars. The CAPE ratio, which is real earnings per share over a 10-year period, is retrieved from the Robert Shiller website.

Mergers and Acquisitions. We have hand collected data on mergers and acquisitions across our sample of life insurers with annuity pricing. The insurer net yields on invested assets around these assets are taken from our S&P Global: Market Intelligence dataset (where available) or directly from insurer financial reports on line. The list of events that we use in our analysis is shown in table (C.1).

4.3 Summary Statistics

Table 1 presents summary statistics for the key variables in our empirical analysis. The average annuity markup on an absolute basis is 6.75%, 5.31% and 4.24% for fixed term, life and guarantee annuities respectively. On an annualised basis, these markups are 1.03%, 1.12% and 0.50% respectively. Our main dependent variable in P&C markets is underwriting profitability, which across this sample has a mean of 0.31% and standard deviation of 3.24%. The average 5-year rolling standard deviations of underwriting profitability at an insurer-level is 2.35%. In our cross sectional analysis, the main independent variable is insurance companies investment return. This averages 2.75% in the P&C industry and 5.97% in our sub-sample of life insurers.

5 Preliminary Evidence

Before testing the model propositions in section 6, in this section we provide preliminary evidence that shows the importance of investment returns to the insurance business model.

Table 2 presents the aggregated industry balance sheets for the Life Insurance industry and P&C Insurance industry. There are two key takeaways that are relevant for our analysis. First, we see that the large asset portfolios are predominately funded by insurance underwriting. The Life Insurance industry has an average equity ratio of 9% and the P&C industry has an equity ratio of 38%, with the dominating source of leverage in both cases being insurance liabilities. Second, we see that insurance companies take lots of investment risk in their asset portfolios. Risk-free asset allocations (cash and Treasuries) are only 8% 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.

Figure 3 next presents the P&C industry's aggregated net income. The total net income is split between the earnings reported from the asset portfolio investments, the earnings reported on the insurance underwriting business and (the residual) other income. The striking feature of Figure 3 is that the industry often loses money through insurance underwriting, and is only profitable once investment income is included. It should be noted that the underwriting losses shown in Panel A do not take time value of money into account. The industry standard for reporting on their underwriting is to ignore this. In Panel B, we adjust for this, increasing (decreasing) underwriting (investment) income by the value of insurance liabilities multiplied by the risk-free rate. Even after this adjustment, we see that returns on investment portfolios are of first order importance to the insurance business model.[9]

Figure 4 presents boxplots of insurers' investment returns in each reporting quarter of our sample, highlighting both the time series trends in insurer investment returns, and the rich heterogeneity in investment returns in the cross section of insurers. In any given quarter in our sample, the range between the 25th and 75th percentiles of investment returns is in excess of 150 bps. These investment returns are insurer's accounting investment returns, which are reported on a quarterly basis. For fixed income assets, the accounting treatment of investment returns is to report the yield at purchase amortised smoothly over the life of the bond. If the bond defaults or the insurer sells with a gain/loss, this

[9] Life industry insurance companies don't report underwriting profits is the same way as P&C insurers, so the equivalent analysis is not possible in this industry. Refer to Appendix A.1 for a discussion of profitability in the Life Insurance Industry.

is also included in their investment return. However, so long as the insurer does not sell or the issuer does not default on the bond, the investment return methodology protects the insurer from mark-to-market volatility on their credit assets.[10] This treatment reflects insurers' long-term buy and hold approach to investing,[11] and is consistent with Chodorow-Reich, Ghent, and Haddad (2020) view of insurers as "asset insulators" that can ride out transitory dislocations in market prices. It is also consistent with our model of insurers being able to earn liquidity premium on illiquid investments.

Table 3 Panel A shows how variation in insurers' asset allocations explain cross sectional variation in insurer investment returns. We regress insurer investment returns (in bps) on asset allocations (in percent) with controls for time fixed effects. We see that insurers with large credit allocations have higher investment returns, while large allocations to treasuries and cash mean lower investment returns. For example, column 1 shows that a 1 percentage point increase in credit and cash allocations result in a 1.25 bps increase and 1.50 bps decrease in investment returns respectively. In column 2 of Table 3 we interact credit allocations with the credit portfolios value-weighted average credit rating.[12] We can see that the effect of credit allocations on investment returns is largely driven by the level of credit risk in these portfolios. Finally, in column 3 of Table 3, we interact credit rating interacted with credit allocation with the previous quarter's credit spread. The effect of credit portfolios on investment returns is larger when credit spreads are higher.

Table 3 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 insurer investment returns, with an insurer's current quarter investment return explaining 37% of their next quarter investment return. Given insurer accounting returns predict next periods investment returns, we interpret cross sectional variation in this measure as cross sectional variation in insurer's *expected* investment return. The auto correlation of investment returns at an insurer level is not surprising given the accounting treatment of investment returns on fixed income assets.

Columns 3-4 of Table 3 Panel B show the macro-level time series drivers of investment

[10]Refer to A.2 for a more detailed description of how accounting investment returns are calculated by insurers.

[11]Schultz (2001) and John Y. Campbell (2003) estimate that insurers hold between 30% and 40% of corporate bonds and yet account for only about 12% of trading volume

[12]The insurance regulator, NAIC, assigns credit into six broad categories (level 1 through 6) based on their credit ratings, with higher categories reflecting higher credit risk. Level 1 bonds are rated AAA-A, level 2 is BBB, level 3 BB, level 4 is B, level 5 CCC and level 6 is all other credit

returns. We see that the large fixed income allocations in insurer portfolios make the risk-free rate, the slope of the yield curve and the credit spread on corporate bonds all very significant drivers of investment returns. On the other hand, the CAPE ratio (capturing expected equity returns) and the TED spread (capturing financial market distress) are unimportant. Our finding that credit spreads predict insurer investment returns is consistent with previous work that show that corporate bonds deliver excess returns to treasuries over the long-term (Krishnamurthy and Vissing-Jorgensen (2012), Gilchrist and Zakrajšek (2012)). In the long-term, the insurers accounting return on investments must equal their economic return. If credit spread only reflected default losses, then credit spreads would have no predictability for insurer investment returns on average.

6 Empirical Results

6.1 Stable Insurance Funding and Illiquid Asset Allocations

We first test Proposition 1's prediction for insurance companies asset allocation decision: insurers with more stable insurance funding hold more illiquid assets. We take this prediction to the data using P&C insurers' historical volatility on insurance underwriting as a proxy for stable funding. For each insurer, we calculate rolling 5-year volatility estimates of insurance underwriting profitability (as defined in equation (19)). We then use volatility lagged one quarter as the independent variable. Our two variables for capturing insurer investment risk is their cash allocation and their credit allocation multiplied by the average credit rating of this portfolio.[13] We report the results in columns 1-6 of Table 4 Panel C.

We see that stable funding predicts low cash allocations and large allocations to risky credit. For example, an insurer with underwriting profitability volatility 1 standard deviation higher than competitors has a 0.22 standard deviations (or by 3 percentage points) higher cash allocation compared to competitors. Following Ge and Weisbach (2020), we include firm size and other variables that capture insurers balance sheet strength as controls. Consistent with their work, we find strong evidence that the size of an insurer is a determinant in the amount of risk in an insurer's investment portfolios. Assuming large insurers have more diversified and stable underwriting businesses, this result is consistent with our model prediction. However, our results take this a step further, showing that

[13] We use a numeric measure of average credit rating, as assigned by the insurance regulator.

even when comparing firms of equal size, the insurer with less volatile underwriting performance takes more investment risk in their credit portfolio. This finding also holds after controlling for a vector of balance sheet strength variables.

Columns 7-9 of Table 4 show that large insurers and those with stable underwriting cash flows also realise higher investment returns. In other words, the increased investment risk translates into higher investment returns. To give a sense of the order of magnitude, an insurer with funding volatility one standard deviation lower than competitors has an investment return that is 21bps higher than it's competitors.

In summary, in this subsection we have documented a relationship between the stability of the funding generated by insurance underwriting and the asset allocation decisions of insurance companies. Insurance companies that are large and have more stable funding take more investment risk and earn higher investment returns. According to our model, the explanation is that insurers use the stability of the insurance funding to earn liquidity premium on their assets.

6.2 Investment Returns Drive the Time Series of Premiums

We next test Proposition 2's prediction for insurance prices and illiquid investment returns in the time series: high expected asset returns mean lower insurance premiums. We take this prediction to the data using credit spreads as a proxy for illiquid investment expected returns.

Figure 1 illustrates our central time series finding using our longest available sample. The figure presents the industry average markup on a 10 year fixed term annuity against the 10 year BAA credit spread from 1989 to 2011. Markups are defined as the quoted price relative to their actuarially fair price. The negative correlation between the markup (left hand axis) and credit spreads (right side axis, inverse) is obvious. In fact, the R-squared from the single variable regression of markups on credit spreads is as high as 77%.

We now show the relationship between annuity markups and credit spreads is present across different life products and sample periods, and robust to controls for other market returns and macroeconomic variables. Motivated by our theory, we focus on the impact of expected investment returns. We control for the global financial crisis using a dummy variable, as it was a period where financially constrained life insurers charged very low markups Koijen and Yogo (2015), which may confuscate our results.[14] We also control for

[14] Section 7 considers the impact of capital constraints within the context of asset-driven insurance pricing

unemployment rate to proxy for shifts in the demand for insurance.

Table 5 reports the parameter estimates from the following regression:

$$m_{ikt} = \beta_c \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot CS_t \times \mathbb{1}_{GFC} + B' \cdot X_t + FE_i + FE_k + \epsilon_{ikt}$$

where m_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in subproduct category k. Subproducts vary depending on age, sex and maturity of the annuities. CS_t is Moody's credit spread of BAA corporate bonds, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010). We include a vector of time series controls, X_t, which includes the risk-free rate, the slope of the yield curve, the TED spread, the CAPE ratio (to capture other drivers of expected investment returns) and US unemployment rate (to capture time variation in the demand for insurance). We also include lagged markups in the control vector to control for potential autocorrelation in the dependent variable. Columns 1-3 report the parameter estimates from time series regressions where for the dependent variable, $\overline{m}_t$, we have averaged across insurers and subproduct categories in each time period. Columns 4-5 report full panel specifications. Panel A, B and C show the results for markups on life, guarantee and fixed-term annuity products respectively.

Across specifications, we see that a 100bps increase in credit spreads lowers annualised markups by 52bps (t-statistic of 5.34). Given that annualised markups are 1% on average, this means that markups fall by 50% when insurers can earn more on their credit portfolios.[15] The explanatory power is also very large. Taking life annuities as an example, the credit spread alone explains 80% of the variation in levels (see the adjusted r-squared in column 1 of Panel A). The main result of this section is also robust to including the vector, X_t, of time series controls. We report estimates for all variables in vector X_t in Appendix Table C.2. Note that the risk-free rate is not significant as the effect of risk-free rates on premiums is captured in the actuarial price (equation 16), which is used in our dependent variable.[16]

in detail.

[15] We use annualised markups (rather than absolute markups) so that it is easier to interpret coefficients across products with different durations. However, all results are qualitatively consistent to specifications with absolute markups.

[16] Table C.4 in the appendix presents results from identical specifications as table 5, but with markups and investment returns in changes rather than levels. Our results are robust to this specification, with estimated sensitivities of similar magnitudes. We proceed with analysis in levels throughout the rest of the empirical results.

Koijen and Yogo (2015) highlight that the financial crisis saw a dramatic fall in markups from November 2008 through to February 2010. Figure 1 shows the annualised 10yr annuity markup fell from 1.25% to -0.75% across the dates. In Columns 3 and 5 we interact credit spreads with $\mathbb{1}_{GFC}$, which is an indicator variable set to one over the same period. The estimated coefficient on the interaction is positive, and generally we find it to be statistically significant. The positive interaction coefficient shows that the baseline coefficient is less negative in the financial crisis. Said differently, the negative relationship between premiums and credit spreads is stronger outside of the global financial crisis period. Nevertheless, our results suggests that credit spreads were still important in this period, with roughly 40% of this drop in markups due to sensitivity of markups to credit spreads. The remaining 60% was due other factors such as capital constraints.[17] We therefore argue that while capital constraints play an important role in insurance pricing, they are not the only factor. Instead, insurance companies also account for expected returns when setting prices, and this mechanism is especially important when insurance companies are unconstrained by regulatory capital requirements.

Table 6 shows how insurance premiums in the P&C industry vary with credit spreads. The table has the same five column specifications as the previously discussed Table 5. In the P&C industry we do not observe prices directly but instead use underwriting profitability (19) as the main dependent variable. This measure is the ratio of their underwriting profit relative to their insurance liabilities. We interpret lower underwriting profitability as lower prices. Given that underwriting profitability reflects insurance premium pricing over the previous year, we use lagged credit spreads on the right hand side of the regression. We find a statistically significant impact of credit spreads, with a 100bps increase in credit spreads lowering underwriting profitability by one percentage point. For a one standard deviation increase in credit spreads, the industry's underwriting profitability decreases by 1.3 standard deviations. Table C.3 presents full specification results, including the control vector coefficients.

In summary, in this subsection we find an economically and statistically significant negative relationship between the time series of insurance premiums and the investment returns insurance companies expect to earn on their investment portfolios.

[17] Credit spreads and markups changed by 320bps and -200bps respectively. The credit spread coefficient, adjusting for the interaction coefficient, is $-0.59 + 0.36 = -0.23$ in the global financial crisis, and thus we see credit spreads account for $0.23 * 320 = 74$bps of the markup change.

6.3 Investment Returns Drive the Cross Section of Premiums

We next test Proposition 3's prediction for insurance prices and investment returns in the cross section of insurers: insurers with higher expected investment returns set relatively lower prices. As with the time series results, we begin with an illustration of our core finding. We use the P&C industry because it is our richest cross section, grouping the 1,240 insurers into 20 portfolios ranked on their investment return. For each portfolio, we then calculate equal weighted underwriting profitability and investment returns. Figure 5 presents a binned scatter graph of the portfolio averages with underwriting performance on the vertical axis and investment returns on the horizontal axis. There is a clear negative correlation with insurers with higher investment yields also reporting lower underwriting profitability.

We now formally test the relationship between insurance prices and the investment returns for both the Life Insurance industry and P&C industry, beginning with the Life Insurance. Table 7 reports the parameter estimate from the following panel regression using the cross section of life insurers:

$$m_{ikt} = \beta_y \cdot y_{it} + \beta_{yFC} \cdot y_{it} \times \mathbb{1}_{GFC} + B' \cdot X_{it-1} + FE_i + FE_k + FE_t + \epsilon_{ikt}$$

where m_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product category k, y_{it} is the insurer's expected investment return, and X_{it} is a vector of lagged variables that have been shown to capture balance sheet strength (Koijen and Yogo (2015)). The control vector includes variables squared to capture any non-linear effects of capital constraints. We additionally control for date fixed effects, product fixed effects and firm fixed effects, and report within group R-squared. Panel A, B and C show the results for markups on fixed-term, guarantee and life annuity products respectively. Columns 4-5 interact investment return with an indicator variable $\mathbb{1}_{GFC}$ set equal to one during the financial crisis. Across specifications and products, we see that an insurer with a investment return 100bps higher than competitors sets annualised markups 3bps lower. In the majority of specifications the relationship is statistically significant.

Table 8 tests the cross sectional relationship between insurance pricing and insurers' expected investment returns in the P&C industry. The table follows the same structure as Table 7, but with insurer underwriting profitability replacing markups as the dependent variable. We also include a variable that controls for the level of reinsurance activity by insurance companies. In the P&C industry, we find that an insurance company with a

100bps higher expected investment return compared to competitors reports underwriting profitability that is 10bps lower. To compare the cross sectional results in both the life industry and P&C industry, we have also calculated standardized coefficients. In the life insurance industry, a one standard deviation higher insurer investment return reduces an insurer's relative markup by 0.05 standard deviations. In the P&C industry, we find an insurer with a one standard deviation higher insurer investment return has an underwriting profitability ratio 0.03 standard deviations lower than competitors.

In summary, in this subsection we have shown that the negative time series relationship between insurance premiums and expected investment returns is also present in the cross section of insurance companies. Insurance companies that expect to earn higher returns on their investment portfolios set lower premiums relative to their competitors.

6.4 A Two-Stage Estimation of the Cross Sectional Analysis

To test the structure implied by the model, we next implement cross sectional analysis with a two-stage estimation. In the first stage of the estimation, investment returns are predicted by stability of funding. This is a replication of the analysis from Section 6.1, with the expected investment returns of insurance companies regressed on their underwriting volatility (Table 9 Column 1) and both underwriting volatility and firm size (Table 9 Column 2). The results show that stability of insurance underwriting is correlated with insurers investment returns, which is consistent with the economic mechanism at play in the model. Stable funding allows insurers to take more investment risk and thus earn higher investment returns.

In the second stage of the estimation, we then take the predicted component of investment returns and regress insurance premiums on these investment returns. According to the model, it is these higher returns in particular (i.e. the returns that are due to insurer's competitive advantage of stable funding) that lead to lower premiums. Columns 3 and 4 of Table 9 report the parameter estimate from this second stage of the regression. It shows that insurance premiums fall by 0.27 percentage points when investment returns are 100bps higher.

The above two-stage estimation is an instrumental variable estimation with stable funding proxies being used as an instrument for insurer investment returns. To the degree that the relevance and exclusion restriction conditions hold, the results are therefore direct evidence of the causality implied by the model. To formally test the relevance condition,

Table 9 reports the Cragg-Donald Wald F-statistic. Running the specification with controls but only volatility as the instrument results in weak instrument concerns Stock and Yogo (2005). We therefore add firm size as an additional instrument. As discussed in Section 6.1, we view this variable as another proxy for the stability of insurance underwriting fund that insurers enjoy.

The exclusion restriction, which requires the estimation instruments to be correlated with insurance premiums through their impact on investment returns only, can not be formally tested. However, there is a concern that firm size is an endogenous choice of the insurance company. On this point, it is worth noting that these are cross sectional regressions with date fixed effects. An insurance companies choice of size can not be changed meaningfully from period to period, with any large change in size taking many periods to build. Indeed, looking at the large insurers in our sample, they have been very consistent through the sample. This makes it plausible that, in any given time period, size can be viewed as being exogenously given to the insurance firm.

When an instrumental variable estimation has multiple instruments, a formal Sargan's χ^2 test of overidentifying restrictions can be run. The large p-value in the Sargan test (Table 9 Column 4) means that we can not statistically reject that the instruments are uncorrelated with the structural error term. While this is reassuring, it does not rule out the possibility that our instruments are endogenous.

In summary, in this subsection we have tested the structure of the model. Indeed, consistent with the model, we have shown that the predicted component of investment returns (due to stable funding) predicts insurance premiums. The coefficients in Table 9 are more negative than those estimated in Table 8, indicating a stronger effect than previously estimated by the raw cross sectional regressions. This is likely because the instrumented investment returns provide a cleaner estimate of the impact of investment strategy on insurance premiums. While the causality implied in the model is also implied by this empirical estimation, exclusion restrictions in the instrumental variables approach can not be ruled out empirically.

6.5 Evidence from Mergers and Acquisitions

In this section, we present evidence on how changes in investment returns due to merger and acquisition affect insurance premiums. We argue that these exogenous shocks to the insurance companies allow us to extract a cleaner estimates of the cross sectional relationship between premiums and investment returns. Figure (6) presents a representative example from our sample. American Heritage was acquired by AllState Insurance in October 1999. In the 12 months proceeding the acquisition, American Heritage earned a return of 7.22% on their investment portfolio and AllState Insurance earned 5.80%. The figure shows that American Heritage's investment returns fell post acquisition, reflecting the more defensive strategy of their acquirer. Critically, the figure also shows an adjustment in pricing on 10yr fixed term annuities. American Heritage were consistently selling annuities at a discount to the industry pre-acquisition. However, following the acquisition, their markup pricing increased significantly.

We next show evidence consistent with the case study but with multiple merger events in Table 10. We have five merger events in our sample, and study the premium impact on three products: 20yr fixed term annuity, life annuity for males aged 50, and 10 year guarantee life annuity for a male aged 50. In a difference-in-differences approach, we use life insurance companies involved in a merger and acquisition event as our treatment group, and other insurance companies as the control group. The treatment period is the two years after the merger event, and the control period is the two years before the merger event. Table 10 reports the parameter estimate from the following regression:

$$m_{ikt} = \beta_D \cdot D_{it} + FE_i + FE_k + FE_t + \epsilon_{ijt}$$

where m_{ikt} is the markup set by insurer i at time t on product k. Our explanatory variable, D_{it}, is the investment return differential between the treatment group insurance company and the other insurance company involved in the transaction. It is set equal to this value for the treatment insurer and treatment time period (i.e. in the two years following the merger for the treatment insurer), and set to zero in all other cases (i.e. two years pre merger event for the treatment group, and in all observations for control group insurers). The interpretation of a positive investment return differential is that insurer i is being acquired by an insurer with a more risky investment strategy, and thus going forward their own investment returns are expected to be higher. In each of our observations, we confirm that investment return differential do indeed lead to a change in the insurers investment returns post transaction in-line with this interpretation. This is illustrated in Figure 6 with the American Heritage example.

By controlling for time and firm fixed effects in the regression, the coefficient β_D captures the impact of the merger induced change in investment return on the treatment insurer's relative markup pricing as compared to the industry average. We see from Table

10 that a 1% increase in investment return following merger activity results in a 0.22% fall in an insurers markup relative to the industry. The t-statistic is 3.44. The coefficient is larger than in Table 8, suggesting the merger sample is better able to identify the relationship between investment returns and insurance premiums. We also note that the sample includes examples of where the investment return differential is both negative and positive. This helps rule out competing interpretations of the results. For example, one could imagine insurers discount products ahead of a merger to increase the value of the merger, which would lead to an increase in markups post merger. However, this can't explain the observations in the sample with an increase in investment returns and fall in markups.

In summary, in this subsection we extend our analysis to show the negative relationship between insurance premiums and expected investment returns in the cross section of insurance companies holds following exogenous shocks to returns and premiums that are due to merger activity.

6.6 Evidence from Excess Bond Returns

Credit spreads can be split into spread that compensates investors for expected default losses and a premium in excess of this. It is the latter component, the excess return, that our model predicts is driving the correlation between credit spreads insurance premiums. Insurance companies use their stable insurance funding to extract liquidity premium on their asset portfolios, with some of the excess return passed on to policyholders through lower premiums.

We test this interpretation in Table 11 by re-estimating the regression specifications in Table 5, but splitting credit spreads between excess bond premium and the fair credit spread given the underlying default risk (Gilchrist and Zakrajšek (2012)). As per our previous analysis, we run specifications with time series averages and the full panel of insurers, as well as specifications with / without an interaction with the financial crisis period. We see that negative correlation between premiums and credit spreads is driven entirely by the excess bond return component of credit spreads, with 100bps increase in excess bond returns reducing the markup by 50bps depending on specification and product. The default risk component of credit is statistically significant only in the panel C (fixed-term annuities). The coefficient on the excess bond return suggests that insurance companies pass back 50bps of excess returns on their credit portfolios to policyholders, and maintain 50bps for equity holders.

In summary, in this subsection we extend our analysis to show the time series correlation between credit spreads and insurance premiums are driven by the excess bond return component of credit spreads. This finding is strong evidence in support of asset-driven insurance pricing.

7 Introducing Insurer Capital Constraints

7.1 Theoretical Background

Capital constraints also affect insurance premiums (Gron (1994), Froot and O'Connell (1999), Koijen and Yogo (2015) andGe (2020). We embed this additional premium pricing mechanism into our existing framework by subjecting the insurer to a statutory capital constraint. The statutory value of each insurance policy is

$$\bar{V} = \frac{\bar{C}}{1 + R^S} \tag{20}$$

where R^S is the statutory discount rate for claims. The total statutory value of all Q claims is therefore $V = Q\bar{V}$. In the spirit of Koijen and Yogo (2015), the insurance company faces a capital constraint

$$\frac{V}{L} \leq \phi \tag{21}$$

where $\phi \leq 1$ is the maximum statutory leverage ratio and L is their total liabilities (equation 5). The likelihood of this constraint binding is decreasing in the statutory discount rate R^S. A higher discount rate reduces the statutory value of each policy and therefore reduces statutory leverage.

The first-order condition of equation (8) with respect to P when the insurer is subject to (21) yields the following proposition.

Proposition 4 (insurance premium with capital constraints). *In equilibrium, a policy with claim $\bar{C}$ will be underwritten with premium*

$$\hat{P} = \frac{\bar{C}}{1 + R^I} \left(\frac{\varepsilon}{\varepsilon - 1} \right) \left(\frac{1 + (\bar{\tau} + \sigma) R + \frac{\eta}{\phi(1+R^S)}}{1 + (\bar{\tau} + \sigma) R + \frac{\eta}{(1+R^I)}} \right). \tag{22}$$

where $\eta \geq 0$ be the Lagrange multiplier on the capital constraint (21).

Note that when the capital constraint is not binding, then $\eta = 0$ and therefore $\hat{P} = P$ as defined in (12). However, our interest in this section is for the case $\eta > 0$, which we explore in detail below.

Proposition 5 (capital constraints vs. no capital constraints). *When an insurer is capital constrained so eq. (21) holds with equality, the optimal price $\hat{P}$ relative to optimal price in the unconstrained case P depends on the relationship between the insurers time value of money R^I, the statutory discounting of claims R^S, and the maximum statutory leverage ratio ϕ. In particular:*

(i) When $\left(1+R^I\right) < \phi\left(1+R^S\right)$ *then* $\hat{P} < P$

(ii) When $\left(1+R^I\right) > \phi\left(1+R^S\right)$ *then* $\hat{P} > P$

(iii) When $\left(1+R^I\right) = \phi\left(1+R^S\right)$ *then* $\hat{P} = P$

This three case proposition extends the main theoretical result of Koijen and Yogo (2015), showing that the impact of insurer investment returns R^I is also important when the regulatory constraint binds. We describe the economic mechanisms below.

Case 1: $\left(1+R^I\right) < \phi\left(1+R^S\right)$**.** In this case the discount rate applied to statutory liabilities is higher than the expected return on assets multiplied by a factor of $\phi^{-1} > 1$. A new policy increases liabilities by $\bar{V}\phi^{-1}$ and increases assets by the premium received P. A higher R^S reduces $\bar{V}$ through the statutory discounting, and if R^S is sufficiently high it can mean new policies create an instantaneous improvement in an insurers statutory capital position. The result is that constrained insurers write policies at cheaper prices than an unconstrained competitor. Although writing policies cheaper reduces final wealth, insurer do it due to the temporary statutory capital relief it creates. Koijen and Yogo (2015) provide a detailed description of the calculation of R^S for different products in the life industry, showing that it was particularly high in the financial crisis. Consistent with their model prediction, they find constrained life insurers reduced annuity and guarantee markups significantly during the financial crisis.

Case 2: $\left(1+R^I\right) > \phi\left(1+R^S\right)$**.** In this case capital constraints lead to an increase in insurance prices. If the insurer sets the unconstrained premium price P, a new policy creates more statutory liabilities than assets, as $\tilde{V}\phi^{-1} > P$. Constrained insurers are therefore forced to increase prices to a level such that the premium received offsets the increase in liabilities. Froot and O'Connell (1999) provide an example of such a case by documenting how supply of catastrophe insurance fell following a negative shock to insurers' capital.

Case 3: $\left(1+R^I\right) = \phi\left(1+R^S\right)$**.** This is a special case where the mechanisms underlying case 1 and 2 offset each other. It means that a binding capital constraint has no impact on an insurer's optimal premium.

Our main time series empirical implementation uses credit spreads, which are likely to be positively correlated with capital constraints, to proxy R^I. Proposition 2 predicts lower premiums when credit spreads (expected returns) increase. At the same time, proposition 5 case 1 predicts lower premiums with higher credit spreads (assuming higher credit spreads mean more financial constraints and lower insurance capital). The predicted impact of capital constraints on premiums is therefore the same as asset-driven insurance pricing, which makes it hard to empirically separate the two channels. However, in case 2 of proposition 5, the sign of the effect of capital constraints is reversed. This means that the asset-driven insurance pricing and capital constraint effects move in opposite directions.

7.2 Controlling for Capital Constraints Empirically

The financial crisis was a period of particularly high capital constraints in the Life Insurance industry (Koijen and Yogo (2015)). We have therefore been careful to separate out the financial crisis in all of our previously discussed results. We show that our findings are robust across periods and apply in *normal* times only. In fact, in most specifications, we find the negative relation between insurance prices and investment returns is less strong in the financial crisis. Said differently, the asset-driven insurance pricing effect holds stronger in normal times where capital constraints are less prevalent. To see this, note the coefficient on credit spreads interacted with the financial crisis indicator is positive and statistically significant. For example, in Table 5 Panel A, we find a coefficient of 0.31 (t-statistic 2.85).

Proposition 5 highlights that the impact of capital constraints on the insurance premiums depends on the level of statutory discount rates relative to expected investment returns. In the second case of the proposition 5, capital constraints predict higher premiums in times of stress, while asset-driven pricing predicts premiums are lower when credit spreads are higher. Empirical settings where insurers are in case two therefore makes it easier to disentangling capital constraints and asset-driven pricing empirically. For P&C markets, liabilities are not discounted ($R^S = 0$) for typical products such as car insurance, with the regulator making no adjustment for the premium's time-value of money (NAIC (2018)). This regulatory feature of the industry means case two always applies in this market. Our time series empirical results in the P&C industry, as documented in Table 6, therefore help to identify asset-driven insurance pricing while controlling for the potential impact of capital constraints.

In the cross sectional analysis, the result that insurer-specific asset portfolios affects relative insurance pricing across insurers is evidence that insurer investment portfolios matter for insurance pricing. However, it is possible that insurers with higher investment returns are also financially constrained and *gambling on resurrection*. To control for this potentially confounding factor, we include standard controls for insurer capital constraints (i.e. leverage, risk-cased statutory capital, asset growth). The results are once again robust.

8 Alternative Mechanisms

8.1 Insurer Default Risk

An alternative interpretation of our cross sectional results is that the insurers taking increased investment risk have higher probability of default, and thus face less demand for the insurance contracts they offer. In respect to this possible channel of insurance pricing, it is important to first note that the insurance industry is tightly regulated from a capital standpoint, with the key purpose of minimising the risk of insurer defaults on policyholders. Insurers are regulated on a risk based capital measure, and have to hold more capital when taking increased risk (including in their investment portfolios). In fact, the measure of investment portfolio credit risk that we use on the right hand side in Table 3 Panel A is the variable used by regulators when assessing how much capital insurers must hold for their credit portfolio investment risk. This means an increase in investment returns is also associated with an increase in the regulatory capital buffer an insurer must hold. All else equal, this should reduce the probability of default.

Finally, A.M. Best provide all insurers with a financial strength rating that ranges from A++ to C-. A lower rating would signify a higher probability of default. The life insurance data we have, taken from from Koijen and Yogo (2015), is for the subset of insurers with an A rating. The fact that we see a sensitivity between investment returns and insurance premiums *within* this group is further evidence of asset-driven insurance pricing at play, controlling for default risk. Further, our cross sectional specifications control for financial variables that demonstrate balance sheet strength. These should also absorb the impact of insurer default risk.

8.2 Reinsurance

Insurance companies use reinsurance markets to hedge or remove some of the underlying risk on the contracts they write. The level of reinsurance activity could therefore be expected to affect profitability of insurance underwriting. To rule out this alternative hypothesis as a driver of our results in Table 8, we include the fraction of underwriting premiums which are reinsured as a control variable. We find that while premiums are significantly lower when an insurer's reinsurance activity is higher (Table C.5), our main result that insurance premiums are lower when investment return are higher is still robust to the inclusion of this variable. The negative effect of reinsurance on premiums suggest that insurance companies that hedge more of the risks on their liabilities through reinsurance are able to charge lower premiums.[18]

9 Conclusion

Asset-driven insurance pricing is a new channel of insurance pricing, which shows that insurance premiums are lower when insurance companies have higher expected investment returns. In a violation of the Modigliani and Miller (1958) capital irrelevance theorem, the pricing of insurer liabilities depends on the expected returns on their asset portfolios. Specifically, insurance companies use the stable nature of insurance funding to take advantage of liquidity premium in illiquid asset markets. When expected returns are higher, insurers compete for funding, and insurance premiums fall.

A recent directive in Solvency II insurance regulation[19] means life insurers can now apply for a *matching adjustment* on some products, which allows them to apply to discount liabilities with the expected return on assets:

"The matching adjustment is an adjustment made to the risk-free interest rate when the insurer sets aside a portfolio of assets to back a predictable portion of their liabilities. It is based on the yield spread over the risk-free rate credit spread of the assigned portfolio of matching assets, minus a fundamental spread that accounts for expected default and downgrade risk. It is designed to reflect the fact that long-term, buy-and-hold investors

[18] We thank Stefano Rossi for this observation.

[19] see Solvency II, art. 77b and 77c

only bear downgrade and default risks as they seek to hold assets to maturity, and allows them to capture other aspects of the spread such as the liquidity premium" – The Actuary [20]

The matching adjustment directive shows that insurers also think about their funding and investing in a similar manner to the arguments put forth in this paper.

We conclude by noting that asset-driven insurance pricing has two potential welfare implications. Firstly, insurers act as pro-cyclical investors, increasing asset allocations to illiquid investments when liquidity premium are higher, dampening asset market volatility. Second, insurers provide households with cheaper access to insurance when financial markets are distressed. These interesting macroeconomic implications of our findings offer interesting avenues for future research.

[20]https://www.theactuary.com/features/2016/06/2016/05/23/matching-adjustment-fit?fbclid=IwAR1GqbTH3ZrG5zaxWJz34YJNMhoip054u-IBRxsHFBda5EwePlmvfNm69tc

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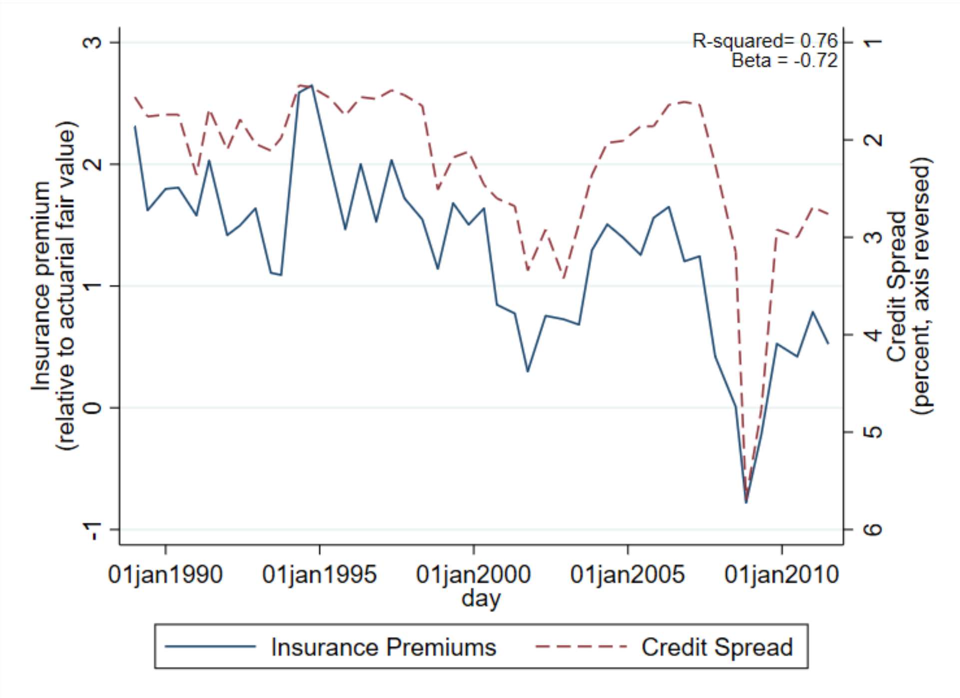
Figure 1: Expected investment returns drive the time series of insurance premiums. This figure shows the relation between insurance premiums and insurer expected investment returns as proxied by credit spreads. Panel A plots the two time series in levels. Panel B plots a scatter plot of the two time series in changes. Insurance premiums 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)

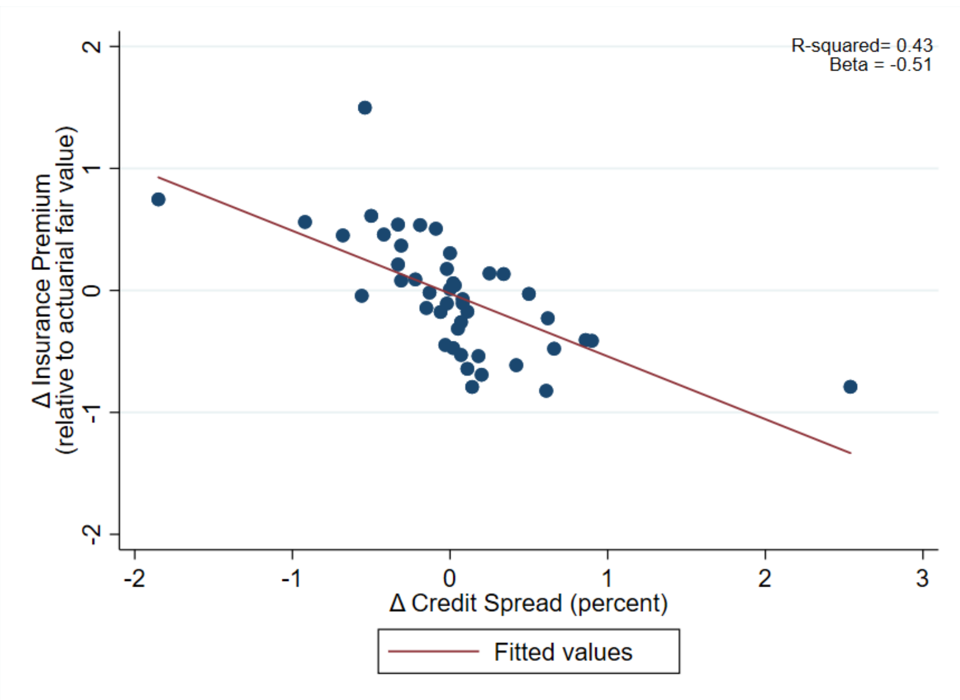
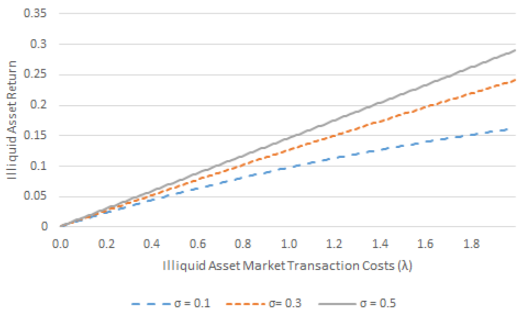
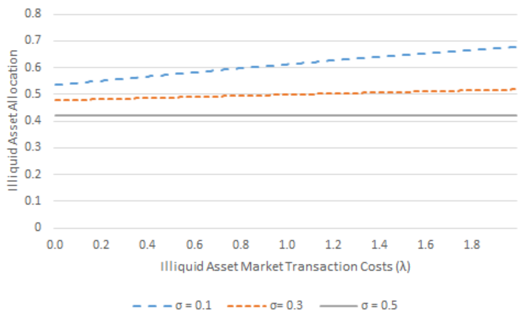


Figure 2: Model predictions. This figure presents numerical solutions of the model with the parameters: asset supply $S = 1$, investors have $\omega = 0.2$ probability of being early consumers, insurance claims arrive at $t = 1$ with probability $\bar{\tau} = 0.5$, elasticity of insurance demand is $\epsilon = 15$, the fixed parameter in the demand function is $k = 1$, claims are $\tilde{C} = 1$, and the insurer is endowed with equity capital $E = 0.25$. Panel A, B and C plot the expected return on the illiquid asset, R, the insurance company's share in illiquid asset, Θ/S, and the premium markup relative to the expected claim, $P/\bar{C} - 1$, respectively. In each panel the variable is plotted as a function of of the asset market illiquidity, λ, with three choices of funding stability, σ.

(a) Return on the Illiquid Asset



(b) Insurer Illiquid Asset Allocation



(c) Premium Relative to Actuarial Fair Price

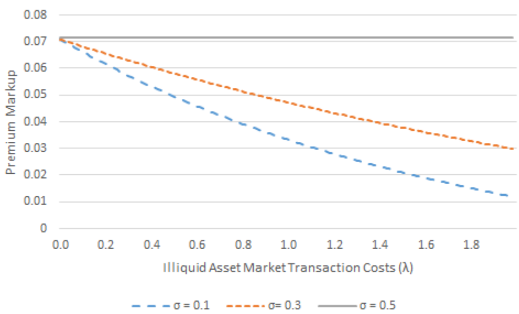
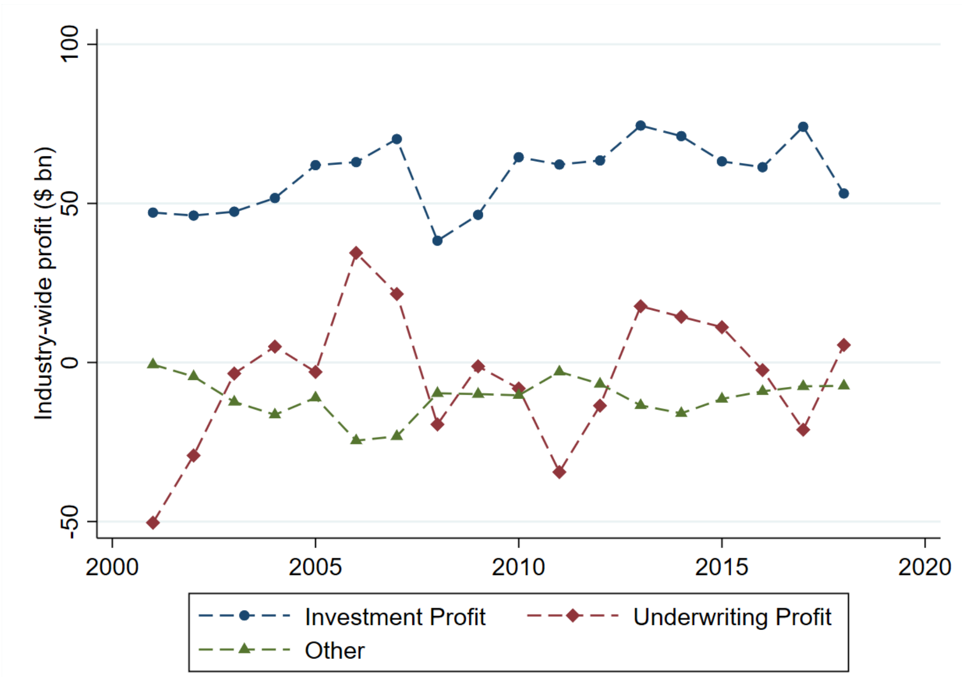


Figure 3: Investment income drives total net income. This figure plots the P&C industry's aggregate net income split between the main contributing sources. The three components are earnings generated from i) insurance underwriting, ii) investment portfolios, iii) other. Together they constitute the total net income of the industry. In Panel A, the profits on insurance underwriting are the premiums earned minus losses and expenses. As per the industry reporting standard, it does not include any adjustment for the time-value of money of underwriting. In Panel B, we increase (decrease) underwriting (investment) income by the value of insurance liabilities multiplied by the risk-free rate. The data comes from US insurance company statutory filings and is provided by SNL Global. Individual company data has been aggregated to show the industry-wide net income.

(a) Net Income as reported by insurance companies



(b) Adjusting for the time-value of money of underwriting funding

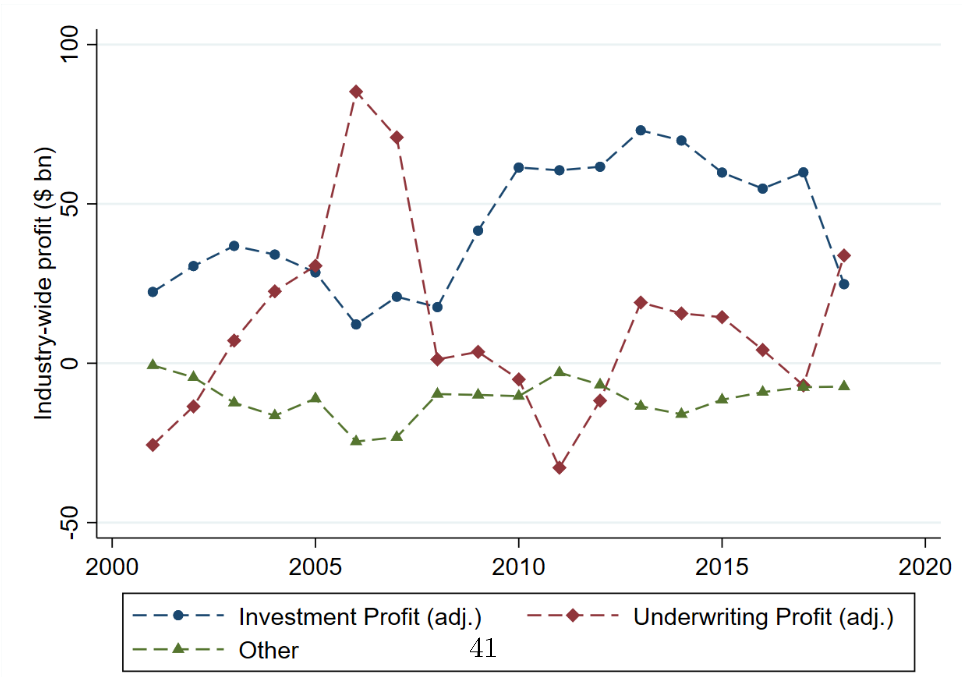


Figure 4: Variation in the expected investment returns of insurance companies. This figure illustrates variation in the expected investment returns of insurance companies in both the time series and cross section. In each reporting quarter of our sample, the figure presents a boxplot of expected investment returns. Our sample includes firm-level data for 1,104 P&C insurers in total. 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.

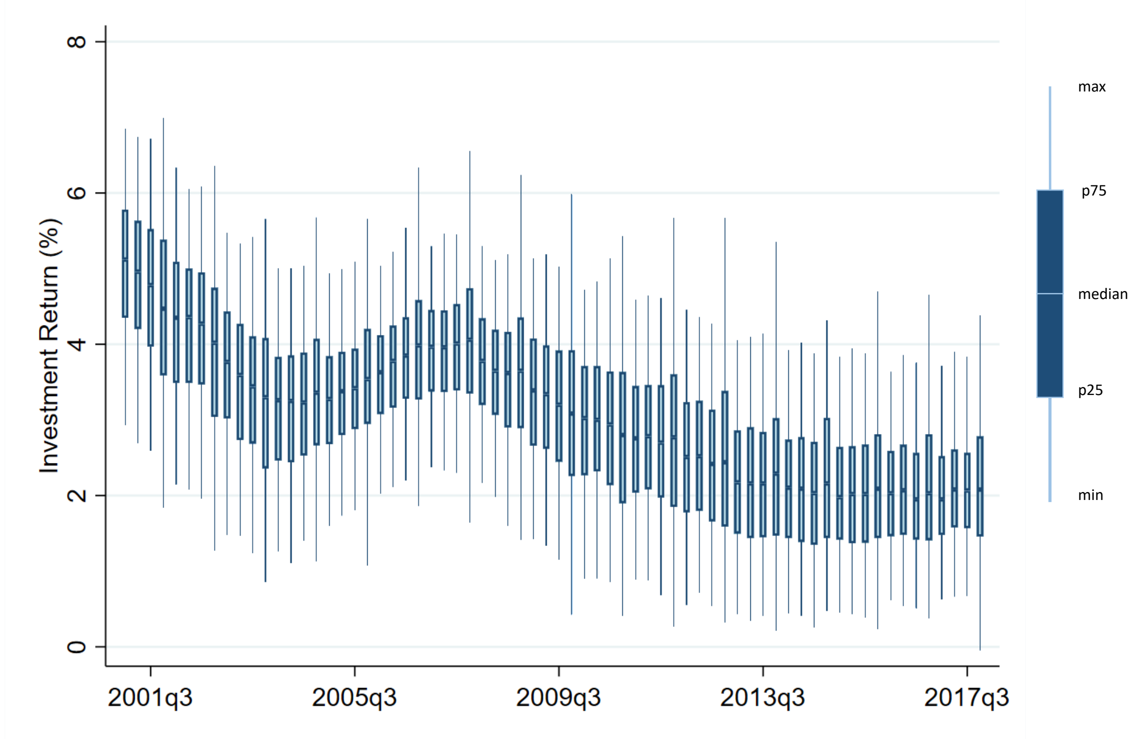


Figure 5: Expected investment returns drive the cross section of insurance premiums. This figure presents a binned scatter plot of insurer's insurance premiums against their expected investment returns. Insurance companies have been grouped into 20 equal sized portfolios based on the ranking of their investment portfolio returns. The figure plots each portfolio's average premium against its average investment return. Insurance premiums are measured as the ratio of an insurer company's insurance underwriting profit to their insurance liabilities. The sample includes firm-level data for 1,104 Property & Casualty (P&C) insurers over the period Q1 2001 to Q4 2017, with a total of 44,780 observations. The data is reported in US insurance company statutory filings and is provided by SNL Global.

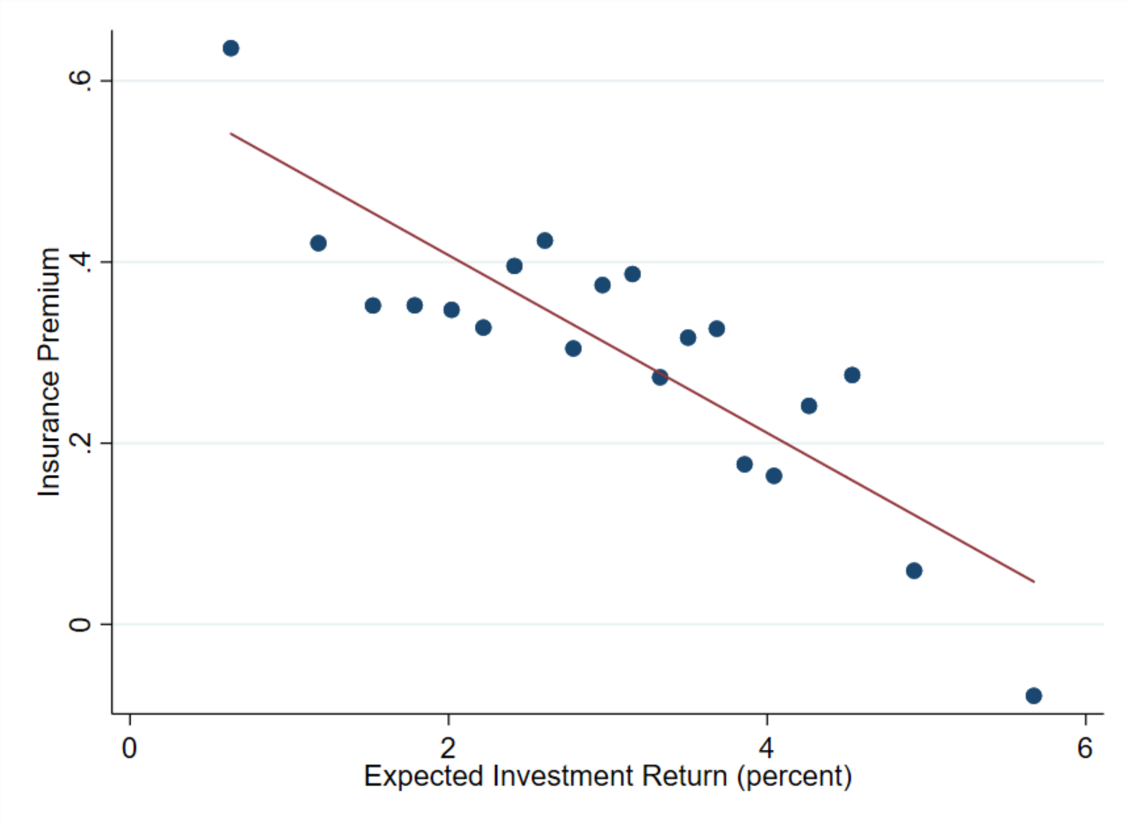


Figure 6: Mergers & acquisitions evidence - american heritage acquisition case study. This figure plots American Heritage's excess markup on a 10yr annuity and their investment portfolio return. The sample period is 1995/2001. On October 1999 American Heritage was acquired by AllState Insurance. The acquisition is denoted by vertical line in the figure. A markup m_{ikt} for insurer i at time t on product k is the percentage deviation of the insurer's quoted price relative to the actuarial fair price. The excess markup $m_{ikt}^{ex} = m_{ikt} - \bar{m}_{kt}$ is the insurer's markup minus the industry average markup at time t on product k. The investment return is the investment portfolio income over the total value of invested assets. Markup data is provided by Koijen and Yogo (2015) and investment returns are collected this from insurer financial statements.

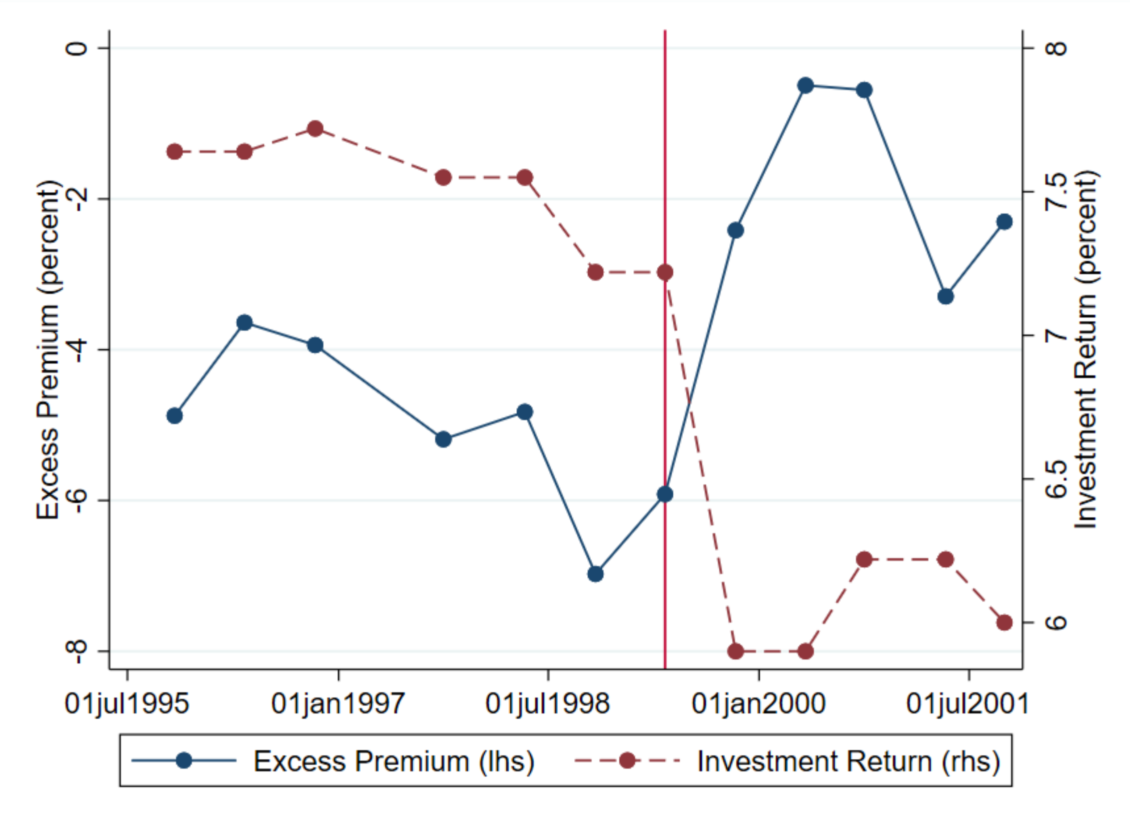


Table 1: Summary statistics

This table presents summary statistics of the variables used in the empirical analysis. The markups on life insurance are available biannually from 1989 through 2011 (Koijen and Yogo (2015)). Financial variables (for both P&C and Life insurance) are available quarterly from March 2001 through December 2017. The financial market and macroeconomic variables are available at monthly frequencies and have been collected from various sources.

	Count	Mean	SD	p05	p25	p50	p75	p95
Annuity Markups								
Life	19,923	6.75	7.07	-24.49	2.45	7.12	11.37	32.34
Life (ann.)	19,923	1.03	0.98	-1.92	0.38	0.96	1.62	4.36
Term	2,927	5.31	5.00	-17.32	2.65	5.79	8.41	32.64
Term (ann.)	2,927	1.12	1.06	-1.73	0.37	0.99	1.81	5.55
Guarantee	10,221	4.24	6.43	-24.70	0.41	4.94	8.34	32.35
Guarantee (ann.)	10,221	0.50	0.68	-2.00	0.05	0.52	0.94	2.93
Property& Casualty Financial Variables								
Underwriting Profitability	44,780	0.31	3.24	-5.09	-1.27	0.14	1.70	6.23
Underwriting Profits Volatility	27,787	2.35	1.34	0.58	1.25	2.17	3.23	4.85
Investment Return	44,780	3.08	1.29	0.95	2.13	3.08	3.97	5.22
Credit Allocation	44,780	54.09	22.40	13.17	37.68	57.98	72.58	84.68
Credit Risk	44,780	1.72	0.97	1.04	1.19	1.38	1.81	3.77
Cash Allocation	44,780	13.59	13.38	1.26	4.29	8.65	17.78	46.58
Treasuries Allocation	44,780	15.98	15.02	0.22	4.33	11.25	23.70	48.59
Stocks Allocation	44,780	11.57	11.38	0.00	1.34	8.72	17.98	36.31
Other Allocation	44,780	3.77	4.90	0.00	0.00	1.76	5.79	14.78
Size (t-1)	41,589	4.92	1.87	2.40	3.33	4.63	6.19	8.53
Asset Growth (t-1)	37,044	6.32	20.61	-11.78	0.00	5.63	11.78	27.29
Leverage (t-1)	41,589	42.54	14.44	21.17	31.62	40.51	52.24	70.58
Risk Based Capital (t-1)	41,589	4.74	2.95	1.32	2.56	3.96	6.03	11.75
Unearned Premia (t-1)	41,589	1.94	0.84	0.36	1.50	1.97	2.31	3.56
Reinsurance Activity (t-1)	41,589	0.13	0.40	-0.73	0.00	0.13	0.33	0.76
Life Financial Variables								
Investment Return	258	5.97	1.68	4.15	5.19	5.62	6.42	8.49
Size	258	16.36	1.12	14.69	15.36	16.38	17.36	18.10
Asset Growth	258	8.30	12.86	-7.99	0.11	7.34	12.91	30.98
Leverage	258	90.86	4.22	83.00	88.19	91.35	93.99	96.97
Risk Based Capital	258	14.60	45.86	-39.00	-24.00	2.00	50.00	102.00
Deferred Annuities	258	11.03	14.24	0.49	1.77	5.87	14.34	45.41
Financial Market and Macroeconomic Variables								
Credit Spread (BAA)	403	2.33	0.72	1.29	1.77	2.20	2.76	6.01
Risk Free (1yr)	469	4.65	3.73	0.10	1.30	4.63	6.64	16.72
Risk Free (5yr)	469	5.54	3.52	0.62	2.54	5.09	7.71	15.93
Slope (5yr - 1yr)	469	0.89	0.74	-1.63	0.38	0.87	1.46	2.50
TED Spread	403	0.57	0.42	0.12	0.26	0.46	0.73	3.35
Excess Bond Risk Premia	434	0.06	0.55	-1.14	-0.31	-0.04	0.28	3.00
US Unemployment Rate	469	6.22	1.68	3.60	5.00	5.70	7.30	10.80
CAPE ratio	469	22.35	8.43	6.64	16.43	22.42	26.79	44.20

Table 2: Insurance funding is invested in illiquid credit assets

This table shows the aggregated balance sheets of the Life Insurance industry and the P&C Insurance Industry as of December 2017. The assets are split by the largest investment allocations, and the liabilities are split into insurance liabilities and other liabilities. The shaded regions highlight two important observations: a) there is a significant amount of credit and liquidity risk taken in insurer asset portfolios, and b) the asset portfolios are predominantly funded by insurance liabilities. The data comes from US insurance company statutory filings and is provided by SNL Global. Individual company data has been aggregated to show the industry-wide balance sheet.

	Life Insurance ($bn)	Property and Casualty ($bn)	Life Insurance (%)	Property and Casualty (%)
Total Assets	**4301**	**1998**	**100%**	**100%**
Cash & Short Term Investments	105	116	2%	6%
Bonds - US Government	235	162	5%	8%
Bonds – Corporate	2199	414	51%	21%
Bonds – Other Credit	539	404	13%	20%
Mortgage Loans	477	17	11%	1%
Stocks	105	415	2%	21%
Other Investments	414	163	9%	9%
Total Cash & Investments	4075	1691	95%	85%
None-Financial Assets	227	306	5%	15%
Total Liabilities	**4301**	**1998**	**100%**	**100%**
Insurance Liabilities	3294	1021	77%	51%
Other Liabilities	615	211	14%	11%
Capital And Surplus (Equity)	393	765	9%	38%

Table 3: 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:

$$y_{it} = \mathrm{B}'W_{it} + \beta_r \cdot risk_{it} + \beta_{w^c r} \cdot w_{it}^{credit} \times risk_{it} + \beta_{w^c rCS} \cdot w_{it}^{credit} \times risk_{it} \times CS_{t-1} + FE_t + \epsilon_{it}$$

where y_{it} is insurer i's investment return at time t and W_{it} is a vector of asset allocations including the allocation to credit, w_{it}^{credit}. We also include a numeric measure of the credit risk in the insurer's credit portfolio, $risk_{it}$, and the previous period credit spread, CS_{t-1}. All specifications in Panel A include time fixed effects FE_t. Investment returns are measured in bps, asset allocations are in percent, and the measure of credit risk range from 1-6 (and are as assigned by the insurance regulator).
Panel B reports the parameter estimate from the following panel regression:

$$y_{it} = \beta_y \cdot y_{i,t-k} + \mathrm{B}' \cdot X_t + FE_i + \epsilon_{it}$$

where $y_{i,t-k}$ is lagged insurer returns, X_t is a vector of time series variables that capture insurer investment opportunities or macroeconomic conditions, and FE_i captures firm fixed effects. All variables in panel B are measured in percent. The sample consists of quarterly observations from March 2001 through March 2018. 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: Asset Allocation and Credit Portfolio Risk

	Investment Return (bps)		
	(1)	(2)	(3)
Credit Allocation	1.25***	0.54*	0.50*
	(11.24)	(1.90)	(1.81)
Cash Allocation	-1.50***	-1.42***	-1.41***
	(-7.89)	(-6.02)	(-5.96)
Credit Risk		14.62***	14.12***
		(4.99)	(4.90)
Credit Allocation × Credit Risk		0.93***	-0.11
		(5.61)	(-0.42)
Treasuries Allocation		-0.99***	-1.00***
		(-3.06)	(-3.16)
Stocks Allocation		-0.19	-0.20
		(-0.61)	(-0.66)
Other Allocation		-0.81*	-0.74*
		(-1.94)	(-1.81)
Credit Allocation × Credit Risk × Credit Spread (t-1)			0.40***
			(4.50)
Date FE	yes	yes	yes
Adj R-sq (Within)	0.168	0.202	0.207
Observations	44,780	44,780	44,780

Panel B: Investment Returns: Persistence and Time Series Variation

	Investment Return (it)			
	(1)	(2)	(3)	(4)
Investment Return (i,t-1)	0.61***	0.47***		
	(17.46)	(16.63)		
Investment Return (i,t-5)		0.19***		
		(9.21)		
Credit Spread (t-1)			0.39***	0.25*
			(7.14)	(1.85)
Risk-free Rate (t-1)			0.52***	0.51***
			(17.36)	(13.68)
Slope (t-1)			0.45***	0.48***
			(6.19)	(6.53)
TED (t-1)				0.10
				(0.61)
CAPE (t-1)				-0.03
				(-1.31)
Firm FE	yes	yes	yes	yes
Adj R-sq (Within)	0.371	0.395	0.341	0.346
Observations	37,044	37,044	37,044	37,044

Table 4: Insurers with stable funding take more investment risk

This table shows the relation between insurer's investment allocation and their insurance funding. The table reports the standardized parameter estimates from the following panel regression:

$$y_{it} = \beta_{vol} \cdot \mathit{Volatility}_{i,t-1} + \beta_{Size} \cdot \mathit{Size}_{i,t-1} + B' \cdot X_{i,t-1} + FE_t + \epsilon_{it}$$

where y_{it} is either insurer i's cash allocation at time t (columns 1-3), insurer i's credit asset allocation at time t multiplied by a numeric measure of the credit risk in these portfolios at time t (columns 4-6), or insurer i's investment return at time t (columns 7-9). Independent variables include, the historical 5-year volatility of insurer i's underwriting profitability up to time and including time $t-1$, $\mathit{Volatility}_{i,t-1}$, the insurers size (log assets), and a vector of other balance sheet measures, X_{it}, that capture balance sheet strength. All specifications include time fixed effects FE_t. Asset allocations and funding volatility are measured in percentage and investment returns are measured in bps. Credit risk is insurer i's credit portfolio value-weighted average credit rating, with bonds assigned a number from 1-6 dependent on their credit risk (as assigned by the insurance regulator, NAIC). The sample consists of quarterly observations from March 2001 through December 2017. t-statistics are reported in the brackets and are calculated using standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Cash Allocation (perc.)			Credit Assets × Risk			Investment Return (bps)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Underwriting Volatility (i,t-1)	0.22***		0.06*	-0.26***		-0.09***	-0.16***		-0.06***
	(7.56)		(1.79)	(-8.91)		(-2.97)	(-7.18)		(-2.66)
Size (t-1)		-0.34***	-0.30***		0.36***	0.31***		0.21***	0.17***
		(-12.57)	(-9.40)		(11.61)	(8.95)		(9.80)	(7.22)
Reinsurance Activity (t-1)			0.08***			-0.00			-0.04**
			(2.75)			(-0.13)			(-2.25)
Risk Based Capital (t-1)			-0.14***			0.03			0.05**
			(-5.28)			(1.07)			(2.43)
Asset Growth (t-1)			0.05***			-0.03***			-0.02**
			(4.63)			(-2.71)			(-2.29)
Unearned Premia (t-1)			-0.05*			0.01			-0.00
			(-1.76)			(0.47)			(-0.11)
Date FE	yes	yes	yes	yes	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.048	0.114	0.146	0.067	0.128	0.135	0.036	0.065	0.075
Observations	25,091	25,091	25,091	25,091	25,091	25,091	25,091	25,091	25,091

Table 5: Investment returns drive the time series of premiums: life insurance

This table shows the time series relation between insurance premiums, as measured by the markups on annuities issued by life insurers, and credit spreads. It reports the parameter estimates from the following regression:

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

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. CS_t is Moody's credit spread of 10 year BAA corporate bonds yields over treasuries, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010). We include a vector of time series controls X_t which includes the risk-free rate, the slope of the yield curve, the TED spread, the CAPE ratio and US unemployment rate. We also include lagged markups in the control vector. Columns 1-3 report the parameter estimates from time series regressions where $\overline{m}_t$ is the average markup across insurers and sub-product categories in each time period. Columns 4-5 report full panel specifications. 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 the time series regressions are calculated using Newey and West (1987) standard errors with automatic bandwith selection. The panel regression also includes firm and fixed effects and 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

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.44***	-0.38***	-0.50***	-0.29***	-0.44***
	(-11.49)	(-5.66)	(-5.47)	(-4.58)	(-4.03)
$\mathbb{1}_{GFC}$			-1.01*		-0.66
			(-1.93)		(-1.51)
Credit Spread × $\mathbb{1}_{GFC}$			0.23*		0.21*
			(1.83)		(1.80)
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.800	0.871	0.876	0.596	0.603
Observations	72	72	72	12,460	12,460

[table continued on next page...]

Panel B: Guarantee Annuity Markups and Credit Spreads

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.46***	-0.32***	-0.43***	-0.26***	-0.41***
	(-12.97)	(-5.43)	(-4.21)	(-4.93)	(-3.99)
$\mathbb{1}_{GFC}$			-1.06***		-0.66
			(-3.18)		(-1.60)
Credit Spread × $\mathbb{1}_{GFC}$			0.24**		0.20*
			(2.43)		(1.82)
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.799	0.875	0.883	0.655	0.664
Observations	53	53	53	14,529	14,529

Panel C: Fixed-Term Annuity Markups and Credit Spreads

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.54***	-0.40**	-0.62***	-0.31***	-0.57***
	(-9.20)	(-2.62)	(-4.50)	(-2.89)	(-4.83)
$\mathbb{1}_{GFC}$			-0.87		-1.13***
			(-1.56)		(-2.72)
Credit Spread × $\mathbb{1}_{GFC}$			0.37**		0.44***
			(2.47)		(3.58)
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.861	0.857	0.873	0.432	0.458
Observations	45	45	45	2,557	2,557

Table 6: Investment returns drive the time series of premiums: P&C Insurance

This table shows the time series relation between insurance premiums, as measured by P&C insurer's underwriting profitability, and credit spreads. It reports the parameter estimates from the following time series regression:

$$u_{it} = \beta_{cs} \cdot CS_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{csGFC} \cdot CS_t \times \mathbb{1}_{GFC} + B' \cdot X_t + FE_i + \epsilon_{it}$$

where u_{it}, is the underwriting profitability for insurer i in quarter t. Underwriting profitability is defined as underwriting profits (premiums earned minus losses and expenses) divided by the premiums earned. c_t is the 1-year rolling average of Moody's credit spread of BAA corporate bonds, $\mathbb{1}_{GFC}$ is an indicator variable set to one over the financial crisis (November 2008 through February 2010), and X_t is a vector of time series controls including 1-year rolling averages of investment returns and macroeconomic variables. Columns 1-3 report parameter estimates from the time series regression where the dependent variable, $\overline{u}_t$, is the average underwriting profitability in quarter t across all insurers. Columns 4-5 report parameter estimates from panel regressions with insurer fixed effects. The sample consists of quarterly observations from March 2001 through December 2017. t-statistics are reported in the brackets and are calculated using Newey and West (1987) standard errors in the time-series specifications, and standard errors clustered by date and firm in the panel specifications. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\overline{u}_t$			u_{it}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.44***	-0.83***	-1.08***	-0.74***	-1.06***
	(-2.71)	(-3.32)	(-4.85)	(-2.94)	(-4.73)
FC			-1.80		-1.64
			(-1.28)		(-0.80)
Credit Spread × FC			0.85**		0.87*
			(2.57)		(1.72)
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Adj R-sq (Within)	0.119	0.222	0.293	0.031	0.039
Observations	67	67	67	41,589	41,589

Table 7: Investment returns drive the cross section of premiums: Life Insurance

This table shows the cross section relation between insurance premiums, as measured by the markups on annuities issued by life insurers, and firm-specific expected investment returns. It reports the parameter estimate from the following panel regression:

$$m_{ikt} = \beta_y \cdot y_{it} + \beta_{yGFC} \cdot y_{it} \times \mathbb{1}_{GFC} + B' \cdot X_{it-1} + FE_i + FE_k + FE_t + \epsilon_{ikt}$$

where m_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product category k, y_{it} is the insurer's investment return, $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010), and X_{it} is a vector of lagged variables that capture balance sheet strength (leverage, risk-based capital, asset growth and deferred annuities). The control vector includes squared variables to capture non-linear effects of capital constraints. We additionally control for date fixed effects, product fixed effects and firm fixed effects, and report within group r-squared. Panel A, B and C show the results for markups on fixed-term, guarantee and life annuity products respectively. The sample consists of quarterly observations from March 2001 through March 2018. 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.

Panel A: Fixed Term Annuities

	(1)	(2)	(3)	(4)	(5)
Investment Return	-0.03***	-0.03***	-0.01	-0.03***	-0.01
	(-2.63)	(-2.86)	(-1.31)	(-2.77)	(-1.20)
Investment Return × $\mathbb{1}_{Fin.Crisis}$				-0.06	-0.10*
				(-0.99)	(-1.74)
Firm Controls Vector		yes		yes	
Firm FE			yes		yes
Date FE	yes	yes	yes	yes	yes
Product FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.010	0.078	0.007	0.078	0.009
Observations	955	955	955	955	955

Panel B: Guarantee Annuities

	(1)	(2)	(3)	(4)	(5)
Investment Return	-0.01***	-0.01***	-0.01***	-0.01***	-0.01***
	(-3.86)	(-4.35)	(-3.21)	(-4.34)	(-2.72)
Investment Return × $\mathbb{1}_{Fin.Crisis}$				0.00	-0.05***
				(0.20)	(-4.70)
Firm Controls Vector		yes		yes	
Firm FE			yes		yes
Date FE	yes	yes	yes	yes	yes
Product FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.121	0.229	0.165	0.229	0.168
Observations	5,989	5,989	5,989	5,989	5,989

[table continued on next page...]

Panel C: Life Annuities

	(1)	(2)	(3)	(4)	(5)
Investment Return	0.00	-0.02***	-0.02***	-0.02***	-0.02***
	(0.37)	(-2.97)	(-3.15)	(-3.48)	(-3.31)
Investment Return × $\mathbb{1}_{Fin.Crisis}$				0.08***	0.03
				(3.55)	(1.54)
Firm Controls Vector		yes		yes	
Firm FE			yes		yes
Date FE	yes	yes	yes	yes	yes
Product FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.001	0.069	0.004	0.072	0.005
Observations	3,410	3,410	3,410	3,410	3,410

Table 8: Investment returns drive the cross section of premiums: P&C Insurance

This table shows the cross section relation between insurance premiums, as measured by P&C insurer's underwriting profitability, and firm-specific expected investment returns. It reports the parameter estimate from the following panel regression:

$$u_{it} = \beta_y \cdot y_{it} + \beta_{yGFC} \cdot y_{it} \times \mathbb{1}_{GFC} + B' \cdot X_{it-1} + FE_i + FE_t + \epsilon_{it}$$

where u_{it} is the underwriting profitability for insurer i at time t, and y_{it} is the insurer's investment return. We additionally control for date fixed effects, firm fixed effects and X_{it}, which is a vector of lagged variables that capture balance sheet strength (leverage, risk-based capital, asset growth and unearned premiums). This includes variables squared to control for non-linear effects of capital constraints. We also include a control for the level of reinsurance activity insurance company i engages in at time t. The samples consist of quarterly observations from Q1 2001 through Q4 2017. In columns 4-5 we interact investment return with an indicator variable $\mathbb{1}_{GFC}$ set equal to one during the global financial crisis (Q4 2008 through Q1 2010). 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.

	(1)	(2)	(3)	(4)	(5)
Investment Return	-0.10**	-0.12***	-0.11***	-0.13***	-0.12***
	(-2.37)	(-3.09)	(-5.19)	(-3.37)	(-5.70)
Investment Return × FC				0.10	0.12**
				(1.52)	(2.56)
Firm Controls Vector		yes		yes	
Firm FE			yes		yes
Time FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.001	0.071	0.001	0.071	0.001
Observations	37,044	37,044	37,044	37,044	37,044

Table 9: P&C Insurance cross section: instrumented variable estimation

This table shows the cross section relation between insurance premiums, as measured by P&C insurer's underwriting profitability, and the instrumented expected investment returns of individual insurance companies. Columns (3) and (4) report the parameter estimate from the following instrumental variable panel regression:

$$u_{it} = \beta_y \cdot y_{it} + B' \cdot X_{it-1} + FE_t + \epsilon_{it}$$

where u_{it} is the underwriting profitability for insurer i at time t, and y_{it} is the instrumented investment return of insurer i at time t. Columns (1) and (2) report the first-stage results from the regression

$$y_{it} = \beta_{vol} \cdot Volatility_{i,t-1} + \beta_{Size} \cdot Size_{i,t-1} + B' \cdot X_{it-1} + FE_t + \epsilon_{it}$$

where the instruments are the historical 5-year volatility of insurer i's underwriting profitability up to and including time $t-1$, $Volatility_{i,t-1}$, and the insurers size (log assets) at $t-1$. First stage results in Columns (1) and (2) correspond to the second-stage results in Columns (3) and (4) respectively . We control for date fixed effect in all specifications, and in (2) and (4) we include an untabulated vector, X_{it-1}, of lagged variables that capture balance sheet strength (leverage, risk-based capital, asset growth and unearned premiums), and the level of reinsurance activity insurance company i engages in at time t. The samples consist of quarterly observations from Q1 2001 through Q4 2017. For the second stage, we report the Cragg-Donald Wald F-statistic, and in the case where we have two instrumental variables (Column 4), we report the p-value from the Sargan's χ^2 test of overidentifying restrictions. t-statistics are reported in bracket and calculated using standard errors clustered by firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	First Stage:		Second Stage:	
	(1)	(2)	(3)	(4)
Underwriting Volatility (t-1)	-0.16***	-0.07***		
	(-7.47)	(-2.63)		
Size (t-1)		0.17***		
		(6.69)		
Investment Return			-0.35***	-0.27**
			(-3.41)	(-2.36)
Control Vector		yes		yes
Date FE	yes	yes	yes	yes
Adj R-sq (Within)	0.040	0.075		
Cragg-Donald F-stat			101.576	2042.461
Sargan test p-value				0.478
Observations	25,091	25,091	25,091	25,091

Table 10: Life Insurance Cross Section: evidence from mergers and acquisitions

This table shows the relation between the annuity markups and investment returns using a difference-in-differences approach around merger events. The treatment group is the life insurance companies involved in a merger and acquisition event over our sample, and the control group is all other life insurance companies. The control time period is the two years pre-mergers, and the treatment is the two years following merger. The table reports the parameter estimate from the following regression:

$$m_{ikt} = \beta_D \cdot D_{it} + FE_i + FE_k + FE_t + \epsilon_{ijt}$$

where m_{ikt} is the markup set by insurer i at time t on product k, and D_{it} is a variable set equal to zero for all observations except for treatment group insurance companies in the treatment period (the two years following their merger or acquisition event). For these observations, the variable is set equal to the treatment group insurance company's investment return minus the investment return of the other insurance company involved in the transaction (i.e. it is the investment return differential). For each individual mergers, we select the two years either side of the event for our sample, with our total sample made up of the union of the individual merger samples. This leads to 941 observations across 20 quarterly dates, with 5 treatment group entities and 48 control group entities. We use one annuity product type for each of our three broad categories of annuity - 20yr fixed term annuity, life annuity for males aged 50, and 10 year guarantee life annuity for a male aged 50. We control for time, company and product fixed effects. Standard errors are clustered by insurance company and date. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	markup (ikt)
Δ Investment Return(it)	-0.22***
	(-3.44)
Firm FE	yes
Date FE	yes
Product FE	yes
Adj R-sq (Within)	0.007
Observations	2318

Table 11: Evidence from excess bond risk premium

This table shows the relation between the markups on annuities issued by life insurers and the expected return component of credit spreads. It reports the parameter estimate from the

$$m_{jt} = \beta_e \cdot EBP_t + \beta_{df} \cdot DF_t + \beta_{eGFC} \cdot EBP_t \times \mathbb{1}_{GFC} + \beta_{dGFC} \cdot DF_t \times \mathbb{1}_{GFC} + FE_i + FE_k + \epsilon_{jt}$$

where $j = (i, k)$ and m_{jt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product category k. Sub-products vary depending on age, sex and maturity of the annuities. EBP_t is the Gilchrist and Zakrajšek (2012) credit spread attributed to excess bond risk premium, DF_t is the credit spread attributed to default losses, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010). We include a vector of time series controls X_t which includes the risk-free rate, the slope of the yield curve, the TED spread, the CAPE ratio and US unemployment rate. We also include lagged markups in the control vector. Columns 1-2 report the parameter estimates where markups, $\overline{m}_t$, are averaged across insurers and sub-products in each time period. Columns 3-4 report full panel specifications. 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. t-statistics in the time series regressions are calculated using Newey and West (1987) standard errors with automatic bandwith selection. The panel regression also includes firm and product fixed effects and standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Life Annuities

	(1)	(2)	(3)	(4)
Excess Bond Risk Premia	-0.36***	-0.61***	-0.31***	-0.46***
	(-4.35)	(-5.39)	(-4.20)	(-5.07)
Default Risk	-0.10	0.27	-0.03	0.18
	(-0.73)	(1.45)	(-0.39)	(1.22)
$\mathbb{1}_{Fin.Crisis}$		0.71		1.21**
		(1.39)		(2.31)
Excess Bond Risk Premia × $\mathbb{1}_{Fin.Crisis}$		0.48***		0.42***
		(4.11)		(4.35)
Default Risk × $\mathbb{1}_{Fin.Crisis}$		-0.43**		-0.48***
		(-2.51)		(-2.75)
Entity FE			yes	yes
Product FE			yes	yes
Time Series Controls	yes	yes	yes	yes
Adj R-sq (Within)	0.871	0.895	0.600	0.618
Observations	72	72	12460	12460

[table continued on next page...]

Panel B: Guarantee Annuities

	(1)	(2)	(3)	(4)
Excess Bond Risk Premia	-0.27***	-0.45***	-0.27***	-0.33***
	(-4.21)	(-10.08)	(-4.75)	(-5.08)
Default Risk	-0.17	-0.06	-0.10	-0.21
	(-1.56)	(-0.29)	(-1.22)	(-1.52)
$\mathbb{1}_{Fin.Crisis}$		0.12		0.18
		(0.20)		(0.34)
Excess Bond Risk Premia × $\mathbb{1}_{Fin.Crisis}$		0.37***		0.23***
		(4.25)		(2.92)
Default Risk × $\mathbb{1}_{Fin.Crisis}$		-0.15		-0.05
		(-0.72)		(-0.27)
Entity FE			yes	yes
Product FE			yes	yes
Time Series Controls	yes	yes	yes	yes
Adj R-sq (Within)	0.884	0.914	0.670	0.685
Observations	53	53	14529	14529

Panel C: Fixed Term Annuities

	(1)	(2)	(3)	(4)
Excess Bond Risk Premia	-0.63***	-0.68***	-0.52***	-0.56***
	(-4.97)	(-5.01)	(-6.60)	(-6.59)
Default Risk	0.35*	0.69*	0.27***	0.37**
	(2.00)	(1.78)	(3.32)	(2.09)
$\mathbb{1}_{Fin.Crisis}$		0.60		1.34**
		(0.70)		(2.41)
Excess Bond Risk Premia × $\mathbb{1}_{Fin.Crisis}$		0.26*		0.58***
		(1.85)		(5.25)
Default Risk × $\mathbb{1}_{Fin.Crisis}$		-0.41		-0.55***
		(-1.22)		(-3.08)
Entity FE			yes	yes
Product FE			yes	yes
Time Series Controls	yes	yes	yes	yes
Adj R-sq (Within)	0.910	0.911	0.472	0.475
Observations	45	45	2557	2557

A Institutional Background

A.1 Underwriting Profit in Life Insurance

Mitchell, Poterba, Warshawsky, and Brown (1999) and Koijen and Yogo (2015) have documented markups an average of 6 to 10 percent on specific life insurance products, which is after adjusting for a time value of money (assumed to be the risk-free rate). While these markups make life insurance underwriting look profitable at first glance, it is important to note that they are gross of operating expenses and commissions. Expenses on the specific products of their studies are not available to make a direct net of expenses assessment. However, on an aggregated basis, the life insurance industry reported commission and expense costs that were 20% of premiums in 2018 (SNL Statutory Files). It is therefore not unreasonable to assume that life insurance, like P&C, is dependent on asset returns for overall profitability.

Indeed, for comparision, in figure C.1 we plot P&C underwriting income between its three main components - claims and expenses (outflows) and earned premium (inflows). It shows that expesnes are significant fraction of premiums, ranging from 25%-30% across the sample. P&C underwriting performance gross of expenses looks extremely profitable. In other words, expenses are critical for an overall understanding of underwriting performance.

A.2 Accounting Treatment of the Investment Returns of Insurance Companies

For cross sectional comparisons of insurer expected investment return, we use their self-reported *Net Yield on Invested Assets.* This is their 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 expected investment portfolio performance.

For fixed income assets, which are the average insurers' main asset allocation, net yield on any asset is simply the amortisation of the purchase yield. Such treatment of assets reflects that insurers are buy and hold investors and can weather mark to market fluctuations. If the insurer does sell a bond before maturity, in the reporting period of sale the realised mark to market gain/loss is also included in the net yield measure. Further, if there are significant revisions to the prospects for a bond (i.e. default appears likely), adjustments may also be made in reported investment income. For equity investments, the net yield is the dividend rate, with mark to market fluctuations once again realised at the point of sale.

To capture insurers' expected returns at an industry-level we use the credit spread on corporate bonds. This is the average insurers' main source of investment risk and thus is our best proxy for industry wide investment opportunities. We also use the excess bond risk premium portion of credit spreads as provided in (Gilchrist and Zakrajšek (2012)), which is a way to strip out expected default loss from the credit spread.

B Proofs

Proof of Proposition 1

i) Investor illiquid allocation.

The first-order condition for the investor's illiquid asset allocation in equation (3) is

$$0 = (1 - \omega) R - \omega \lambda \theta \tag{23}$$

from which the optimal allocation (10) follows. ■

ii) Insurer illiquid allocation.

We have already defined in equation (14) the lower bound on the insurer's optimal asset allocation. By a similar logic we can also define an upper bound. To see this, note that $\tau = \bar{\tau} - \sigma$ is the minimum fraction of claims that will arrive early. The insurer therefore knows they will be forced to sell assets of at least $(\bar{\tau} - \sigma) C$ at time 1. Optimally they hold at least this amount in liquid assets, which leads to the following definition

$$\overline{\Theta} = \begin{cases} L - (\bar{\tau} - \sigma) C & \text{if } L - (\bar{\tau} - \sigma) C < S \\ S & \text{otherwise.} \end{cases} \tag{24}$$

In the first case, investing $\Theta > \overline{\Theta}$ would mean paying sales costs on illiquid assets of amount $\Theta - \overline{\Theta}$ with no expectation of earning the liquidity premia R. In the second case, the insurer knows that if they invest more than total size of the illiquid asset market, it requires other investors to go short the asset. This would result in a negative R, which makes the asset more unattractive to the insurer. They therefore cap their investment at the total size S of the illiquid asset market.

The key implication of the upper bound $\overline{\Theta}$ is that the insurer does not sell illiquid assets when $\tau = \bar{\tau} - \sigma$ realizes. We can therefore restate wealth (7) in two cases that depend on the fraction τ of claims arriving early

$$W = \begin{cases} L\left(1+R^F\right) - C + \Theta R & \text{if } \tau = \bar{\tau} - \sigma \\ L\left(1+R^F\right) - C + \underline{\Theta} R - \frac{1}{2}\lambda\left(\Theta - \underline{\Theta}\right)^2 & \text{if } \tau = \bar{\tau} + \sigma \end{cases} \tag{25}$$

with both cases occurring with equal probability. The first case shows the simple outcome where the insurer holds enough liquid assets to cover early claims. In the second case, the insurer sells all their liquid assets plus a portion of their illiquid asset portfolio to cover remaining $t = 1$ claims. Dollar amount $\tau C - (L - \Theta) = (\bar{\tau} + \sigma) C - (L - \Theta)$ of illiquid assets are sold early. Substituting in equation (14) this can be restated $\Theta - \underline{\Theta}$. The residual $\underline{\Theta}$ illiquid assets are held to maturity, earning the liquidity premia R.

The insurers objective function (8) is therefore be restated

$$\max_{P,\,\Theta} \; L\left(1+R^F\right) - C + \frac{1}{2}\left(\Theta + \underline{\Theta}\right) R - \frac{1}{4}\lambda\left(\Theta - \underline{\Theta}\right)^2. \tag{26}$$

The first-order condition for the illiquid asset dollar investment is

$$0 = \frac{1}{2}R - \frac{1}{2}\lambda\left(\Theta - \underline{\Theta}\right) \tag{27}$$

and thus the optimal solution Θ^* in equation (11) follows. ■

Note 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.

Proof of Theorem 1

The proof is shown with the insurer facing a generalised convex cost function of selling illiquid assets. We now assume that the 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 (26) is thus

$$\max_{P,\,\Theta} \; L\left(1+R^F\right) - C + \frac{1}{2}\left(\Theta + \underline{\Theta}\right) R - \frac{1}{2}\lambda f(x) \tag{28}$$

where $x = \Theta - \underline{\Theta}$ is the dollar amount of illiquid assets sold.

The first-order condition with respect the illiquid asset allocation Θ is

$$0 = \frac{1}{2}R - \frac{1}{2}\lambda f'(x)\frac{\partial x}{\partial \Theta}$$

where we have used the chain rule and assumed the insurer takes the illiquid asset return R as fixed. Given $\frac{\partial x}{\partial \Theta} = 1$, the first-order condition solves to

$$R = \lambda f'(x). \tag{29}$$

From this condition we can see the marginal benefit R of an extra dollar of illiquid investment is equal to the marginal cost $\lambda f'(x)$ of an extra dollar of illiquid investment. The insurer optimally increases their illiquid investment allocation until this holds for any convex cost function.

Meanwhile, for fixed illiquid asset allocation, the first-order condition on (28) for the insurance price is

$$0 = \frac{\partial L}{\partial P}\left(1 + R^F\right) - \frac{\partial C}{\partial P} + \frac{1}{2}\frac{\partial \underline{\Theta}}{\partial P} R - \frac{1}{2}\lambda f'(x)\frac{\partial x}{\partial P} \tag{30}$$

where $\frac{\partial x}{\partial P} = -\frac{\partial \underline{\Theta}}{\partial P}$. Using the envelope theorem, we now substitute in condition 29 from the optimal illiquid asset decision to simplify to

$$0 = \frac{\partial L}{\partial P}\left(1 + R^F\right) - \frac{\partial C}{\partial P} + \frac{\partial \underline{\Theta}}{\partial P} R. \tag{31}$$

Note that the only impact of the excess return R on the optimal insurance price comes via the lower bound of illiquid investment $\underline{\Theta}$. This is the portion of the assets that the insurer knows it will not be forced to sell at $t = 1$. Substituting in the lower bound of the illiquid asset allocation (14) we have

$$0 = \frac{\partial L}{\partial P}\left(1 + R^F + R\right) - \frac{\partial C}{\partial P}\left(1 + (\bar{\tau} + \theta) R\right). \tag{32}$$

and using equations 5 and 6 and the product rule, the first order condition is thus

$$0 = \left(Q + \frac{\partial Q}{\partial P} P\right)\left(1 + R^F + R\right) - \frac{\partial Q}{\partial P}\bar{C}\left(1 + (\bar{\tau} + \theta) R\right) \tag{33}$$

$$= P(1 - \epsilon)\left(1 + R^F + R\right) + \epsilon \bar{C}\left(1 + (\bar{\tau} + \theta) R\right) \tag{34}$$

where the second line has been multiplied through by $\frac{P}{Q}$ and uses

$$\epsilon = -\frac{\partial \log Q}{\partial \log P} > 1. \tag{35}$$

Equation 34 is rearranged to give the final solution 12. ■

Proof of Proposition 2

Equation 15 proof

By the chain rule we have

$$\frac{\partial P}{\partial R} = \frac{\partial P}{\partial R^I}\frac{\partial R^I}{\partial R}. \tag{36}$$

From equation 12 we can see

$$\frac{\partial P}{\partial R^I} = -\frac{P}{1+R^I} < 0 \tag{37}$$

and from 13 we can see

$$\frac{\partial R^I}{\partial R} = \frac{1-\bar{\tau}-\sigma}{\left(1+\left(\bar{\tau}+\sigma\right)R\right)^2} > 0 \tag{38}$$

given $\bar{\tau}+\sigma<1$. ■

Exogenous shocks to equilibrium asset returns

The asset market clearing condition (9) states

$$S = \frac{(1-\omega)}{\omega}\frac{R}{\lambda} + L - \left(\bar{\tau}+\sigma\right)C + \frac{R}{\lambda} \tag{39}$$

$$= \frac{1}{\omega\lambda}R + \underline{\Theta}. \tag{40}$$

In the first line we have used the equilibrium asset demands (10) and (11). In the second line we have substituted in $\underline{\Theta}$ from equation (14) and rearranged.

We therefore have the equilibrium condition

$$R = \omega\lambda\left(S-\underline{\Theta}\right) \tag{41}$$

with recognition that $\underline{\Theta}(R)$ is endogenous. The derivative with respect λ[21] is therefore

$$\frac{\partial R}{\partial \lambda} = \omega\left(S - \underline{\Theta} - \lambda\frac{\partial\underline{\Theta}}{\partial R}\frac{\partial R}{\partial \lambda}\right) \tag{42}$$

where we have used the product rule, and chain rule with respect the endogenous variable. The derivative rearranges to

$$\frac{\partial R}{\partial \lambda} = \frac{\omega\left(S-\underline{\Theta}\right)}{1+\lambda\frac{\partial\underline{\Theta}}{\partial R}} \tag{43}$$

and we can see that to show $\frac{\partial R}{\partial \lambda} > 0$, we require to show both

1. $S > \underline{\Theta}$
2. $\frac{\partial\underline{\Theta}}{\partial R} > -\frac{1}{\lambda}$

[21] or derivative wrt ω. The proof for each variable from here is identical. We proceed by showing with λ.

Part 1. holds by definition 24. The insurer will not hold more than the total illiquid asset market. The rest of the proof focuses on part 2.

We will, in fact, show that $\frac{\partial \underline{\Theta}}{\partial R} > 0$. The result is intuitive. If R increases then insurer's set cheaper insurance (see 15), which increases the number of contracts they underwrite. Stable funding is constant fraction of claims. An increase in claims is therefore an increase in stable funding, which allows the insurer to invest more in illiquid assets (i.e. $\underline{\Theta}$ increases).

To show the following result

$$\frac{\partial \left[E + QP - (\bar{\tau} + \sigma) Q\tilde{C}\right]}{\partial R} > 0 \tag{44}$$

we can see that we must show

$$\frac{\partial QP}{\partial R} - (\bar{\tau} + \sigma) \tilde{C} \frac{\partial Q}{\partial R} > 0. \tag{45}$$

To proceed from here, we use $Q = kP^{-\epsilon}$ from equation (4) and the chain rule to show

$$\begin{aligned} \frac{\partial Q}{\partial R} &= \frac{\partial Q}{\partial P}\frac{\partial P}{\partial R} \\ &= -\varepsilon \frac{Q}{P}\frac{\partial P}{\partial R}. \end{aligned}$$

Using this result and the product rule we also show

$$\begin{aligned} \frac{\partial QP}{\partial R} &= \frac{\partial Q}{\partial R}P + \frac{\partial P}{\partial R}Q \\ &= -\varepsilon \frac{\partial P}{\partial R}Q + \frac{\partial P}{\partial R}Q \\ &= (1-\varepsilon) \frac{\partial P}{\partial R}Q. \end{aligned}$$

Substituting these two derivatives into inequality (45), we thus have:

$$(1-\varepsilon) \frac{\partial P}{\partial R}Q + (\bar{\tau} + \sigma) \tilde{C}\varepsilon \frac{Q}{P}\frac{\partial P}{\partial R} > 0$$

and dividing through by (the negative) $\frac{Q}{P}\frac{\partial P}{\partial R}$ we have

$$P(1-\varepsilon) + \varepsilon (\bar{\tau} + \sigma) \tilde{C} < 0$$

and dividing through by (the negative) $(1-\varepsilon)$ we have

$$P - M(\bar{\tau} + \sigma) \tilde{C} > 0$$

where we have used $M = \frac{\varepsilon}{\varepsilon - 1}$. Finally, we substitute the equilibrium premium price 12 and simplify

$$
\begin{aligned}
M \frac{1 + R(\bar{\tau} + \sigma)}{1 + R} \tilde{C} - M(\bar{\tau} + \sigma)\tilde{C} &> 0 \\
1 + R(\bar{\tau} + \sigma) - (1 + R)(\bar{\tau} + \sigma) &> 0 \\
1 - (\bar{\tau} + \sigma) &> 0
\end{aligned}
$$

which we know holds. The fraction $\tau \in \{\bar{\tau} - \sigma, \bar{\tau} + \sigma\}$ of insurer claims arriving at time 1 can not exceed one. ■

Proof of Proposition 4

The Lagrangian for the insurer's optimisation problem (8) when subject to (21) is

$$
\mathcal{L}(P, \Theta, \eta) = W + \eta \left(L - \frac{C}{1 + R^S} \phi^{-1} \right). \tag{46}
$$

Following the proof of proposition **??**, the corresponding first order condition for the insurance premium can be stated

$$
0 = \frac{\partial L}{\partial P}(1 + R) - \frac{\partial C}{\partial P}(1 + (\bar{\tau} + \theta) R) + \eta \left(\frac{\partial L}{\partial P} - \frac{\frac{\partial C}{\partial P}}{1 + R^S} \phi^{-1} \right). \tag{47}
$$

Using equations 5, 6 and 4, and the product rule, the first order condition is rearranged to

$$
P(1 - \epsilon)\left(1 + R^I\right)\left(1 + \frac{\eta}{1 + R^I} \frac{1}{1 + (\bar{\tau} + \sigma) R}\right) = -\epsilon \tilde{C} \left(1 + \frac{\eta}{\phi(1 + R^S)} \frac{1}{1 + (\bar{\tau} + \sigma) R}\right) \tag{48}
$$

and we rearrange this formula to solve the equilibrium price (22).

Proof of Proposition 5

This result follows straight from the equilibrium price 22, with the cases depending on whether

$$
\frac{1 + (\bar{\tau} + \sigma) R + \frac{\eta}{\phi(1 + R^S)}}{1 + (\bar{\tau} + \sigma) R + \frac{\eta}{(1 + R^I)}}
$$

is greater or less than 1.

C Appendix Figures and Tables

Figure C.1: P&C Insurance - Industry Wide Insurance Underwriting Cashflows. This figures plots the industry-wide insurance underwriting cashflows in Property & Casualty markets. Total income from insurance underwriting are the premiums received minus the claims paid and the operating expenses associated with the running of an insurance underwriting business (pricing, reserving, marketing, operations etc.). The data comes from quarterly US insurance company statutory filings 2001:2018 and is provided by SNL Global. Individual company data has been aggregated to show the industry-wide net income.

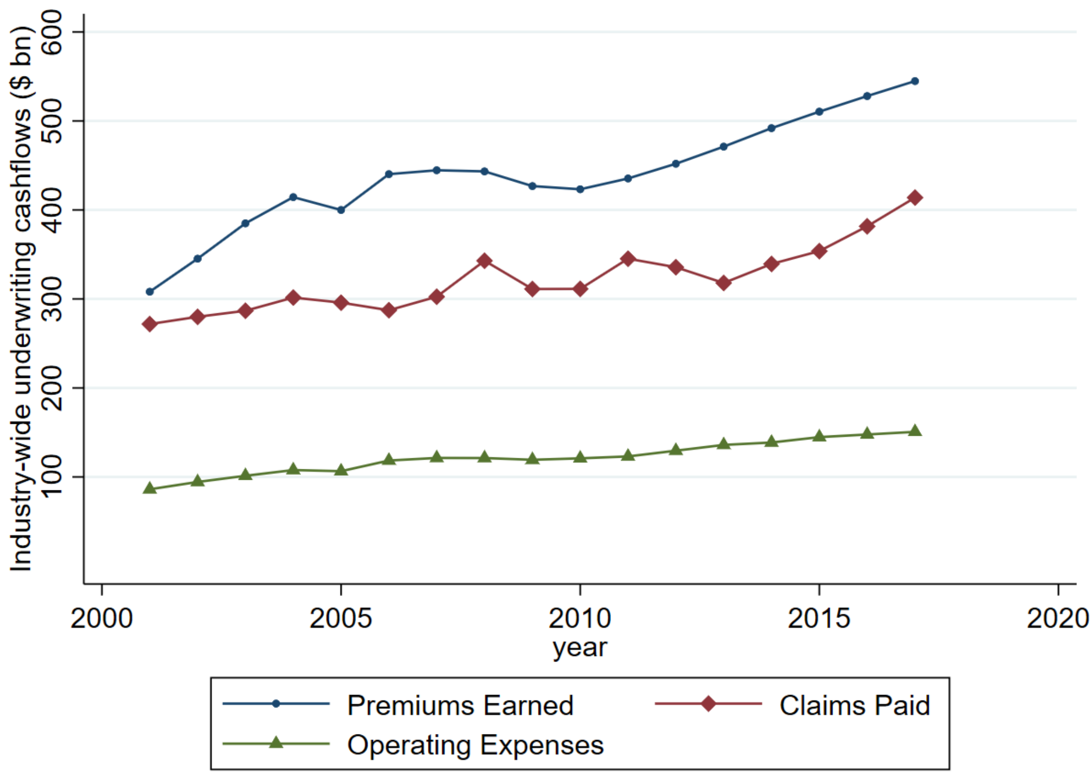
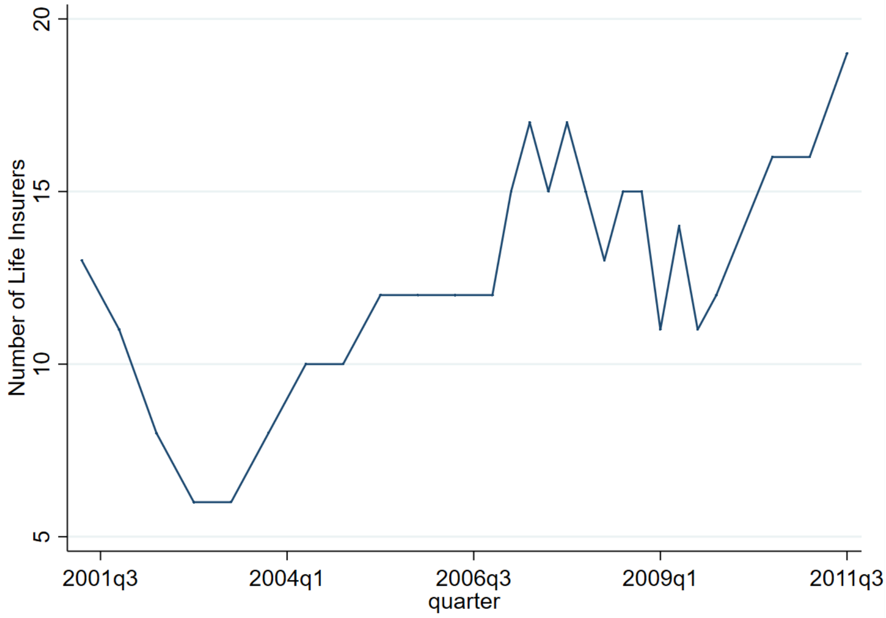


Figure C.2: Entities in the Cross-Section

This figures plots the number of entities observed in the cross-section for each time-period. Panel A plots the number of life insurance companies in annuity cross-sectional regressions. Panel B plots the number of Property & Casualty entities.

(a) Life Insurers (annuities)



(b) P&C Insurers

Table C.1: Mergers and Acquisitions Sample

This table shows the sample of mergers and acquistions that exist for our life insurance company dataset. The insurance companies underlined are those for which we have markup data for both pre and post the event.

Company A	**Company B**	**Deal Type**	**Date of Completion**
American Heritage	AllState Insurance	Acquisition	October 1999
General Electric Capital Assurance	Genworth Financial	Acquisition	January 2003
John Hancock	ManuLife	Acquisition	April 2004
Jefferson-Pilot	Lincoln National	Merger	April 2006

Table C.2: Life Insurance Time Series - Full Specification Estimates

This table shows the relation between the markups on annuities issued by life insurers and credit spreads. It reports the parameter estimates from the following regression:

$$m_{ikt} = \beta_c \cdot c_t + \beta_{GFC} \cdot \mathbb{1}_{GFC} + \beta_{cGFC} \cdot c_t \times \mathbb{1}_{GFC} + B' \cdot X_t + FE_i + FE_k + \epsilon_{ikt}$$

wherem_{ikt} is the annualised markup set by insurer i at time t for an annuity which is in sub-product category k. Sub-products vary depending on age, sex and maturity of the annuities. c_t is Moody's credit spread of BAA corporate bonds, and $\mathbb{1}_{GFC}$ is an indicator variable set to one over the global financial crisis (November 2008 through February 2010). We include a vector of time series controls X_t which includes the risk-free rate, the slope of the yield curve, the TED spread and US unemployment rate. Columns 1-3 report the parameter estimates from time series regressions where for the dependent variable, $\overline{m}_t$, we have averaged across insurers and sub-product categories in each time period. Columns 4-5 are full panel specifications. Panel A, B and C show the results for markups on fixed-term, guarantee and life annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. The t-statistics in the time series regressions are calculated using Newey and West (1987) standard errors with automatic bandwith selection. The panel regression also includes firm and fixed effects and standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Life Term Annuities

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.44***	-0.38***	-0.50***	-0.29***	-0.44***
	(-11.49)	(-5.66)	(-5.47)	(-4.58)	(-4.03)
$\mathbb{1}_{GFC}$			-1.01*		-0.66
			(-1.93)		(-1.51)
Credit Spread $\times$ $\mathbb{1}_{GFC}$			0.23*		0.21*
			(1.83)		(1.80)
markup (j,t-1)		0.23***	0.18**	0.47***	0.46***
		(2.74)	(2.06)	(7.63)	(7.57)
Risk Free (5yr)		0.11	0.11	0.12***	0.09***
		(1.38)	(1.59)	(4.01)	(2.92)
Slope (5yr - 1yr)		0.18	0.22**	0.16***	0.23***
		(1.48)	(2.06)	(2.79)	(3.97)
Ted Spread		-0.08	-0.03	0.00	0.07
		(-0.94)	(-0.32)	(0.04)	(0.73)
CAPE ratio		0.01**	0.02***	0.01	0.01*
		(2.42)	(3.22)	(1.25)	(1.81)
Unemployment Rate		0.10**	0.14***	0.12***	0.11***
		(2.39)	(2.93)	(3.04)	(2.72)
Duration (j,t)	-0.34***	0.12	0.16		
	(-3.08)	(0.48)	(0.78)		
Constant	5.10***	-0.88	-1.30		
	(5.57)	(-0.36)	(-0.61)		
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.800	0.871	0.876	0.596	0.603
Observations	72	72	72	12,460	12,460

[table continued on next page...]

Panel B: Guarantee Annuities

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.46***	-0.32***	-0.43***	-0.26***	-0.41***
	(-12.97)	(-5.43)	(-4.21)	(-4.93)	(-3.99)
$\mathbb{1}_{GFC}$			-1.06***		-0.66
			(-3.18)		(-1.60)
Credit Spread × $\mathbb{1}_{GFC}$			0.24**		0.20*
			(2.43)		(1.82)
markup (j,t-1)		0.23*	0.23*	0.45***	0.43***
		(1.77)	(1.75)	(6.73)	(6.44)
Risk Free (5yr)		0.12*	0.14	0.14***	0.12*
		(1.70)	(1.47)	(3.14)	(1.91)
Slope (5yr - 1yr)		0.06	0.13***	0.14**	0.20***
		(0.85)	(2.75)	(2.43)	(4.08)
Ted Spread		-0.08	-0.02	-0.06	-0.01
		(-0.94)	(-0.26)	(-0.79)	(-0.12)
CAPE ratio		0.01	0.01	0.00	0.01
		(0.99)	(0.84)	(0.40)	(0.69)
Unemployment Rate		0.10**	0.15***	0.12***	0.12**
		(2.38)	(3.44)	(3.08)	(2.46)
Duration (j,t)	-0.04	-0.13*	-0.19**		
	(-0.42)	(-1.75)	(-2.69)		
Constant	2.06**	1.26	1.56*		
	(2.24)	(1.58)	(1.73)		
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.799	0.875	0.883	0.655	0.664
Observations	53	53	53	14,529	14,529

Panel C: Term Annuities

	$\overline{m}_t$			m_{ikt}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.54***	-0.40**	-0.62***	-0.31***	-0.57***
	(-9.20)	(-2.62)	(-4.50)	(-2.89)	(-4.83)
$\mathbb{1}_{GFC}$			-0.87		-1.13***
			(-1.56)		(-2.72)
Credit Spread × $\mathbb{1}_{GFC}$			0.37**		0.44***
			(2.47)		(3.58)
markup (j,t-1)		0.13	0.15	0.39***	0.39***
		(1.02)	(1.13)	(4.72)	(4.79)
Risk Free (5yr)		0.06	0.06	0.17***	0.13***
		(1.14)	(1.60)	(4.03)	(4.08)
Slope (5yr - 1yr)		0.05	0.11	0.14*	0.20***
		(0.49)	(0.98)	(1.76)	(3.07)
Ted Spread		-0.17	-0.28**	-0.13	-0.23*
		(-0.83)	(-2.25)	(-0.77)	(-1.98)
CAPE ratio		0.01	0.01	0.02**	0.02***
		(1.34)	(1.65)	(2.19)	(3.52)
Unemployment Rate		0.01	0.00	0.10**	0.09**
		(0.30)	(0.04)	(2.60)	(2.63)
Duration (j,t)	-0.28***	-0.23***	-0.19***		
	(-6.28)	(-3.48)	(-2.84)		
Constant	4.22***	2.83***	2.99***		
	(17.09)	(3.02)	(3.54)		
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Product FE				yes	yes
Adj R-sq (Within)	0.861	0.857	0.873	0.432	0.458
Observations	45	45	45	2,557	2,557

Table C.3: P&C Time Series - Underwriting Profitability and Credit Spreads

This table shows the relation between quarterly P&C insurance underwriting profitability and credit spreads. Columns 1-3 report the parameter estimate from the following time series regression:

$$\overline{u}_t = \alpha + \beta_c \cdot c_t + \beta_{cFC} \cdot c_t \times \mathbb{1}_{FC} + B' \cdot X_t + \epsilon_t$$

where $\overline{u}_t$ is the average underwriting profitability in quarter t across all insurers. Underwriting profitability is defined as underwriting profits (premiums earned minus losses and expenses) divided by the premiums eared. c_t is the 1-year rolling average of Moody's credit spread of BAA corporate bonds, $\mathbb{1}_{FC}$ is an indicator variable set to one over the financial crisis (November 2008 through February 2010), and X_t is a vector of time series controls with 1-year rolling averages of investment returns and macroeconomic variables. we also run the regression in the full panel of insurance companies by estimating the model:

$$u_{it} = \beta_c \cdot c_t + \beta_{cFC} \cdot c_t \times \mathbb{1}_{FC} + B' \cdot X_t + FE_i + \epsilon_{it}$$

where u_{it}, is the underwriting profitability for insurer i in quarter t. Reported adjusted r-squared are within groups for panel specifications. The sample consists of quarterly observations from 2001Q1 through to 2018Q3. T-statistics are reported in the brackets and are calculated using Newey and West (1987) standard errors in the time-series specifications when possible, and standard errors clustered by date and firm in the panel specifications. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	$\overline{u}_t$			u_{it}	
	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.44***	-0.83***	-1.08***	-0.74***	-1.06***
	(-2.71)	(-3.32)	(-4.85)	(-2.94)	(-4.73)
Risk Free (1yr)		-0.35**	-0.34***	-0.17*	-0.18*
		(-2.63)	(-2.81)	(-1.70)	(-1.97)
Ted Spread		1.10***	0.05	0.76*	-0.36
		(2.71)	(0.10)	(1.67)	(-0.73)
Slope (5yr - 1yr)		-0.26	-0.35**	0.12	-0.02
		(-1.24)	(-2.08)	(0.65)	(-0.09)
Unemployment Rate		-0.05	-0.07	-0.11	-0.12
		(-0.56)	(-0.75)	(-1.36)	(-1.47)
Reinsurance Activity (t-1)		0.28	0.63	-0.10*	-0.10
		(0.16)	(0.39)	(-1.68)	(-1.65)
Risk Based Capital (t-1)		-0.51*	-0.42	0.22***	0.22***
		(-1.69)	(-1.56)	(12.33)	(12.60)
FC			-1.80		-1.64
			(-1.28)		(-0.80)
Credit Spread × FC			0.85**		0.87*
			(2.57)		(1.72)
Constant	1.52***	5.69***	6.35***		
	(3.54)	(3.30)	(3.85)		
Time Series Controls Vector		yes	yes	yes	yes
Entity FE				yes	yes
Adj R-sq (Within)	0.119	0.222	0.293	0.031	0.039
Observations	67	67	67	41,589	41,589

Table C.4: Life Insurance Time Series - Estimates in Changes

This table shows the relation between the markups on annuities issued by life insurers and credit spreads. It reports the parameter estimates from the following regression:

$$\Delta m_{jt} = \beta_c \cdot \Delta c_t + \beta_{FC} \cdot \mathbb{1}_{FC} + \beta_{cFC} \cdot \Delta c_t \times \mathbb{1}_{FC} + B' \cdot \Delta X_t + FE_i + FE_k + \epsilon_{ikt}$$

where $j = (i, k)$ and Δm_{jt} is the change in the annualised markup set by insurer i at time t for an annuity which is in sub-product category k. Sub-products vary depending on age, sex and maturity of the annuities. Δc_t is the change in the Moody's credit spread of BAA corporate bonds, and $\mathbb{1}_{FC}$ is an indicator variable set to one over the financial crisis (November 2008 through February 2010). We include a vector of time series controls ΔX_t in changes, which includes the risk-free rate, the slope of the yield curve, the TED spread and US unemployment rate. Columns 1-3 report the parameter estimates from time series regressions where for the dependent variable, $\overline{m}_t$, we have averaged across insurers and sub-product categories in each time period. Columns 4-5 are full panel specifications. Panel A, B and C show the results for markups on fixed-term, guarantee and life annuity products respectively. The sample consists of biannual observations from January 1989 through July 2011. The t-statistics in the time series regressions are calculated using Newey and West (1987) standard errors with automatic bandwith selection. The panel regression also includes firm and fixed effects and standard errors clustered by date and firm. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

Panel A: Life Annuities

	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.51***	-0.22**	-0.32***	-0.32***	-0.41***
	(-3.73)	(-2.22)	(-2.82)	(-5.37)	(-4.66)
$\mathbb{1}_{Fin.Crisis}$			0.16**		0.12
			(2.47)		(1.43)
Credit Spread × $\mathbb{1}_{Fin.Crisis}$			0.16		0.11
			(1.11)		(1.16)
Entity FE				yes	yes
Product FE				yes	yes
Time Series Controls		yes	yes	yes	yes
Adj R-sq (Within)	0.239	0.521	0.527	0.420	0.426
Observations	72	71	71	11388	11388

[table continued on next page...]

Panel B: Guarantee Annuities

	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.41***	-0.31***	-0.49***	-0.32***	-0.47***
	(-4.23)	(-3.37)	(-3.82)	(-4.64)	(-5.46)
$\mathbb{1}_{Fin.Crisis}$			0.09		0.14*
			(1.25)		(1.76)
Credit Spread × $\mathbb{1}_{Fin.Crisis}$			0.21*		0.16**
			(1.78)		(2.03)
Entity FE				yes	yes
Product FE				yes	yes
Time Series Controls		yes	yes	yes	yes
Adj R-sq (Within)	0.302	0.404	0.387	0.397	0.415
Observations	53	52	52	12927	12927

Panel C: Fixed-Term Annuities

	(1)	(2)	(3)	(4)	(5)
Credit Spread	-0.49***	-0.34***	-0.39**	-0.36***	-0.45***
	(-4.76)	(-3.46)	(-2.32)	(-4.24)	(-4.75)
$\mathbb{1}_{Fin.Crisis}$			0.38**		0.33***
			(2.35)		(3.14)
Credit Spread × $\mathbb{1}_{Fin.Crisis}$			0.05		0.12
			(0.41)		(1.18)
Entity FE				yes	yes
Product FE				yes	yes
Time Series Controls		yes	yes	yes	yes
Adj R-sq (Within)	0.343	0.657	0.662	0.373	0.383
Observations	45	44	44	2247	2247

Table C.5: Investment returns drive the cross section of premiums: P&C Insurance

This table shows the relation between quarterly returns to P&C insurance underwriting and firm-specific expected investment returns. It reports the parameter estimate from the following panel regression:

$$u_{it} = \beta_y \cdot y_{it} + \beta_{yFC} \cdot y_{it} \times \mathbb{1}_{FC} + B' \cdot X_{it-1} + FE_i + FE_t + \epsilon_{it}$$

where u_{it} is the underwriting profitability for insurer i at time t, and y_{it} is the insurer's investment return. We additionally control for date fixed effects, firm fixed effects and X_{it}, which is a vector of lagged variables that capture balance sheet strength (leverage, risk-based capital, asset growth and unearned premiums). This includes variables squared to control for non-linear effects of capital constraints. The samples consist of quarterly observations from March 2001 through March 2018. In columns 4-5 we interact investment return with an indicator variable $\mathbb{1}_{FC}$ set equal to one during the financial crisis (Q4 2008 through Q1 2010). 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.

	(1)	(2)	(3)	(4)	(5)
Investment Return	-0.10**	-0.12***	-0.11***	-0.13***	-0.12***
	(-2.37)	(-3.09)	(-5.19)	(-3.37)	(-5.70)
Size (t-1)		-0.07***		-0.07***	
		(-2.94)		(-2.93)	
Reinsurance Activity (t-1)		-0.22*		-0.22*	
		(-1.95)		(-1.95)	
Reinsurance Activity (t-1)		0.00			
		(.)			
Risk Based Capital (t-1)		0.41***		0.41***	
		(6.38)		(6.37)	
Asset Growth (t-1)		0.01***		0.01***	
		(4.16)		(4.15)	
Unearned Premia (t-1)		-0.01		-0.01	
		(-0.15)		(-0.15)	
(Risk Based Capital)^2		-0.01*		-0.01*	
		(-1.69)		(-1.68)	
(Asset Growth)^2		0.00**		0.00**	
		(2.26)		(2.27)	
(Leverage)^2		-0.00		-0.00	
		(-1.00)		(-0.99)	
Investment Return × FC				0.10	0.12**
				(1.52)	(2.56)
Reinsurance Activity (t-1)				0.00	
				(.)	
Firm Controls Vector		yes		yes	
Entity FE			yes		yes
Time FE	yes	yes	yes	yes	yes
Adj R-sq (Within)	0.001	0.071	0.001	0.071	0.001
Observations	37,044	37,044	37,044	37,044	37,044