Summary: Regulatory Limits to Risk Management (Ishita Sen, Harvard)

What are the consequences for risk management when regulatory and economic incentives are misaligned for financial institutions? I examine this question using variable annuities (VA) as a setting, which are retirement products sold by life insurers that provide minimum return guarantees on mutual fund investments. At over \$2 trillion, VA liabilities make insurers vulnerable to declines in the equity market and in interest rate, which is at an unprecedented low level. Unsurprisingly, the NYU Stern Volatility-Lab designates insurers as among the most systemically risky institutions in the US. Yet the regulatory framework treats VA as largely interest rate risk insensitive, which means that the regulatory value of the liabilities does not change with changes in interest rates, even though economic value of the liabilities shifts. This introduces a wedge between economic and regulatory hedging. Hedging economic exposures leads to more volatility in regulatory capital. As a result, insurers with low regulatory capital do not have the incentives to hedge interest rate risk.

Despite its importance, there exists no systematic evidence on how financial institutions hedge and respond to regulatory incentives. In part, this is due to the lack of data on derivative positions. This is the first paper to exploit detailed position-level data on derivatives to study risk management of institutions. Using 2.6 million contracts, I construct a long history of risk exposures from interest rate and equity derivative instruments. This allows me to shed light on several novel facets of hedging decisions and how they interact with regulatory incentives, including whether and how much to hedge, the use of different instruments, how hedging responds to changing interest rate conditions, and how insurers manage collateral. I also identify a unique regulatory setting in which regulatory risk management incentives vary for different types of VA guarantees even though they have similar economic risks.

I show that inconsistencies in regulation restrict interest rate risk hedging for a large fraction of VA liabilities. My estimates imply a shortfall in hedging exposures equal to \$23 billion, bulk of which is concentrated within the ten largest insurers amounting to 22% of their regulatory capital. In response, insurers shift risk exposures to off-balance sheet entities (shadow insurers), which are less well monitored and put the stability of the broader financial system at risk. I show that the regulatory incentives interact with monetary policy to switch off hedging incentives as interest rates rise, which has consequences for the fragility of life insurers and how monetary policy is propagated through this sector. Insurers' lack of hedging has consequences across fixed income markets as they are among the largest investors in corporate, municipal, and asset-backed bond markets. Insurers' hedging decisions also have implications for banks and households, as banks are counter-parties in over 60% of the derivative positions, and as households rely on the VA market for guaranteed retirement savings given that the market for defined benefit pension contracts has largely shut down.

Regulatory Limits to Risk Management

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Abstract

Using derivative positions and a regulatory change that results in different regulatory risk sensitivities for economically similar products, I show that inconsistencies in regulatory incentives restrict hedging and increase shadow insurance for U.S. life insurers. Insurers exposed to products that became fully risk sensitive increase interest rate and equity risk hedging. However, insurers exposed to products that became sensitive only to equity movements, hedge equity but not interest rate risk, and shift exposures to shadow insurers. My findings have implications for the fragility of insurers as regulation interacts with monetary policy to shut down hedging incentives when interest rates rise.

Keywords: Interest Rate Risk Management, Minimum Return Guarantees, Capital Regulation, Shadow Insurance, Collateral Constraints.

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The fragility of the financial sector during the Great Recession has left many questions unanswered about the risk management practices and hedging strategies of financial institutions. Regulators have responded by passing sweeping regulations across many parts of the financial sector. Some of these changes may have resulted in inconsistencies, which potentially impact the risk management choices and the fragility of financial institutions. Despite its significance, there exists no systematic evidence on how hedging decisions of financial institutions respond to regulatory incentives.[1] In part, this is due to the lack of detailed data on derivatives and hedging positions of financial institutions, which makes measurement of hedging a challenge.[2] Moreover, it is difficult to identify inconsistencies in regulatory incentives without knowing what optimal regulation is.

In this paper, I make progress on this question by studying the risk management incentives of U.S. life insurers. I construct a long history of risk exposures from derivatives using position-level data on interest rate and equity instruments, which allows me to precisely measure hedging across multiple risk factors. I also identify a unique setting where there are inconsistencies in the regulatory treatment of products that have quantitatively similar economic risk exposures. Using this unique set-up, I show that inconsistencies in regulation limit risk management and increase risk transfers to shadow insurers.

U.S. life insurers sell a variety of minimum return *guarantees*, called Variable Annuities (VA), which represent the largest component of life insurance liabilities.[3] The guarantees are basically long-dated put options, which insure households against market risks. When interest rates fall or equity markets decline, the guarantees become more in-the-money, and the insurer's liabilities increase. However, the regulatory framework has historically largely been insensitive to these risk factors. This implies that the regulatory value of liabilities does not change from one valuation date to the next, even though the market (economic) value changes with fluctuations in the equity market or the yield curve. On the other hand, derivatives are risk sensitive, i.e. the regulatory value of derivatives fluctuate with movements in the underlying risk factors. Thus, life insurers may have an incentive to *not* hedge because derivatives appear as pure mismatch risk on the regulatory balance sheet and lead to more volatility in regulatory capital. This lack of hedging, however, could translate into a higher mismatch between assets and liabilities in economic terms.

[1] The risk management literature has traditionally focused on non-financial firms; see, for example, Froot, Scharfstein, and Stein (1993), Smith and Stulz (1985), Stulz (1984), Breeden and Viswanathan (1990), and Rampini and Vishwanathan (2010). A recent literature has started to examine the hedging decisions of banks, however it does not explicitly focus on the effects of regulation on risk management decisions.

[2] See, for example, Begenau, Piazzesi, and Schneider (2015), Rampini, Vishwanathan, and Vuillemey (2016), and Hoffman, Langfield, Pierobon, and Vuillemey (2017) who examine these data for banks.

[3] Approximately, $1.8 trillion or 35% of life insurance liabilities in 2016 are VA.

The regulatory framework, however, shifted in 2009 and made some guarantees, but *not all*, sensitive to interest rates. At the same time, *all* guarantees became sensitive to equity market movements. Thus, while some guarantees became fully risk sensitive (**RS**), that is, sensitive to both interest rate and equity risk, others only became partially risk sensitive (**PRS**), that is, sensitive to equity risk but not to interest rate risk. It is puzzling why products that have similar economic risk exposures are treated differently by the regulation.[4] Insurance liabilities are computed as the maximum of the value of liabilities under two different frameworks, where only one of the frameworks is sensitive to interest rates while both frameworks are sensitive to equity risk. Which framework is ultimately binding depends on idiosyncratic contract features that are unrelated to interest rates, as I discuss in Section 1. For example, the insensitive framework is more stringent on mortality risk, which results in the insensitive framework dominating for one type of guarantee but not others.

This inconsistency results in different regulatory incentives for risk management for different guarantees, risk factors (interest rate and equity), and time. Yet, economic interest rate and equity risk exposures are quantitatively similar for *all* guarantees under various interest rate and equity market conditions, which I show using a standard pricing model. This allows me to identify whether the differences in hedging outcomes are a result of shifts in economic exposures or shifts in regulatory incentives.

Life insurers also report every single position and transaction in derivatives, including all instruments (swaps, options, futures, and forwards) and for all risk factors (interest rate, equity, credit, and currency). Several features make these data unique. First, detailed contract characteristics are available for each position. I use textual analysis to extract all relevant contract features, including trade direction, strike, and underlying. I can, therefore, compute the total risk exposures from derivatives, which helps to accurately measure the extent of hedging across multiple risk factors. Second, the data are available over a long period of time, starting in 2004, which allows me to study the evolution of hedging behavior over various interest rate, equity market, and regulatory regimes. Third, for each position in recent years, I observe why the position is taken and which balance sheet item is hedged. Finally, I observe the counterparties and collaterals posted, which allows me to test competing theories on the limits to risk management due to collateral constraints.[5]

To illustrate the risk management implications, I first develop a stylized model of interest rate risk hedging where insurers face conflicting risk management objectives due to the insensitivity of the regulatory framework to interest rate movements. The key state variable

[4] In the same vein, Agarwal, Lucca, Seru, and Trebbi (2014) have documented inconsistencies in the regulatory treatment for the same bank across state and federal regulators.

[5] See, for example, Rampini and Viswanathan (2010) and Rampini, Vishwanathan, and Vuillemey (2016).

is the wedge between the interest rate sensitivity of market value of capital and regulatory value of capital. When the wedge is large, due to the insensitivity of regulatory capital, hedging is low. An increase in the sensitivity of regulatory capital, thus, implies an increase in hedging and a higher propensity for dynamic hedging of interest rate risk mismatch. Moreover, tighter regulatory constraints imply lower hedging when the regulatory framework is insensitive. In other words, if insurers target the volatility of regulatory capital, and as a result hedge less, they do so precisely when they are constrained by regulatory capital.

Exploiting the differences in the regulatory sensitivities across guarantees, risk factors, and over time, I document five facts to show that inconsistencies in regulation limit risk management choices. First, I show that risk exposures from interest rate derivatives increase substantially after the regulation shifts in 2009. For the sector as a whole, a 1% parallel shift in the yield curve would have resulted in a negligible change in the interest rate derivatives portfolio before 2009; however, at its peak in 2016, the same shift would have led to a change of over $22 billion, or 8% of total capital and surplus. Moreover, the increase in interest rate risk hedging is concentrated only among insurers that are highly exposed to RS guarantees. Hedging remains unchanged for insurers highly exposed to PRS guarantees, which are economically similar but have no regulatory sensitivity to interest rates.

Second, I show that not only hedging increased after 2009, but insurers also start to dynamically hedge duration mismatch as interest rates shift. Life insurers are exposed to declines in interest rates as assets are short-dated relative to liabilities and because insurers sell minimum return guarantees. I show that, indeed, as rates fall (rise), hedging increases (decreases). Crucially though, the covariation between changes in hedging and changes in interest rates exists only for insurers that are highly exposed to RS guarantees, and only after the regulatory framework became sensitive to interest rates.

Third, along with interest rate risk exposures, risk exposures from equity derivatives also increased. In the aggregate, a 10% decline in the S&P 500 would have resulted in an increase of about 8 times between 2008 and 2016. However, this increase is for all insurers that sell VA, irrespective of the types of guarantees they sell. Thus, consistent with the incentives provided by the regulatory framework, insurers that sell more PRS guarantees, hedge equity, but not interest rate risk, which helps to rule out across firms differences in preferences, risk aversion, or ability to hedge as explanations of my findings.

Fourth, I show that the shift in regulatory risk sensitivities generates a larger increase in hedging for constrained insurers, who place a higher weight on the volatility of regulatory capital and thus hedge less ex-ante. Moreover, tighter regulatory constraints leads to lower hedging when the regulation is insensitive, which helps to pin-down the mechanism clearly.

Fifth, I show differences in reinsurance activities across guarantees. Reinsurance is an alternative way to manage risks as insurers can transfer exposures off-balance sheet, either to captives (shadow insurers) or to third party reinsurers, where the regulatory framework is closer to market values. After 2009, when the framework became differentially risk sensitive, reinsurance for PRS guarantees increased relative to RS guarantees. Moreover, bulk of these exposures move to the less regulated shadow insurers. These findings imply that insurers exposed to RS guarantees substitute out of reinsurance and into derivatives. In contrast, insurers exposed to PRS guarantees use more reinsurance to alleviate the regulatory frictions. However, due to limits on the amount of reinsurance activity, insurers can shift only part of the PRS exposures, which exposes them to mismatch risk in economic terms.

A number of additional analyses help to rule out alternative explanations of these findings. First, using recent disclosures on why a derivative position is taken, I show that hedging varies within the same insurer, depending on the regulatory sensitivity of the item being hedged. Thus, differences in risk attitudes, hedging abilities, and interest rate expectations are less likely to drive my results. Second, using data on collateral posted to counterparties and bond and cash holdings, I show that insurers hold more securities that qualify as eligible collateral than they actually post. Thus, collateral constraints are an unlikely explanation for the observed heterogeneity in hedging. Third, I show that my results are not driven by the differential exposures of insurers to the financial crisis. Finally, I show that the heterogeneity in how bond exposures have shifted does not correlate with the type of VA guarantee. Thus, the increase in hedging for RS guarantees is not due to substitution away from bonds or the lack of hedging for PRS guarantees is not mitigated by an increase in bond exposures.

My findings have important consequences for the fragility of life insurers. I quantify the extent of hedging in terms of the ex-post reduction in volatility of regulatory capital. Interest rate derivatives alone reduce the volatility of capital by close to 50% in the aggregate. However, while there is a large reduction for the average insurer exposed to RS guarantees (26%), there is no discernible reduction for insurers that underwrite PRS guarantees. My estimates imply that had regulation shifted in a consistent manner, insurers exposed to PRS guarantees would have an additional exposure of $23 billion from interest rate derivatives in 2016. In addition, as PRS liabilities are highly concentrated, 90% of this shortfall rests within ten of the largest insurers and amounts to over 22% of their capital and surplus.

The regulatory framework also interacts with shifts in monetary policy. As interest rates go up, the insensitive framework is more likely to bind, which implies that the regulatory incentives to hedge may completely switch off, even for RS guarantees. This highlights an important channel through which monetary policy interacts with risk regulation to impact the fragility of life insurers and for the propagation of monetary policy through the insurance sector. Moreover, when hedging incentives switch off, shadow insurance goes up, which could be regulatory blind spots and put the stability of the broader financial system at risk.

Related Literature: This paper is related to the broader insurance literature on regulatory and financial frictions and its implications.[6] I am the first to show how inconsistencies in regulatory incentives impact risk management decisions and the use of derivatives. My paper most closely relates to Koijen and Yogo (2017), which examines the impact of financial frictions on product market outcomes for VA, and Koijen and Yogo (2016), which studies the large-scale use of shadow insurance as a tool to alleviate regulatory constraints. I provide one potential explanation for why insurers were incompletely hedged going into the crisis and why reinsurance activities increased, both of which can be traced back to the hedging incentives provided by the regulatory framework. My paper also relates to Ellul, Jotikasthira, Kartasheva, Lundblad, and Wagner (2018), which documents the impact of mis-calibrated risk weights and hedging on illiquid bond investments of VA providers. I identify an alternative source of variation in hedging incentives, which could provide a useful identification to trace the impact of hedging incentives on asset allocation decisions.

This paper also contributes to several broad strands of recent research on the hedging incentives of financial institutions. First, whether derivatives cause a build up of systemic risk or whether they are used for hedging and capital management has been a central question since the financial crisis. Begenau, Piazzesi, and Schneider (2015) show that interest rate derivatives amplify balance sheet fluctuations for U.S. banks.[7] Hoffman, Langfield, Pierobon, and Vuillemey (2017) find the opposite for Euro area banks. I show that U.S. life insurers use interest rate and equity derivatives to hedge the risks embedded in VA guarantees.[8]

Second, several papers provide evidence of large heterogeneity in the extent of interest rate risk hedging among banks. The key explanations include product composition (Hoffman et al. (2017)), financial frictions (Vuillemey (2016)), collateral constraints (Rampini, Viswanathan, and Vuillememy (2015)), financial distress (Purnanandam (2007)), and low mismatch risk due to banks' market power in deposit markets (Drechsler, Savov and Schnabl (2017)). I show that differences in the regulatory treatment of different products can

[6] See, Ellul, Jotikasthira and Lundblad (2011), Becker and Ivashina (2015), and Ellul, Jotikasthira, Lundblad, and Wang (2015) for asset side implications. Koijen and Yogo (2015a), Ge (2017), and Sen and Humphry (2016) study the effects of regulatory frictions on the product market.

[7] McDonald and Paulson (2015) show that large bets on the real estate market through securities lending and selling CDS on residential mortgage-backed securities resulted in AIG's near failure in 2008.

[8] Life insurers may also have risk shifting motives due to implicit and explicit government guarantees. Becker and Ivashina (2015) document the reaching for yield behavior; Lee, Mayers, and Smith (1997) show that the introduction of guaranty funds led to a small increase in the riskiness of assets.

lead to substantial heterogeneity in the hedging behavior across financial institutions. Moreover, most of these papers study the risk management of banks with aggregated data. The richness of the insurance data allows me to shed light on several novel facets of hedging decisions, including whether to hedge with derivatives or not, how much to hedge, hedging multiple risk factors (interest rate and equity), the use of different instruments, and how hedging responds to changing interest rate conditions.

My paper also contributes to the broader risk management literature on why firms hedge.[9] The idea is most closely related to Smith and Stulz (1985) and DeMarzo and Duffie (1992), who propose that firms care about the volatility in accounting exposures instead of economic exposures when managers' compensation contracts depend on accounting earnings. The mechanism in my paper is related, but instead stems from the incentives provided by regulation. A leading explanation for the absence of hedging is also collateral and borrowing constraints (Rampini and Vishwanathan (2010) and Mello and Parsons (2000)). Using data on collateral posted to counterparties, I show that lower hedging for life insurers is not due to collateral constraints. My findings highlight the absence of regulatory incentives as a new mechanism to explain why financial institutions incompletely hedge risk exposures.

The paper is organized as follows. Section 1 describes the VA guarantees and the regulatory framework. Section 2 presents the model. Section 3 describes the data and the empirical strategy. Section 4 presents the main empirical findings on interest rate risk hedging. Section 5 presents the empirical results on equity risk hedging, reinsurance, and collateral constraints. Section 6 discusses broader implications and concludes.

1. Institutional Background

1.1. Variable Annuities

Variable annuities (VA) are retirement and savings products, which combine investment in a mutual fund with a minimum return guarantee. For a fee, insurance companies guarantee households a certain return on the mutual fund, regardless of the actual performance of the fund. There are four broad categories of guarantees, typically referred to as "GMxB", that is, Guaranteed Minimum Benefit of type "x", where "x"denotes "A"(accumulation), "D"(death), "I"(income), or "W"(withdrawal). The guarantees can be thought of as a complex put option on the mutual fund. To illustrate how they work, I present a numerical example below. A formal description of each guarantee is in Appendix A.

[9] The main explanations include (i) market frictions (Smith, Smithson and Wilford (1990); Stulz (1990); Froot, Scharfstein and Stein (1993); Smith and Stulz (1985); Froot and Stein (1998)) and (ii) agency costs (Stulz (1984); Breeden and Viswanathan (1990); Stulz (1990); DeMarzo and Duffie (1992)).

Suppose, the contract holder invests $100 today. In a GMAB, she gets the greater of the value of the mutual fund (account value) or an annual guaranteed rate of return (say 5%) at maturity. If the mutual fund does poorly, and the account value is say just $120 at maturity in 10 years, she still gets $163, or $100 compounded at 5% for 10 years, because of the guarantee. Similarly, in a GMDB, the contract holder gets the greater of the account value or a guaranteed rate of return, but only if she dies during the coverage period. On the other hand, in a GMIB, the contract holder can convert the accumulated guaranteed benefit into a lifetime annuity, where the annuity rate is either a guaranteed rate decided at the onset or the market annuity rate. Assuming she chooses the guaranteed annuity rate (say 5%), she gets a lifetime income of $8.1, or 5% of $163. Finally, in a GMWB, the contract holder can withdraw a fixed share of the accumulated guaranteed benefit. The amount not withdrawn, stays invested, however, the contract holder is guaranteed to receive the total accumulated benefit even if the account value reduces to zero in the future. Assuming withdrawals set at 5%, the contract holder gets an income of $8.1 and any positive fund value that remains at the end. Table A.1 summarizes the payoffs.

1.2. Economic Risk Exposures

Minimum return guarantees expose the liabilities of life insurers to fluctuations in interest rates and equity markets. When equity markets or interest rates decline, the value of the embedded put option goes up and insurers' risk exposures increase.[10] To quantify the risk exposures, I compute the risk sensitivities of the different guarantees numerically using a standard pricing model, where the short rate dynamics are given by the Cox-Ingersoll-Ross (1985) model and equity market dynamics are as under the Black-Scholes model. Appendix A provides the main results and the details on the model and the numerical simulations. For a realistic range of parameter specifications and under various interest rate and equity market (moneyness) conditions, I show that the guarantees have quantitatively similar economic interest rate and equity risk sensitivities (Table A.2). This implies that shifts in interest rates and the equity market affect the economic value of each guarantee in the same way at different points in time even as market conditions and interest rates change.

1.3. Regulatory Valuation Framework

In this section, I describe the regulatory treatment of the VA guarantees. Traditionally, the "statutory" (regulatory) valuation framework has been close to historical cost for all insurance

[10] In particular, interest rate risk arises as the accumulation, annuity or withdrawal rates are fixed at the start of the contract. A decline in interest rates, therefore, implies an increase in the value of the guarantees.

liabilities, including VA. Liabilities are largely insensitive to equity market movements and discounted at the "valuation rate", the prevailing interest rate at the time a contract is originated, which does not change over the life of a contract, even though actual interest rates change. Thus, the value of insurance liabilities does not change, from one valuation date to the next, despite changes in the actual interest rates and equity market conditions.

Traditional insurance liabilities (e.g. fixed annuities) are relatively easily matched on the asset side with bonds; thus the traditional valuation approach sufficed, in general, to capture the mismatch between assets and liabilities. VA are long dated options, and financial markets typically have no traded contracts that allow insurers to perfectly replicate the payoffs, which implies that the mismatch between assets and liabilities can fluctuate wildly.[11] Over time, as the product mix changed towards VA, the traditional approach became increasingly inappropriate to capture the risk exposures of insurers' balance sheets.

As a result, in September 2008, the National Association of Insurance Commissioners (NAIC) adopted Actuarial Guideline 43, with an implementation date of December 31, 2009, which resulted in greater sensitivities to equity market and interest rate changes compared to before.[12] All VA contracts issued on or after 1981 are affected, thus the scope and magnitude of the shift is large. Under the new framework, regulatory liabilities for VA are given by the maximum of liabilities computed under two alternative valuation methodologies:

$$\text{Regulatory Liabilities} = \max\big(\underbrace{\text{Standard}}_{\text{Partially sensitive}},\ \underbrace{\text{Stochastic}}_{\text{Sensitive}}\big)$$

Under the Stochastic framework, liabilities are computed by simulating the value of the VA portfolio for a range of interest rate and equity market paths and then taking an average for the worst 30% of the paths, which is similar to a conditional expected loss measure. As the interest rate paths are drawn from the *current* swap curve, movements in interest rates from one valuation date to the next impact the value of liabilities. In contrast, the Standard framework requires insurers to stress the portfolios for a large instantaneous drop in equity markets *but no changes* in interest rates. Liabilities continue to be discounted at the valuation rate, which is insensitive to changes in interest rates. Thus, while both frameworks are sensitive to equity market changes, only the Stochastic framework is sensitive to interest rate changes.[13]

[11] Insurers, therefore, often rely on dynamic hedging to hedge VA, which introduces model risk and basis risk, all of which often result in a mismatch between assets and liabilities.

[12] The previous valuation regimes for VA (AG 34 and AG 39), were deterministic in nature and had lower market sensitivities. See, Junus and Motiwalla (2010), page 10 or the NAIC Valuation Manual 20 (2012).

[13] Neither the Stochastic framework nor the Standard framework imply that regulatory values resemble market values as the prescribed scenarios are not picked under the risk neutral measure.

Moreover, the relative importance of the two frameworks varies for the different guarantees. The rate insensitive Standard framework dominates for GMDB and GMIB with a higher likelihood, while the rate sensitive Stochastic framework dominates for GMAB and GMWB. The next paragraph summarizes the key actuarial assumptions behind this.[14]

The prescribed assumption for mortality rate is higher in the Standard framework than in the Stochastic framework. This implies higher Standard liabilities for GMDB as a higher probability of death leads to higher payouts in a GMDB.[15] In contrast, the higher mortality rate under the Standard framework has an opposite effect on GMAB as payouts occur if a contract holder is alive. The Standard framework also prescribes higher election rates, the rate at which individuals annuitize the accumulated amount. This implies that cash flows start earlier, which leads to higher present value of liabilities for GMIB under Standard framework.[16] In contrast, the Standard framework is less likely to bind for GMWB, even though the election rates are same for both GMWB and GMIB. This is because, for GMWB, the account value is treated as a liability only when the values turn negative. This is more likely to occur under Stochastic because under a series of bad equity market draws, the values can turn negative even in the short term. In contrast, in the Standard framework, the immediate drop in the equity market is followed by a continuous recovery, which makes it more likely that the values fall below zero only late in the life of a contract.

These regulatory features imply that, under the new regulation, the interest rate sensitivities of regulatory liabilities diverged for the different guarantees. While GMAB and GMWB became sensitive, GMIB and GMDB remained interest rate insensitive. In contrast, equity risk sensitivities increased for all guarantees as both the Standard and the Stochastic frameworks became more sensitive to the equity market.

Figure 1 summarizes these changes. Panel A depicts the risk sensitivities and the binding framework for each guarantee and Panel B presents stylized balance sheets to show the shift in the regulatory risk sensitivities over time. To simplify the exposition and capture the differences in interest rate sensitivities, I henceforth classify the VA guarantees where the Stochastic framework dominates as risk sensitive (**RS**), that is, sensitive to both interest rate and equity risk, and where the Standard framework dominates as partially risk sensitive

[14] Junus and Motiwalla (2009) discuss why the Standard framework dominates for GMDB and GMIB. See, Table (4) and Table (11) and pages 31-32. Also, see Credit Suisse (2012).

[15] Mortality rates equal 70% of the 1994 Minimum Guaranteed Death Benefits (MGDB) table under Standard. Stochastic uses lower values, e.g. 65% of the 1994 MGDB (Junus and Motiwalla (2009)).

[16] The election rates under the Standard framework are increasing in the contract's moneyness: 0-10% in-the-money (ITM) (5%); 10-20% ITM (15%), and over 20% ITM (25%). This interacts with the assumption of a large drop in equity markets, which makes contracts in-the-money, and increases the Standard liabilities for GMIB further. The election rates are lower and the equity market drop is not as punitive under the Stochastic framework, which dampen the impact of moneyness on election rates for Stochastic liabilities.

(**PRS**), that is, sensitive to equity risk but not to interest rate risk.

Risk management implications: The risk management distortions arise because hedge positions (derivatives) are fully risk sensitive, i.e. marked-to-market, while the regulatory liabilities are insensitive to interest rate movements for some VA guarantees. Hedging, therefore, leads to more volatility in regulatory capital than not hedging because the value of hedge positions change with shifts in interest rates but the value of regulatory liabilities do not. This creates an incentive to not hedge interest rate risk exposures, to the extent that insurers care about the volatility of regulatory capital.[17] Both state regulators and credit rating agencies pay close attention to insurers' *Risk Based Capital*, which is the amount of regulatory capital in excess of minimum capital requirements. Volatility in regulatory capital could result in more regulatory actions and rating downgrades, which in turn affects the future demand and pricing of insurance products (Koijen and Yogo (2015a)).

It is, however, puzzling why there is a difference in the treatment of derivatives and liabilities that embed derivatives. In theory, the regulatory valuation is not different. However, it requires insurers to prove that the hedge closely replicates the liability being hedged, a measure known as "hedge effectiveness". In practice, hedge effectiveness is difficult to achieve as VA are long-dated options and the market for traded long-dated derivatives tend to be thin. In the data, less than 10% of derivative positions (by gross notional values) meet this criteria and derivatives end up getting treated differently from regulatory liabilities.

2. Model

There are two dates, $t = 0, 1$. The insurer has initial assets A_0 and liabilities L_0, where assets and liabilities are defined in terms of their respective market values. At time 0, the insurer chooses a hedge portfolio to manage interest rate risk by investing in derivatives. To describe the risk management problem which arises due to the frictions in the regulatory framework, I solely focus on a single factor model given by interest rate y.[18]

Interest rate exposures are represented by portfolio durations. At time 0, assets and liabilities have dollar durations β_A and β_L respectively. By assumption, assets are short-dated relative to liabilities $\beta_A < \beta_L$,[19] thus the insurer has a duration mismatch given by $\beta_G = \beta_L - \beta_A$. The mismatch depends on the level of interest rates and increases when

[17] Indeed, the 10K filings of insurers suggest that they target the volatility of regulatory capital in making hedging decisions. See, Metlife's annual report (2014), page 87.

[18] In reality, insurers manage risk exposures to various factors, such as interest rates, credit, and equity risk. The same logic that I develop for interest rates extends to other factors as well.

[19] For example, a number of companies cite the lack of matching long-dated assets as a reason for the duration mismatch in 10K filings, see e.g. Prudential (2017, page 34) or Metlife (2014, page 154).

rates fall (Domanski, Shin, and Shusko (2015)), thus $\beta'_G(y) < 0$.[20] The insurance company hedges the duration mismatch by investing in zero-cost interest rate derivatives with a dollar duration δ_0, such as swaps.[21]

The assets and liabilities in market values evolve as:

$$A_1 = A_0 - \beta_A \Delta y - \delta_0 \Delta y, \tag{1}$$

$$L_1 = L_0 - \beta_L \Delta y. \tag{2}$$

Insurance companies operate subject to "statutory" regulation. The regulatory value of the assets and liabilities evolve as:

$$\widehat{A}_1 = \widehat{A}_0 - \psi \beta_A \Delta y - \delta_0 \Delta y, \tag{3}$$

$$\widehat{L}_1 = \widehat{L}_0 - \psi \beta_L \Delta y, \tag{4}$$

where "$\widehat{\ }$" indicates that assets and liabilities are evaluated as per the regulatory framework. The sensitivities of regulatory quantities are given by $\psi\beta$, where $\psi \in [0, 1]$. $\psi = 1$ implies that the regulatory framework uses market values, while $\psi = 0$ implies that the regulatory framework is insensitive to changes in interest rates. Thus, $\psi < 1$ denotes the wedge between the sensitivity of market values and regulatory values due to the insensitivity of the regulatory framework to shifts in interest rates. Under the regulatory framework, derivatives are marked-to-market, thus derivatives are not impacted by ψ.

Following Koijen and Yogo (2015-2017), I define the insurer's regulatory capital, $\widehat{K}_1$, as:

$$\widehat{K}_1 = \widehat{A}_1 - \widehat{L}_1 - \phi \widehat{L}_1, \tag{5}$$

where $\widehat{A}_1 - \widehat{L}_1$ denotes the available capital and $\phi \widehat{L}_1$ captures the riskiness of liabilities, which can be interpreted as the minimum regulatory capital requirement. $\phi > 0$ implies that regulation is conservative. $\widehat{K}$ therefore corresponds to an insurer's risk based capital.

[20]This could be driven by both asset and liability side factors. For example, the presence of mortgage-backed assets or callable bonds which have negative convexity implies that asset duration increases at a smaller rate when interest rates fall. Similarly, minimum return guarantees imply that the effective duration of liabilities is longer as fewer policies lapse when rates fall.

[21]In addition to swaps, insurers also use rate options, however in relatively lower quantities.

At time 1, the return on capital, ρ, in market values is given by:

$$\rho = \frac{K_1}{K_0} = 1 + (\widehat{\beta}_L - \widehat{\beta}_A - \widehat{\delta}_0)\Delta y \theta_0, \tag{6}$$

where $K_t = A_t - L_t$. I define $\widehat{\beta}_L = \beta_L/\widehat{K}_0$, $\widehat{\beta}_A = \beta_A/\widehat{K}_0$, $\widehat{\delta}_0 = \delta_0/\widehat{K}_0$, to facilitate comparisons with the empirical tests where I scale dollar durations by regulatory capital. Thus, $\theta_0 = \frac{\widehat{K}_0}{K_0}$ emerges because of the change in scaling from economic to regulatory capital.

Equation (6) says that the return on capital at time 1 equals the total interest rate mismatch multiplied by the change in interest rate (Δy).[22]

I define changes in regulatory capital as:

$$\frac{\widehat{K}_1}{\widehat{K}_0} = 1 + \Big((1+\phi)\psi\widehat{\beta}_L - \psi\widehat{\beta}_A - \widehat{\delta}_0\Big)\Delta y. \tag{7}$$

The insurance company has mean-variance preferences over the return on equity in market values, but faces the cost of regulatory frictions. Following Koijen and Yogo (2015-2017), I model the cost of regulatory frictions through a convex cost function, $C(\widehat{K})$, which captures the cost of regulatory action or a rating downgrade due to low regulatory capital. Thus, the insurance company chooses its hedge portfolio in derivatives such that:

$$\max_{\widehat{\delta}_0} \quad \mathbb{E}(\rho) - \frac{\xi}{2}\sigma^2(\rho) - \mathbb{E}[C(\widehat{K})], \tag{8}$$

where ξ captures the insurer's aversion to volatility in the return on equity. For tractability and ease of interpretation, I define the expected regulatory cost to be proportional to its variance:

$$\mathbb{E}[C(\widehat{K})] = \frac{\gamma}{2}\sigma^2\Big(\frac{\widehat{K}_1}{\widehat{K}_0}\Big)\lambda(\widehat{K}_0), \tag{9}$$

where $\gamma\lambda(\widehat{K}_0)$ captures the importance of volatility in regulatory capital. I assume $\lambda'(\widehat{K}_0) < 0$, implying that insurers that are weakly capitalized are more averse to fluctuations in regulatory capital.[23] Equation (9) is also observationally equivalent to a Value-at-Risk constraint, written as proportional to the variance of changes in regulatory capital, as in Adrian and

[22] I ignore the dependence of duration on y as the insurer only duration hedges by assumption. The insurer, therefore, ignores the volatility in capital that arises due to shifts in duration at t=1 due to shifts in y.

[23] If insurers could raise more capital and move away from the regulatory constraint, then the volatility of regulatory capital would be less costly. In the model, I shut down this possibility, following the insurance literature that suggests that raising capital is costly and that regulatory constraints impact firms' decisions.

Shin (2014) and Miranda-Agrippino and Rey (2016), where $\lambda(\widehat{K}_0)$ is the Lagrange multiplier on the VaR constraint. The tighter the constraint, the higher the multiplier $\lambda(\widehat{K}_0)$.

The first-order condition yields the following solution for optimal hedging:

$$\widehat{\delta}_0 = \frac{-\mathbb{E}(\Delta y)\theta_0}{(\gamma\lambda(\widehat{K}_0) + \xi\theta_0^2)\sigma^2} + (\widehat{\beta}_L - \widehat{\beta}_A)\frac{\gamma\psi\lambda(\widehat{K}_0) + \xi\theta_0^2}{\gamma\lambda(\widehat{K}_0) + \xi\theta_0^2} + \phi\psi\widehat{\beta}_L\frac{\gamma\lambda(\widehat{K}_0)}{\gamma\lambda(\widehat{K}_0) + \xi\theta_0^2}, \tag{10}$$

where σ^2 is the volatility of interest rate shocks. I prove equation (10) in Appendix B. Equation (10) implies that the optimal demand for derivatives consists of three terms. The first term is due to a speculation motive, which depends on the expected changes in interest rates, $\mathbb{E}(\Delta y)$, the volatility of interest rate shocks, and total risk aversion, $\gamma\lambda(\widehat{K}_0) + \xi\theta_0^2$. The second and third term are due to a hedging motive and depend on the duration gap, $\widehat{\beta}_L - \widehat{\beta}_A$, the wedge between market and regulatory values, ψ, and capital requirements, ϕ.

Implication 1: When the expected regulatory cost is low, and assuming the insurer does not use derivatives for speculation, $\mathbb{E}(\Delta y) = 0$, the insurer moves towards full *economic* hedging:

$$\lim_{\gamma\lambda(\widehat{K}_0)\to 0} \widehat{\delta}_0 = (\widehat{\beta}_L - \widehat{\beta}_A) \tag{11}$$

When the expected regulatory cost is high, the insurer moves towards full *regulatory* hedging:

$$\lim_{\gamma\lambda(\widehat{K}_0)\to\infty} \widehat{\delta}_0 = \psi(\widehat{\beta}_L - \widehat{\beta}_A) + \phi\psi\widehat{\beta}_L \tag{12}$$

Equation (11) implies that without regulatory costs, and in the absence of a speculation motive, the insurer fully hedges the volatility in return on equity, which depends on the interest rate mismatch between assets and liabilities. Equation (12) on the other hand implies that when the regulatory costs are sufficiently high, the insurer only cares about the volatility in regulatory capital, which depends on interest rate mismatch, but crucially also on ψ and ϕ, resulting in a wedge between economic hedging and regulatory hedging.

Implication 2: *The effect of an insensitive regulatory framework:* The optimal hedging demand increases with the sensitivity of the regulatory framework ψ, as $\frac{\partial\widehat{\delta}_0}{\partial\psi} > 0$.

Intuitively, insurers minimize the volatility of changes in regulatory capital in order to reduce the expected regulatory cost. The volatility is higher when the insurer hedges than when it does not, as only derivatives are sensitive to interest rates, while the rest of the regulatory balance sheet is insensitive, or only partially sensitive. Thus, when ψ is low, hedging is lower.

Implication 3: *The effect of conservative capital regulation:* The optimal hedging demand increases due to conservative regulation $\phi > 0$, as $\frac{\partial \widehat{\delta}_0}{\partial \phi} > 0$.

Thus, as regulation becomes more conservative and regulatory capital requirements increase, that is ϕ goes up, hedging increases as well.

2.1. Testable Predictions

The shift in the regulatory framework resulted in an increase in ψ as some VA guarantees became more sensitive to interest rate changes. Moreover, due to the differences in the amount of RS guarantees underwritten, the shift in the regulation resulted in heterogeneity in ψ in the cross-section of insurers, that is, insurers that have more RS guarantees have a higher ψ. This gives the following testable predictions:

Prediction 1: *Magnitude of hedging*: Over time, an increase in ψ leads to an increase in hedging, all else being equal, as shown in implication 2. Moreover, for two firms, i and j, all else being equal, if $\psi_i > \psi_j$ then $\widehat{\delta}_{0i} > \widehat{\delta}_{0j}$. Thus, the impact of the shift in the regulation on hedging demand is higher for firms with a higher ψ.

Prediction 2: *Dynamics between hedging and interest rates*: An increase in ψ implies a higher sensitivity of hedging demand to interest rates, all else being equal, as $\frac{\partial^2 \widehat{\delta}_0}{\partial \psi \partial y_0} < 0$. In other words, if interest rates fall, hedging demand increases, but the increase is higher when ψ is higher. Moreover, for two firms, i and j, all else being equal, if $\psi_i > \psi_j$ then $\frac{\partial \widehat{\delta}_{0i}}{\partial y_0} < \frac{\partial \widehat{\delta}_{0j}}{\partial y_0}$. Thus, firms with a higher ψ, adjust hedging demand more in response to changes in interest rates, than firm with lower ψ, all else being equal.

Prediction 3: *Interaction with regulatory constraints*: (A) The tighter the regulatory constraints, $\lambda(\widehat{K}_0)$, the greater the marginal effect of a shift in ψ as $\frac{\partial^2 \widehat{\delta}_0}{\partial \lambda(\widehat{K}_0) \partial \psi} > 0$. In other words, an increase in the sensitivity of the framework generates a larger increase in hedging for insurers that are more capital constrained. (B) Moreover, the tightness of regulatory constraints affects hedging in opposite ways depending on the magnitude of ψ. When $\psi = 0$, $\frac{\partial \widehat{\delta}_0}{\partial \lambda(\widehat{K}_0)} < 0$. Thus, an increase in the tightness of regulatory constraints leads to a decrease in the hedging demand. However, when $\psi = 1$, $\frac{\partial \widehat{\delta}_0}{\partial \lambda(\widehat{K}_0)} > 0$. Thus, an increase in the tightness of the regulatory constraints leads to an increase in hedging demand due to conservative regulation ϕ. I prove prediction 3 in Appendix B.

I test these implications using detailed contract level data on interest rate derivatives. The exact empirical methodology, measurement of interest rate risk hedging, ψ, and regulatory constraints are described in the next Section.

3. Data and Measurement

I combine position-level data on interest rate and equity derivatives and the collateral posted against these positions to counterparties with data on VA guarantees, regulatory capital, ratings, and other characteristics to examine the impact of regulatory inconsistencies on hedging outcomes.

3.1. Derivatives Data and Measurement of Interest Rate Risk Hedging

Insurers report quarterly positions and transactions in derivative instruments across risk exposures, including interest rate, equity, credit, and currency, which I collect from the NAIC's Schedule DB database. The following features make these data particularly unique. First, detailed contract characteristics are available for each position, including notional amount, fair value, maturity, strike, type of underlying, direction of trade, and trading information. This allows me to compute risk exposures of derivative positions, as opposed to examining just notional values. Second, the data are available over a long period, starting in 2004, which allows me to study the evolution of hedging strategies over various interest rate, equity market, and regulatory regimes. Third, for each position in recent years, I observe why the position is taken and which balance sheet item is hedged. Finally, I observe the counterparties and collaterals posted, which allows me to test competing theories on the limits to risk management due to collateral constraints (Rampini and Viswanathan (2010)).

In aggregate, the data contain 2.6 million derivative positions over the entire sample from 2004 to 2016. Roughly 95% of the positions (by gross notionals) are earmarked as "hedging risk exposures". I zoom in on interest rate and equity risk hedging positions. From 2009, insurers directly report which risk factor is being hedged by each position, but not before. Therefore, to select interest rate and equity risk hedging positions before 2009, I use textual analysis and extract the information required to discern which risk factor is being hedged from the position descriptions.[24] Figure 2 shows a breakdown of the gross notional values by risk factors. Interest rate risk is the largest risk factor being hedged, followed by equity risk. Moreover, interest rate and equity derivative holdings have significantly increased, unlike other risk factors, when the regulation shifted in 2009.

[24] See, Appendix D for the methodology and further details.

I next describe the interest rate derivatives data and measurement of risk exposures. There are over 775,000 positions, equaling over \$41 trillion in notional value during the period 2004 to 2016. Of these, 65% are interest rate swaps, 31% are rate options (caps, floors, and swaptions), and 4% are futures, forwards and other instruments by gross notional values. I restrict my analysis to swaps and options only, as these comprise more than 95% of all contracts by gross notional values.[25] Table 1 shows a snapshot of the data as of 2016:Q4 at an aggregate level, which reveals significant heterogeneity in the types of instruments and in the contract features, including maturity and the direction of exposure.

To account for this heterogeneity, I compute the interest rate risk exposures for each position due to a 100 basis points shift in the yield curve. I measure the risk exposures of swaps by dollar duration and of rate options by option "deltas" as implied by the Black (1976) model. Thus, I assume parallel shifts of the yield curve, which as term structure decompositions show, account for a vast majority of the variation in yields.[26] [27]

The measurement of risk exposures itself is a three-step process. First, I compute the exposures of standard instruments using actual market data as of the valuation date t. The zero and forward curves are bootstrapped from the Libor and swap rates. I collect forward swap rates and the term structure of implied volatilities (Black swaption volatility cube) for different option expiries, swap tenors, and strikes from Bloomberg. Figure E.1 and Table E.1 report the exposures of standard instruments.

Second, I apply exposures to the position-level data, fully incorporating all contract features. As not all features of a contract are directly reported, I use textual analysis or the reported fair values to infer the relevant contract features. For swaps, I need the direction (receive-fixed-swap (RFS) or pay-fixed-swap (PFS)), remaining maturity, and the swap rate. I infer the swap's direction from the reported fair values. Theoretically, the fair value of an RFS is the present value of the annuity given by the difference between the swap rate at initiation and the current MTM swap rate of a comparable maturity swap.[28] For each position, I observe (i) the date on which the swap was initiated, which gives the MTM swap rate at initiation s^* and (ii) the remaining maturity, which gives the current MTM swap rate s_t. Comparing the reported and the theoretical fair values reveals the swap's direction.

[25]Kirti (2017) examines the risk taking behavior of U.S. insurance companies and uses positions data on interest rate derivatives, focusing on interest rate swaps.

[26]Litterman and Scheinkman (1991) show that most of the variation in returns of fixed income securities can be explained by three factors: level, slope, and curvature, where the level factor corresponds to a roughly parallel shift of the yield curve. See, also Cochrane and Piazzesi (2005).

[27]Begenau, Piazzesi and Schneider (2015) measure risk exposures using factor regressions, which account for non-parallel movements in yields as well. My data contain a substantial portion of options, where a factor regression can be challenging to implement due to a lack of reliable returns data.

[28]The MTM swap rate is the swap rate that makes the fair value of the swap equal to zero.

For example, if $s^* > s_t$, then an RFS has a positive fair value. If the reported fair value is also positive, then I conclude that it is an RFS, otherwise it is a PFS.[29] For rate options, I require the strike, maturity, and the trade direction, which are either reported directly or have to be parsed from the position descriptions. Overall, I compute the exposures for 92% of the positions (by gross notional values) and exclude 8% of the positions due to missing information (Table E.2). Appendix E provides further details.

Finally, I compute the total dollar risk exposures δ_{it} for insurer i at time t by aggregating across positions as follows:

$$\delta_{it} = \sum_j \Delta_{ijt} \times N_{ijt} \tag{13}$$

where Δ_{ijt} is the exposure of position j at time t for insurer i, computed for a hypothetical \$1 in notional value and N_{ijt} is the actual notional value. Aggregation across positions allows offsetting positions to net out and accounts for the differences in maturity and moneyness. Figure 3 shows the time-series of total dollar exposures from interest rate derivatives for the sector as a whole, which reveals a substantial increase in interest rate risk hedging.[30]

The analysis on equity derivatives follows exactly the same steps. I postpone discussing the data and the measurement of risk exposures to Section 5, to simplify the exposition. However, just to preview, Figure 4 shows the evolution of equity risk exposures for the sector as a whole, which also reveals a substantial increase in hedging over the last decade.

3.2. Variable Annuities Data and Measurement of Regulatory Risk Sensitivities

Insurers report total liabilities for each VA guarantee at an annual frequency starting in the year 2005.[31] These liabilities measure the value of the guarantees underwritten, that is, the value of the embedded put option within a VA contract. I compute the net liabilities, which are gross liabilities underwritten minus liabilities ceded to another entity (re-insured). Thus, the net liabilities measure the portion of the liabilities that still remain on the insurer's balance sheet and affect the sensitivity of regulatory liabilities and capital. Table 2 shows descriptive statistics of gross liabilities, reinsurance, and net liabilities for the different types

[29] I also extract a swap's direction by parsing the description string and show that it yields similar outcomes as the fair value approach. For example, a univariate regression between the two outcomes has a statistically significant coefficient above 0.9 and an R-sq of 87%.

[30] δ_{it} can shift due to shifts in both Δ_{ijt} due to changes in interest rates and shifts in N_{ijt}, that is, changes in actual positions. Thus, I construct an alternative measure where I fix Δ_{ijt} as of 2010:Q2, which is the date closest to the average 10 year yield during my sample, and find that exposures have increased primarily due to changes in actual positions.

[31] See, Section 9.2 General Interrogatories Part 2 of the regulatory financial statements.

of VA guarantees as of 2016:Q4.

The new regulatory framework resulted in a shift in the regulatory risk sensitivities of VA guarantees that have similar economic risk exposures. I measure this shift by the ex-ante ratio of VA guarantees to total capital and surplus (shortened to capital henceforth). I denote the ratio of total VA guarantees to capital by G_i. I split this into two parts: the ratio of risk sensitive guarantees to total capital, RS_i and the ratio of partially risk sensitive guarantees to total capital, PRS_i. Specifically, I define:

$$
\begin{aligned}
G_i &= \frac{(\text{Net Liabilities in VA Guarantees})_{i,2007}}{(\text{Regulatory Capital})_{i,2007}} \\
&= \frac{(\text{Net RS Liabilities} + \text{Net PRS Liabilities})_{i,2007}}{(\text{Regulatory Capital})_{i,2007}} \\
&= RS_i + PRS_i,
\end{aligned}
\tag{14}
$$

where the components of RS and PRS guarantees are as described in Section 1.3. Table 2 shows the distribution of RS_i and PRS_i. A higher RS_i implies that regulatory capital became more sensitive to both interest rate and equity market movements after 2009. In contrast, a higher PRS_i implies that regulatory capital became more sensitive to equity market but not interest rate movements after 2009.

I define these ratios as of year end 2007 for two reasons. First, I want to avoid the endogeneity concern that companies simultaneously choose their exposure in these products that are somehow correlated with the change in the regulation itself. Second, insurers report the VA liabilities after accounting for hedging. Thus, ex-post it is unclear whether high liabilities are due to high pre-exposures or low hedging. As the regulatory framework was adopted in 2008 and because insurers hedged little before 2008-2009 (Figure 3 and Figure 4), using liabilities as of 2007 helps to circumvent both issues.

The identification strategy exploits the variation in regulatory risk sensitivities along three dimensions: across VA guarantees, over time, and across different risk factors. I use the cross-sectional variation in ex-ante ratio of VA guarantees to total capital (RS_i and PRS_i) to trace the hedging behavior across insurers, over time, and for different risk factors (interest rate and equity). Intuitively, there are similarities and differences in the regulatory risk sensitivities across VA guarantees. In the data, I test whether the hedging behavior falls in line with these similarities and differences. The exact empirical specifications are discussed in Section 4.

3.3. Measurement of Regulatory Constraints

Tightness of regulatory constraints impacts how much insurers care about the volatility of regulatory capital, as shown in Section 2. To assess the extent of regulatory constraints, I collect data on the *Risk Based Capital* ratio (RBC) from SNL Financial, which are reported at an annual frequency. RBC is the ratio of regulatory capital (assets minus liabilities) to required capital, which state and federal regulators use to determine whether a insurer's capital level is sufficient. Required capital is the total minimum capital requirements due to credit, equity, interest rate, insurance, and other risk exposures.[32] A higher RBC ratio indicates that an insurer is well capitalized relative to its capital requirements.

3.4. Data on Traditional Determinants of Hedging

The risk management literature finds that heterogeneity in capital market frictions (Froot, Scharfstein and Stein (1993)), the ability to hedge,[33] and collateral constraints (Rampini and Vishwanathan (2010)) affect hedging outcomes. These characteristics are typically measured in the literature by firm size, leverage, credit ratings, and other measures of financial strength. I compile these variables from NAIC's financial statements. The log of total assets measures the size and general account assets divided by total capital measures leverage. I also collect AM Best's credit ratings, Capital Adequacy Ratio (BCAR), and the guideline BCAR that sustains current ratings, which is another measure of an insurer's financial strength. I examine the relationship between collateral constraints and hedging using data on collateral posted by insurers to counterparties in Section 5.

3.5. Sample Selection

The sample includes insurers that held interest rate derivatives during the period 2004-2016. I aggregate balance sheets and derivative exposures at the group level using NAIC company code to group code mappings. As I compare hedging before and after the shift in the regulatory framework, I only include insurers that have been in operation for at least two years in each regulatory regime. I also exclude insurers that have less than $100 million gross notional in rate derivatives combined across all quarters. The final sample contains 53 insurers, which account for 89.3% of the sector's total assets at the end of 2016. I discuss the descriptive statistics and the main empirical findings in the next section.

[32] RBC measures an insurance company's exposure to various forms of risks which include, C0: subsidiary insurers risk; C1: asset risk; C2: insurance risk; C3: interest rate risk; and C4: business risk.

[33] Nance, Smith, and Smithson (1993), Geczy, Minton, and Schrand (1997), Graham and Rogers (2002), and Carter, Rogers, and Simkins (2006) show that small firms hedge less, despite volatile cash flows and restricted access to capital.

4. Regulatory Incentives and Interest Rate Risk Hedging

4.1. Aggregate and Cross-sectional Facts

I start by documenting stylized facts on interest rate risk hedging. First, the interest rate derivatives portfolio has a positive duration on average (Table 3). Insurers are exposed to declines in interest rates as assets are short-dated relative to liabilities and because insurers supply products that embed minimum return guarantees, such as VA. A positive duration overall implies that derivatives gain in value when interest rates fall, implying that insurers buy protection against declines in interest rates. Second, hedging exposures have increased substantially since 2009. A 100 basis points parallel shift in the yield curve would have resulted in a negligible change in the value of the interest rate derivatives portfolio before 2009, however, at its peak in 2016, the same shift would have led to a change of over $22 billion, or 8% of total capital and surplus, for the sector as a whole (Figure 3).[34]

Third, hedging is highly concentrated. For example, of the 220 insurers, 57 held interest rate derivatives at some point during my sample period. The extensive margin is correlated with total assets, as also documented for non-financial firms and banks, the composition of liabilities, and RBC ratio. Large firms, firms with more VA guarantees, and unconstrained firms (high RBC ratio) use derivatives (Table 4).

However, conditional on hedging, heterogeneity in both the level of exposures (intensive margin) and volatility of exposures are primarily associated with the composition of liabilities. I estimate a cross-sectional mean specification, in which I regress the time-series average of hedging exposures and volatility of hedging exposures for each insurer on their time-series average RS ratio, PRS ratio, total assets, leverage, and RBC ratio:

$$\overline{Y_i} = \alpha + \overline{RS_i} + \overline{PRS_i} + \overline{Log(assets)_i} + \overline{Leverage_i} + \overline{RBC_i} + \epsilon_i,$$

where $\overline{Y_i}$ is either $\overline{\widehat{\delta}_i}$, the average hedging exposure scaled by capital, or $\sigma(\widehat{\delta}_i)$, the standard deviation of hedging exposure scaled by capital. Table 4 reports the results. Insurers with a high RS ratio have higher interest rate hedging exposures. Moreover, these insurers also have hedging exposures that are more volatile, suggesting that they frequently re-balance their derivative positions.

[34] In contrast, during the same period, interest rate risk hedging of non-financial S&P 500 firms has decreased (Bretscher, Mueller, Schmid, and Vedolin (2016)).

4.2. Impact of Regulatory Incentives

4.2.1. Magnitude of Hedging

I next examine the impact of regulatory incentives on the evolution of interest rate risk hedging by estimating the specification below, which relates the shift in interest rate hedging across insurers after 2009, with the cross-sectional variation in the ratio of different types of VA guarantees to total capital,[35]

$$\widehat{\delta_{it}} = \alpha + \sum_{J=RS,PRS} \beta^J (J_i \times Post_t) + \gamma' X_{it-1} + \alpha_i + \alpha_t + \epsilon_{it}, \tag{15}$$

where $\widehat{\delta_{it}}$ is the total exposure from interest rate derivatives scaled by capital for insurer i at time t. $J = RS$ is the ratio of RS guarantees to capital and $J = PRS$ is the ratio of PRS guarantees to capital, as defined in equation (14). $Post_t$ is a dummy variable that takes a value of 1 for years on or after 2009, and X_{it-1} are insurer-specific controls, which I discuss below. The pre-period is 2004 to 2008 and the post period is 2009 to 2016. I include insurer fixed effects to control for non-time varying unobservables across insurers and time fixed effects to control for time trends, which absorb RS_i, PRS_i, and $Post_t$ respectively.

The coefficients of interest are β^{RS} and β^{PRS}, which measure the correlation between the shift in interest rate risk hedging after 2009 and the exposure of insurers to RS and PRS guarantees respectively. If insurers do not care about regulatory incentives, then interest rate hedging outcomes for both RS and PRS guarantees would be similar as the economic interest rate exposures are similar for both RS and PRS guarantees, as shown in the simulations (Table A.2). However, if regulatory incentives matter, then hedging outcomes would be different because regulatory interest rate sensitivities are different for RS and PRS guarantees.

Table 5 presents the results. I estimate a positive and statistically significant coefficient (at the 10% level (column I)) when I use the ratio of total VA guarantees to capital, G_i, as the main regressor.[36] I next split the variable into its constituents, RS_i and PRS_i. I estimate a positive and statistically significant coefficient β^{RS}, which captures the interaction between RS_i and the post 2009 dummy, at the 1% level. However, β^{PRS} is statistically insignificant (column II). In columns III and IV, I introduce the two variables separately, however the estimates of β^{RS} and β^{PRS} do not change materially. Figure 5 further corroborates this by showing the dynamics of the shift in hedging for the RS and PRS ratios immediately around

[35] The estimations are at an annual frequency because important control variables, e.g. the RBC ratio, guarantee ratio, MBS and callable bond share are only available at an annual frequency. Estimations on quarterly data, without these control variables, produce extremely similar results.

[36] All standard errors are clustered at the insurer level.

the introduction of the new regulation. Thus, the increase in hedging after 2009 correlates positively and significantly with RS_i, however, it does not correlate with PRS_i, although PRS guarantees have similar economic interest rate risk exposures as RS guarantees.

The magnitude of the increase for insurers which have a high RS ratio is large. For example, the difference in the shift in the ratio of hedging exposures to capital between the 90th and 10th percentile of RS ratio is close to 5%.[37] In other words, 5% more of total capital is protected against a 100 basis points decline in interest rates (roughly a one standard deviation change), for insurers at the 90th percentile vis-a-vis the 10th percentile of the RS ratio. I quantify the extent of hedging in terms of the actual reduction in volatility of capital in Section 4.3.

If durations gaps were static over time, then economic exposures get differenced out in my specification and thus the shift in hedging can be attributed to the shift in regulatory incentives. A natural identification concern, therefore, is whether duration gaps increase faster for high RS insurers than high PRS insurers when interest rates decline due to differences in convexity of exposures. If this is the case, then the RS ratio measures not only the shift in the regulatory risk sensitivities, but also the shift in the economic risk exposures, which could explain the relative increase in interest rate risk hedging over time.

However, PRS guarantees have quantitatively similar economic interest rate exposures as RS guarantees under different interest rates and equity market (moneyness) levels as shown in the simulations (Table A.2). Thus, the shift in economic exposures as a result of changes in interest rates and equity market levels are similar for both types of guarantees. In other words, PRS guarantees are equally convex. Thus, the observed differences in hedging outcomes across guarantees after 2009 implies that insurers indeed care about regulatory incentives.

To mitigate the concern about differences in economic exposures further, I control for a number of variables that affect balance sheet convexities, which I label as convexity controls in Table 5. On the liability side, more generous guarantees imply a higher convexity, as effective durations are higher at lower interest rates because fewer contracts are surrendered by households[38]. I control for the generosity of guarantees using the ratio of the value of guarantees to total account value, as in Koijen and Yogo (2017). On the asset side, a higher proportion of mortgage-backed securities (MBS) or callable bonds could also imply a differential shift in duration gaps as these securities have a negative convexity (Hanson

[37] I multiply the coefficient in Table 5 by the difference between 90th and 10th percentile of RS ratio, i.e. $1.975\times$ (2.5%-0.0%).

[38] See, Domanski, Shin, and Shusko (2015) and Berends et. al. (2013).

(2014)), which implies an increase in the duration gap when rates fall.[39] To address this, I control for the share of MBS and callable bonds in total assets. I also include the guarantee ratio quartile and MBS and callable bond share quartile cross year fixed effects in columns V and VI. The estimates remain unaffected. For additional robustness, I measure the interest rate exposures of stock returns and show that interest rate sensitivities of stock returns are not correlated with the RS ratio (Table C.1).[40]

My empirical specification addresses several other alternative explanations, in addition to differences in economic risk exposures. For example, heterogeneity in risk aversions could lead to different hedging choices, even though the underlying economic exposures are similar. To account for differences in risk aversion, I use insurer fixed effects. To understand whether the measures of shift in regulatory sensitivities, RS_i and PRS_i, correlate with other determinants of cross-sectional heterogeneity in hedging behavior, I regress the RS and PRS ratios on various firm characteristics. Table C.2 presents the results. The RS ratio does not correlate with most firm characteristics, except firm size. This is not surprising because my analysis conditions on insurers which hold derivatives and are, therefore, likely to be highly similar along most dimensions. However, differences in size could proxy for a firm's ability to hedge as larger firms have more sophisticated risk management practices. To account for this, I include the log of total assets in all specifications. I also include size quartile cross year fixed effects in column VII. The loadings on the RS and PRS ratios are robust to these factors.

Collectively, these findings are consistent with **Prediction 1** that the increase in the risk sensitivity of the regulatory framework led to an increase in hedging by reducing the wedge between economic and regulatory incentives for insurers more exposed to RS guarantees. Hedging did not change for insurers more exposed to PRS guarantees, where the wedge between economic and regulatory incentives remained largely unaffected.

4.2.2. Hedging Dynamics with Interest Rates

As the duration gap increases when interest rates fall, an increase in hedging in response to a fall in interest rates reveals dynamic hedging of duration mismatch. I next examine the impact of regulatory incentives on hedging dynamics with interest rates by estimating the following specification, which studies the correlation between changes in hedging and changes in interest rates in the cross-section and over time:

[39] Moreover, Ellul, Jotikasthira, Kartasheva, Lundblad, and Wagner (2018) show that the increase in equity risk hedging for VA underwriters coincided with an increase in the incentive to invest in illiquid assets, such as mortgage backed securities.

[40] Actual measures of duration gaps are unavailable as insurers do not report the maturity of liabilities.

$$\Delta\widehat{\delta_{it}} = \alpha + \sum_{J=RS,PRS} \beta^J_{D1}(R_{10t} \times J_i \times Post_t) + \sum_{J=RS,PRS} \beta^J_{D2}(R_{10t} \times J_i) + \sum_{J=RS,PRS} \beta^J_{D3}(J_i \times Post_t) + \gamma' \Delta X_{it} + \alpha_i + \alpha_t + \epsilon_{it},$$

where $\Delta\widehat{\delta_{it}}$ is the quarterly change in hedging and R_{10t} is the quarterly return on a 10 year treasury bond from CRSP, which captures changes in interest rates. All variables are as defined previously. I include insurer fixed effects and time fixed effects, which absorb J_i, $R_{10t} \times Post_t$, R_{10t}, and $Post_t$. The main coefficient of interest is the loading on the triple interaction term β^J_{D1}, which measures the correlation between the shift in the sensitivity of changes in hedging due to changes in interest rates and RS_i and PRS_i.

Table 6 shows that changes in hedging are sensitive to changes in interest rates (column I). As interest rates decrease, and bond prices (thus, bond returns) rise, hedging increases. A 1% increase in bond returns leads to a 13.3 basis points change in hedging exposure per dollar of capital. Moreover, this relationship is positively and significantly correlated with the RS ratio and uncorrelated with the PRS ratio (column II). As the RS ratio increases, covariation between hedging and interest rates also increases. The degree of co-movement is economically large and statistically significant at the 1% level. For example, a 1% increase in bond returns leads to an 8 basis points change in hedging for the average insurer.

Columns III-V show the effect of the shift in the regulation. The coefficient of interest β^{RS}_{D1} is positive and statistically significant (at the 1% level) and economically large in magnitude. Thus, insurers with a high RS ratio have a higher covariation between changes in hedging and interest rates. Moreover, the covariation is significantly higher after 2009 than before 2009. In contrast, I find a negligible relationship between the PRS ratio and the co-variation between changes in hedging and interest rates in either sample period. Thus, insurers with a high PRS ratio, not only did not increase hedging, but also did not rebalance old positions as interest rates decreased significantly after 2009, which further substantiates the prediction of less hedging amongst insurers that underwrite PRS guarantees.

To account for confounding effects, I control for a number of firm characteristics, e.g. changes in size, changes in leverage, size interacted with bond returns which accounts for the differential hedging ability of large firms, the guarantee ratio interacted with bond returns, and MBS and callable bond share interacted with bond returns to account for a faster change in economic exposures due to a higher convexity of assets or liabilities. The loading on β^{RS}_{D1} remains significant and β^{PRS}_{D1} remains insignificant and quantitatively similar in magnitude.

Overall, these results are consistent with **Prediction 2** that the increase in the regulatory risk sensitivity led insurers to dynamically hedge the duration mismatch of RS guarantees, but not of PRS guarantees.

4.2.3. Hedging and Regulatory Constraints

I now evaluate the relationship between the impact of regulatory incentives on hedging and regulatory constraints. The model implies that an increase in the regulatory risk sensitivities generates a larger increase in hedging for insurers that place a higher relative weight on the volatility of regulatory capital ex-ante. To test this, I divide the sample of insurers into two equal sub-groups by RBC ratio in 2007: low and high, and re-estimate equation (15) for each sub-group separately. Table 7 reports the results. Consistent with the model, the impact of a shift in the regulatory risk sensitivities on hedging is more pronounced for insurers that had low RBC ratios. These insurers are more likely to place a higher relative weight on the volatility of regulatory capital prior to the shift in the regulatory risk sensitivities and thus hedge less.

To take this idea further, I next examine the covariation between hedging and RBC ratio, over time and in the cross-section, using the following model:

$$\begin{aligned}\widehat{\delta_{it}} = \alpha + \beta^{RS}_{R1}(RBC_{it-1} \times RS_i \times Post_t) + \beta^{RS}_{R2}(RBC_{it-1} \times RS_i) + \beta^{RS}_{R3}(RBC_{it-1} \times Post_t) \\ + \beta^{RS}_{R4}(RBC_{it-1}) + \beta^{RS}_{R5}(RS_i \times Post_t) + \gamma^{'} X_{it-1} + \alpha_i + \alpha_t + \epsilon_{it},\end{aligned}$$

where I measure RBC at time $t-1$. All other variables are as defined before. Insurer fixed effects and time fixed effects absorb RS_i and $Post_t$, which are omitted. The coefficients of interest are β^{RS}_{R1} to β^{RS}_{R4}. β^{RS}_{R1} measures the shift in the covariation after 2009 due to a shift in the regulatory risk sensitivities. β^{RS}_{R2} measures the baseline covariation at different RS ratio levels. β^{RS}_{R3} and β^{RS}_{R4} measures the shift in the covariation after 2009 and the baseline covariation for insurers with no RS guarantees, and therefore no regulatory interest rate risk sensitivity.

Table 8 shows the results. Hedging is positively and statistically significantly related to the RBC ratio (column I). As the RBC ratio falls (constraints become tighter), hedging decreases. Moreover, the covariation between the tightness of constraints and hedging changes over time and varies in the cross-section, depending on the RS ratio (column II-III). Low RS insurers (low regulatory sensitivity) hedge less when RBC declines. In contrast, high RS insurers (high regulatory sensitivity) hedge more when RBC declines, but only after 2009. The estimates of the full model in column IV confirm these results. β^{RS}_{R1} is negative and statistically significant and β^{RS}_{R2} is positive and statistically significant. This implies that the covariation between hedging and RBC changes after 2009, when insurers start to hedge more as they become more constrained. Moreover, this shift in the covariation is stronger for insurers who experienced a larger shift in the regulatory risk sensitivities (high RS ratio). In addition, β_{R4}^{RS} is positive and statistically significant and β_{R3}^{RS} is insignificant. Thus, for insurers with no regulatory interest rate risk sensitivity ($RS_i = 0$), hedging falls as they become more constrained, and there is no shift in this covariation over time. This implies that the tightness of regulatory constraints affects hedging in opposite ways depending on the sensitivity of the regulatory framework.

Overall, these findings confirm **Prediction 3** and the mechanism proposed in this paper. Insurers target the volatility of regulatory capital, and as a result hedge less, precisely when they are constrained by regulatory capital. The fact that constrained insurers hedge less is a result similar to Rampini, Viswanathan, and Vuillemey (2016) who show that constrained banks hedge less due to collateral constraints. To distinguish between collateral constraints and regulatory incentives, I test the relationship between collateral constraints and hedging using data on collateral posted by insurers to counterparties in Section 5.

4.3. Quantification

Reduction in volatility: I next quantify the extent of hedging in terms of the *ex-post* reduction in volatility of regulatory capital due to the use of derivatives over time and in the cross-section. Following Koijen and Yogo (2015b), I compute the volatility of changes in capital *with* and *without* derivatives. The total growth in capital without derivatives is the growth in capital with derivatives *minus* total capital gains (losses) during the year due to derivatives, which insurers report at an annual frequency starting in the year 2002.[41] Figure 6 depicts the reduction in volatility graphically.

Three key facts stand out. First, derivatives reduced the volatility of regulatory capital by 42% between 2002 and 2016 at an aggregate level (Table 9). Thus, derivatives are quantitatively important and dampen balance sheet fluctuations in a large way. Second, I decompose the reduction in volatility into the exact risk factor being hedged. To do so, I reconstruct the capital gains (losses) from the position-level data, where I observe the exact risk factor being hedged by each position.[42] Interest rate derivatives alone account for about 70% of the total reduction in the volatility of capital. Equity (25%) and credit and currency (5%) account for the remaining reduction.

Third, I show that the *ex-post* reduction in volatility is concentrated among insurers that

[41] See, the exhibit of capital gains and losses and net investment income.

[42] In doing so, I account for (i) changes in unrealized gains (losses), (ii) investment income (expenses) during the year on all derivative instruments held, and (iii) realized gains (losses) for all closed transactions, using Schedule DB Section 2, which provides information on terminated positions during the year.

have a high RS ratio, exactly in line with the evidence on *ex-ante* hedging exposures in Section 4.2. I regress the reduction in volatility, computed as the volatility of log changes in capital without derivatives, $\sigma_{without}$, minus the volatility of log changes in capital with derivatives, σ_{with}, on RS and PRS ratios:

$$(\sigma_{without} - \sigma_{with})_i = \alpha + \sum_{J=RS,PRS} \beta^J J_i + \epsilon_i.$$

Table 9 shows the results. The reduction is economically large and positively and statistically significantly related to the RS ratio. The reduction in volatility for the average insurer which is exposed to RS guarantees is about 0.04. In percentage terms, this implies a 26% reduction in volatility for the average insurer. In contrast, there is no discernible correlation between reduction in volatility and the PRS ratio. As these data are directly reported, these results also serve as a useful validation of the data exercise described in Section 3.

Hedging shortfall: How much additional interest rate hedging exposures would be there if regulation had shifted in a consistent manner for PRS guarantees? Using the estimates in Table 5, I quantify this shortfall for the year 2016. The average insurer has a PRS ratio of about 3.2%. My estimates therefore imply that the average insurer would have had an additional interest rate exposure from derivatives equal to \$0.40 billion.[43] I compute the shortfall for all insurers exposed to PRS guarantees. In aggregate, the sector as a whole would have had an additional exposure equal to \$23 billion in 2016, which implies that a 100 basis points decline in interest rates should have led to a \$23 billion increase in the hedging portfolio.[44] Moreover, these liabilities are highly concentrated. The bulk of the shortfall in exposures, or about \$19.8 billion, is concentrated within just ten of the largest insurers. In the absence of these hedging exposures, the interest rate shocks are absorbed by total capital and surplus, which for the largest ten insurers amounts to about 22% of their total capital and surplus.

4.4. Additional Explanations and Robustness

4.4.1. Financial Crisis

An alternative explanation of my results could be that a systematic shift in risk aversion due to differential exposure to the financial crisis led to the increase in hedging after 2009.

[43] I multiply 3.2% by 1.8, which is the difference in the coefficients β_{RS} and β_{PRS} (Table 5), to get 5.8%. The average company has total capital equal to \$7 billion in 2016, which gives a dollar exposure equal to \$0.40 billion.

[44] I use the PRS ratio in 2016 for these estimates. I exclude TIAA, which does not write guaranteed living or death benefits. Source: TIAA Statutory Financials. I also use the PRS ratio as of 2015 for Prudential due to potential data anomalies in 2016.

My empirical specifications therefore include the RBC ratio, leverage, and BCAR relative to the guideline, which proxy for the exposure to the financial crisis. For additional robustness, I include the size of the shock experienced during the financial crisis, measured as changes in capital between 2007:Q4 and 2009:Q1, interacted with a post crisis dummy in Table C.3. If the changes in hedging are driven just by shifts in risk aversion due to differential exposure to the crisis, then insurers that suffered a larger shock during the crisis should increase hedging post crisis and the loadings on RS and PRS ratios should be subsumed. As Table C.3 shows, the loadings on the RS and PRS ratios remain unaffected and the loading on the size of the shock is insignificant, which imply that the increase in hedging is not concentrated among insurers that were adversely affected during the crisis.

4.4.2. Hedging With Bonds

I next evaluate the differences in interest rate exposures across insurers arising from bond holdings. Insurers report positions in fixed income securities, including treasuries and government securities, agency and mortgage backed debt, and corporate bonds at an annual frequency, which I collect from the NAIC's schedule D database. For each position, I observe the total par and market values, remaining maturity, coupon paid, and rating. Using these data, I compute the total dollar duration of bond holdings for each insurer at an annual frequency from 2004 to 2016.[45] I exclude positions where market values or maturity dates are not populated. I also exclude floating rate positions, which have no meaningful interest rate risk exposures.

I next estimate the specification in equation (15) with interest rate exposures from bonds. Table C.4 reports that there is no discernible difference in the shift in interest rate exposures from bonds for RS or PRS ratios after 2009, when exposures from derivatives diverged for the RS ratio. Thus, there is no heterogeneity across insurers in how bond exposures have shifted over time, unlike derivatives. This is important as it implies that the increase in hedging for high RS insurers is not simply a substitution away from bonds. Moreover, high PRS insurers do not substitute into bonds despite lack of hedging with derivatives.

It may be puzzling why PRS insurers do not hedge more with bonds, given that bonds, like liabilities, are held at book value. However, dynamic trading in cash markets leads to the same issues as holding a portfolio of derivatives. Realized gains and losses from trading bonds reflect in capital, but corresponding changes in liabilities do not. Second, corporate bonds are illiquid and therefore not ideal for dynamic trading at high frequency, as are swaps, which is important for VA, as insurers rebalance interest rate derivatives actively

[45] The methodology is same as that used to compute the duration of swaps. See, Appendix E, equations (E.5) and (E.6). I treat all bonds as straight bonds.

in response to shifts in interest rates.[46] Moreover, as swaps are levered positions, the fair values are significantly lower than bonds, but exposures are similar, which helps alleviate the insurer's solvency constraint (Domanski et. al (2015)). A combination of these factors imply that insurers either leave the interest rate mismatch for PRS guarantees unhedged or make other adjustments. In Section 5.2, I show that insurers shift some of these exposures, *but not all*, off-balance sheet.

4.4.3. Direct Evidence From Hedging Disclosures

I next provide evidence of differential hedging across products within the same insurer. In recent years (from 2010:Q1), insurers started disclosing which balance sheet item has been hedged by each position. The disclosures do not reveal exactly which guarantee is hedged within VA, however, I can classify positions into hedging either (i) VA or (ii) non-VA (which includes life, fixed annuities, and equity indexed contracts), which is useful because they differ in their regulatory interest rate risk sensitivities. Non-VA liabilities are insensitive as the valuation rate does not depend on the current market interest rates (see Section 1.3). On the other hand, VA are sensitive given that bulk of the shift in hedging is attributed to RS guarantees and not PRS guarantees, which are insensitive.

I find that while positions earmarked as VA are sensitive to changes in interest rates, positions earmarked as non-VA are insensitive to changes in interest rates (Table C.5). Thus, hedging varies, even within the same insurer, depending on the regulatory risk sensitivity of the item being hedged. This test helps to rule out a number of identification concerns to the extent that hedging is done at the firm level and not at the product level. First, it implies that my results are not likely driven by differences in risk attitudes. Second, as the same insurer responds differently to shifts in interest rates depending on why a particular derivative is bought implies that my results are also less likely to be about differences in interest rate expectations. Finally, it further helps to mitigate the concern about differential hedging abilities driving my results.

5. Equity Risk Hedging, Reinsurance, and Collateral Constraints

5.1. Equity Risk Hedging

5.1.1. Data and Aggregate Facts

In this section, I discuss the key facts related to the hedging of equity risk embedded in a VA guarantee. To transform derivative positions into risk exposures, I select positions

[46] Corporate bonds are not long enough (7 years average maturity) and insurers invest a small fraction of assets in treasuries.

where the underlying is the S&P 500. These positions represent more than 70% of all equity derivative positions by gross notional amount. To assess the extent of VA related hedging, I restrict attention to futures and put options as the bulk of these instruments are earmarked in the data as hedging VA guarantees.[47]

I next compute the equity risk exposures for each position due to a 10% shift in the S&P 500 index as of the last trading date of each quarter. For a $1 change in the index, the risk sensitivities of futures are either +1 (long position) or -1 (short position) and to quantify the sensitivities of put options, I compute the Black-Scholes deltas. To compute the option deltas, I need the contract characteristics, including strike, maturity, and the trade direction, which I extract from description strings using textual analysis wherever they are not directly reported. I also need market data, e.g. the level of the index and implied volatilities at different levels of moneyness and maturities, which are from Bloomberg. A more detailed description of the procedure to map positions into exposures is in Appendix F. After computing the exposures for each position for a 10% shift in the index, I aggregate the exposures at the insurer level, by multiplying exposures by the actual number of contracts.

Figure 4 shows the evolution of equity risk hedging exposures over time for the sector as a whole. First, consistent with hedging the embedded put option in a VA guarantee, insurers have taken long positions in put options and short positions in futures on a net basis. The risk exposures of equity derivatives are negative. Thus, the portfolio of equity derivatives gains in value when the index falls. Second, just as interest rate hedging exposures increased, equity risk hedging exposures have also increased over the last decade. Moreover, exposures have remained high, despite a rise in the level of the S&P 500 during this period. I next examine the impact of regulatory incentives on equity risk hedging.

5.1.2. Regulatory Incentives and Equity Risk Hedging

The evaluation of equity hedging outcomes provides a useful counter-factual to the regulatory incentives hypothesis. Unlike interest rates, the regulatory equity risk sensitivities increased for all guarantees under the new regulation as both the Standard and the Stochastic frameworks became sensitive to shifts in the equity market (Figure 1). Moreover, as the simulations show, the economic equity risk exposures are similar across guarantees (Table A.2). Thus, unlike interest rate hedging outcomes, the introduction of the new regulation should result in an increase in equity risk hedging for both RS and PRS guarantees. To test this idea, I next estimate the model in equation (15) with equity hedging exposures.

[47] See, also Ellul et. al. (2018). The major instruments in the data include calls, puts, and futures. The bulk of the call options are earmarked for replicating equity indexed insurance contracts. As the analysis focuses on VA, I exclude the data on call options.

Table 10 documents the key findings. I estimate a negative and statistically significant coefficient (at the 1% level) for the ratio of total VA guarantees to capital, G_i (column I). The negative sign simply captures the negative exposures for equity derivatives, that is, long positions in put options and short positions in futures gain in value when the equity market declines. A larger negative coefficient implies an *increase* in equity risk hedging. I next split the variable into its constituents RS_i and PRS_i. Both β^{RS} and β^{PRS} are statistically significant (columns II-IV). Thus, the shift in equity risk hedging after 2009 correlates not just with the RS but also with the PRS ratio. Moreover, the magnitude of the shift in hedging is similar for RS and PRS ratios (Figure 5).

Along with the results on interest rate risk hedging, this implies that insurers with a high RS ratio hedge both interest rate and equity risk exposures. However, insurers with a high PRS ratio hedge equity risk but not interest rate risk, which is consistent with the differential incentives provided by the regulatory framework for PRS guarantees, but not consistent with firm level differences driving hedging outcomes, including preferences, risk aversion, and hedging abilities.

Two other findings strengthen the identification further. First, consistent with the model, the impact of a shift in the regulatory risk sensitivities is more pronounced for insurers that had a low RBC ratio in 2007 and, therefore, cared more about the volatility of regulatory capital ex-ante (Table C.6).

Second, as the equity market goes up, the guarantee goes out-of-the-money and equity exposures decline (Table A.2). If insurers were already sufficiently hedged before the new regulation was introduced, then it is unclear why equity risk hedging increased at a time when the equity market has gone up significantly.[48] To take this idea further, I split the sample of insurers and restrict attention to those for whom the bulk of VA sales occurred before 2009.[49] These insurers largely have a legacy portfolio written before 2009, when the equity market levels were lower than they have been in recent times. Thus, legacy underwriters have a relatively out-of-the-money portfolio, whose equity risk exposures have declined since 2009. In contrast, I find statistically significant and economically large coefficients β^{RS} and β^{PRS}, that is, hedging increased for legacy underwriters after 2009 (Table C.6). Given that the increase in interest rate risk hedging came during a period of declining interest rates, the increase in equity risk hedging at a time when equity market went up, further corroborates the hypothesis that regulatory incentives explain hedging outcomes.

[48]In simulations, I confirm that the effect of a decrease in interest rates on equity deltas is smaller than the effect of rising equity market levels on equity deltas.

[49]VA sales data are from Morningstar Annuity database.

5.2. Reinsurance and Off-Balance Sheet Activity

I next evaluate reinsurance activities across guarantees. Reinsurance is a process by which insurers move risk exposures off-balance sheet. Traditional reinsurance is a transfer to third-party reinsurers, while shadow insurance is a transfer from operating companies to captives, which are special purpose vehicles or offshore domiciles within the same holding company but face lax regulation. Using data on ceded reinsurance for the various types of guarantees, I show that inconsistencies in regulation result in greater off-balance sheet risk transfers, most of which goes to shadow insurers.

Figure 7 plots the proportion of liabilities that was reinsured for the two types of guarantees. On average, the proportions of liabilities reinsured were relatively similar until 2009 for both RS and PRS guarantees, when regulatory incentives to hedge were similar and the framework was largely risk insensitive. After 2009, when the framework became differentially risk sensitive, reinsurance started to diverge: while reinsurance for RS guarantees declined slightly, reinsurance for PRS guarantees increased significantly. Moreover, close to 75% of all reinsurance for VA goes to captives (Figure 7).

To evaluate the increase in reinsurance formally, I regress the proportion of RS and PRS liabilities reinsured on a post 2009 dummy variable. As an increase in reinsurance activity has been linked to financial constraints (Koijen and Yogo (2016)), I control for leverage, RBC ratio, credit rating, BCAR ratio, and firm size. Table 11 documents the main results. The average insurer increased PRS reinsurance by 7.7% after the shift in the regulation (Panel A). However, RS reinsurance remained largely unchanged. The shift in the difference between the RS and PRS reinsurance is statistically significant (at the 10% level). To confirm the regulatory incentives hypothesis, I re-estimate the specification in equation (15) with PRS reinsurance as the dependent variable. Panel B presents the results. I show that the increase in PRS reinsurance after 2009 is correlated with the ex-ante PRS ratio, i.e. the increase in reinsurance is concentrated among insurers that do not hedge interest rate risk exposures with derivatives.

These findings show that there is a shift in the composition of how risk exposures are managed after the new regulation took effect. While the use of derivatives increases for RS guarantees, a greater proportion of liabilities move off-balance sheet for PRS guarantees, where interest rate risk hedging with derivatives is largely absent. This relative increase in PRS reinsurance vis-a-vis RS reinsurance after 2009 shows that insurers substitute out of reinsurance and into derivatives for RS guarantees, which helps to interpret the empirical findings as regulation putting limits on the hedging choices for PRS guarantees.

Moreover, these findings have importance for the fragility of insurers. First, only a part of PRS exposures can move off-balance sheet due to the limits on the amount of reinsurance activity. This exposes insurers to mismatch risks in economic terms due to the lack of interest rate risk hedging with derivatives. Second, shadow insurers are largely opaque and less well regulated. As a higher proportion of risk exposures move to shadow insurers, it could potentially create regulatory blind spots and put the stability of the broader financial system at greater risk (OFR (2016)).

5.3. Collateral Constraints

I next show that the lack of hedging is not due to collateral constraints. Starting in 2013, insurers report the collateral posted to counterparties to support derivatives positions. The data include a description of the types of securities posted, types of margin, fair values, and counterparties. Cash and treasuries constitute a large proportion of what is posted as collateral, followed by agency and corporate debt (Figure 8). At the same time, insurers also hold a large stock of highly rated bonds and treasuries. I combine the data on posted collateral with bond and cash holdings to construct a measure of *collateral capacity* at the insurer level, which I define as the fair value of eligible collateral owned minus the fair value of collateral posted. I define eligible collateral as cash and cash equivalents, treasuries, and highly rated (AAA, AA, and A) agency and corporate bonds.

Figure 8 shows collateral capacity as a percentage of eligible collateral for the average insurer. There is significant unused capacity, that is, insurers hold significantly more securities which qualify as good collateral than they actually post. Even restricting the set of eligible collateral to include only treasuries and cash (and exclude agency and corporates bonds), there is significant unused capacity.

This implies that collateral constraints (Rampini and Viswanathan (2010))[50] are an unlikely explanation of the observed heterogeneity in hedging as, due to the large unused capacity, collateral constraints are unlikely to bind for these institutions. To confirm this, I next evaluate the relationship between collateral constraints and interest rate and equity risk hedging in the cross-section. Table C.7 shows the results of a univariate regression between hedging exposures and collateral capacity, both scaled by total capital. I find no relationship between collateral capacity and hedging, that is, insurers with a low collateral capacity do not hedge any less than insurers with a high collateral capacity. Overall, these findings provide further support that collateral constraints do not drive my results and that

[50] Rampini, Vishwanathan, and Sufi (2013) show collateral constraints impact the hedging behavior of airlines and Rampini, Vishwanathan, and Vuillemey (2016) show the same for banks.

inconsistencies in the regulatory framework limit risk management.

6. Broader Implications and Conclusion

6.1. Monetary Policy and Financial Fragility

An important aspect of the new regulation is that it interacts with monetary policy shifts to create inconsistencies in risk management incentives over time. When interest rates are low, the Stochastic framework dominates with a higher likelihood because interest rate scenarios are drawn from the current yield curve. Thus, as interest rates rise, Stochastic liabilities could fall below Standard liabilities. Using survey data, Milliman estimates that the Standard framework dominated for a large number of VA underwriters when the regulation was first introduced, which flipped as interest rates fell.[51] Thus, going forward, as interest rates start to rise, the Standard framework may start to dominate and the incentives to hedge could switch off even for guarantees that are currently risk sensitive.

Moreover, the threshold rate, y^*, above which Standard framework binds varies in the cross-section as it depends on past underwriting and past interest rates. Thus, the sensitivity of regulatory capital ψ depends on current interest rates and the threshold rate:

$$\psi = \begin{cases} \psi^{High} & \text{if} \quad y_0 < y^* \quad \Longrightarrow \text{Stochastic binding} \\ 0 & \text{if} \quad y_0 \geq y^* \quad \Longrightarrow \text{Standard binding} \end{cases}$$

where $\psi^{High} > 0$. Given the relationship between hedging and regulatory risk sensitivities, therefore, for two firms, i and j, all else being equal, if $y_i^* > y_0 > y_j^*$, then $\widehat{\delta}_i > \widehat{\delta}_j$.

At the firm level, differences in y^* arise because the valuation rate (discount rate for liabilities) is the rate at the time a contract is originated and does not change over the life of a contract. Thus, differences in the timing of underwriting drives differences in y^*. Insurers that have underwritten in years when rates were low (high), have a lower (higher) valuation rate and a higher (lower) propensity to have the Standard framework binding.

To test this idea, I collect sales data from Morningstar Annuity which provides information on when underwriting occurred. I split my sample into legacy and new underwriters. New (legacy) underwriters have originated the majority of the VA liabilities after (before) 2009, when interest rates were lower than before 2009, and therefore are more (less) likely to have the Standard framework binding. I next compare changes in hedging between 2009 and 2012, when the 10-year yield fell significantly, and 2012 and 2016, when the 10-year

[51] Junus and Motiwalla (2010), page 4.

yield picked up slightly after the U.S. elections. Table 12 shows that legacy underwriters increased hedging between 2009 and 2012, and maintained hedging at the same level as 2012 until 2016, as seen from a positive and significant coefficient for the change in hedging between 2009 and 2012 and a coefficient of nearly zero between 2012 and 2016. In contrast, while new underwriters increased hedging between 2009 and 2012, they reduced hedging in 2016, as seen from a negative coefficient for the change in hedging between 2012 and 2016. The estimate, however, is noisy and statistically insignificant.

These findings imply that when interest rates eventually rise, incentives to hedge may completely switch off (even for RS guarantees) and shadow insurance could increase further, which highlights an important channel though which monetary policy interacts with risk regulation to impact the fragility of the insurance sector. Moreover, there are consequences for the propagation of monetary policy through the insurance sector. Greenwood and Vissing-Jorgensen (2018) show that changes in demand from pensions and insurance industry, due to changes in the regulatory discount curve, has price effects on long horizon discount rates. As incentives to hedge switch off, insurers could offload hedge positions at a time when bond prices are declining, which could further amplify price movements.

6.2. Product Market

In the standard insurance pricing model (Koijen and Yogo (2015a)), optimal prices depend on the cost of regulatory frictions, which increase the marginal cost of supplying insurance. Hedging increases the expected regulatory costs by increasing the volatility of regulatory capital, if the framework is insensitive. However, as the framework becomes sensitive, hedging reduces the expected regulatory costs by decreasing mismatch risks and capital requirements. The regulatory changes, therefore, have consequences for the VA product market. First, the shift in hedging incentives impact relative prices across guarantees and impact the market share of insurers exposed to different guarantees. Second, there are consequences for market structure and concentration. Larger insurers with greater risk management capabilities stand to gain market share, as they reduce marginal costs by hedging, at the expense of smaller insurers with lower risk management capabilities, which implies an increase in the concentration of the insurance sector. Finally, in the absence of alternative ways to decrease the expected regulatory costs (e.g. reinsurance), insurers could cut back on valuable product features, which impact future product design and market completeness.

6.3. *Conclusion*

Little is known about the direct risk management incentives of financial institutions and how regulation shapes these incentives. In this paper, I quantify the hedging incentives for U.S. life insurers using a unique position level data on derivatives and a set-up where the regulatory risk management incentives vary for products that have similar economic risks. I show that inconsistencies in regulation restrict interest rate risk hedging and increase shadow insurance activities. My findings have implications for the fragility of the insurance sector, which is exacerbated by shifts in monetary policy as regulatory incentives to hedge shut down when interest rates rise.

It is not obvious that regulators should necessarily incentivize insurers to hedge the mark-to-market volatility in capital and transfer risk exposures to other parts of the financial sector. VA protects against aggregate risks and insurers might be better suited to bear such risks in equilibrium as they do not have debt that is as run prone as banks. It is unclear, therefore, which one of these regulatory frameworks counts towards optimal regulation of the insurance sector. Nevertheless, large insurers across developed markets have failed on account of selling protection against aggregate risks.[52] These failures led to significant disruptions in the supply of both market risk insurance and traditional insurance.[53] Moreover, shadow insurance could potentially be regulatory blind spots and put the stability of the broader financial system at risk. Quantifying the impact of regulatory incentives on risk management decisions is the starting point to understand all the trade-offs.

The incentives described in the paper also apply more broadly, not only to insurance companies globally, but also to banks. For example, the regulatory framework governing insurers in Europe (Solvency II) has important deviations from market values. Moreover, there are differences in risk sensitivities and how hedges are treated in the model-based versus the standardized frameworks within Basel III, which could affect the sensitivity of capital to market movements and may affect the hedging incentives of banks.

[52]Equitable Life, the largest insurance company in the U.K. failed in 2000; Hartford and Lincoln National were bailed out under TARP in 2008; others, e.g. Allstate, Genworth Financial, Protective Life and Prudential Financial also applied for TARP but were either disqualified or withdrew themselves.

[53]See, Sen and Humphry (2016) and Koijen and Yogo (2017).

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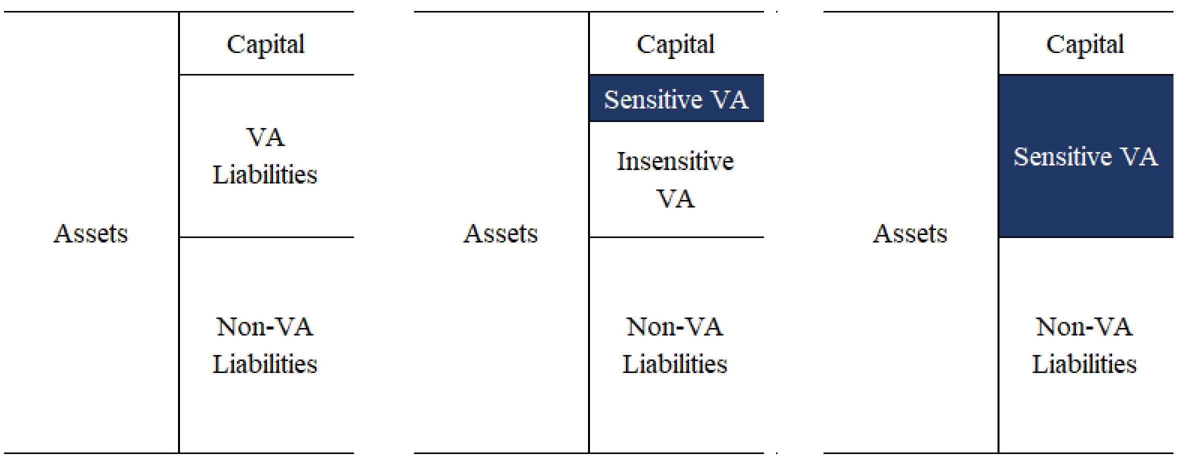
Figure 1: Regulatory Valuation Framework

Panel A summarizes the risk sensitivities of the regulatory framework and identifies the binding framework for each VA guarantee. Panel B shows stylized balance sheets before and after the shift in the regulation for VA in 2009. Blue (white) areas depict risk sensitive (insensitive) liabilities.

Panel A: Summary of Risk Sensitivities

	Risk Sensitivities		Binding Framework			
Framework	Interest Rate	Equity	GMAB (RS)	GMWB (RS)	GMIB (PRS)	GMDB (PRS)
Standard		✓			✓	✓
Stochastic	✓	✓	✓	✓		

Panel B: Stylized Balance Sheet



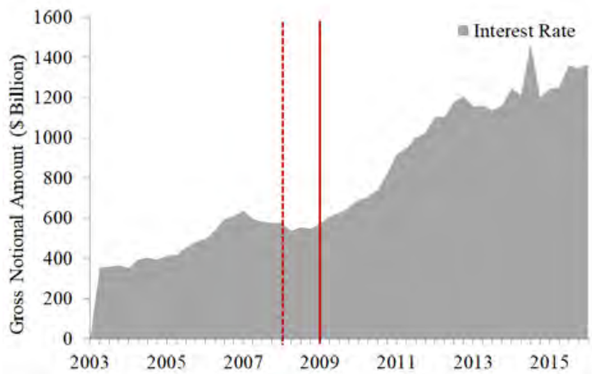
Pre 2009
Interest Rate & Equity

Post 2009
Interest Rate

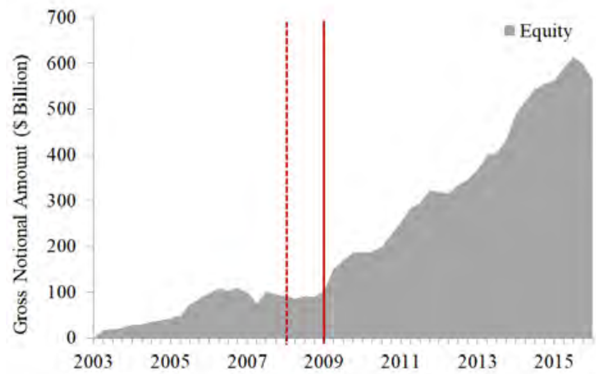
Post 2009
Equity

Figure 2: Risks Hedged By Derivatives

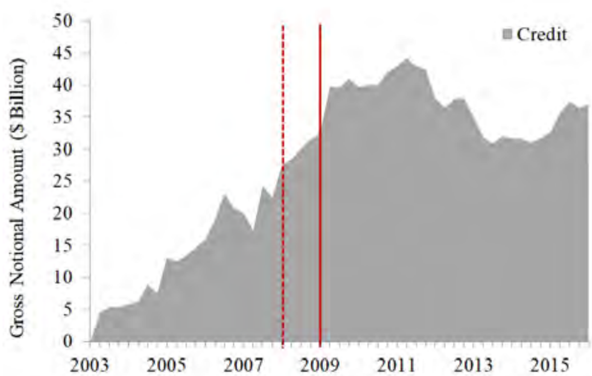
This figure shows a breakdown of the total gross notional values by risk factors hedged for life insurers in the aggregate. I plot gross notionals, aggregated across instruments, for each risk factor from 2004 to 2016 at a quarterly frequency. Interest rate risk is the largest hedged risk factor, followed by equity risk. Together the two risk factors account for over 90% of the total positions by gross notionals in Q4:2016. The solid red line (dotted red line) shows the implementation (adoption) of the new regulation. The start date is dictated by the availability of the derivatives data.



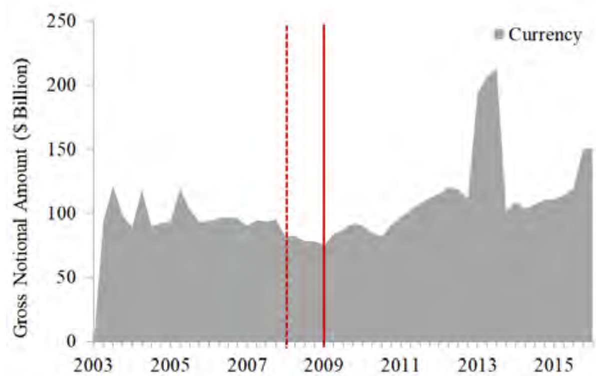
(a) Interest Rate Risk



(b) Equity Risk



(c) Credit Risk



(d) Currency Risk

Figure 3: Interest Rate Risk Exposures From Derivatives

This figure shows the total dollar risk exposures from interest rate derivatives due to a 100 basis points parallel shift in the yield curve. I incorporate all contract characteristics, including direction of the position, maturity, and moneyness (see Section 3). The dark blue bars show exposures from swaps and the light gray bars show exposures from options. Positive (negative) exposures imply that the derivative portfolio gains (loses) in value when interest rates fall. The solid red line (dotted red line) shows the implementation (adoption) of the new regulation. Exposures are aggregated for all the insurers in the sample that hold interest rate derivatives. The data frequency is quarterly from 2004:Q1 to 2016:Q4, and the start date is dictated by the availability of the derivatives data.

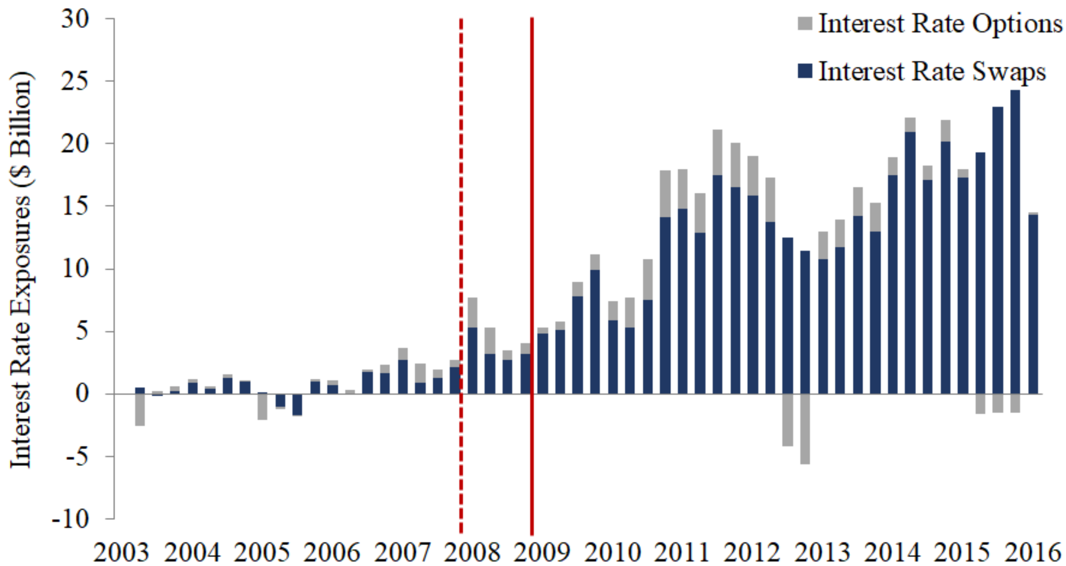


Figure 4: Equity Risk Exposures From Derivatives

The figure shows the total dollar risk exposures from equity derivatives for a 10% shift in the S&P 500 index. I incorporate all contract characteristics, including direction of the position, moneyness, and maturity. The dark blue bars show exposures from equity futures and the light gray bars show exposures from put options. Negative (positive) exposures imply that the derivative portfolio gains (loses) in value when the index falls. The solid red line (dotted red line) shows the implementation (adoption) of the new regulation. Exposures are aggregated for all the insurers in the sample that hold equity derivatives. The data frequency is quarterly from 2004:Q1 to 2016:Q4, and the start date is dictated by the availability of the derivatives data.

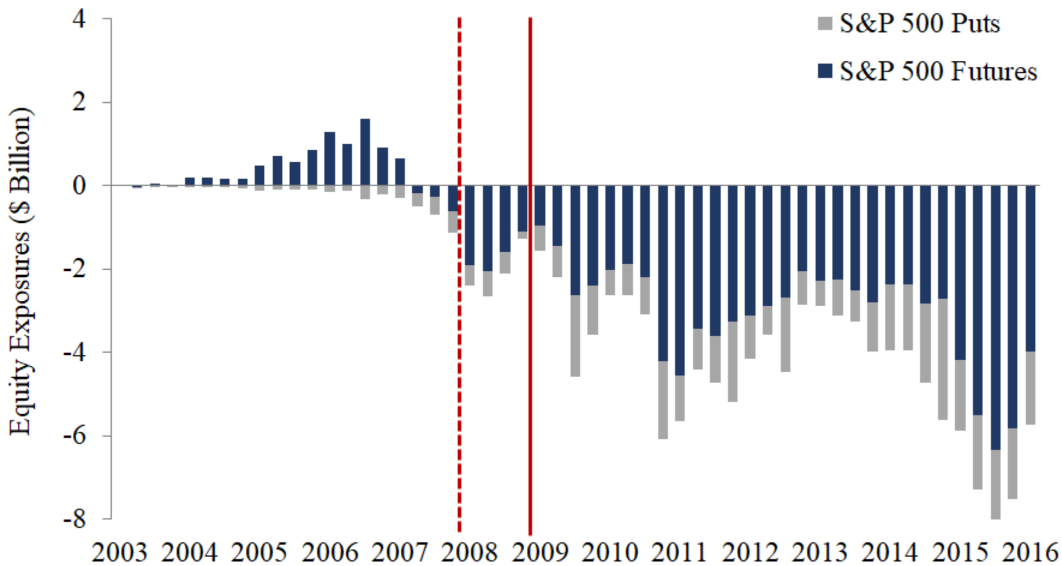
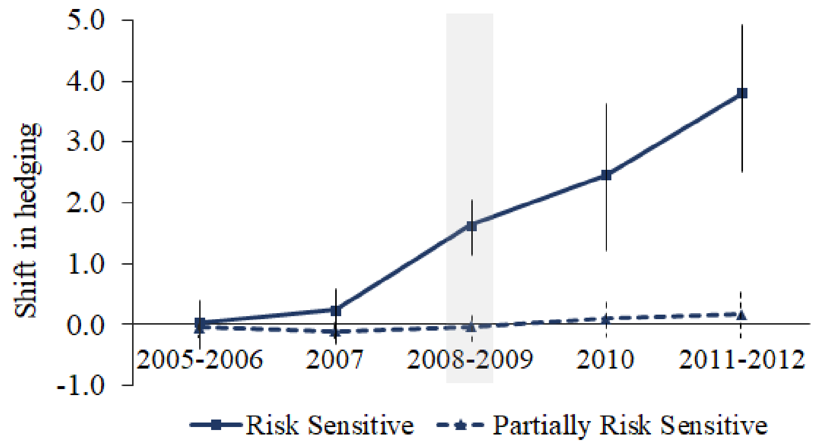
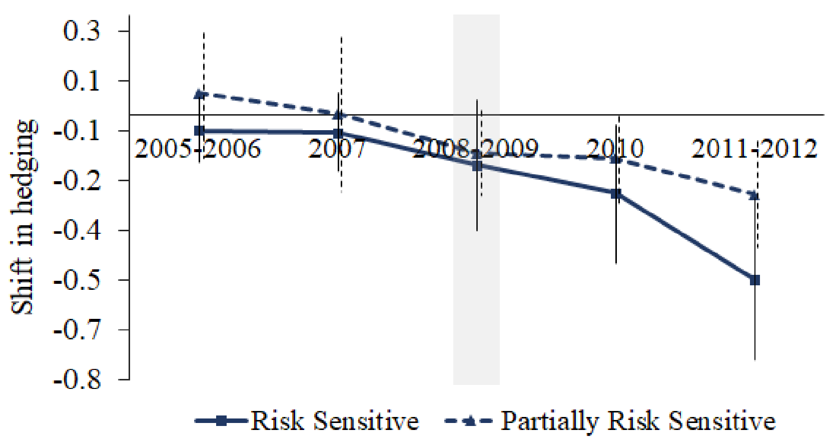


Figure 5: Regulatory Incentives and Shift in Hedging Exposures

This figure shows the dynamics of the shift in hedging for the RS and PRS ratios immediately around the regulatory change. I regress the main dependent variables, interest rate hedging exposures scaled by capital (panel A) and equity hedging exposures scaled by capital (panel B) on the interaction term between RS and PRS ratios and time dummies for 2-3 years before, 1 year before, during, 1 year after, and 2-3 years after the regulatory change. The figure plots the coefficients and the 95% confidence intervals. The base year is 2004. The grey bar shows the adoption (2008) and implementation (2009) period. The sample includes insurers that hold interest rate or equity derivatives. Frequency of the data are annual.



(a) Interest Rate Risk



(b) Equity Risk

Figure 6: Are Derivatives Quantitatively Important? Reduction in Volatility of Capital due to Derivatives

This figure illustrates the importance of derivatives in reducing the volatility of regulatory capital for life insurers in the aggregate. I compute growth in capital *with* and *without* derivatives. The total growth in capital without derivatives is the growth in capital with derivatives minus capital gains (losses) during the year due to derivatives. The data are from the exhibit of capital gains and losses and net investment income and start in 2002. The frequency is annual.

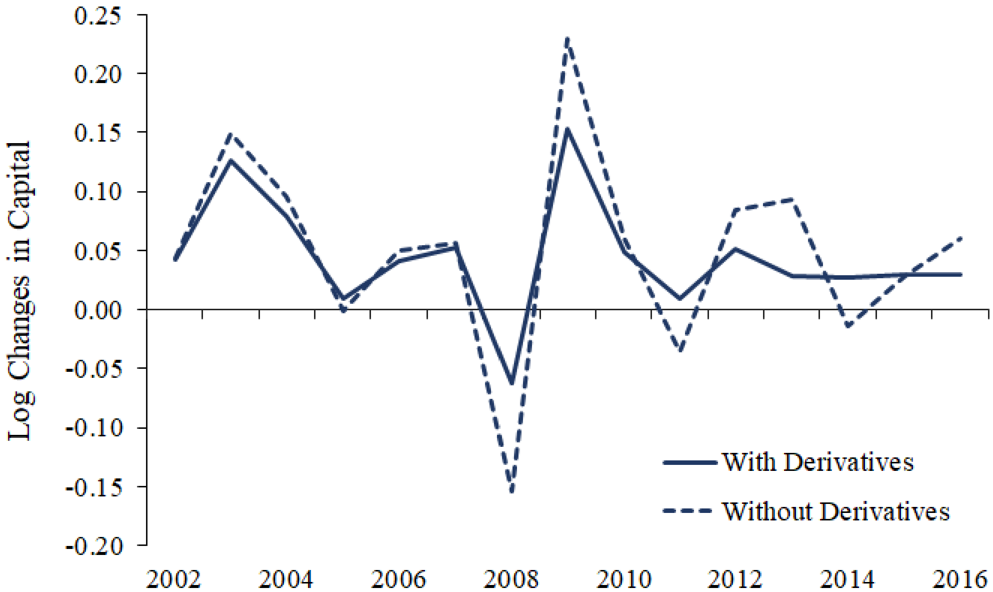
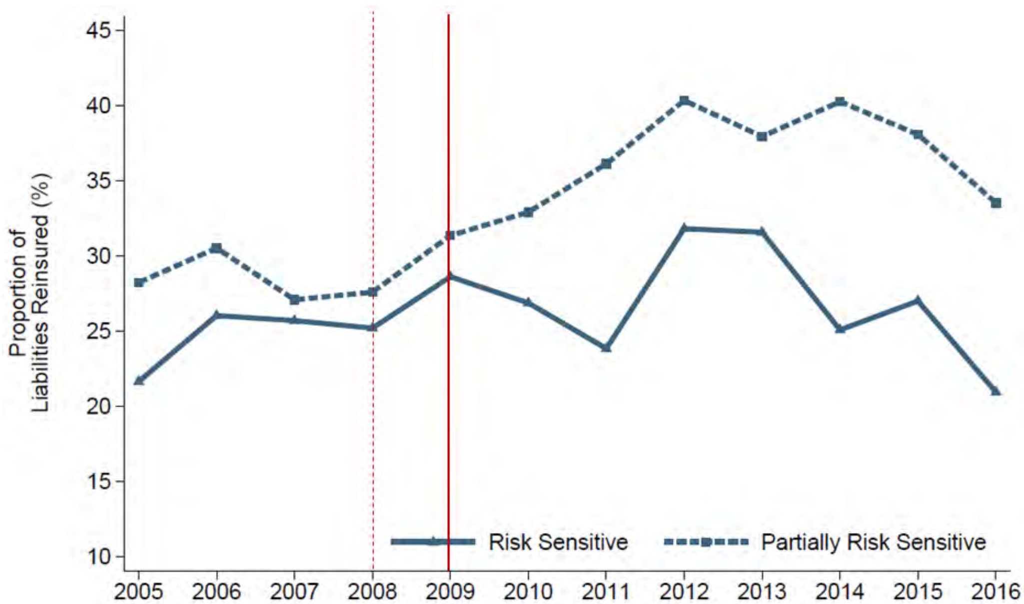
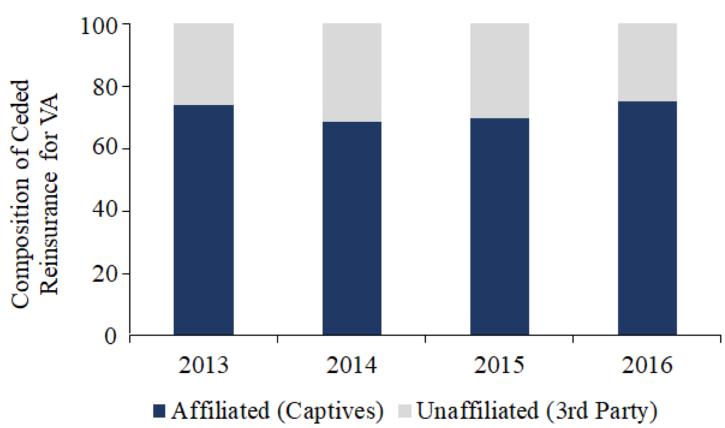


Figure 7: Regulatory Incentives and Off-Balance Sheet Risk Transfers

Panel A shows the evolution of proportion of liabilities reinsured for the two types of VA guarantees: RS (dark blue line) and PRS (dotted blue line). The solid red line (dotted red line) shows the implementation (adoption) of the new regulation. The sample comprises insurers that hold interest rate derivatives and the data frequency is annual from 2005 to 2016. Panel B shows the breakdown of reinsurance for VA into captives (shadow insurers) and third party reinsurers at the aggregate level. The start dates are dictated by data availability.



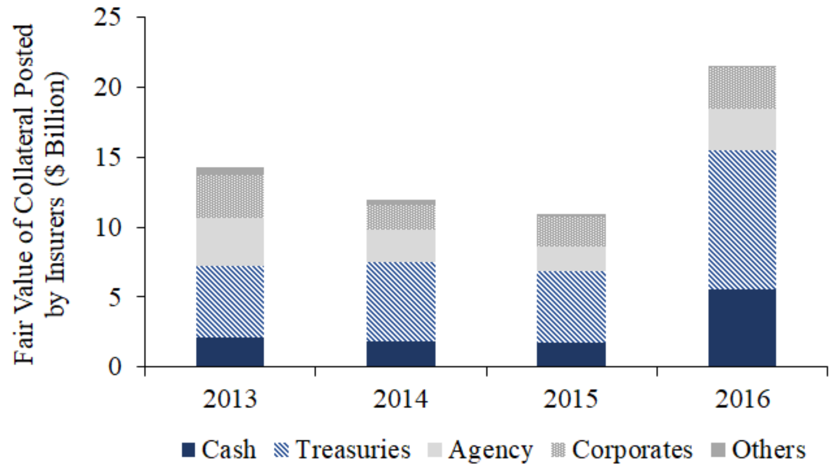
(a) Evolution of Reinsurance Activities



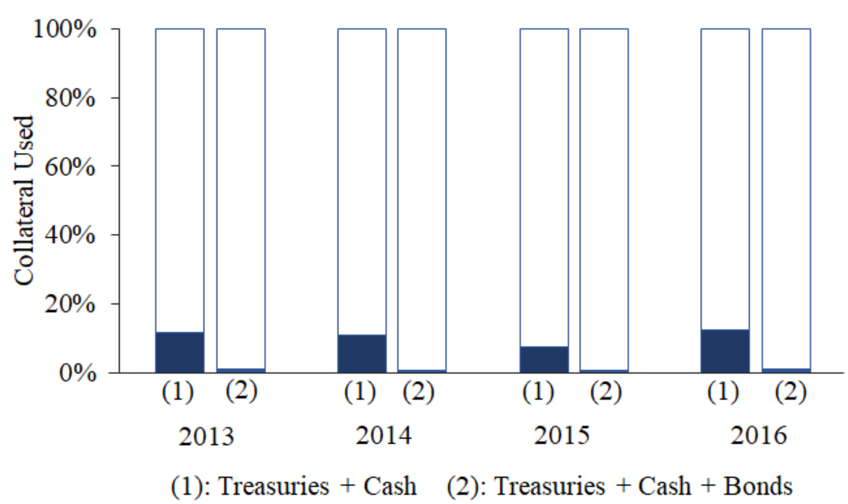
(b) Composition of Ceded Reinsurance

Figure 8: Assessing Collateral Constraints

The top panel shows the composition and the dollar value of collateral posted by life insurers to counterparties at an aggregate level. The bottom panel shows the average collateral capacity. Collateral used (blue area) is the ratio of the fair value of posted collateral to the fair value of eligible owned collateral. Collateral capacity (white area) is 1 minus collateral used. The first bar includes only treasuries and cash as eligible collateral. The second bar includes all other highly rated bonds, in addition to treasuries and cash. The sample includes insurers that hold interest rate or equity derivatives. The start date is dictated by the availability of the collateral data.



(a) Collateral Composition



(b) Collateral Capacity

Table 1: Descriptive Statistics - A Snapshot of Derivative Positions

The table shows a snapshot of derivative positions for the insurance sector as a whole as of Q4 2016. I break the positions into (i) *risks hedged*: interest rate derivatives (panel A) and equity derivatives (panel B); (ii) *instruments*: swaps, caps, floors, and swaptions for interest rate derivatives and puts and futures for equity derivatives; (iii) *trade direction*: rate decrease (increase) and equity fall (rise) shows positions that gain in value when interest rates decrease (increase) and the equity market falls (rises); (iv) *maturity* (in years), which is split as less than 1 year, 1 to 10 years, and greater than 10 years. I report gross notionals for interest rate derivatives and the total number of contracts for equity derivatives.

Panel A

Interest Rate Derivatives

(Gross notionals, $ billion)

	Rate Decrease			Rate Increase		
Maturity (years)	≤ 1	1 - 10	≥ 10	≤ 1	1 - 10	≥ 10
Swaps	26	183	274	27	165	192
Caps	-	4	0	50	182	0
Floors	5	8	0	4	-	-
Swaptions	16	11	3	8	7	3

Panel B

Equity Derivatives

(Number of contracts, million)

	Equity Fall			Equity Rise		
Maturity (years)	≤ 1	1 - 10	≥ 10	≤ 1	1 - 10	≥ 10
Puts	53	21	1	8	3	-
Futures	25	-	-	7	-	-

Table 2: Descriptive Statistics - VA Guarantees and Firm Characteristics

Panel A shows descriptive statistics on VA guarantees. Total liabilities and reinsurance data are as of Q4:2016. *Gross liabilities* are total liabilities underwritten. *Net liabilities* are liabilities after reinsurance. *Reinsured* is the proportion of gross liabilities that is reinsured. *Ex-ante RS and PRS ratios* are the ratio of net RS and PRS liabilities to total capital as of 2007 (see equation (14)). Panel B provides descriptive statistics as of Q4:2016 on other characteristics. (i) *Total assets* are admitted assets; (ii) *Capital and surplus* measures total available capital; (iii) *Leverage* is the ratio of total general account assets to total available capital; (iv) *RBC ratio* is the ratio of total available capital to total required capital; (v) *Rating* is the AM Best rating converted to a numeric scale from 1 (A++) to 15 (F); (vi) *BCAR minus guideline* is the difference between AM Best's capital adequacy ratio and the guideline ratio to sustain the current rating; (vii) *Shock* is the change in capital between 2007:Q4 and 2009:Q1; (viii) *Separate account share* is the total account value in VA divided by total liabilities; (ix) *Generosity* is the ratio of net liabilities in VA guarantees divided by the total account value; (x) *MBS and callable share* is the total fair value of MBS and callable bonds divided by the total fair value of the bond portfolio. The sample includes insurers that hold interest rate derivatives.

Panel A: VA Guarantees

Variable	Mean	SD	P10	P25	Median	P75	P90
Total Liabilities & Reinsurance ($ billion)							
Total (Gross)	1.28	2.94	0.00	0.01	0.13	0.86	3.94
RS (Gross)	0.08	0.17	0.00	0.00	0.01	0.10	0.27
PRS (Gross)	1.19	2.93	0.00	0.00	0.09	0.48	3.28
Total (Net)	0.56	1.58	0.00	0.00	0.04	0.33	1.02
RS (Net)	0.04	0.08	0.00	0.00	0.01	0.04	0.11
PRS (Net)	0.52	1.57	0.00	0.00	0.03	0.24	0.73
Reinsured: Total (%)	32	39	0	0	5	72	96
Reinsured: RS (%)	20	34	0	0	1	35	94
Reinsured: PRS (%)	33	40	0	0	6	77	95
Ex-ante RS and PRS Ratios (%)							
Total Ratio: G_i	4.0	8.1	0.0	0.0	0.4	4.1	15.5
RS Ratio: RS_i	0.8	2.2	0.0	0.0	0.0	0.3	2.5
PRS Ratio: PRS_i	3.2	7.7	0.0	0.0	0.2	1.7	10.2

Panel B: Firm Characteristics

Variable	Mean	SD	P10	P25	Median	P75	P90
Total Assets ($ billion)	120	134	20	29	59	179	291
Capital & Surplus ($ billion)	7	8	1	2	5	9	20
Leverage	10.2	4.2	5.0	7.9	9.4	12.8	15.8
RBC Ratio	9.8	2.4	6.9	8.2	9.9	11.3	12.3
Rating	2.7	1.0	1.0	2.0	2.7	3.0	4.0
BCAR - Guideline	129	143	29	54	93	180	276
Shock	0.92	0.20	0.64	0.81	0.95	1.02	1.18
Separate Account Share (%)	31	26	0	10	31	58	70
Generosity (%)	3	14	0	0	0	1	3
MBS Share (%)	21	11	7	14	20	27	33
Callable Share (%)	32	22	7	18	26	54	68

Table 3: Descriptive Statistics - Cross-sectional Distribution of Hedging

The table provides descriptive statistics on interest rate (panel A) and equity derivative (panel B) positions, including gross notionals, exposures, and exposures per unit of capital for interest rate and the total number of contracts, exposures, and exposures per unit of capital for equity positions. I compute averages for each insurer separately for the two regulatory regimes, 2004-2008 and 2009-2016, using quarterly data and then report the cross-sectional distribution. The sample includes insurers that hold interest rate or equity derivatives.

Panel A: Interest Rate Risk

Variable	Mean	SD	P10	P25	Median	P75	P90
2004-2008							
Gross Notionals ($ billion)	8.01	15.03	0.00	0.02	0.35	9.43	22.25
Exposures ($ billion)	0.04	0.22	-0.08	0.00	0.00	0.01	0.16
Exposure/ Capital	0.5	4.0	-0.8	0.0	0.0	0.4	2.1
2009-2016							
Gross Notionals ($ billion)	16.73	32.29	0.01	0.15	0.93	18.90	53.64
Exposures ($ billion)	0.26	0.50	0.00	0.00	0.01	0.36	0.84
Exposure/ Capital	3.4	6.9	-0.3	0.0	0.5	4.3	9.7

Panel B: Equity Risk

Variable	Mean	SD	P10	P25	Median	P75	P90
2004-2008							
Number Contracts (million)	0.37	1.47	0.00	0.00	0.07	0.19	0.37
Exposures ($ million)	0.78	52.10	-24.48	-6.34	0.00	0.00	13.06
Exposure/ Capital	0.23	1.97	-0.41	-0.09	0.00	0.00	0.43
2009-2016							
Number Contracts (million)	2.33	6.11	0.00	0.00	0.16	1.53	6.56
Exposures ($ million)	-88.2	221.4	-298.4	-54.6	-13.7	-0.09	2.03
Exposure/ Capital	-1.37	2.95	-5.92	-1.00	-0.36	0.00	0.11

Table 4: Cross-sectional Evidence on Extensive and Intensive Margin of Interest Rate Risk Hedging

The table reports the results of the cross-sectional linear regression to understand the determinants of the extensive and the intensive margin of interest rate risk hedging. For the extensive margin, the dependent variable is 1 or 0 depending on whether an insurer used interest rate derivatives at any point during the sample period. The sample includes all insurers that existed for at least two years in either regulatory regime. For the intensive margin, the dependent variables are (i) time-series average of hedging exposures scaled by capital $\overline{\widehat{\delta_i}}$ and (ii) standard deviation of hedging exposures scaled by capital $\sigma(\widehat{\delta_i})$ for each insurer, which I compute using quarterly data from 2004 to 2016. The sample includes insurers that held interest rate derivatives at some point during the sample period. The independent variables are time-series averages of each variable computed for each insurer using the entire available sample. Intercept is estimated but not reported. The table shows standard errors in parentheses. Significance: * 10%; ** 5%; *** 1%.

	Extensive Margin	Intensive Margin	
		Level $\overline{\widehat{\delta_i}}$	Volatility $\sigma(\widehat{\delta_i})$
$\overline{G_i}$	1.520***		
	(0.459)		
$\overline{RS_i}$		1.217***	1.121***
		(0.234)	(0.198)
$\overline{PRS_i}$		0.083	0.068
		(0.074)	(0.063)
$\overline{Log(assets)_i}$	0.106***	0.006	0.010**
	(0.008)	(0.005)	(0.004)
$\overline{Leverage_i}$	-0.0003	0.0018	0.0013
	(0.002)	(0.0015)	(0.0013)
$\overline{RBC_i}$	0.0013***	0.0002	0.0002
	(0.0004)	(0.0002)	(0.0001)
N	220	53	53
Adj R^2	0.56	0.43	0.52

Table 5: Regulatory Incentives and Magnitude of Interest Rate Risk Hedging

The table shows the relationship between shifts in interest rate risk hedging and the exposure to different VA guarantees. The dependent variable $\widehat{\delta_{it}}$ is the hedging exposure scaled by capital for firm i at time t. The main independent variables are (i) G_i, (ii) RS_i, and (iii) PRS_i, as defined in equation (14), each interacted with $Post_t$, a dummy variable that takes a value of 1 for years on or after 2009 and 0 before 2009. Estimations are on annual data. The pre-period is 2004 to 2008 and the post-period is 2009 to 2016. The sample includes insurers that hold interest rate derivatives. The controls include log(assets), leverage, RBC ratio, credit rating, BCAR relative to guideline, and separate account share. The convexity controls are guarantee ratio, MBS and callable bond share. Fixed effects are denoted at the bottom of each panel. For robustness, I also include characteristic × Year fixed effects, where I divide the sample of insurers into four groups. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	I	II	III	IV	V	VI	VII
$G_i \times Post_t$	0.354*						
	(0.203)						
$RS_i \times Post_t$		1.975***	2.044***		1.955***	1.996***	1.952***
		(0.256)	(0.242)		(0.235)	(0.234)	(0.278)
$PRS_i \times Post_t$		0.171		0.238			
		(0.136)		(0.166)			
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Convexity Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Guarantee Ratio × Year Fixed Effects					Yes		
Asset Convexity × Year Fixed Effects						Yes	
Size × Year Fixed Effects							Yes
N	624	624	624	624	624	624	624

Table 6: Regulatory Incentives and Hedging Dynamics with Interest Rates

The table shows the relationship between changes in interest rate risk hedging and bond returns. The dependent variable $\Delta\widehat{\delta_{it}}$ is the quarterly change in hedging for firm i at time t. The main independent variables are the interactions between the quarterly return on a 10 year treasury bond R_{10t}, RS_i, PRS_i, and $Post_t$, which is a dummy variable that takes a value of 1 for years on or after 2009 and 0 before 2009. RS_i and PRS_i are as defined in equation (14). Estimations are on quarterly data. The pre-period is 2004:Q2 to 2009:Q3 and the post-period is 2009:Q4 to 2016:Q4. The sample includes insurers that hold interest rate derivatives. The controls are the change in log(assets), change in leverage, size interacted with R_{10t}, and guarantee ratio interacted with R_{10t}, and MBS and callable bond share interacted with R_{10t}. Fixed effects are denoted at the bottom of each panel. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	I	II	III	IV	V
R_{10t}	0.133***	0.037			
	(0.05)	(0.039)			
$R_{10t} \times RS_i$		10.404***	3.849		4.439
		(2.962)	(2.893)		(2.859)
$RS_i \times Post_t$			-0.054		-0.047
			(0.044)		(0.043)
$R_{10t} \times RS_i \times Post_t$			9.866***		9.671***
			(1.731)		(1.693)
$R_{10t} \times PRS_i$		0.423		-0.818	0.567
		(0.404)		(1.487)	(1.031)
$PRS_i \times Post_t$				-0.016	-0.015
				(0.013)	(0.013)
$R_{10t} \times PRS_i \times Post_t$				0.709	0.407
				(0.802)	(0.665)
Controls			Yes	Yes	Yes
Convexity Controls			Yes	Yes	Yes
Firm Fixed Effects		Yes	Yes	Yes	Yes
Time Fixed Effects			Yes	Yes	Yes
N	2668	2668	2668	2668	2668

Table 7: Interest Rate Risk Hedging and Regulatory Constraints - Cross-sectional Evidence

The table shows the estimations on two equal sub-groups: low RBC and high RBC, using the RBC ratios in 2007. The dependent variable $\widehat{\delta_{it}}$ is the interest rate hedging exposure scaled by capital for firm i at time t. The independent variables are RS_i and PRS_i, as defined in equation (14), each interacted with $Post_t$, a dummy variable that takes a value of 1 for years on or after 2009 and 0 before 2009. Estimations are on annual data. The pre-period is 2004 to 2008 and the post-period is 2009 to 2016. The sample includes insurers that hold interest rate derivatives. The controls include log(assets), leverage, RBC ratio, credit rating, BCAR relative to guideline, and separate account share. The convexity controls are guarantee ratio, MBS and callable bond share. Fixed effects are denoted at the bottom of each panel. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	Low RBC	High RBC
$RS_i \times Post_t$	2.126***	1.03
	(0.095)	(0.712)
$PRS_i \times Post_t$	0.176	-0.218
	(0.126)	(0.339)
Controls	Yes	Yes
Convexity Controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Time Fixed Effects	Yes	Yes
N	318	306
Insurers	27	26

Table 8: Interest Rate Risk Hedging and Regulatory Constraints - Within Firm Evidence

The table shows the relationship between interest rate risk hedging and RBC ratio over time and in the cross-section. The dependent variable $\widehat{\delta_{it}}$ is the hedging exposure scaled by capital for firm i at time t. The main independent variable of interest is the RBC ratio of firm i lagged one period. RS_i is the ratio of net liabilities in RS guarantees divided by total capital as of 2007 and $Post_t$ is a dummy variable that takes a value of 1 for years on or after 2009 and 0 before 2009. Column II and III show the results for sub-samples, where low (high) RS are insurers with a below (above) median ex-ante RS ratio. Estimations are on annual data. The pre-period is 2004 to 2008 and the post-period is 2009 to 2016. The sample includes insurers that hold interest rate derivatives. The controls are as described in Table 5. Fixed effects are denoted at the bottom of each panel. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	I	II	III	IV
		Low RS	High RS	
RBC_{it-1}	0.0004**	0.0001**	0.004	0.0002*
	(0.0002)	(0.0001)	(0.005)	(0.0001)
$RBC_{it-1} \times Post_t$	-0.0005	0.000	-0.008**	-0.0002
	(0.0004)	(0.0001)	(0.004)	(0.0003)
$RBC_{it-1} \times RS_i$				0.353***
				(0.114)
$RBC_{it-1} \times RS_i \times Post_t$				-0.547***
				(0.188)
$RS_i \times Post_t$				6.807***
				(1.608)
Controls	Yes	Yes	Yes	Yes
Convexity Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
N	624	302	322	624

Table 9: Reduction in Volatility of Capital due to Derivatives

Panel A presents aggregate evidence on the reduction in volatility of regulatory capital due to derivatives. I compute the growth in capital *with* and *without* derivatives. The total growth in capital without derivatives is the growth in capital with derivatives minus capital gains (losses) during the year due to derivative instruments. I then compute the volatility of log changes in capital *with* and *without* derivatives. I decompose the reduction in volatility into the exact risk exposure being hedged for the sample 2010 to 2016, when the reporting of the relevant accounting variables for the decomposition started. Panel B presents the estimates of an OLS regression of the reduction in volatility (dependent variable) on the ex-ante RS and PRS ratios (independent variables), as defined in equation (14).

Panel A

Reduction in Volatility: Aggregate Evidence

	All Derivatives			Decomposition		
Sample	$\sigma_{Without}$	σ_{With}	Reduction	Rates	Equities	Others
2002-2016	0.086	0.050	42.0%			
2010-2016	0.053	0.014	73.4%	70%	25%	5%

Panel B

Reduction in Volatility and Regulatory Incentives

RS_i	2.501***
	(0.266)
PRS_i	-0.027
	(0.076)
Intercept	0.006
	(0.007)
N	53
Adj R-sq	0.62

Table 10: Regulatory Incentives and Magnitude of Equity Risk Hedging

The table shows the relationship between shifts in equity risk hedging and the exposure to different VA guarantees. The dependent variable is the equity risk hedging exposure scaled by capital for firm i at time t. The independent variables are (i) G_i, (ii) RS_i, and (iii) PRS_i, as defined in equation (14), each interacted with $Post_t$, a dummy variable that takes a value of 1 for years on or after 2009 and 0 before 2009. Estimations are on annual data. The pre-period is 2004 to 2008 and the post-period is 2009 to 2016. The sample includes insurers that hold equity derivatives. The controls include log(assets), leverage, RBC ratio, credit rating, BCAR relative to guideline, and separate account share. Fixed effects are denoted at the bottom of each panel. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	I	II	III	IV
$G_i \times Post_t$	-0.191***			
	(0.062)			
$RS_i \times Post_t$		-0.239***	-0.317***	
		(0.088)	(0.076)	
$PRS_i \times Post_t$		-0.179**		-0.198***
		(0.077)		(0.076)
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
N	578	578	578	578

Table 11: Reinsurance and Off-Balance Sheet Transfers

Panel A shows the estimations to quantify the shift in reinsurance for RS and PRS guarantees. The dependent variables are the proportion of RS liabilities reinsured, PRS liabilities reinsured, and the difference between proportion of PRS and RS liabilities reinsured for firm i at time t. The main independent variable is a dummy variable $Post_t$ that takes a value of 1 for years on or after 2009. The controls are log(assets), leverage, RBC ratio, credit rating, and BCAR relative to guideline. Panel B shows the relationship between shift in reinsurance and the shift in regulatory incentives. The dependent variable is the proportion of PRS liabilities reinsured. The independent variables are RS_i and PRS_i, as defined in equation (14), each interacted with $Post_t$. Estimations are on annual data. The pre-period is 2005 to 2008 and the post-period is 2009 to 2016. Fixed effects are denoted at the bottom of each panel. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

Panel A

Shift in Reinsurance

	PRS	RS	Difference
$Post_t$	0.077**	-0.005	0.082*
	(0.039)	(0.026)	(0.043)
Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
N	510	510	510

Panel B

Impact of Regulatory Incentives

	PRS
$RS_i \times Post_t$	-1.254
	(2.079)
$PRS_i \times Post_t$	1.63***
	(0.299)
Controls	Yes
Firm Fixed Effects	Yes
Time Fixed Effects	Yes
N	510

Table 12: Monetary Policy Implications

I compare the changes in hedging between 2009 and 2012 and between 2012 and 2016 for two subgroups of insurers. Old (New) are underwriters for whom more than 50% of the VA sales occurred before (after) 2009. The dependent variable is the interest risk hedging exposure scaled by capital for firm i at time t. The main independent variables of interest are dummy variables that take a value of 1 if year = 2012 (first panel) and if year = 2016 (second panel). Estimations are on annual data. The sample includes insurers that hold interest rate derivatives. I control for the amount of RS guarantees scaled by total capital and firm fixed effects. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	2009 vs. 2012		2012 vs. 2016	
	Old	New	Old	New
$Y_{2012} = 1$	0.044***	0.04***		
	(0.016)	(0.012)		
$Y_{2016} = 1$			0.006	-0.017
			(0.019)	(0.017)
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
N	52	32	50	32

A. Characterization of Risk Exposures in Variable Annuities

I start by describing the VA guarantees formally and compute their interest rate and equity risk exposures numerically using Monte Carlo simulations. I consider single premium contracts given by an amount P. I assume that F_t denotes the account value at time t, G_t denotes the deterministic guaranteed benefit, which grows at a constant promised guaranteed rate of δ, also known as the roll-up rate. Thus, $G_t = Pe^{\delta t}$.[54]

GMDB: In a GMDB, the contract holder is promised upon death a payoff that is the maximum of the account value F_t or the guaranteed amount G_t. Assuming a coverage period until time T, the benefit B_t^D is given by:

$$B_t^D = \max(F_t, G_t), \quad t \leq T, \quad \text{if } t = t(death) \tag{A.1}$$

GMAB: In a GMAB, the contract holder if alive is promised, upon maturity T, a payoff that is the maximum of the random account value F_T or the guaranteed amount G_T. Thus, the benefit B_T^A is given by:

$$B_T^A = \max(F_T, G_T) \tag{A.2}$$

GMIB: A GMIB provides a lifetime annuity from a specified future point in time T. The amount to be annuitized is the maximum of the random account value F_T or the guaranteed amount G_T, where G_T is the same as in a GMAB. The contract holder can annuitize the random account value F_T at the market annuity rate prevailing at time T, a_T, or the guaranteed amount G_T at the fixed annuity rate $\bar{a}$ set at the outset of the contract. Thus, the contract holder receives a constant income stream B_t^I from time $T+1$ until death given by:

$$B_t^I = \max(a_T F_T, \bar{a} G_T), \quad t > T \tag{A.3}$$

GMWB: A GMWB allows a contract holder to withdraw a fixed percentage of the account value as an income stream either over her lifetime or over a fixed period after an initial accumulation period, which is the same as a GMIB. The contract holder is assured this sum even if the account value reduces to zero, which may happen because of negative fund performance or longevity. Crucially, the remaining amount stays invested in the fund. The contract holder withdraws a fixed proportion of the maximum of the random account

[54] The guaranteed value can sometimes be given by the highest account value recorded at a specified time. This feature is called "ratchet". A combination of roll-up and ratchet is also possible, in which case $G_t = \max(Pe^{\delta t}, \max_{t_i < t} F_{t_i})$. To simplify, I ignore the ratchet feature.

value F_T or the guaranteed amount G_T. Assuming a fixed withdrawal rate given by h, set at the outset of the contract, the payoff B_t^W is given by:

$$B_t^W = h \max(F_T, G_T) + \max(F_{T'}, 0), \quad T < t <= T' \tag{A.4}$$

where T' denotes the end of the withdrawal period, which could be a specific time in the future or until death, and $F_{T'}$ denotes any remaining value in the fund after all the withdrawals have taken place, that is, $F_{T'}$ is the fund value minus all withdrawals and plus all returns.

Table A.1 describes the cash flows using a hypothetical numerical example. I assume an initial investment of \$100 and a guaranteed roll-up rate of 5% during the accumulation phase, which ends in 10 years. For GMDB, I assume death occurs at year 12. For GMIB, I assume that the contract holder annuitizes at the end of the accumulation period at year 10. For GMWB, I also assume that withdrawals start at the end of the accumulation period and the contract holder makes withdrawals at a constant rate equal to the promised rate. I assume that both the promised annuity and withdrawal rate are 5%. For GMWB, I denote any positive fund value that remains after all the withdrawals have taken place by $F_{T'}^+$.

Table A.1: Numerical Example of Variable Annuity Guarantees

Year	G_t	F_t	GMAB	GMDB	GMIB	GMWB
1	105	102				
2	110	105				
...						
10	163	120	163			
11					8.1	8.1
12	180	140		Death; 180	8.1	8.1
13					8.1	8.1
14					8.1	8.1
15					8.1	8.1
16					8.1	8.1
17					8.1	8.1
18					8.1	8.1
19					8.1	8.1
20					8.1	8.1
21					8.1	8.1
22					8.1	8.1
23					8.1	8.1
24					8.1	8.1
25					8.1	8.1
...					...	...
T'					8.1	8.1 + $F_{T'}^+$

Risk Exposures: I next compute the interest rate and equity risk exposures of VA guarantees using numerical techniques. I assume that the short rate r_t follows the Cox-Ingersoll-

Ross (1985) model. Thus, under the risk neutral measure, the short rate r and the fund value F satisfy a system of stochastic differential equations of the form:

$$dr_t = a(b - r_t)dt + \sigma_r \sqrt{r_t} dW_t^1 \tag{A.5}$$

$$dF_t = F_t[r_t dt + \sigma_F(\rho dW_t^1 + \sqrt{1-\rho^2} dW_t^2)] \tag{A.6}$$

where W_t^1 and W_t^2 are two independent standard Brownian motions, a is the speed of mean reversion to the long term average of the short rate, b, σ_r is the volatility parameter, σ_F is the volatility of the fund and ρ is the correlation between interest rate shocks and the shocks to the fund value. The value of the guarantee is obtained by computing the average discounted value of the payoffs over many simulated paths of the fund value F and the short rate r, where the two are generated using the dynamics described above.

To compute interest rate and equity market sensitivities, I calculate the partial derivatives by finite difference approximation. I recompute the value of the guarantee by increasing and decreasing the interest rate by 100 basis points and increasing and decreasing the initial fund value by \$10. The difference in the value of the contract divided by the magnitude of the change approximates the partial derivative, when the number of simulations is high enough:

$$\frac{\partial V}{\partial \theta} \approx \frac{V(\theta + \Delta\theta, \widetilde{\theta}) - V(\theta - \Delta\theta, \widetilde{\theta})}{2\Delta\theta} \tag{A.7}$$

where V denotes the value of the guarantee, θ denotes the interest rate or the initial fund value, and $\widetilde{\theta}$ denotes all other contract parameters, which are held constant.

As VA are retirement products targeted at the pre-retirement age group, I model a US male aged 55 years at the start of the contract. I then select the most commonly sold guarantees in the market. For example, I select a 10 year GMAB, which provides protection prior to reaching retirement at the age of 65. I select a 20 year GMDB as it typically provides protection until a maximum age of 75 years. GMIB and GMWB provide a post-retirement income stream. I assume both guarantees have an accumulation period until age 65, at which point annuitization or withdrawals start. I assume both products offer a lifetime income stream.

To price the guarantees, I obtain the mortality rates from the American Society of Actuaries 2000 Annuity Mortality Basic Table. I assume that there are no fees and no surrenders. I also assume that the underlying fund is a stock fund. I obtain estimates of the parameters describing the short rate using monthly data on the 3-month Libor rate from 1995 to 2016. I get $a = 0.09$, $b = 0.029$, and $\sigma_r = 0.045$.[55] I choose the volatility of the fund value $\sigma_F = 0.18$ to match the volatility of the market portfolio as proxied by the Fama-French market portfolio. I select the correlation $\rho = 0.11$ to match the correlation between the market portfolio and 10 year yield changes.

Table A.2 shows the interest rate and equity risk exposures for the VA guarantees, where "RS" implies risk sensitive and "PRS" implies partially risk sensitive, that is, sensitive to equity risk, but not interest rate risk. The first panel reports semi-elasticities, computed as the dollar exposure due to a 100 basis points change in interest rates (or a \$10 change in the fund value) as shown in equation (A.7), divided by the value of the guarantee.[56] I compute the exposures at three different interest rate levels: 2%, 4%, and 6% and three different equity market levels: \$75 (in-the-money), \$100 (at-the-money), and \$125 (out-of-the-money).

Table A.2: Economic Risk Exposures

		Interest Rates			Equity		
		2%	4%	6%	75	100	125
Semi-Elasticities (%)							
GMAB	RS	13.9	14.7	15.6	11.3	11.9	12.2
GMWB	RS	13.7	14.4	15.0	10.6	10.8	10.6
GMIB	PRS	15.0	16.2	17.2	10.3	10.9	11.1
GMDB	PRS	13.9	14.6	15.4	9.2	9.3	8.9
Relative Exposures							
GMAB	RS	1.25	1.00	0.78	1.26	1.00	0.76
GMWB	RS	1.26	1.00	0.78	1.27	1.00	0.75
GMIB	PRS	1.27	1.00	0.76	1.23	1.00	0.78
GMDB	PRS	1.27	1.00	0.78	1.25	1.00	0.76

A 100 basis points change in interest rates would result in a 14.7% (GMAB), 14.4% (GMWB), 16.2% (GMIB), and 14.6% (GMDB) change in the values, when rates are at 4%. Similarly, when the level of the equity market is at \$100 (at-the-money), a \$10 change would result in a 11.9% (GMAB), 10.8% (GMWB), 10.9% (GMIB), and 9.3% (GMDB) change in the values. Thus, under these contract characteristics and parameter specifications,[57] a

[55]The mean reversion parameter, a, is picked to match the persistence of the 3-month Libor rate by fitting an AR(1) model. The long-run average rate, b, is the average rate during the sample period. I choose σ_r such that the average standard deviation under the CIR model is equal to 80 basis points, which is the annualized standard deviation of monthly changes in the short rate during this sample period. I set $0.008^2 = \mathbb{E}(Var(dr_t)) = \sigma_r^2\,\mathbb{E}(r_t)$ to get $\sigma_r = 0.045$.

[56]I compute $\left(\frac{V(\theta+\Delta\theta,\widetilde{\theta})-V(\theta-\Delta\theta,\widetilde{\theta})}{2\Delta\theta * V(\theta,\widetilde{\theta})}\right)$.

[57]In an alternative calibration, I choose $a = 0$ and $\sigma_r = 0.043$ to match the model-implied volatility of 10

GMIB is the most interest rate risky guarantee, while GMAB, GMWB, and GMDB have a relatively lower and similar interest rate risk. Equity risk exposures are relatively similar for GMWB and GMIB, higher for GMAB, and lower for GMDB.

The second panel reports relative dollar exposures. Specifically, for interest rates, I compute the ratio of dollar exposure at 2%, 4%, or 6% divided by the dollar exposure at 4%. For equity, I compute the ratio of dollar exposure at $75, $100, or $125 divided by the dollar exposure at $100. Intuitively, this shows the change in hedging required for any contract when interest rates or equity market levels change, as compared to a baseline number. The table shows that as interest rates or equity markets decline, risk exposures increase. Moreover, the shift in exposures are similar across guarantees. For example, when rates fall from 4% to 2%, interest rate exposures increase by 25% to 27% across guarantees. When the equity market rises, equity exposures decrease by 22% to 25% across guarantees.

In summary, I find that the PRS guarantees (GMIB, GMDB) are at least as or more interest rate risky as RS guarantees (GMAB, GMWB). Similarly, I find that PRS and RS guarantees have comparable equity risk, with GMDB having slightly smaller exposure than the rest.

year yield changes with the volatility in the data. The RS guarantees remain less interest rate risky than PRS guarantees. The equity risk exposures remain almost identical.

B. Proofs

Substituting equations (6), (7), and (9) in equation (8) and taking the first order condition with respect to $\widehat{\delta}_0$, I get:

$$-\mathbb{E}(\Delta y)\theta_0 + \xi\theta_0^2(\widehat{\beta}_L - \widehat{\beta}_A - \widehat{\delta}_0)\sigma^2 + \gamma((1+\phi)\psi\widehat{\beta}_L - \psi\widehat{\beta}_A - \widehat{\delta}_0)\lambda(\widehat{K}_0)\sigma^2 = 0 \tag{B.1}$$

Solving for $\widehat{\delta}_0$ yields equation (10).

Implication 1 As $\lambda(\widehat{K}_0) \to 0$, the speculation term converges to $\frac{-\mathbb{E}(\Delta y)}{\xi\theta_0\sigma^2}$ and the hedging term converges to $(\widehat{\beta}_L - \widehat{\beta}_A)$. When $\mathbb{E}(\Delta y) = 0$, I get equation (11). As $\lambda(\widehat{K}_0) \to \infty$, the speculation term converges to 0 and the hedging term converges to $\psi(\widehat{\beta}_L - \widehat{\beta}_A) + \phi\psi\widehat{\beta}_L$.

Implication 2 The partial derivative of $\widehat{\delta}_0$ with respect to ψ is:

$$\frac{\partial\widehat{\delta}_0}{\partial\psi} = \Big((1+\phi)\widehat{\beta}_L - \widehat{\beta}_A\Big)\frac{\gamma\lambda(\widehat{K}_0)}{\gamma\lambda(\widehat{K}_0) + \xi\theta_0^2} > 0 \tag{B.2}$$

as $(\beta_L - \beta_A) > 0$ and $\phi > 0$ by assumption. This implies **Prediction 1** directly.

Implication 3 The partial derivative of $\widehat{\delta}_0$ with respect to ϕ is $\frac{\partial\widehat{\delta}_0}{\partial\phi} = \psi\widehat{\beta}_L\frac{\gamma\lambda(\widehat{K}_0)}{\gamma\lambda(\widehat{K}_0)+\xi\theta_0^2} > 0$ for $\psi > 0$.

Prediction 2 Taking the partial derivative of the expression in equation (B.2) with respect to y_0, I get the following expression for the cross-partial derivative of $\widehat{\delta}_0$ with respect to ψ and y_0: $\frac{\partial^2\widehat{\delta}_0}{\partial\psi\partial y_0} = \frac{\partial((1+\phi)\widehat{\beta}_L - \widehat{\beta}_A)}{\partial y_0}\frac{\gamma\lambda(\widehat{K}_0)}{\gamma\lambda(\widehat{K}_0)+\xi\theta_0^2} < 0$ as $\frac{\partial(\beta_L - \beta_A)}{\partial y_0} < 0$ by assumption.

Prediction 3 Taking the partial derivative of the expression in equation (B.2) with respect to $\lambda(\widehat{K}_0)$, I get the following expression for the cross-partial derivative of $\widehat{\delta}_0$ with respect to ψ and $\lambda(\widehat{K}_0)$: $\frac{\partial^2\widehat{\delta}_0}{\partial\lambda(\widehat{K}_0)\partial\psi} = ((1+\phi)\widehat{\beta}_L - \widehat{\beta}_A)\frac{\gamma\xi\theta_0^2}{(\gamma\lambda(\widehat{K}_0)+\xi\theta_0^2)^2} > 0$ as $(\beta_L - \beta_A) > 0$ and $\phi > 0$ by assumption.

Moreover, $\frac{\partial\widehat{\delta}_0}{\partial\lambda(\widehat{K}_0)}\Big|_{\psi=0} = (\widehat{\beta}_L - \widehat{\beta}_A)\frac{-\gamma\xi\theta_0^2}{(\gamma\lambda(\widehat{K}_0)+\xi\theta_0^2)^2} < 0$ and $\frac{\partial\widehat{\delta}_0}{\partial\lambda(\widehat{K}_0)}\Big|_{\psi=1} = \phi\widehat{\beta}_L\frac{\gamma\xi\theta_0^2}{(\gamma\lambda(\widehat{K}_0)+\xi\theta_0^2)^2} > 0$ for $\phi > 0$, that is, if regulation is conservative.

C. Additional Tables and Figures

Table C.1: Relationship between Stock Returns and Interest Rates

In this section, I compare the interest rate sensitivities of insurer stock returns. Following Berends et. al. (2013), I measure sensitivities using a two factor model, where I regress stock returns R_{it} on the market R_{Mt} and 10 year treasury returns R_{10t} for the sub-sample of insurers that are publicly traded.[58] The loading on R_{10t} gives the sensitivity of an insurer's stock returns to interest rate changes. To assess whether interest rate sensitivities are different for firms with a high RS ratio, I interact treasury returns with RS_i:

$$R_{it} = \alpha + \beta R_{Mt} + \gamma R_{10t} + \gamma_1 R_{10t} \times RS_i + \alpha_i + \epsilon_{it},$$

where α_i are firm fixed effects. The coefficient of interest is γ_1, which captures whether insurers with a high RS ratio have a higher interest rate sensitivity. The stock returns are from SNL Financial. To obtain the stock returns, I map group codes to the ultimate parent using SNL Financial's group code to ultimate institute key mappings. 25 out of the 53 insurers in my sample are publicly traded. The sample starts in 2001 and ends in 2016 and the data are monthly. I divide the sample into two sub-periods to differentiate between the two regulatory regimes and leave out the crisis (as in Berends et. al. (2013)). I show that interest rate sensitivities are not correlated with the RS ratio. Sensitivities of stock returns to interest rates increase during the low rate period for all insurers,[59] however sensitivities are not higher for insurers that have a higher RS ratio. I also check this using a difference-in-differences specification and for different analysis frequencies (weekly and quarterly) (results not shown).

	2001:Q1-2007:Q4		2009:Q2-2016:Q4	
	I	II	I	II
Market	0.82***	0.818***	1.332***	1.332***
	(0.103)	(0.103)	(0.084)	(0.084)
Bond	-0.439***	-0.331**	-0.993***	-0.924***
	(0.114)	(0.134)	(0.147)	(0.173)
Bond $\times RS_i$		-6.52		-4.09
		(6.591)		(4.209)
Firm Fixed Effects	No	Yes	No	Yes
N	1872	1872	2275	2275

[58] See, Brewer, Mondschean and Strahan (1993).

[59] Berends et. al. (2013) have already documented this. I replicate their results for my sample of insurers.

Table C.2: Correlation Between RS and PRS Ratios and Firm Characteristics

I regress RS_i and PRS_i on various firm characteristics. I estimate:

$$Y_i = \alpha + \beta X_i + \epsilon_i,$$

where all variables are as of 2007. X_i includes log(total assets), leverage, RBC ratio, rating, and BCAR relative to guideline. An intercept is estimated but not reported. The sample includes insurers that hold interest rate derivatives. The table shows standard errors in parentheses. Significance: * 10%; ** 5%; *** 1%.

	RS_i	PRS_i
$Log(Assets)_i$	0.006*	0.006
	(0.003)	(0.011)
$Leverage_i$	0.000	-0.004
	(0.001)	(0.003)
RBC_i	0.001	-0.008*
	(0.001)	(0.005)
$Rating_i$	-0.002	0.009
	(0.004)	(0.013)
$(BCAR - Guideline)_i$	0.000	0.000
	(0.000)	(0.0001)
N	53	53
Adj R-sq	0.087	0.022

Table C.3: Effect of the Financial Crisis

To test whether the increase in hedging for high RS ratio insurers is due to differential exposure to the financial crisis, I include the capital shock experienced during the crisis interacted with a post crisis dummy in the main specification. I estimate:

$$\widehat{\delta_{it}} = \alpha + \sum_{J=RS,PRS} \beta^J (J_i \times Post_t) + \gamma_1 (Shock_i \times Post_t) + \gamma^{'} X_{it-1} + \alpha_i + \alpha_t + \epsilon_{it}.$$

The dependent variable $\widehat{\delta_{it}}$ is the interest rate hedging exposure scaled by capital for firm i at time t. The independent variables are RS_i and PRS_i, each interacted with $Post_t$, a dummy variable that takes a value of 1 for years on or after 2009 and 0 before 2009. Estimations are on annual data. The pre-period is 2004 to 2008 and the post-period is 2009 to 2016. The sample includes insurers that hold interest rate derivatives. The controls are as described in Table 5. Fixed effects are denoted at the bottom of each panel. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

$RS_i \times Post_t$	1.914***
	(0.326)
$PRS_i \times Post_t$	0.177
	(0.125)
$Shock_i \times Post_t$	0.01
	(0.038)
Controls	Yes
Convexity Controls	Yes
Firm Fixed Effects	Yes
Time Fixed Effects	Yes
N	624

Table C.4: Hedging with Bonds

This table shows the relationship between shifts in interest rate exposures from bonds and the exposure to different VA guarantees. I estimate:

$$\widehat{\delta_{it}^{B}} = \alpha + \sum_{J=RS,PRS} \beta^{J}(J_i \times Post_t) + \gamma^{'} X_{it-1} + \alpha_i + \alpha_t + \epsilon_{it}.$$

The dependent variable $\widehat{\delta_{it}^{B}}$ is the total dollar exposure of the bond portfolio scaled by total capital for firm i at time t. The independent variables are G_i, RS_i, and PRS_i, as defined in equation (14), each interacted with $Post_t$, a dummy variable that takes a value of 1 for years on or after 2009 and 0 before 2009. Estimations are on annual data. The pre-period is 2004 to 2008 and the post-period is 2009 to 2016. The sample includes insurers that hold interest rate derivatives. The controls are as described in Table 5. Fixed effects are denoted at the bottom of each panel. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	I	II	III	IV
$G_i \times Post_t$	0.289			
	(0.388)			
$RS_i \times Post_t$		0.162	0.265	
		(0.585)	(0.517)	
$PRS_i \times Post_t$		0.303		0.308
		(0.45)		(0.445)
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
N	624	624	624	624

Table C.5: Regulatory Incentives and Hedging Dynamics with Interest Rates - Within Firm Evidence From Hedging Disclosures

The table shows the relationship between changes in interest rate risk hedging and bond returns across products *within* the same insurer. The regulatory liabilities for VA are sensitive and non-VA are insensitive to interest rate movements. I estimate:

$$\Delta\widehat{\delta_{ikt}} = \alpha + \beta_1^D(R_{10t} \times I_{ik}) + \beta_2^D R_{10t} + \beta_3^D I_{ik} + \alpha_i + \epsilon_{ikt},$$

where $\widehat{\delta_{ikt}}$ denotes the hedging exposure for insurer i, balance sheet item k and time t, I_{ik} is a dummy variable that takes a value of 1 for VA hedging exposures and otherwise zero, R_{10t} is the quarterly return on a 10 year treasury bond, and α_i denotes insurer fixed effects. I also use insurer cross time fixed effects to control for time varying unobservable characteristics of an insurer, such as changes in the ability to hedge or risk aversion. The coefficient of interest is β_1^D, which measures whether the hedging positions earmarked as VA have different interest rate sensitivities relative to non-VA hedging positions. The sample includes insurers that hold interest rate derivatives. As the disclosures started from 2010:Q1, the sample for the regression is 2010:Q2 to 2016:Q4. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	VA	Non-VA	Both
R_{10t}	0.047***	0.007	
	(0.012)	(0.005)	
$R_{10t} \times I_{ik}$			0.039***
			(0.013)
Firm Fixed Effects	Yes	Yes	
Balance sheet Fixed Effects			Yes
Firm × Time Fixed Effects			Yes
N	1403	1403	2806

Table C.6: Equity Risk Hedging - Cross-sectional Evidence on Regulatory Constraints and Underwriting Timing

The table shows the results of the estimation on two separate sub-groups. The first two columns show estimations on low RBC and high RBC insurers, using the RBC ratios in 2007. The third and fourth columns show estimations on old and new underwriters. Old (New) are underwriters for whom more than 50% of the VA sales occurred before (after) 2009. The dependent variable is the equity risk hedging exposure scaled by capital for firm i at time t. The independent variables are RS_i and PRS_i, as defined in equation (14), each interacted with $Post_t$, a dummy variable that takes a value of 1 for years on or after 2009 and 0 before 2009. Estimations are on annual data. The pre-period is 2004 to 2008 and the post-period is 2009 to 2016. The sample includes insurers that hold equity derivatives. The controls are log(assets), leverage, RBC ratio, credit rating, BCAR relative to guideline, and separate account share. Fixed effects are denoted at the bottom of each panel. The table shows standard errors, clustered at the insurer level, in parentheses. Significance: * 10%; ** 5%; *** 1%.

	Regulatory constraints		Underwriting timing	
	Low RBC	High RBC	Old	New
$RS_i \times Post_t$	-0.334***	-0.229	-0.254**	-1.155
	(0.045)	(0.357)	(0.107)	(0.979)
$PRS_i \times Post_t$	-0.149*	0.357*	-0.26*	-0.203**
	(0.081)	(0.209)	(0.135)	(0.08)
Controls	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
N	282	296	255	217

Table C.7: Collateral Constraints and Hedging

The table shows the results of a univariate cross-sectional OLS regression to understand the relationship between collateral constraints and hedging. The dependent variables are (i) gross notional amounts and (ii) exposures, scaled by capital. The independent variable is collateral capacity, defined as total eligible collateral owned minus collateral posted scaled by capital, where eligible collateral includes treasuries, cash, and highly rated bonds. For each insurer, I collapse the data by computing a time-series average for the entire sample, from 2013 to 2016, where the start date is dictated by the availability of the collateral data. The table shows standard errors in parentheses. Significance: * 10%; ** 5%; *** 1%.

	Gross Notionals		Exposures	
	Interest Rate	Equity	Interest Rate	Equity
Collateral Capacity	-0.004	-0.0003	0.001	0.001
	(0.228)	(0.008)	(0.004)	(0.001)
Intercept	2.393*	0.049	0.035	-0.009*
	(1.255)	(0.041)	(0.023)	(0.005)
Controls	No	No	No	No
N	52	46	52	46
Adj R^2	0%	0%	0%	0%

D. Derivatives Data

The schedule DB regulatory disclosures provide quarterly information on derivative positions and transactions starting in 2004. From 2004 to 2009, positions were reported under section 1 of parts A (Options, Caps, Floors owned), B (Options, Caps, Floors written), C (Collar, Swap and Forwards), and D (Futures). After 2010, reporting changed and positions were reported under section 1 of parts A (Options, Caps, Floors, Collars, Swaps, Forwards) and B (Futures). Similarly, insurers report all instruments terminated during the year in the same parts under section 2.

Data are at the position-level and contain the following variables: NAIC company code, line number, text strings describing the contract and/or strike, initiation and maturity dates, notional and fair value, number of contracts, risks hedged (from 2010), balance sheet item hedged (from 2010), exchange traded or OTC, and counterparty for OTC positions. In addition, the data contain accounting variables, which I use to compute gains and losses from derivatives during the year, including income earned, unrealized gains and losses for open positions and realized gains and losses for closed positions.

The line number field helps to identify whether a row in the data is a summary of positions. For example, line number ending in 9999 indicates rows where the insurer reports total positions, in addition to each individual position. I remove all such rows to avoid double counting. I also use the line number to identify the instrument type, e.g. options (call, put, caps, floors, etc.), swaps or forwards and to identify the trade direction (long or short) for options. The line number also indicates the purpose of the positions: "hedging effective", "hedging other", "income generation", "replication", or "other". Roughly 95% of the positions (by gross notionals) are earmarked as hedging (effective and other), thus I retain all derivative positions in my analysis. As reporting changed in 2010, the line number mapping to identify instrument type, direction and the purpose of the position also changed over time. The up-to-date line number mapping is provided by the NAIC.

Classification of Risk Factors: From 2010, insurers started reporting the risk factor being hedged by a position. The major risks hedged are interest rate risk, equity risk, currency risk and credit risk. Before 2010, risk factors were not directly reported, however, the position description provides relevant information, which I use to classify the positions into risk factor being hedged by textual analysis. I first create a mapping between position descriptions and risk factors using the 2010-2016 sample, when risk factors are available. I then use these mappings to assign factors to the 2004-2009 sample, when only descriptions are available. For example, strings such as "interest rate swaps", "pay fixed, receive floating", etc were classified as interest rate hedging positions, while "S&P", "equity hedge", and "MSCI" were classified as equity risk hedging positions. In addition, for options, I also incorporate the strike prices as the strike is typically either a rate or a dollar amount, which helps identify a rate hedging position from an equity risk hedging position.

In aggregate, the data contain 2.6 million derivative positions over the entire sample across risk factors. The summary statistics are given in Table D.1. Interest rate derivatives account for 775,000 positions, equaling over $41 trillion in notional value in total during the period 2004 to 2016. Of these, 65% are interest rate swaps, 31% are rate options, and 4% are futures and forwards. Equity derivatives account for 1.6 million contracts and $12 trillion in notional value, the majority of which are options. In addition, the data contain currency and credit risk hedging positions in smaller quantities.

Table D.1: Summary Statistics on Derivatives Data

Risks Hedged	Number of Positions ('000)	Gross Notional ($ trillions)
[A] Interest Rate	775	41
(i) Swaps	649	27
(ii) Options	76	12
(iii) Futures & Forwards	49	2
[B] Equity	1582	12
(i) Swaps	52	1
(ii) Options	1469	10
(iii) Futures & Forwards	62	1
[C] Currency	177	6
(i) Swaps	114	4
(ii) Options	4	1
(iii) Futures & Forwards	59	1
[D] Credit	89	1
(i) Swaps	88	1
(ii) Options	1	0
(iii) Futures & Forwards	0	0

In the next two sections, I discuss the measurement of interest rate and equity risk hedging exposures. The data issues, particularly those related to contract characteristics, which are key to precisely measuring hedging exposures are discussed in the relevant sections.

E. Measuring Interest Rate Risk Exposures From Derivatives

E.1. Interest Rate Swaps

An interest rate swap is an agreement between two parties to exchange a fixed interest rate for a floating interest rate, typically the 3-month LIBOR at quarterly frequency for the duration of the contract. The amount on which the interest payments are computed is known as the notional amount. A swap is thus a levered portfolio in bonds. For example, when the fixed leg is paid and the floating leg is received, the swap (Pay Fixed Swap (PFS)) is a short position in the fixed rate bond and a long position in the floating rate bond of the same maturity and principal. Similarly, in the opposite case (Receive Fixed Swap (RFS)), the investor is long a fixed rate bond and short a floating rate bond of the same maturity and principal. The fair value of the swap and bond are therefore related as:

$$V_{RFS} = V_{Fixed} - V_{Floating}, \tag{E.1}$$

$$V_{PFS} = V_{Floating} - V_{Fixed}. \tag{E.2}$$

Interest Rate Risk Exposures: I measure risk exposures by the dollar duration of the swap Δ, which is given by the difference between the dollar durations of the underlying fixed and floating bonds. As the sensitivity of the swap is largely due to the sensitivity of the fixed rate bond[60], I measure the risk exposure of swaps by the dollar duration of the fixed rate bond only. Thus:

$$\Delta_{RFS} = \Delta_{Fixed} \tag{E.3}$$

$$\Delta_{PFS} = -\Delta_{Fixed} \tag{E.4}$$

where the dollar duration of the fixed rate bond is computed as:

$$\Delta_{Fixed} = -\frac{MacDur \times V_{Fixed}}{1+y} \tag{E.5}$$

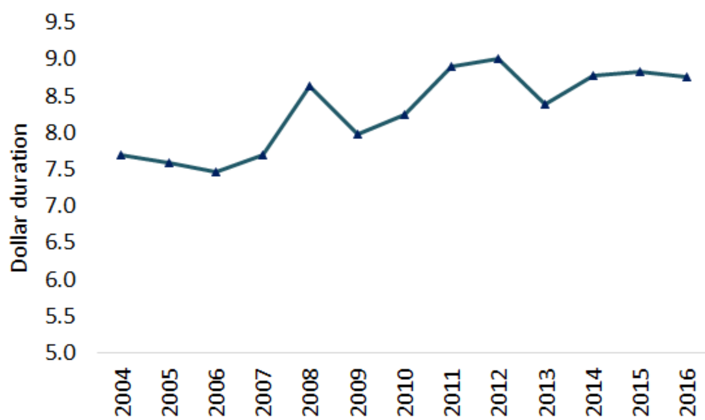
$$MacDur = \frac{1+y}{y} - \frac{1+y+N(c-y)}{c((1+y)^N - 1) + y} \tag{E.6}$$

[60] The dollar duration of the floating bond is small, especially closer to the reset dates (Fabozzi (2001)).

where $MacDur$ is the Macaulay duration, that is, the weighted average time to maturity and y is the prevailing yield to maturity of the fixed rate bond, N is the number of periods to expiry, c is the coupon, and y is the yield to maturity (Smith (2011)).

To compute the durations, I construct the zero curve by bootstrapping using Libor rates (3 and 6 months) and swap rates (1 to 10, 15, 20, 25, 30 years) from Datastream. Figure E.1 plots the dollar durations of a 10-year par bond from 2004 to 2016. A 10-year receive-fixed swap which is at par has an exposure of 8.8% at the end of 2014. This implies that if rates decline by 100 basis points, a portfolio of $1 in notional value would increase by 8.8%.

Figure E.1: Exposure of a 10 Year Receive-Fixed-Swap



To compute the durations at the position-level, I apply the durations of standard instruments by matching contract characteristics. I need the following information for each position: (i) direction of the swap, whether it is a PFS or a RFS; (ii) the remaining maturity of the swap; and (iii) the swap rate.

I infer the direction of the swap in two ways: (i) *Textual analysis approach:* Insurers report the swap direction in a string that describes the contract. The string also contains other information, e.g. the underlying rate on which the swap is written, swap rate, etc. I extract the direction of the swap from the string by textual analysis where I look for the keywords “Receive Fixed”, “Payer”, “RFS”, “Pay LIBOR”, etc. However, companies report this information in different formats that can change over time. Thus, to avoid errors in parsing the string, I also use an alternative approach by using the swap's fair value.

(ii) *Fair value approach:* The fair value of the swap with maturity $T - t$ at valuation date t is the present value of the annuity given by the difference between the swap rate at initiation s^* and the mark to market swap rate s_t of a swap whose maturity equals the remaining maturity of the swap.

$$V_t = I \times (s^* - s_t) \times A_{tT} \tag{E.7}$$

where A_{tT} is the annuity factor, that is, the sum of all discount factors $D(t, i)$ up to maturity T; $A_{tT} = \sum_{i=t+1}^{i=T} D(t, i)$ and $I = 1$ for RFS and $I = -1$ for PFS.

For each contract, I observe (i) the date on which the swap was initiated, which gives the mark-to-market swap rate as of initiation s^*, (ii) its remaining maturity as of the valuation date, which gives s_t, and (iii) the fair value of the swap as of the valuation date. I look up s^* and s_t using the daily swap rate data from Datastream. I then infer the direction of the swap as follows. If $s^* > s_t$, then $V_t > 0$ for RFS. If the fair value reported in the data is also positive then I conclude it is an RFS, otherwise it is a PFS. Similarly, if $s^* < s_t$, then $V_t < 0$ for RFS. If the fair value reported in the data is also negative then I conclude it is an RFS, otherwise it is a PFS.

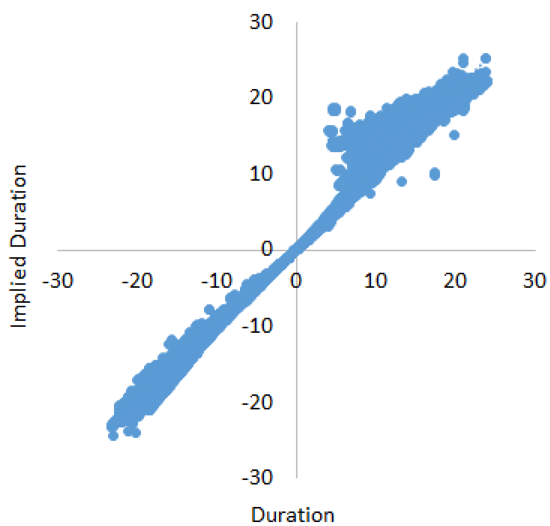
I compare the results from the parsing and fair value approaches. I find that inferring the swap's direction using the fair values yields very similar results to parsing the string in general. A univariate regression between the two outcomes has a statistically significant coefficient above 0.9 and an R-squared of 87%. However, the match rate between the two approaches varies across companies. For example, the two approaches give almost identical results in the case of Metlife, while for AXA, parsing gives confounding results as the descriptions strings are not as clear. As a further check, therefore, for companies like AXA where the match rate is low, I compare the interest rate exposures as computed from either approach with the realized gains and losses from derivatives, which companies report in their financial statement. I find that the fair value approach is significantly better at explaining the ex-post outcomes. In my analysis, I use the direction inferred from the fair value approach as it is easier to implement and is more transparent compared to parsing.

Similarly, to avoid errors in parsing the string for the swap rate, I use the mark-to-market rate of the swap as of the initiation date (s^*) as the contract's swap rate. I thus have all the information required to compute the fair value of the swap using equation (E.7) and thus the fair value of the fixed rate bond V_{Fixed} using equations (E.1) and (E.2), where I assume that the floating rate bond is priced at par and has a price equal to the notional amount of the swap.

Finally, given the fair value of the fixed rate bond, the principal (notional amount), remaining maturity (remaining maturity of the swap), and coupon (swap rate), I compute its yield to maturity and Macaulay duration. I drop positions where the trade date or maturity date are missing. Some insurers report the two legs of the swap in separate rows; I identify such cases by matching the line number, notional amount, trade and maturity date, and counterparty. Table E.2 contains the final statistics on the clean data.

An alternative approach to using the market swap rate as of initiation date s^* as the contract's swap rate is to back out the swap rate from the swap's reported fair values using equation (E.7). I find that both approaches give very similar results. For example, a univariate regression between the duration computed using the market swap rate as of the initiation date (duration) and the duration computed using the swap rate implied from the fair value (implied duration) has a statistically significant coefficient of 0.98 and an R-squared of 99.5% across the entire sample. I plot a comparison of the durations computed using the two approaches for all open interest rate swap positions in 2016 in Figure E.2.

Figure E.2: Duration Comparison



E.2. Interest Rate Options

Caps and Floors

Interest rate caps (floors) are a basket of European call (put) options on the Libor rate[61] (typically the 3 month Libor rate). Each call (put) option, also called a caplet (floorlet), has the same strike but a different expiration date. Thus, a cap or a floor is a basket of options, each on a different forward Libor rate, with different expiry dates and moneyness. For example, a five-year cap struck at 6% represents a portfolio of 19 separately exercisable caplets with quarterly maturities ranging from one-half to five years,[62] where each caplet has

[61] See, Longstaff, Santa-Clara, Schwartz (2001).

[62] Note that the very first period is excluded from the cap: this is because the current Libor fixing is already known and no optionality is left in that period.

a strike price of 6%. I evaluate the sensitivity of a portfolio of caps and floors by breaking them down into the constituent caplets and floorlets.

The cash flow associated with a caplet expiring at time T is $N\delta(max(0, L(\tau, T) - K)$ where $L(\tau, T)$ is the value at time τ of the Libor rate applicable from time τ to T, K is the strike price, δ is the year fraction,[63] and N is the notional amount. By convention, the cash flow on this caplet is received at time T and the Libor rate is determined at time τ. Similarly, the cash flow from a floorlet with expiration date T is $N\delta(max(0, K - L(\tau, T))$.

Black (1976) Valuation: Market prices for caps and floors are universally quoted relative to the Black (1976) model, which I use to value these rate options. Specifically, let $D(t, T)$ denote the value at time t of a discount bond maturing at time T, and let $F(t, \tau, T)$ denote the value at time t for the Libor forward rate applicable to the period from time τ to T. Since $L(\tau, T) = F(\tau, \tau, T)$, a caplet can be viewed as an option on an individual Libor forward rate. Applying the Black model (Brigo and Mercurio (2006)) to this forward rate implies that the time zero value of a caplet with expiration date T is given by:

$$C(0, \tau, T, F, K, \sigma) = D(0, T)\delta N[F(0, \tau, T)\Phi(d_1) - K\Phi(d_2)],$$

$$\text{where } d_1 = \frac{ln(F(0, \tau, T)/K) + (\sigma^2/2)\tau}{\sigma\sqrt{\tau}},$$

$$d_2 = d_1 - \sigma\sqrt{\tau}$$

$\sigma = \sigma(F(0, \tau, T))$ is the spot volatility, that is, the volatility of the forward rate applicable to the period from time τ to T.

Similarly, the value of the corresponding floorlet is:

$$FL(0, \tau, T, F, K, \sigma) = D(0, T)\delta N[K\Phi(-d_2) - F(0, \tau, T)\Phi(-d_1)].$$

Interest Rate Risk Exposures: I use option deltas to measure the sensitivity of the option value to its underlying rate. The delta of a caplet (floorlet) is the sensitivity of the price of the caplet with respect to the underlying forward rate:

$$\Delta_C = \frac{\partial C}{\partial F} = D(0, T)\delta N\Phi(d_1), \tag{E.8}$$

$$\Delta_{FL} = \frac{\partial FL}{\partial F} = D(0, T)\delta N(\Phi(d_1) - 1), \tag{E.9}$$

[63] The actual number of days during the period from τ to T divided by 360.

where $d_1 = \frac{ln(F(0,\tau,T)/K)+(\sigma_m^2/2)\tau}{\sigma_m\sqrt{\tau}}$ and σ_m is the implied volatility of the caplet and floorlet.

As a cap (floor) is a portfolio of caplets (floorlets), the price of a cap (floor) is the sum of the prices of the constituent caplets (floorlets), where each caplet (floorlet) is priced using the appropriate maturity forward rate (F_j) and its volatility (σ_j). Similarly, the delta of the cap (floor) is the sum of all the individual caplet (floorlet) deltas within the cap (floor).

Swaptions

A swaption gives its holder the right to enter a swap contract at a future date. There are two types of swaption contracts: (i) a receiver swaption gives its holder the right to receive fixed payments and pay Libor; (ii) a payer swaption is the option to enter a swap and pay a fixed rate and receive Libor. For example, let τ be the expiration date of the swaption, c be the coupon rate on the swap, and T be the final maturity date on the swap. The holder of this option has the right at time τ to enter into a swap with a remaining term of $T - \tau$, and receive the fixed annuity of c. Note that τ is the maturity of the option and $T - \tau$ is called the tenor of the underlying swap. Suppose that the swap rate for a $T - \tau$ year swap starting at time τ is $FSR(0, \tau, T)$, then the payoff from the swaption consists of a series of cash flows equal to $N\delta(max(0, c - FSR(0, \tau, T)))$. This cash flow is received $1/\delta$ times per year for the life of the swap. Thus, a swaption is a single option on the forward swap rate with repeated payoffs.

Black (1976) Valuation: The market convention is to quote prices in terms of the implied volatility relative to the Black (1976) model as applied to the forward swap rate. To illustrate, consider a τ by T European payer swaption where the fixed coupon rate equals c. Under the assumption that the forward swap rate follows a lognormal process, the Black model implies that the value of this payer swaption at time zero is

$$PS(0, \tau, T, FSR, c, \sigma) = \sum_{i=\tau+1}^{i=T} D(0, i)\delta N[FSR(0, \tau, T)\Phi(d_1) - c\Phi(d_2)],$$

$$d_1 = \frac{ln(FSR(0, \tau, T)/c) + (\sigma^2/2)\tau}{\sigma\sqrt{\tau}},$$

$$d_2 = d_1 - \sigma\sqrt{\tau},$$

where $\sigma = \sigma(FSR(0, \tau, T))$ is the volatility of the forward swap rate.

Interest Rate Risk Exposures: The delta of a swaption is the sensitivity of the price of the swaption with respect to the underlying forward swap rate. Thus, the delta of a payer swaption (Δ_{PS}) and receiver swaption (Δ_{RS}) are:

$$\Delta_{PS} = \frac{\partial PS}{\partial FSR} = A\delta N\Phi(d_1), \tag{E.10}$$

$$\Delta_{RS} = \frac{\partial RS}{\partial FSR} = A\delta N(\Phi(d_1) - 1), \tag{E.11}$$

where $A = \sum_{i=\tau+1}^{i=T} D(0,i)$.

To compute the durations, I construct the zero curve and forward curve by bootstrapping. For swaptions, I gather the forward swap rates at quarter ends for various combinations of expiry dates and swap tenors from Bloomberg. I linearly interpolate for expiries and tenors in between. In addition to the zero and forward curve, for rate derivatives I also require the term structure of implied volatilities. I download the Black *swaption volatility cube* from Bloomberg at quarter ends.[64] The cube provides implied volatilities for the following option expiries: 3 months, 6 months, 9 months, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 15, 20, 25, and 30 years; and swap tenors: 1, 2, 3, 4, 5, 7, 10, 12, 15, 20, 25, and 30 years. The volatility cube is available for various strikes. I choose the following strikes: 0.25%, 0.50%, 1.0%, 1.5%, 2.0%, 3.0%, 4.0%, 5.0%, 7.0%, and 10.0%. I linearly interpolate for the remaining expiries, strikes, and swap tenors.

To derive the caplet volatilities from the swaption volatility cube, I use the following equivalence. A payer swaption with a tenor of 3 months expiring in T years is the same as a caplet expiring in T years. A payer swaption with tenor of 3 months gives its holder the right to pay a fixed rate K in exchange for the prevailing Libor. As the swap has a maturity of only 3 months, it is the same as a caplet with strike K as only one payment is exchanged. However, since the swaption volatility cube does not directly provide implied volatilities for swaps with a tenor of 3 months, I linearly extrapolate using the 1 and 2 year points.

I impute the appropriate forward rate and implied volatility in equations (E.8) and (E.9) to get the caplet and floorlet deltas. Analogously, for example, the delta of a receiver (payer) swaption with an expiry of 1 year, an underlying swap life of 5 years, and a fixed rate of 3% is computed by looking up the appropriate implied volatility from the cube, $\sigma_{1,5,3\%}$ and $FSR_{0,1,5}$ and using them in equations (E.10) and (E.11).

Table E.1 shows the risk exposures of standard 10 year instruments computed for a hypothetical \$1 in notional value as of 2014:Q4. Long positions in interest rate floors had

[64] A swaption volatility cube object provides implied volatilities for the triplet of maturity (expiry), swap tenor, and strike. It is constructed from bootstrapped cap volatilities, ATM swaption implied volatilities and caplet and swaption smile models (Hagan and Konikov (2004)).

exposures of 8.2 (deep in-the-money), 3.36 (at-the-money), and 0.13 (deep out-of-the-money). Similarly, deep in-the-money receiver swaptions had an exposure of about 8.8. Thus, in-the-money contracts have similar exposures as swaps of comparable maturity, while at-the-money and out-of-the-money contracts have smaller exposures. Long positions in pay fixed swaps, interest rate caps and payer swaptions have similar exposure profiles but are exposed to interest rates in the opposite way as they decrease in value when rates fall.

Table E.1: Deltas of standard rate options as of 2014:Q4

Instrument / Strike	ATM	0.25%	10%
Caps	-5.64	-8.8	-0.78
Floors	3.36	0.13	8.20
Payer Swaption	-4.78	-8.8	-0.00
Receiver Swaption	4.22	0.00	8.8

To compute the interest rate exposures for rate options, I need the strike, maturity, trade direction, underlying rate for caps and floors and the underlying swap for swaptions.

Caps and Floors: As the majority of the interest rate caps and floors are written on the USD Libor, I therefore use the forward USD Libor curve as the underlying for the caps and floors which gives us $F(0, \tau, T)$, that is, the time zero forward rate between τ and T. Insurers report the maturity date of the cap and floor, thus I compute the remaining maturity as of the valuation date. This gives me the number of caplets and floorlets within each cap and floor. I assume quarterly settlement as is the convention for these instruments. The contract's direction, long or short, is directly reported.

50% of the interest rate caps (by notional amount) are corridor options, which I identify in the data by parsing the description of the option. In a corridor option, the buyer has a long position in a cap struck at a lower strike and a short position in a cap struck at a higher strike price. The notional value and maturities are identical. Insurers report both strike prices. I assume the higher strike to be the short position. All other caps are vanilla and a single strike is reported for them. Floors are typically vanilla products with a single strike reported for a contract. Collars are a portfolio of options with a long position in a cap and short position in a floor, where the cap is struck at a higher strike. The notional value and maturities are identical. Insurers report both strike prices. I assume the higher strike to be the long cap position.

Swaptions: To compute the exposures for swaptions, I need information on the swap tenor, whether the swap is receiver or payer, the option expiry, strike and the direction of the trade. Swaption positions have relatively more gaps compared to interest rate swaps, caps or floors. I next describe the gaps and assumptions made to clean this part of the data.

I classify contracts as receiver or payer by parsing the description string for keywords that describe the swap as pay fixed or floating. In addition, if the position is described as a call (put) option on a swap, then I classify it as receiver (payer), as is market convention. Roughly, 12% of cases (by notional amount) could not be classified as receiver or payer. The contract's direction, long or short, is directly reported. Similarly, the strike is directly reported.

I parse the description string for the swap tenor, e.g. by looking for keywords like "10YEARSWAP", "5YR", etc. For cases where the tenor is directly reported (44% by notional value), I use the difference between the reported remaining maturity and reported swap tenor as the option expiry. Whenever an insurer does not directly report the swap tenor (56% by notional value), I use the remaining maturity as the swap tenor and take the option expiry to be 0.25 years. For robustness, I also try various other combinations. For example, I assume all swaptions were written on a 5 year or 10 year swap and the difference between the assumed tenor and reported remaining maturity to be the option expiry as before. However, this does not alter the exposures materially.

I remove positions where the contract features necessary for computing exposures are missing. Table E.2 reports the starting and ending notional amount for each instrument across all years after all the steps described above were carried out. Roughly 8% of positions by gross notional values were removed due to missing contract characteristics. Interest rate exposures were computed on the remaining data. Figure 3 reports the total interest rate exposures for the insurance sector in the aggregate, which reveals an increase in hedging since 2009.

Table E.2: Interest Rate Derivatives Data

	Gross Notional ($ trillion)	
Instrument	Before	After (%)
Rate Swaps	27	25 (92%)
Rate Options	12	11 (91%)
Total	40	36 (92%)

F. Measuring Equity Risk Exposures From Derivatives

I first select equity risk hedging positions where the underlying is the S&P 500 index (SPX), which are 70% of all equity hedging positions by total notional value. The major instruments include calls, puts, and futures. I next select positions that are hedging VA guarantees. From 2010, insurers report which balance sheet item is being hedged by a position. I find that 80% of all put options and 90% of all futures contracts are earmarked as hedging VA guarantees, while the bulk of call options are earmarked for non-VA products, especially equity indexed contracts. I therefore select all put and futures contracts to assess the extent of equity risk hedging for VA guarantees.

I next compute the equity risk sensitivities (exposures) for these positions for a 10% change in the index. Futures have an exposure of either +1 (long) or -1 (short) position for a $1 change in the index. I compute the Black-Scholes deltas for put options for a $1 change in the index. Short futures and long put positions have negative exposures, that is, they gain in value when the index falls.

To compute the Black-Scholes deltas, I need the contract characteristics. I calculate the remaining maturity for each position as of the last trading date of each quarter (valuation dates). I parse the position descriptions to get the strikes. In the 2% of cases where the strike is unavailable, I assume that the options were struck at-the-money and imputed the index value as of the trade date. I obtain the index values on valuation dates to compute the moneyness of the positions. 85% of the contracts (by notional value) are vanilla instruments. The remaining contracts are exotic options, primarily barrier options, which I assume to be vanilla. I assume all contracts to be European as the SPX index option is a European style option. I obtain the implied volatilities on valuation dates from Bloomberg by matching the moneyness and remaining maturity of a position. I obtain the discount factors from the zero curves constructed earlier (Appendix E).

To compute the total exposures, I need the number of contracts for each position. For put options, the number of contracts are not well populated, but notional amounts are. However, notional amounts do not follow a consistent definition. For example, notional amounts for equity options are typically defined as the number of contracts $\times$ 100 $\times$ strike. However, a range of other definitions seem to exist in the data, e.g. number of contracts $\times$ 100; number of contracts $\times$ 100 $\times$ index value at initiation (or valuation); number of contracts $\times$ strike, etc. Moreover, reporting conventions vary from company to company.

To deal with this, I first compute the Black-Scholes price of a single put option given the contract characteristics provided. I then divide the reported fair value by the price of a single option to infer the number of contracts. I compare this with the notional value to determine whether it has been scaled by strike or the index value (as of initiation or valuation dates) and whether it has been scaled by 100 or not. If the notional amounts are scaled by strike or index values, I de-scale them. As each SPX contract has a multiplier of $100, the final number of contracts is the number of contracts × 100. I do this separately for every insurance group. After 2010, groups report notional amounts and the number of contracts in separate fields. Before 2010, companies chose to report only one of them, without specifying which, under one field. I follow the same methodology to circumvent this problem by using a combination of the reported number of contracts or notional amounts with fair values to obtain the right number of contracts.

Futures are more straightforward as the number of contracts are reported without any scaling. I apply the following multipliers: SPX futures have a multiplier of 250, E-mini S&P 500 futures have a multiplier of 50 and S&P 400 futures have a multiplier of 100. Thus, the final number of contracts is equal to the number of contracts × multiplier.

In the final step, to compute the total exposures, I multiply the exposure of each position by the number of contracts. Figure 4 reports the total equity exposures for the insurance sector in the aggregate, which reveals an increase in hedging since the crisis.