Why do life insurers use shadow insurance?

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ABSTRACT

This paper empirically investigates whether life insurers use shadow insurance to gain competitive advantages over their peers. Using a difference-in-difference approach and a panel-IV design, we measure the causal effect of life insurers ceding reinsurance to affiliated, unauthorized, and unrated *shadow insurers* after a regulatory change in the life insurance sector on firm outcomes. We find strong evidence that using shadow insurance results in less profitability, slightly improves ratings and risk-based capital ratios, and marginally increases market share. Our findings suggest that life insurers do not engage in shadow insurance activities to issue more policies and increase profits, but rather maintain better capital requirements and thus, improve ratings.

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1 Introduction

Insurers have strong incentives to manage capital efficiently, reduce costs and provide attractive prices for customers. In addition, insurers face pressure from minimum risk-based capital (RBC) requirements. Since capital provides a cushion to a company against insolvency, insurers are required to hold at least the theoretical amount of capital needed to absorb the risks of running a business, and will otherwise face various levels of regulatory intervention. Responding to the adoption of stricter capital requirements for life insurers by the National Association of Insurance Commissioners (NAIC) in the early 2000s, U.S. life insurers now engage heavily in non-traditional reinsurance transactions involving captive reinsurers. Relatively new captive laws introduced in some states allow life insurers to cede large parts of their liabilities to affiliated off-balance-sheet firms that are not subject to the strict reserve requirements and thus, provide life insurers with an effective way of managing their capital. However, the frequent use of these captive reinsurance agreements has been heavily discussed by regulators, managers, and academics alike, as a large fraction of these transactions are with affiliated but less regulated "shadow insurers". While captive reinsurance provides an efficient way for life insurer to manage capital and fulfill statutory capital requirements, it might also bear additional risks that stem from the lack of transparency associated with less regulated captives. Against this background, this study provides an empirical assessment of the reasons to use shadow insurance within life insurers' capital management and its effects on firm outcomes, ratings, and market shares.

Our main findings suggest that shadow insurance is not used to increase profitability but rather to maintain risk-based capital requirements. Compared to non-users of shadow insurance, the group of life insurers engaging in shadow insurance activities from 2002 to 2014 is significantly less profitable following the introduction of Regulation XXX/AXXX than their non-using counterparts. Nevertheless, ratings and market share of shadow insurance users remain substantially higher than those of non-users. Life insurers that engage in reinsurance with affiliated shadow insurers are usually larger, have a high level of RBC ratios, but are also more affected by the change in regulation as their business models relies more on term life insurance than, e.g., annuity products.

Since the implementation of Regulation XXX/AXXX in 2000/2003 by the NAIC, life insurers have to hold more statutory reserves on newly issued term life insurance and universal life insurance with secondary guarantees. Life insurers adapted to this policy and over the years made extensive use of captive reinsurance as a way to manage their capital more efficiently and also to reduce risk-based capital (RBC) through regulatory arbitrage. While these reinsurance arrangements allow life insurers to operate more smoothly with lower costs and insurance prices, they may also bear additional risks that have not been assessed to a satisfying degree. Reinsurance agreements of U.S. life insurers with affiliated (captive) reinsurers have drawn substantial attention of several parties in recent years. Most prominently, Koijen and Yogo (2016b) detect significant growth of reinsurance ceded to *affiliated*, *unauthorized*, and *unrated reinsurers*, which they classify as so called "shadow insurers". Estimating a structural model of the life insurance market they reveal that employing shadow insurance indeed reduces prices for life insurance policyholders. However, the use of shadow insurers as a vehicle for managing, possibly undesirable, liabilities is controversial. Koijen and Yogo (2016b) and Schwarcz (2015) also recognize shadow insurance as a potential threat to insurers and the financial system as it now makes up a large proportion of the reinsurance ceded by life insurers. For example, due to a lower degree of transparency of shadow insurers, these transactions may entail hidden risks that are, e.g., not reflected in the rating of the ceding company such as the funding structure and quality of shadow insurers.

In this study, we assess the consequences of using shadow reinsurance and engaging in shadow insurance activities for firm outcomes of life insurers. First, we analyze the incentives of life insurers to cede reinsurance to affiliated entities and provide empirical evidence for the risks and benefits of these transactions on firm outcomes. On the one hand, due to lower statutory reserve levels of the life insurer ceding to captives that report under the less strict Generally Accepted Accounting Principles (GAAP), life insurers are able to lower costs which is in the interest of its policyholders (see Harrington, 2014, 2015). On the other hand, the shifting of liabilities to affiliated off-balance-sheet entities may reduce risk-based capital demands of life insurers, but does not remove the risks associated with these liabilities from the overall insurance group. The fact that not all U.S. life insurers make use of captives and shadow insurance raises the concern whether there are drawbacks in these transactions that are not obvious. We first ask which life insurers were most affected by Regulation XXX/AXX and whether these insurers are more likely to use shadow insurance and question their incentives to use such agreements rather than traditional reinsurance. Next, we test whether the use of shadow insurance had a differential effect on the performance of life insurers. In further analyses, we analyze the effect of shadow insurance usage during the financial crisis as the use of shadow insurance could be both positively and negatively related with the firm outcomes during the crisis. Insurers engaging in such activities may have an advantage over non-users as they are able to move their risky liabilities to other entities. In reverse, using shadow insurance may backfire when the funding of the shadow insurers is not sustainable (e.g., banks do not renew short-term LOCs) and life insurers are no longer allowed to take reserve credits. Finally, we search for determinants of the differences among shadow insurance users and non-users.

Our sample consists of all life insurers reporting to the NAIC from 1997 to 2014. We identify whether reinsurance is ceded to affiliated entities and extract several characteristics of these transactions. First, we perform a difference-in-difference analysis around the change in regulation in 2000 in which we estimate the effect of Regulation XXX/AXXX on affected life insurers. Second, we run regressions of shadow insurance usage dummy variables on several firm characteristics. We further estimate regressions that involve alternative measures of shadow insurance usage such as the percentage of reinsurance ceded to the subset of affiliated, unauthorized, and unrated reinsurers as dependent variables. Third, we employ difference-in-difference and instrumental variable estimation procedures to investigate whether shadow insurance is a beneficial factor for the performance of life insurers as our main analysis. Fourth, we explore the role of shadow insurance during the financial crisis with panel regressions. Finally, we match users and non-users of shadow insurance based on several firm and insurer group characteristics to assess the differential effect of differences in several insurer characteristics on differences in profitability. Also, we investigate whether shadow insurance was a beneficial factor for the performance and financial strength of life insurers during the crisis by estimating additional panel regressions.

We contribute to the discussion on shadow insurance as a new form of regulatory arbitrage used by U.S. life insurers. Since the New York State Department of Financial Services (NYSDFS) initiated an investigation in July 2012 and published a report one year later, shadow insurance has been named "a little-known loophole that puts insurance policyholders and taxpayers at great risk" (see Lawsky, 2013). The most prominent study on shadow insurance is provided by Koijen and Yogo (2016b) in which the authors recognize its significant growth in the last decade and also estimate a structural model for life insurance policies that accounts for insurers ceding reinsurance to shadow insurers. Further, they conclude that the use of shadow insurance is not reflected in a life insurer's rating. In response, Harrington (2014, 2015) provides an overview of captive reinsurance agreements and argues that transparency has already improved due to new reported information provided since 2013 and thus, overall risk coming from shadow insurance transaction is limited. A comprehensive discussion on the different types of shadow insurance and potential risks involved in these activities is given in Schwarcz (2015). We complement these studies by analyzing the differential effect of using shadow insurance over other types of reinsurance on firm outcomes and thus, explore life insurers' motivation to engage in such activities.

Our paper is also related to studies on capital management in (life) insurance companies. One of the main motivators to use shadow insurance as part of capital management in a life insurer's operation is that it is costly to hold capital due to market frictions (see Froot et al., 1993; Froot and Stein, 1998; Harrington and Niehaus, 2003; Froot, 2008; Myers and Majluf, 1984, for several arguments). Nevertheless, life insurers might have different strategies when it comes to proper management of their capital. For example, Altuntas et al. (2015) show that the cross-section of capital structures of insurers differs substantially across countries. Differences occur because of differences in regulation, governments, or access to developed financial markets. Even on the national level the regulatory landscape may vary substantially, as the case of captive reinsurance in some states in the U.S. illustrates. However, in times of crisis, life insurers might decide to make changes to their usual capital management. This certainly happened during the recent financial crisis as life insurers had several strategies to deal with the adverse effects of distress in the financial system. Koijen and Yogo (2015) estimate the costs of selling long-term policies at a very high discount during the crisis to cope with shocks to their balance-sheets and to increase statutory capital. Their findings are complemented by Berry-Stölzle et al. (2014) who argue that U.S. life insurers were able to maintain their capital ratios through external issuance and dividend reductions.[1] The role of shadow insurance as a tool for efficient capital management during the crisis, however, is not sufficiently explored.

Finally, this study is motivated by recent work on systemic risk and regulation in the insurance sector. Parts of the literature deal with the determinants of common measures of exposure and contribution to systemic risk of insurance companies (see, e.g., Bierth et al., 2015; Mühlnickel and Weiß, 2015; Weiß and Mühlnickel, 2014). An overview and discussion of potential risks is given by, e.g., Cummins and Weiss (2014) or Schwarcz and Schwarcz (2015). Insurers can be systemically relevant if they are of such size and importance to distress large parts of the financial system. For example, Chiang and Niehaus (2015) document that life insurers tend to herd on their investments, as they are frequent buyers of the same corporate bonds and therefore play an important role in these markets. Furthermore, insurers face and pose potential systemic risks in case they are highly interconnected (see, e.g., Billio et al., 2012; Chen et al., 2014). We extend this growing strand of literature by investigating incentives, benefits, and risks of life insurers ceding reinsurance to less transparent shadow insurers that provide linkages to the banking sector as banks play a part in financing such vehicles.

The remainder of this article is structured as follows. We provide an overview of captive reinsurance and shadow insurance in Section 2. Section 3 describes the data and variables we use in this study. Empirical results are presented in Section 4 while Section 5 concludes.

[1] Niehaus (2016) also shows that life insurers decreased dividends during the crisis and documents internal capital injections within insurance groups.

2 Captive reinsurance and shadow insurers

While affiliated reinsurance has been used long before 2000, it is important to understand the setting that led to extensive usage of affiliated reinsurance over traditional reinsurance in the last decade. Therefore, we now give an overview of the changes in regulation of U.S. life insurers since 2000, the underlying mechanics of *captive reinsurance*, and discuss the risks and benefits of *shadow insurance* as well as the related literature.

REINSURANCE IN THE LIFE INSURANCE INDUSTRY

As an important risk management vehicle, reinsurance has broad implications for the solvency, earnings, and tax management of life insurance companies and directly impacts their economic value. The literature on reinsurance in the life insurance industry states that reinsurance improves the financial condition of the primary insurance company. Therefore, it is a particularly important mechanism as policyholders tend to have fixed long-term contractual claims which need protection against future financial mishap (see Adams, 1996). Mayers and Smith (1990) underline that reinsurance as a way of managing risks can help insurers to lower the expected costs of financial distress. Due to the long-term nature of the contracts and the specialized insurance policies that make up the liabilities of life insurers, agency incentive conflicts are accentuated in the life insurance industry (see Adams, 1995). Reinsurance, especially affiliated reinsurance, helps mitigate agency conflicts between owners and managers by combining the two parties. Powell and Sommer (2007) point out that approximately 80% of reinsurance activities occur within groups rather than with unaffiliated reinsurers. Regarding the demand for reinsurance in the life insurance industry, (see Adams, 1996) contends that life insurers tend to have higher demand for reinsurance when they approach the solvency constraints prescribed by internal actuarial rules or external regulations. The reasoning in Adiel (1996) is that reinsurance can not only reduce life insurers' liabilities (in the form of unearned premiums), but also increase their current earnings (via the receipt of reinsurance commission). As a result, regulatory intervention can be avoided. More recently, Kader et al. (2013) find evidence that life insurers with high underwriting risk increase their demand for reinsurance, while more financially sound life insurance firms have lower levels of reinsurance.

CAPTIVE REINSURANCE AGREEMENTS

An insurer's capital is given by the excess of its assets over liabilities. If liabilities are reduced, the life insurer is perceived as more solvent with higher capital. One way to reduce liabilities on insurers' balance-sheet is to cede reinsurance and in return receive reserve credit, which is relevant for the calculation of RBC requirements. Since 2000, when the NAIC proposed via

Regulation XXX/AXXX that life insurers are required to hold more statutory capital for a subset of their products[2], life insurers are looking for alternative ways than traditional reinsurance to reduce their liabilities and fulfill RBC requirements.[3] Traditional reinsurance may be more costly, e.g., because non-affiliated reinsurers are subject to statutory accounting principles as well. Instead, U.S. life insurers increasingly use captive reinsurance agreements for efficient capital management in order to reduce capital requirements as documented in Koijen and Yogo (2016b).[4] In return to paying premiums, the life insurer is allowed to assume reserve credit on reinsurance ceded, if it is collateralized either through (unconditional) letters of credit (LOC) or a trust fund (usually provided by a bank) (see NAIC, 2011).[5] Using, e.g., special purpose financial captives (see, e.g., NAIC, 2013) to manage capital is advantageous for the ceding life insurance company as the affiliated captives, e.g., report under the less strict U.S. GAAP.[6] However, these captive reinsurance agreements with affiliated entities do not alter the overall risks present in the ceding insurance firm. Further, they often lack transparency in their financial statements, which has been one of the main points raised by critics of these transactions (see Koijen and Yogo, 2016a,b; Schwarcz, 2015; Lawsky, 2013).

RISKS AND BENEFITS IN USING CAPTIVE REINSURANCE

Life insurers increasingly use captive reinsurance for lean capital management. Captive reinsurance is favorable for several reasons: First, it enables life insurers to operate at lower costs and eventually reduces prices for life insurance policyholders (see Koijen and Yogo, 2016b). Second, setting up captives in certain on-shore and off-shore locations often requires only little capital and may have a flexible funding structure, e.g., LOCs that count as collateral which is needed to authorize the reinsurance transaction (see NAIC, 2011, 2013) are used to cover the spread between statutory and economic reserves. However, funding via LOCs can cause a maturity mismatch as insurer liabilities are usually long-term in contrast to short-term LOCs, which have to be renewed frequently. Further, the low capitalization of captives does not provide huge buffers in case of distress.[7] Another concern about these transactions is a general lack of transparency of captives, which hampers accurate monitoring and risk assessment of the reinsurance agreements. Finally,

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[2]According to Stern (2014), statutory reserves under the requirement should equal the greater of the amount determined under "segmented valuation method" and the amount determined under "unitary valuation method". While prior to Regulation XXX, statutory reserves were determined only under unitary valuation method.

[3]A more detailed history of captive reinsurance agreements is given in Harrington (2014, 2015).

[4]The original function of captive insurers is to cover the risks of a non-insurer's corporate affiliates and parents (see Costle and Schauer, 2000).

[5]Another captive reinsurance agreement type includes *modified coinsurance*, in which the ceding life insurers receives credit in its required regulatory capital but its associated assets and liabilities remain on its balance sheet.

[6]Schwarcz (2015) provides an overview of the different types of captive reinsurance transaction.

[7]For example, $250,000 in capital are sufficient to set up a captive in the state of Vermont (see Koijen and Yogo, 2016a,b).

as reinsurance is ceded to affiliated captive reinsurer, the risks associated with liabilities remain within the insurance group.

SHADOW INSURANCE

Recent investigations have initiated a debate on the use of specific types of affiliated reinsurers, so called "shadow insurers" (see Lawsky, 2013). Affiliated reinsurers are independent firms that are within the company group and possibly owned by the parent company that have the purpose to assume reinsurance ceded by a firm within the group. These affiliated reinsurers can be either captives or non-captives[8]. Koijen and Yogo (2016b) define *shadow insurers* as *affiliated*, *unauthorized* reinsurers that have no A.M. Best rating. These shadow insurers are captives and non-captives that can be either located on-shore or off-shore. Shadow insurance is the reinsurance ceded to those shadow insurers.[9] For example, on-shore reinsurers (that may have a NAIC company code) can be viewed as shadow insurers if they are *affiliated* to the ceding company, are *unrated* by rating agencies, and are also *not authorized* to assume reinsurance from the ceding life insurer. However, if these reinsurers are captives, it is reasonable to define them as shadow insurers as they are not subject to the statutory reserve requirements and thus, can circumvent the XXX/AXXX reserve pressure. Since 2013, life insurers are required to report additional information on reinsurance ceded to (unauthorized) entities. Most importantly, it is now possible to identify whether life insurers use affiliated, unauthorized, *captive* reinsurance.[10] With the new information from 2013 and 2014 NAIC reports, it is possible to identify whether affiliated, unauthorized reinsurers are captives or non-captives.

RISKS OF SHADOW INSURANCE

One of the main points raised by critics of these shadow insurance transactions is the lack of transparency of the entities life insurers cede reinsurance to and thus, regulators and rating agencies are unable to assess the actual risk involved. Schwarcz (2015) distinguishes between four different types of risk stemming from shadow insurance arrangements: *reinsurance default risk*, *recapture risk*, *correlation risk* and *interconnectedness risk*. If a (captive) reinsurer is unable to meet its financial obligations, the ceding insurer has to follow through with paying its policyholders while coping with the unanticipated changes to its balance-sheet. While this risk is present with any reinsurance counterparty, it is certainly more pronounced for captives. These affiliated reinsurers have a higher insolvency risk due to few possibilities to diversify their risks and are, most of the

[8]For example, certain special purpose vehicles (SPV) are classified as shadow insurers (see Schwarcz, 2015).

[9]Reinsurance ceded is determined as the sum of *reserve credit taken* and *modified coinsurance* (see, e.g., Harrington, 2015; Koijen and Yogo, 2016b).

[10]In addition, information on the provided collateral, which is needed to allow the ceding insurance company to assume reserve credit, now has to be disclosed by all life insurers.

time, thinly capitalized. Further, the ceding insurer and its captive are more likely to have similar investment and risk management approaches (or risk profiles) as they are operated by the same set of managers. Thus, the correlation of life insurers' and captives' financial distress is higher than in usual reinsurance agreements. In such a scenario, it is very likely that the parent company is inclined to step in via a parental guarantee or capital injections if the captive is distressed, leading to higher correlation risk between the captive and the parent company as well.

When the funding of a captive dries up, e.g., when short-term LOCs are not renewed by corresponding banks, life insurers have to recapture the risks they shifted away from their balance-sheet. This will result in a significant drop in risk-based capital and financial ratings, and will eventually impact policyholders in the form of higher prices, as estimated by the model of Koijen and Yogo (2016b). Finally, the insurance sector becomes more connected to the banking sector, e.g., via the issue of LOCs as collateral and to secure funding for captives. Banks are directly exposed to risks stemming from the insurance sector as they are now partially tied to shadow insurers. In 2012, about one third of the shadow insurance amount was collateralized by LOCs which translates into approximately \$100 billion, which is a non-negligible amount that can threaten financial stability when insurers systematically default on their obligations (see Schwarcz, 2015).

SHADOW INSURANCE AND RATING

According to Koijen and Yogo (2016b), captive reinsurance arrangements follow inadequate regulatory oversight and scrutiny by insurance rating agencies, and thereby substantially understate life insurers' insolvency risk. However, a contrary view is taken by Harrington (2014) who states that using captive reinsurance is an important tool for efficiently managing capital and shrink the gap between statutory and economic reserves, which are closely monitored by regulators and rating agencies. Financial ratings are based on the likelihood of insurers' financial difficulties, including the likelihood that the insurer will become subject to regulatory "impairment" and regulatory action. Reports by A.M. Best suggest that the evolution of XXX solutions and its impact on ceding insurers' capital strength, with consideration of transactions that could result in sending reserves back to the parent company, has been monitored closely (see A.M. BEST, 2006). According to A.M. BEST (2013), ratings and risk-based capital fully reflect the risk of shadow insurance. The report in A.M. BEST (2013) concludes that "A.M. Best's rating process entails a full understanding of insurance companies' use of U.S. and offshore captives, and incorporates through both quantitative and qualitative assessments- how the captive impacts an issuing insurance group's balance sheet strength." As to this point, there is no clear consensus in the literature on the relation of the use of shadow insurance and life insurers' rating.

3 Data and variables

In this section, we describe our sample construction, the choice of variables used in this study, and provide descriptive statistics on our data.

Sample construction

We start building our sample of life insurers by employing all life insurers that report to the NAIC between the year 1997 and 2014. We retrieve company level data from the annual NAIC financial statements.[11] The important data on reinsurance ceded to affiliated and unaffiliated entities are retrieved from the NAIC Life annual statement Schedule S part 3 and part 4 (see Koijen and Yogo, 2016a,b).[12] Additionally, we merge our sample with Best Key Rating Guide provided by A.M. Best Company to obtain rating data. We then apply several filters to our initial data sample. First, we exclude from our sample all firms without any affiliated members. Firm-year observations with negative total assets, negative liabilities, negative surplus, or negative premiums written are deleted to eliminate reporting errors. Further, we drop all observations that have a ratio of premiums ceded to total premiums written above one or below zero in any given year. We include only companies with total assets greater than $1 million to remove potential outliers.[13] The final sample includes 11,490 firm-year observations from 1997 to 2014.

We now introduce the most important variables used in our empirical analysis, which include general firm characteristics, variables on shadow insurance, and features specific to the groups life insurers are affiliated with. In Table 1, we present simple summary statistics on most of our variables.

[Insert Table 1 about here.]

We report descriptive statistics for the full sample and for the subsamples of shadow insurance users and non-users. For the latter two subsamples, we perform two-sided t-tests on equality of the means of each sample for all variables.

Measures of shadow insurance

In this study, reinsurance ceded is defined as the sum of reserve credit taken and modified coinsurance reserve. Life insurers may take reserve credits when they reinsure their risks, which they may

[11] Specifically, we also use the parts Five-Year Historical Data, Summary of Operations, Liabilities, Surplus and Other Funds, among others.

[12] Note that we include data from general and separate accounts.

[13] In addition, all variables are later winsorized at the 1st and 99th percentiles to reduce the impact of outliers.

do by ceding reinsurance to affiliated entities. As long as sufficient collateral is provided, even if it is an unauthorized reinsurer in a given state or other domicile, the life insurer may take reserve credit and reduce balance-sheet liabilities (see, e.g., NAIC, 2011). Another important option for the ceding insurer to back its unauthorized reinsurance is to structure the reinsurance transaction with funds withheld or modified coinsurance. In the latter case, the ceding insurer retains control of its assets and the liabilities remain on its balance-sheet (see, e.g., Schwarcz, 2015). We follow Koijen and Yogo (2016a,b) and define shadow insurers as *affiliated*, *unauthorized*, and *unrated* reinsurers. Using this definition, we create two different variables that proxy for the use of shadow insurance. The first main variable of interest is an indicator coded as one if a life insurer cedes reinsurance to shadow insurers in a given year and zero otherwise. There are about 13.4% of life insurers being marked as a shadow insurance user (2002-2014). The second proxy is the fraction of shadow insurance ceded by a life insurer to its total reinsurance ceded. On average, life insurers cede 7% of total reinsurance to shadow insurers.

Life insurer characteristics

PROFITABILITY

In this study, we employ four different measures of (insurance) firm profitability: return on assets (ROA), return on equity (ROE), and underwriting return on assets and equity (UW ROA/UW ROE). Descriptive statistics in Table 1 reveal that values of ROA range from -21% to +25%, while ROE is between -87% and +67%. The two measures of underwriting profit are mostly negative with mean values of -3.1% and -32.8% within the full sample, respectively. When we compare ROA of shadow insurance users and non-users we see that the latter subsample has a mean value almost three times higher than shadow insurance users (1.8% compared to 0.63%). The mean value of ROE is higher for non-users as well. In order to compare profitability of the two subsamples over time, we calculate mean values of profitability measures for each year from 1997 to 2014. For this purpose, we assign a life insurer to the "shadow insurance users group" if it engages in any shadow insurance activities in 2002-2014. "Non-users" are those life insurers that do not engage in any shadow insurance transactions in this time period. The respective plot of the time evolution of mean values is shown in Figure 1.

[Insert Figure 1 about here.]

In every year, we can observe that ROA is significantly lower for life insurers that cede reinsurance to shadow insurers than for those who do not engage in shadow insurance activities. The spread of users' versus non-users' ROA widens after 2000 and is extremely high in 2008, where shadow insurance users experienced a negative mean ROA. In general, ROA and ROE were lowest in 2009.

For life insurers' ROE, we find a mixed picture and no clear pattern, but notice that ROE is slightly higher for shadow insurance users in most years after 2008.

Turning to the two underwriting profit measures, we observe that both are, on average, always negative. Mean values of underwriting ROAs are about the same before 2000, but diverge after the introduction of Regulation XXX/AXXX in 2000/2003. The average value of the two groups converge to about the same in 2009 and the years following. Underwriting ROE is always lower for shadow insurance users (by about 20%). The spread is even wider in the crisis years 2007 and 2008. Only for the year 2009, we find that mean values are similar and also differ less afterwards.

RATING, RISK-BASED CAPITAL, AND MARKET SHARE

A.M. Best ratings are broadly grouped into two categories, "secure" or "vulnerable". Ratings between A++ and B+ are considered as "secure" whereas all ratings below B+ are considered "vulnerable". In order to assign numerical values to ratings, we create a cardinal measure of a life insurer's financial health rating by converting the A.B. Best Rating category according to the BCAR guidelines (see A.M. BEST, 2015). The cardinal rating measure ranges from 0% to 175%, whereas 175% represents the highest rating and 0% is the lowest rating or indicates an unrated status. In our sample, insurers' ratings range from A++ to F, and others without any rating have been marked as unrated. The mean value of rating in the sample is 104%, corresponding to a rating of B. Shadow insurance users and non-users have an average rating of A- (133.7%) and B (100.7%), respectively.

Risk-based capital (RBC) serves as a regulatory measure of a firm's financial strength and is often presented as a RBC ratio. A higher RBC ratio suggests that the insurer maintains sufficient capital relative to the amount required by regulators. Our variable RBC ratio is defined as the ratio of total adjusted capital to company action level risk-based capital. The mean RBC ratio in our sample is 24.5, with a minimum RBC ratio of 0.85 and a maximum of over 900. Users of shadow insurance, on average, have a significantly lower RBC ratio than non-users. This result, however, has to be taken with caution as the subsample observations of RBC ratios may contain some significant outliers, even after winsorization.

In Figure 2, we show the time evolution of mean values of rating, RBC ratios, and market share for the "group of shadow insurance users and non-users" (as defined above).

[Insert Figure 2 about here.]

Obviously, ratings are substantially higher for shadow insurance users throughout the whole time period from 1997 to 2014. Users' average ratings range from about 120% to 140% (B++ to A) while non-users' cardinal rating is around 100% (B). Rating in both subsamples is lowest in 2004-2006, but otherwise relatively constant over time.

Although supposed to be a major determinant of ratings, life insurers' mean RBC ratios are much lower for the group of shadow insurance users. The magnitude of RBC ratios in both samples is very high, as there are several large outliers in the sample, as indicated by the descriptive statistics above. Nevertheless, we observe that RBC ratios increased in both samples after the introduction of stricter regulation in 2000 and fell immensely after 2003 for shadow insurance users. Over the long run, RBC ratios of non-users decreased as well, but not as rapid as for users. Interestingly, mean RBC ratios are similar for both groups in 2012.

Market share of shadow insurance users is around 40% in 1997 and increases until 2001, where it is at its peak with over 50% of term life insurance market share. Over time, the market share of this subsample is relatively stable but has been slowly decreasing to a little above 40% again in 2012.

CONTROL VARIABLES

We employ several proxies that account for the size, leverage, or business structure of a life insurance firm. For example, we employ the natural logarithm of total assets and total liabilities. In terms of total assets, the size of a life insurer ranges from one million to over one-hundred billion dollars. Shadow insurance users are, on average, more than five times larger than non-users.

Leverage is the ratio of a life insurer's total debt over its total assets and is relatively high with 66.5% for the full sample. However, those life insurer observations for leverage ratios that are associated with shadow insurance users are much higher with a mean value of 84.1%. Our measure of liquidity is the ratio of current assets to total liabilities, which is, on average, twice as high for non-users. The same holds for life insurers' surplus ratio, which is is surplus divided by total assets.

Another important variable we employ is the term life insurance ratio, which we calculate as the term life insurance in force divided by total insurance in force. Term life insurance was most affected by the changes in regulation and thus, we suspect that life insurers with a higher term life insurance ratios have strong motives to use shadow insurance as part of their capital management, or alternatively change their business model. As we can see from the descriptive statistics, this variable has a mean value of almost 50% for shadow insurance users, but only made a little less than 30% of non-users' business strategy.

Insurer group characteristics

GROUP PROFITABILITY AND RBC RATIOS

For the purpose of comparison to individual life insurers, we report an insurer's group's return on assets, return on equity, and RBC ratio. Insurer groups of shadow insurance users have a lower

RBC ratios and are substantially less profitable. The magnitude of these differences is comparable to the findings on individual life insurers.

GROUP LIABILITIES, AFFILIATES, LEVERAGE

A life insurer's group size is measured as the natural logarithm of the group's total liabilities. Since the size of group members is not consistent within groups, we measure insurers' relative size within their group by using the ratio of a firm's total assets to the total assets of the group (company-to-group size). For example, the company to group size ratio ranges from less than 1% to almost 100%, with an average of 40.5%. Looking at group leverage ratios, we observe that insurance groups of shadow insurance users were more levered than their non-user counterpart groups, but the difference between the two is not as striking.

The number of group members can have impacts on the supply of affiliated reinsurance within a group, and therefore affect the demand for affiliated reinsurance. The variable used to control for these effects is the natural logarithm of the number of affiliates in an insurer's group. The average number of affiliates within a group is 4.7, but is around 6.5 for shadow insurance users.

4 Empirical results

In this section, we present the results of various multivariate analyses on the effects of using shadow insurance on a life insurer's business.

4.1 Did Regulation XXX/AXXX affect life insurers?

The introduction of Regulation XXX in 2000 was a shock to the term life insurance business. Thus, life insurers that are heavily engaged in this line of business (compared to, e.g., annuities) should be more concerned about the higher statutory reserve requirements. We would expect that "affected" insurers issue less policies and are less profitable than their competitors as it is more expensive to underwrite term (and universal) life insurance policies. As a consequence, affected life insurers would be more likely to engage in shadow insurance activities to escape the tightened regulatory capital requirements.

We want to measure the impact of Regulation XXX/AXXX on life insurers' (underwriting) profitability and other variables on affected versus unaffected life insurers. To do so, we employ a difference-in-difference approach with *affected* life insurers as our treatment group and *unaffected* insurers as control group. We define "affected" life insurers as those insurance companies that underwrite a substantial fraction of their policies in term life insurance. As it is not clear, which threshold for this fraction is most appropriate for our definition, we propose several definitions for being affected by Regulation XXX. We employ the ratio of the face value of term life insurance in force over total insurance in force and create a dummy variable "AFFECTED" that is one if the term life insurance ratio is above 25%, 33% (one third), 50%, or 75% in the year 1999, right before the change in regulation. In order for the difference-in-difference approach to be valid, we need our treatment group to remain the same over the chosen time period. It is possible that life insurers change their business strategy and move away from underwriting term life insurance. However, this is not the case in our sample. In Figure 3, we show the time evolution of the mean term life insurance ratios of affected and unaffected life insurers (according to the respective definition).

[Insert Figure 3 about here.]

By definition, the term life insurance ratios of affected life insurers are substantially higher than their unaffected counterparts. However, we also observe that the unaffected life insurers exhibit a term life insurance ratio below 20% almost all the time, regardless of the definition chosen for this group. Thus, term life insurance either plays a significant role in a life insurance company, with ratios above 50%, or it is a rather small part of the insurer's underwriting business. Finally, we see that the definitions of the treatment and control group are consistent over the whole time period.

Our sample period for the difference-in-difference analysis runs from 1997 to 2003. In Figure 1, we compare different measures of profitability for this time period.

[Insert Figure 4 about here.]

In general, unaffected insurers have higher profitability than affected insurers, who write more than 25% of their business in term life insurance. We also observe a similar trend in profitability for both groups of insurers, except for the year when Regulation XXX was introduced. In year 2000, affected insurers exhibit a decrease in mean values of both ROA and ROE while unaffected insurers experience a slight increase in ROA and have a constant ROE. Regarding underwriting ROA and underwriting ROE, we can see no sudden impact but rather a slight increase for both groups in this two profitability measures around 2000. Thus, Regulation XXX in 2000 serves as a shock to the profitability of term life insurance underwriters, but most likely not through the channel of underwriting performance.
To quantify the effect of Regulation XXX on several characteristics of life insurers, we run OLS regressions of the following form:

$$\mathrm{Y}_{i,t} = \alpha_i + \mu_t + \beta \cdot \mathrm{AFFECTED}_i + \gamma \cdot (\mathrm{AFFECTED}_i \times \text{POST-XXX}_t) + \varepsilon_{i,t}. \tag{1}$$

The variable POST-XXX$_t$ is one in the years 2000 to 2003 and is interacted with our treatment group dummy variable AFFECTED$_i$. The dependent variable is either one of the four profitability measures – return on assets (ROA), return on equity (ROE), underwriting ROA and underwriting ROE – or an insurer's rating, RBC ratio, or market share.

One concern about this empirical setup is that some of the life insurers were using shadow insurance beginning in 2002 and 2003 and thus, could have a higher profitability because of this comparative advantage. However, empirical evidence in Koijen and Yogo (2016a,b) suggests that shadow insurance was ceded extensively only after 2003 and was only sparsely used in 2002 and 2003. We therefore believe that our difference-and-difference analysis setup is reasonable. The estimated coefficient of the interaction term (difference-in-difference term) γ reveals the influence of Regulation XXX/AXXX on (underwriting) profitability of affected life insurers. If insurers that are mostly engaged in the term life insurance business are negatively affected by the stricter regulation, we expect γ to be significantly different from zero with a negative sign. In other words, if the change in the regulatory environment had significant adverse effects on some of the life insurance companies, these firms are more inclined to set up captives or special purpose vehicles to circumvent the new restrictions.

We report the results of our DID analyses in Table 2 and 3.

[Insert Table 2 and 3 about here.]

The results from Table 2 show that Regulation XXX in 2000 is associated with a decrease in profitability for life insurers with substantial business in term life insurance. We use four different versions of our *AFFECTED* variable, based on different levels of term life business ratio, and thus generate four interaction (DID) terms. For each interaction term, we run regressions with all measures of profitability as dependent variable. In particular, when measuring profitability with ROA, the coefficients of all interaction terms are negative, and three of them are statistically significant. Also, coefficients of interaction terms for Underwriting ROA model are negative, with significance presented in two of them - *AFFECTED* (33%) and *AFFECTED* (50%). As to the ROE and Underwriting ROE regressions, the signs of effects from Regulation XXX are mixed, although there is no significance for any of the DID terms.

In addition to profitability, we use a DID analysis to examine how life insurers' rating, risk-based capital ratio, and market share react to the regulation change in 2000. From Table 3, we can see that the introduction of Regulation XXX enhances the financial rating of life insurers. Coefficients of interaction (DID) terms are positive and statistically significant in the rating regression. However, all of the interaction terms in RBC ratio regression have negative and significant coefficients, reflecting the burden of excess reserve introduced by the new regulation on insurers' term life business. We also observe that for life insurers with more than 75% of their policies written in term life insurance, the new regulation adds negative effect to their market share.

Overall, we infer that the stricter regulation introduced in 2000 had a weakening effect on life insurers that underwrite a substantial amount of risks in term life insurance market. Also, a boost in financial ratings is present. As a consequence, life insurers have more incentive to engage in shadow insurance activities, alleviating the pressure from tightened regulatory reserve requirements and seeking an effective way to manage capital.

4.2 Which life insurers use shadow insurance?

Our findings so far suggest that the tighter statutory reserve requirements affected some life insurers more than others. Therefore, some life insurers have a strong incentive to bypass this new regulation, possibly by engaging in regulatory arbitrage via shadow insurance transactions. As our next step, we therefore investigate which life insurers are most likely to engage in shadow insurance. There are several factors that explain which life insurers cede reinsurance to less transparent shadow insurers. Shadow insurance is mostly used by the large insurance groups rather than the smaller and medium sized insurers (see Harrington, 2014, 2015; Koijen and Yogo, 2016b, for empirical evidence). This is intuitive, as smaller life insurers only collect a small fraction of premiums in the insurance market to make such a transaction worthwhile. However, medium sized insurers might be able to use it but refuse to do so. Similar arguments may hold for life insurers with already high capital ratios. Insurers with higher RBC ratios have a cushion against the potential adverse effects of shadow insurance, while taking benefits from such reinsurance arrangements. Life insurers that have a low RBC ratio are possibly more reluctant to implement shadow insurance agreements in their capital management, as they are already under pressure from regulatory oversight. Additionally, private rating agencies rely heavily on proprietary capital models that overlap with the formulas that produce state RBC ratios (see Pottier and Sommer, 1997). For insurers with more competitive financial ratings, the benefits of using shadow insurance may outweigh the potential risks arriving from such arrangements. Thus, we test the following hypotheses:

Hypothesis 1: Insurers with higher RBC ratio are more likely to use shadow insurance.
Hypothesis 2: Insurers with higher financial rating are more likely to use shadow insurance.

Insurers' mean RBC ratio presented in Figure 2 shows that average RBC ratio for companies using shadow insurance is substantially lower than the ratio of companies not using shadow insurance. As we have discussed, shadow insurance is considered as an efficient tool for capital management, it is intuitively to hypothesize that companies with less capital sufficiency are more eager to gain benefits of capital management from using shadow insurance. Since such arrangements provide an efficient tool for ceding insurers to meet rating agency criteria at lower cost than without (see Harrington, 2015), insurers with a relatively lower financial rating might seek a way to raise their rating and attract customers who willing to pay higher prices to be insured by companies with higher quality (e.g., higher rating). We arrive at the following two (alternative) hypotheses:

Hypothesis 1(a): Insurers with lower RBC ratio are more willing to use shadow insurance.
Hypothesis 2(a): Insurers with lower financial rating are more likely to use shadow insurance.

LOGIT AND TOBIT REGRESSIONS

We test the relation of several firm characteristics and the likelihood of a life insurer to cede reinsurance to shadow insurers by estimating logistic regressions. Explanatory variables include several firm characteristics in 1999 or 2001. We run separate regressions of shadow insurance usage on RBC ratios and ratings, as these two variables may be simultaneously determined. When estimating the logistic regressions, we also include fixed effects based on the financial size category provided by A.M Best.

Since we have a large sample of life insurers that report to the NAIC, most of the firms do not engage in shadow insurance activities. Therefore, our dependent variable used is zero for more than one half of all observations. Thus, we further estimate a tobit model with a continuous shadow insurance variable, the result of which is shown in column (10) of Table 4. In this way, we also determine the characteristics of insurers having a larger proportion of shadow insurance in their reinsurance portfolio.

Table 4 presents the results of logistic regressions and tobit regressions.

[Insert Table 4 about here.]

We first compare the incentives for using shadow insurance just before and after the introduction of Regulation XXX, by running logistic regressions for the years 1999 and 2001 respectively. For both years, RBC ratio provides strong incentive for life insurers to engage in shadow insurance activities. As presented in the table, life insurers with one units increase in RBC ratio are 0.5-0.6% more likely to be involved in shadow transactions. Coefficients of rating are positive across all models, with some significance in year 1999, indicating a positive relation between insurers' financial rating and their willingness to cede shadow reinsurance. Thus, results from logistic regressions support our hypotheses that higher RBC ratio and higher financial ratings provide life insurers stronger incentive to cede shadow reinsurance.

Since shadow insurance is extensively used since 2002, we further implement logistic regression and Tobit regression to examine the use of shadow insurance from 2002 to 2014, with an indicator for insurers that have ever engaged in shadow business during 2002 to 2014 as our dependent variable. Other firm characteristics provide some explanations for the use of shadow insurance as well. For the whole sample period, term life insurance ratio to a large extent encourages the use of shadow insuranceone percentage increase in insurers' term life insurance ratio is associated with 0.9-1% higher probability of using shadow insurance. Firms with higher leverage, lower return on equity, larger size, or more affiliated group members are more likely to be involved in such transactions.

4.3 Does shadow insurance provide a competitive advantage?

Do life insurers that cede reinsurance to shadow insurers have a competitive advantage over their peers? By ceding reinsurance to shadow insurers, life insurance companies are able to reduce marginal costs and are theoretically able to issue more policies or take on more underwriting risks. Increasing underwriting profits is a strong and intuitive incentive for a life insurers to use shadow insurance as part of their capital management. Further, life insurers want to display strong financial health ratings, which is another motive to cede to shadow insurers (under the assumption that shadow insurance transactions are not properly reflected by current ratings as suggested in Koijen and Yogo (2016b)). It is reasonable to suspect that shadow insurance should provide a competitive advantage for those life insurers engaging in it. On the other hand, using shadow insurance might have a negative effect on life insurers' profitability, as it is associated with additional maintenance costs within the insurance group. Buying reinsurance from outside of the company could be more efficient in some cases. Further, since transparency is low and risks are possibly not properly quantified, investors and policyholders could punish life insurers for using shadow insurance. We test these hypotheses using a difference-in-difference approach and regressions involving instrumental variables to establish causality.

4.3.1 Difference-in-difference analysis

In order to quantify the effect of shadow insurance usage on life insurers' performance, we employ the change in regulation in 2000 as an exogenous event affecting the U.S. life insurance sector. A difference-in-difference analysis then yields the effect of this change on two groups of life insurers: those that engage in shadow insurance activities (treatment group) and those who decide not to do so (control group). Using difference-in-difference analysis is a common approach to capture the effect of regulatory interventions on firm outcomes of differently affected groups.

Our treatment group are life insurers that use shadow insurance in 2002-2014 in at least one year and the control group do not engage in shadow insurance activities at all. TREAT_i is a dummy variable that indicates whether a life insurer belongs to the treatment group (one) or control group (zero). This definition of the treatment group is chosen so that the composition of treatment and control group remains the same over time (see, e.g., Balsmeier et al., 2016, for a similar approach). Some of the life insurers start to use shadow insurance only after a couple of years from 2002, which is a problem when defining the treatment group for such a long time period. However, we observe that most of the shadow insurance users engage in these activities for a longer period of time so that our definition of the treatment group is still reasonable.

The important independent variable in our DID regressions is the interaction of the treatment dummy and a time dummy that is one after the introduction of Regulation XXX/AXXX. Since we have two regulatory changes, one in 2000 (XXX) and the other in 2003 (AXXX), we include both interaction terms in OLS panel regressions of the following type:

$$\begin{aligned}\text{Y}_{i,t} &= \alpha_i + \mu_t + \beta \cdot \text{TREAT}_i + \gamma \cdot (\text{TREAT}_i \times \text{POST-XXX}_t) \\ &\quad + \delta \cdot (\text{TREAT}_i \times \text{POST-AXXX}_t) + \varepsilon_{i,t},\end{aligned}$$

where $\text{Y}_{i,t}$ is either an insurer's (underwriting) profitability, rating, RBC ratios, or market share. Results of these difference-in-difference regressions with fixed effects and year dummies are shown in Table 5.

[Insert Table 5 about here.]

Columns with odd numbers report regression results using the interaction of the treatment group dummy with the time dummy that is one after 2000 and columns with even numbers report estimates where both interaction terms are employed in the regressions. The most striking result is that the first interaction term is highly significant with a negative sign in all regressions involving profitability as dependent variable. Shadow insurance users experienced less profits after Regulation XXX/AXXX. On average, shadow insurance users had a 0.5-0.8% lower ROA and 3.6-4.5% lower ROE. The combined negative effect of both regulatory events in 2000 and 2003 is about -1% on ROA, which is also statistically significant on the 10% level. A similar picture can be seen when using underwriting ROA/ROE as dependent variable. The cumulative impact of both events on shadow insurance users' underwriting ROA is -2%, compared to non-users.

Turning to the other dependent variables, we observe that shadow insurance users gained more market share in term life insurance than non-users after Regulation XXX/AXXX, which is highly statistically significant. The additional effect of the regulatory update in 2003 also has a positive effect on market share of shadow insurance users, but is not relevant at conventional statistical significance levels (p-value of 13.2%). For the relation of shadow insurance usage and life insurers' financial strength rating, we find no statistical significance. However, shadow insurance usage is positively related to RBC ratios, a major determinant of ratings, but is only statistically significant on the 10% level. Thus, we find some evidence that shadow insurance is increasingly used after Regulation XXX/AXXX to maintain better RBC ratios. This result, however, has to be taken with caution as the RBC ratio observations include some outliers, an issue we address in later analyses.

We now briefly comment on the coefficient estimates of our control variables. Larger life insurers and insurers within a larger insurance group are generally more profitable. Liquidity is significantly negatively related to (underwriting) profits and rating, while a higher proportion of surplus has a positive effect on these outcome variables. This could be due to the fact that the more cash and other short-term assets a life insurer holds, the less it invests in long-term and high-yield assets and thus, reduces profitability. Extremely levered life insurers generally have lower profits and also substantially lower RBC ratios. Company to group size is only relevant for market share, e.g., flagship companies within an insurance group also have a higher (term life insurance) market share. The number of affiliates within an insurer's company group does not seem to impact any of the firm outcomes.

4.3.2 Panel-IV design

We want to quantify the effect of shadow insurance usage on life insurers' profitability and other firm outcomes. Shadow insurance usage, however, might be endogenous to those variables, e.g., due to reversed causality.[14] Therefore, to address these issues, we construct a panel-IV identification strategy in the spirit of, e.g., Azar et al. (2015). We employ both discrete and continuous instrumental variables to instrument our shadow insurance usage dummy variable and the ratio of shadow insurance to total reinsurance ceded as these are the two, discrete and continuous, main variables of interest, respectively.

Discrete treatment

When relating life insurer ratings and shadow insurance, Koijen and Yogo (2016b) instrument a shadow insurance dummy with the market share in the term life insurance market in 1999 (interacted with a stock dummy). The disadvantage of using this approach is that subsequent regressions can only be performed as pooled (OLS) regressions with year dummies to account for time variation in the data, but not using, e.g., fixed effects. However, to construct a panel-IV strategy, we pick up the idea of using a life insurer's term life insurance market share in 1999, as it is exogenous to outcomes in 2002 and after. Similar to Azar et al. (2015), we define a variable POST-2001$_t$ to be one in years after 2001 and zero otherwise. This specific time-dummy is then interacted with another binary variable that splits our life insurer sample into two subsamples. The dummy TREAT$_i$ is one for life insurers that are in the top tercile of insurers' respective term life insurance market share in 1999 and zero for observations in the bottom tercile.[15] As our main independent variable of interest, we use a shadow insurance usage dummy variable, which we instrument with the discrete interaction term TREAT$_i$ $\times$ POST-2001$_t$ in the first stage regressions.[16] We also include year dummies and our usual control variables in the first stage model and thus, estimate the following regression model:

$$\text{SHADOW}_{i,t} = \beta \cdot (\text{TREAT}_i \times \text{POST-2001}_t) + \Theta \cdot \text{CONTROLS}_{i,t} + \mu_t + u_{i,t}, \qquad (2)$$

A larger presence in the term life insurance market incentivizes life insurers to maintain that status by possibly engaging in shadow insurance. We therefore expect that our instrumental variable is significantly positively related to shadow insurance usage.[17]

[14] Unprofitable life insurers decide to cede reinsurance to shadow insurers to increase their profitability again.

[15] Observations in the second tercile are removed for the discrete treatment approach.

[16] In a robustness check, we also employ the actual value of the term life insurance market share as a continuous treatment. The continuous approach might yield more variation in the instrument, but the binary instrument provides us with a clear picture and is less prone to measurement errors (see Azar et al., 2015). The results we find are very similar to the ones obtained from the discrete treatment.

[17] As an additional instrumental variable, we follow Koijen and Yogo (2016b) and employ a life insurer's market share in term life insurance in 1999 interacted with a stock dummy in the first stage of the regression above. We run OLS regressions with year dummies and fixed effects based on the financial size ratings and obtain similar results.

Continuous treatment

Major shadow insurance activities began in 2002 and the frequency of ceding reinsurance to shadow insurers has been increasing over the last decade. One reason to use shadow insurance for capital management in life insurance firms is to circumvent the high standards of new regulatory requirements and thus, increase risk-based capital ratios by reducing the amount of risk-based capital needed. Koijen and Yogo (2016a,b) point out that *if* risk-based capital and leverage ratios *were adjusted for shadow insurance*, the overall probability of default for shadow insurance users would increase dramatically. Therefore, reducing risk-based capital is a strong incentive to use shadow insurance.

We adjust risk-based capital ratios in 2001 by pretending that shadow insurance transactions were available to insurers before 2002. The adjusted RBC ratios are calculated in the following way:

$$\widehat{\mathrm{RBC}}_{i,t,2001} := \mathrm{RBC}_{i,2001} \times \frac{\mathrm{L}_{i,2001}}{\mathrm{L}_{i,2001} + \widehat{\mathrm{L}}_t}, \tag{3}$$

where $\mathrm{RBC}_{i,2001}$ is an insurer's actual RBC (ratio) in 2001, $\mathrm{L}_{i,2001}$ is a life insurer's total liabilities in 2001 and $\widehat{\mathrm{L}}_t$ is the amount of shadow insurance (the shadow insurer's liabilities) in year t.[18] We exploit the variation in changes of RBC ratio adjustments to identify the causal effect of shadow insurance usage on firm profitability. The implied difference in RBC ratios should be a strong predictor of shadow insurance usage and can be thought of as a treatment to the life insurance sector (as it is now possible to manipulate such ratios with shadow insurance). The larger the difference in actual and adjusted risk-based capital, the more incentives a life insurer has to engage in shadow insurance activities. We use the difference of the implied and the actual RBC ratio in 2001 to construct a continuous instrument for shadow insurance usage. The first stage of our panel-IV regressions is of the following form:

$$\left(\frac{\text{SHADOW}}{\text{REINSURANCE}}\right)_{i,t} = \beta \cdot \left(\left[\mathrm{RBC}_{i,2001} - \widehat{\mathrm{RBC}}_{i,t,2001}\right] \times \text{POST-2001}_t\right) + \Theta \times \text{CONTROLS}_{i,t} + \mu_t + u_{i,t}, \tag{4}$$

To calculate the implied differences in actual and adjusted RBC ratios, we employ the amount of shadow insurance ceded in each respective year.[19]

[18]Note that we assume shadow insurers' equity to be zero as it is done in Koijen and Yogo (2016b).

[19]For example, we take the amount of shadow insurance ceded by life insurers in 2006 to calculate the adjusted RBC ratio $\widehat{\mathrm{RBC}}_{i,2001}$ in 2001 and use the difference as observation for 2006.

Panel-IV results

The second stage regressions estimate the impact of shadow insurance usage (discrete and continuous) on our outcome variables $Y_{i,t}$ and are of the following type:

$$\mathrm{Y}_{i,t} = \alpha_i + \mu_t + \beta \times \mathrm{SHADOW}_{i,t} + \Theta \times \mathrm{CONTROLS}_{i,t} + \varepsilon_{i,t}, \tag{5}$$

where $\mathrm{SHADOW}_{i,t}$ is either the shadow insurance usage dummy variable or the ratio of shadow insurance to total reinsurance ceded. First and second stage regression results are given in Table 6 and 7, respectively.

[Insert Table 6 and 7 about here.]

First, we observe that our discrete instrumental variable in Table 6 is a strong predictor of shadow insurance usage. The estimated coefficient of $\mathrm{TREAT}_i \times \mathrm{POST\text{-}2001}_t$ is positive and statistically significant at the 1% level. Similarly, our control variables in the first stage enter the regression with the expected sign. Second, we find that in the second stage, when shadow insurance usage enters the regression as explanatory variable, we again have a negative and significant relation of shadow insurance and profitability. Only for underwriting ROE, we find a slightly significant but positive coefficient. In contrast to our difference-in-difference approach, we find some significant results for the impact of shadow insurance on life insurers' ratings. The coefficient of $\mathrm{SHADOW}_{i,t}$ in column (5) is negative and significant.

When using the continuous instrumental variable in the first stage, we find that it is positively and significantly related to the ratio of shadow insurance over total reinsurance ceded. Employing the latter proxy of shadow insurance usage as explanatory variable in the second stage in Table 7, we obtain conceptually similar results to the discrete case. However, the estimated coefficients of $\mathrm{SHADOW/REINSURANCE}_{i,t}$ are only negative and statistically significant at the 10% level for ROA and ROE. Coefficients in other regressions are not significant at relevant levels.[20]

We now address several issues that might bias our results such as selection bias, an unbalanced sample, or outliers.

4.3.3 Heckman two-stage selection procedure

The fact that most of life insurers in our sample do not engage in any shadow insurance activities at all raises the question, whether our results are distorted by selection bias. The shadow insurance dummy variable may reflect differences in shadow insurance user and non-user characteristics, but

[20]Note that results may also differ as we exclude firms that are in the mid-tercile of term life market share in 1999 in the discrete specification.

not the effect of shadow insurance on firm outcomes such as profitability or rating. We address this issue by using a Heckman two-stage selection procedure (see Heckman, 1979) with our shadow insurance usage dummy variable as our dependent variable in the first stage.

First, we estimate a probit regression model of the shadow insurance dummy on our instrument from the previous analyses and control variables. Using the predicted values, we construct the self selection parameter inverse Mills ratio (or λ). Then, we run regressions that include the inverse Mills ratio along with our shadow insurance variables and controls as explanatory variables to account for self selection. The results are shown in Table 8.

[Insert Table 8 about here.]

In Panel A, we show results using data from 1999-2014 and Panel B is concerned with the time period 2002-2014. Irrespective of the time period chosen, we find that shadow insurance usage is still negatively related to ROA and underwriting ROA. The negative relation also holds for (underwriting) ROE, but not at the desired significance levels. When looking at the shorter time frame of 2002-2014, we observe a significant and negative relation between the shadow insurance usage dummy and market share, which is consistent with our panel-IV results, but in contrast to the DID analyses.

4.3.4 Propensity Score Matching

One possible concern about our difference-in-difference analyses and panel-IV regressions above is that most of the sample life insurers do not engage in shadow insurance activities and thus, drive our main results. To mitigate this problem, we construct a balanced sample of shadow insurance users and non-users with propensity score matching (PSM). For each life insurer ceding shadow insurance, we match another life insurer with similar firm characteristics so that the major difference between those two firms becomes the usage of shadow insurance.

First, we estimate probit regressions of our treatment dummy variable from the DID analysis on several insurer characteristics with which we would like to compare life insurers. Then, we perform a matching based on characteristics of the insurance group the life insurer is affiliated to in 2001.[21] For group variables, we employ a group's total liabilities, leverage, log of the number of affiliated firms, and company to group size. We obtain propensity scores (p-scores) and use nearest neighbor matching with replacement to assign a non-user of shadow insurance. In this way, we match 189 life insurers in our treatment group with 127 unique insurers of the control group. Then, we construct a balanced panel using the data of the matched pairs from 2002 to 2014 and run two-

[21] We choose 2001 as our basis for the matching as it is the year before shadow insurance usage began increasing rapidly.

stage least squares (2SLS) regressions of our outcome variables $Y_{i,t}$ on shadow insurance usage.[22] Results are given in Table 9.

[Insert Table 9 about here.]

Using the balanced sample, we confirm our main result that using shadow insurance decreases the profitability of life insurers. However, we do not find any significant coefficient in regressions using underwriting ROE or RBC ratio as dependent variables. In addition, using the balanced sample, we can observe that shadow insurers users' and non-users' ratings are substantially different. Shadow insurance users have a higher rating than non-users that are in a similar insurance group. Again, we find a negative relation between shadow insurance and market share, although statistical significance is only present in regressions employing the shadow insurance dummy as independent variable.

4.4 What explains the differences between shadow insurance users and non-users?

Our results indicate that shadow insurance decreases profitability of life insurers and is weakly related to other firm outcomes. What are the driving forces behind these findings? What firm characteristics systematically differentiate the performance of shadow insurance users from non-users? To answer this question, we assess the differential effect of firm characteristics of shadow insurance users versus non-users on life insurers' profitability, rating, RBC ratio, and market share. In particular, as shown by equation (6), we employ the balanced sample obtained from the propensity score matching procedure and regress the differences in our dependent variables on differences in explanatory variables. Year dummies are included to account for variation across time.[23] By doing so, we are able to gain insights into which of the characteristics of shadow insurance users are responsible for the effect of using shadow insurance on firm outcomes.

$$\Delta \mathrm{Y}_{i,t} = \mu_t + \beta \times \Delta \text{FIRM CHARACTERISTICS}_{i,t} + \varepsilon_{i,t}. \tag{6}$$

Results from these regressions using bootstrapped standard errors are reported in Table 10.

[Insert Table 10 about here.]

[22] Note that we can not estimate fixed effects panel regressions, as some data of matched life insurers are repeated in the balanced sample.

[23] This approach is similar to, e.g., studies as Bartram et al. (2012), who explain differences in stock volatility across countries with differences in country variables (see also Lee and Wahal, 2004; Drucker and Puri, 2005; Bartram et al., 2011, for other studies using this method).

Relying predominantly on either term life insurance, which was mostly affected by Regulation XXX, or writing premiums in annuity products, is the dominant determinant of the worse profitability of shadow insurance users. Both differences in these variables exhibit a highly statistically significant coefficient estimate with a negative sign. In terms of economic significance, however, they are less relevant. Goings from a 48% term life insurance ratios (mean value of shadow insurance users) to 28% (non-users), results in a change of -0.23% in ROA. Similarly, changes in ROE and underwriting ROA, according to the estimated models in (2) and (3) of Table 10, are -0.91% (-0.0454×0.20) and -0.29% (-0.0147×0.20). The difference in mean values of annuity ratios of the two subsamples is around 0.14 ($= 0.32 - 0.18$), which translates into differences in ROA and ROE of -0.13% and -1.38%, respectively. A higher term life insurance ratio is also responsible for higher levels of insurers' ratings, RBC ratios, and market shares. Further, we find some evidence that profitability might improve because shadow insurance users are mostly large companies, which are more profitable in general. Differences in liquidity are also positively associated with differences in profitability, rating, and RBC ratio.

4.5 Shadow insurance during the financial crisis

During crisis times, users of captive reinsurance may have an advantage over non-users as they are able to shove their riskier liabilities, which are possibly exposed to the adverse effects of the crisis, to the captives and display better capital ratios. Also, affiliated annuity reinsurance experienced a sharp increase starting 2007 although Regulation XXX/AXXX does not apply to annuities (see Koijen and Yogo, 2016a,b). Life insurers could move (variable) annuity liabilities to affiliated reinsurers reporting under GAAP to smooth reserves during the financial crisis. It is often argued that insurance companies were victims of the recent financial crisis rather than perpetrators (see, e.g., Chen et al., 2014). Thus, one could infer that the crisis and subsequent regulation of financial institutions hit the life insurance sector like a shock, although there was only little involvement of life insurers in general.[24] It is hard to view the crisis in 2008 as a perfect exogenous event in the life insurance sector and thus, a difference-in-difference approach is not suitable.

In the light of recent findings on the capital management of life insurers in response to the financial crisis (see Berry-Stölzle et al., 2014; Koijen and Yogo, 2015; Niehaus, 2016), we nevertheless exploit the variation in the use of shadow insurance across life insurance firms during those times. In particular, we employ a panel regression approach in which we regress measures of profitability, rating, RBC ratio, and market share of life insurers on firm characteristics and again include a shadow insurance usage dummy as our variable of interest. In addition, we include the interaction of the shadow insurance dummy and a (post-)crisis dummy. We estimate panel regressions of the

[24] The active role of American International Group during the crisis, however, was unambiguous (see Harrington, 2009).

following form:

$$\begin{aligned}\mathrm{Y}_{i,t} &= \alpha_i + \mu_t + \beta \cdot \mathrm{SHADOW}_{i,t} + \gamma \cdot (\mathrm{SHADOW}_{i,t} \times \mathrm{CRISIS}_t) \\ &\quad + \delta \cdot (\mathrm{SHADOW}_{i,t} \times \text{POST-CRISIS}_t) + \Theta \cdot \mathrm{CONTROLS}_{i,t} + \varepsilon_{i,t}.\end{aligned}$$

$\mathrm{SHADOW}_{i,t}$ is interacted with dummy variables CRISIS_t and POST-CRISIS_t which are one if an observation is in year 2007-2009 and 2010-2014, respectively. Results are shown in Table 11.

[Insert Table 11 about here.]

Column (1) to (4) in Table 11 report regression results using profitability measures as dependent variables while the models in (5) to (7) employ rating, risk-based capital ratios, and market share of life insurers. The coefficient of $\mathrm{SHADOW}_{i,t}$ can be interpreted as the correlation of shadow insurance usage and firm outcomes before the crisis period (2002-2006), while the interaction terms indicate the relation in 2007-2009 and 2010-2014, respectively.

In almost all of the regressions, $\mathrm{SHADOW}_{i,t}$ is highly statistically significant with a negative sign of the coefficient. This is in line with our previous findings that life insurers ceding reinsurance to shadow insurers are not necessarily more profitable although they use cost-efficient affiliated reinsurance. Further, using shadow insurance is negatively related to both, RBC ratios and market share using the full sample from 2002 to 2014. This result, however, only holds on a relevant statistical significance level when using the shadow usage dummy variable but not the ratio of the actual amount of shadow insurance over total reinsurance ceded as explanatory variable. For neither of the two definitions of shadow insurance usage variables, we find a significant relation during the crisis. Only after the crisis, from 2010 to 2014, we find that using shadow insurance is positively related to profitability. This result is robust for both shadow insurance variables when using ROA and ROE as profitability measures. Interestingly, we see that shadow insurance users had a lower rating and higher RBC ratios after the crisis. This is possibly the result of bad performance of these life insurers during the crisis years and thus, they had to increase risk-based capital afterwards.

5 Conclusion

In this paper, we study the effects of engaging in shadow insurance activities on the financial performance of life insurance firms. We analyze profitability, ratings, and market shares of a large panel of life insurance companies in the United States from 1997 to 2014. As our main result, we find that life insurers ceding liabilities to affiliated shadow insurers are not necessarily more profitable, despite reduced marginal costs and perceived advantages. We find some evidence that shadow insurance was used after the change in regulation of term life insurance products in 2000 to increase risk-based capital ratios.

First, we show that life insurers with a higher share of term life insurance in their business portfolio were more affected by Regulation XXX/AXXX and thus, were more incentivised to engage in shadow insurance activities. Further, life insurers mainly enter shadow insurance agreement when they have a high level of RBC ratios and secure financial ratings. Second, in difference-in-difference regressions, we reveal that Regulation XXX/AXXX affected profitability, ratings, and market shares of certain groups of life insurers differently. Those life insurers that used shadow insurance after Regulation XXX were less profitable, but exhibited a slight increase in RBC ratios and market share. Third, using a panel-IV identification strategy with discrete and continuous instruments, we show the causal relation of shadow insurance usage and lower profitability. A Heckman two-stage selection procedure and propensity score matching confirm the robustness of our results. Finally, we look at the effect of shadow insurance usage in different periods of time: before, during, and after the crisis. Before the crisis, shadow insurance usage was negatively related to profitability, but after the crisis, we see that it had a slight positive effect on profits and RBC ratios.

The amount of shadow insurance ceded has been growing continuously since 2002 and has kindled a lively discussion about the benefits and risks involved in these transactions. We complement the few studies on shadow insurance by providing a comprehensive analysis of the incentives of life insurers to use affiliated reinsurers to manage their capital. One argument in favor of using shadow insurance is that it reduces costs and is therefore beneficial for both life insurers and their policyholders. However, as we show in this study, the use of shadow insurance is not necessarily associated with more profitability and thus, the incentives of shadow insurance users have to be questioned. When shadow insurance is only used to display better financial ratings by employing regulatory arbitrage, the regulation of the life insurance sector has to be reviewed to obtain more sustainable solutions.

Appendix I: Variable definitions.

The appendix presents definitions for all dependent and independent variables that are used in the empirical study. The insurer characteristics were retrieved from life insurers' annual NAIC reports and rating data is obtained from A.M. Best Company.

Variable	**Description**
Profitability measures:	
ROA	Insurer's net income over total assets.
ROE	Insurer's net income over total equity.
Underwriting profit (assets)	Net underwriting income divided by total assets. Net underwriting income is the net operating gain before taxes plus net realized capital gain minus net investment income and miscellaneous income.
Underwriting profit (equity)	Net underwriting income divided by total equity. Net underwriting income is the net operating gain before taxes plus net realized capital gain minus net investment income and miscellaneous income.
Reinsurance variables:	
Reinsurance ceded	The sum of reserve credit taken and modified coinsurance reserve.
Shadow insurance	Reinsurance ceded to affiliated, unauthorized, and unrated reinsurers.
Shadow user	Dummy variable that is one if shadow insurance ceded is positive and zero otherwise.
Insurer characteristics:	
Rating	A.M. Best rating, converted to ordered categorical or cardinal value according to BCAR.
RBC	Risk-based capital ratio, which is the total adjusted capital divided by company action level RBC.
Leverage	Insurer's liabilities to assets ratio.
Current Liquidity	Ratio of current assets to total liabilities.
Log(liabilities)	Natural logarithm of total liabilities.
Surplus ratio	Surplus divided by total assets.
Log(assets)	Natural logarithm of the insurer's total assets.
Term life insurance ratio	Term life insurance in force divided by total insurance in force.
Annuity ratio (DPW)	Direct premiums written in annuities over direct premiums written.
Market share (TPW)	Insurer's total premiums written (TPW) in one year to the aggregated amount of TPW of the industry in that year.
Term life insurance market share	Term-life insurance in force over aggregated market term-life insurance in force.
Group characteristics:	
Log(#affiliates)	Natural logarithm of the number of companies in the insurer's group.
Company to group size	Ratio of the insurer's assets to the group total assets.
Log(Group liabilities)	Natural logarithm of the insurer's group total liabilities.
Group leverage	Insurer's group's liabilities to assets ratio.
Group ROA	Insurer's group's net income over total assets.
Group ROE	Insurer's group's net income over total equity.

References

ADAMS, M. (1995): "Balance Sheet Structure and the Managerial Discretion Hypothesis: An Exploratory Empirical Study of New Zealand Life Insurance Companies," *Accounting and Finance*, 35, 21–45.

ADAMS, M. B. (1996): "The Reinsurance Decision in Life Insurance Firms: An Empirical Test of the Risk-Bearing Hypothesis," *Accounting and Finance*, 36, 15–30.

ADIEL, R. (1996): "Reinsurance and the Management of Regulatory Ratios and Taxes in the Property-Casualty Insurance Industry," *Journal of Accounting and Economics*, 22, 207–240.

ALTUNTAS, M., T. BERRY-STÖLZLE, AND S. WENDE (2015): "Does One Size Fit All? Determinants of Insurer Capital Structure Around the Globe," *Journal of Banking and Finance*, forthcoming.

A.M. BEST (2006): "Review of BCAR Treatment for XXX Captives," A.M. Best Methodology.

——— (2013): "Rating Factors for Organizations Using Life Captive Reinsurers," Best's Special Report.

——— (2015): "Best's Credit Rating Methodology: Global Life and Non-Life Insurance Edition," A.M. Best Methodology.

AZAR, J., M. SCHMALZ, AND I. TECU (2015): "Anti-Competitive Effects of Common Ownership," Working paper, University of Michigan.

BALSMEIER, B., L. FLEMING, AND G. MANSO (2016): "Board Independence and Innovation," *Journal of Financial Economics*, forthcoming.

BARTRAM, S., G. W. BROWN, AND J. CONRAD (2011): "The effects of derivatives on firm risk and value," *Journal of Financial and Quantitative Analysis*, 46, 967–999.

BARTRAM, S. M., G. W. BROWN, AND R. M. STULZ (2012): "Why Are U.S. Stocks More Volatile?" *Journal of Finance*, 67(4), 1329–1370.

BERRY-STÖLZLE, T., G. P. NINI, AND S. WENDE (2014): "External Financing in the Life Insurance Industry: Evidence From the Financial Crisis," *Journal of Risk and Insurance*, 81, 529–562.

BIERTH, C., F. IRRESBERGER, AND G. WEISS (2015): "Systemic Risk of Insurers Around the Globe," *Journal of Banking and Finance*, 55, 232–245.

BILLIO, M., A. W. LO, M. GETMANSKY, AND L. PELIZZON (2012): "Econometric Measures of Connectedness and Systemic Risk in the Finance and Insurance Sectors," *Journal of Financial Economics*, 104(3), 535–559.

CHEN, H., J. D. CUMMINS, K. S. VISWANATHAN, AND M. A. WEISS (2014): "Systemic Risk and the Interconnectedness Between Banks and Insurers: An Econometric Analysis," *Journal of Risk and Insurance*, 81(3), 623–652.

CHIANG, C.-C. AND G. NIEHAUS (2015): "Investment Herding by Life Insurers," Working paper.

COSTLE, E. R. AND K. A. SCHAUER (2000): "The captive alternative: A regulatory perspective," *Journal of Insurance Regulation*, 19, 304–322.

CUMMINS, J. D. AND M. A. WEISS (2014): "Systemic Risk and the U.S. Insurance Sector," *Journal of Risk and Insurance*, 81(3), 489–528.

DRUCKER, S. AND M. PURI (2005): "On the benefits of concurrent lending and underwriting," *Journal of Finance*, 60, 2763–2799.

FROOT, K. A. (2008): "Risk Management, Capital Budgeting, and Capital Structure Policy for Insurers and Reinsurers," *Journal of Risk and Insurance*, 73, 273–299.

FROOT, K. A., D. S. SCHARFTSTEIN, AND J. C. STEIN (1993): "Risk Management: Coordinating Corporate Investments and Financing Policies," *Journal of Finance*, 48, 1629–1658.

FROOT, K. A. AND J. STEIN (1998): "Risk Management, Capital Budgeting, and Capital Structure Policy for Financial Institutions: An Integrated Approach," *Journal of Financial Economics*, 47, 55–82.

HARRINGTON, S. AND G. NIEHAUS (2003): "Capital, Corporate Income Taxes and Catastrophe Insurance," *Journal of Financial Intermediation*, 12, 365–389.

HARRINGTON, S. E. (2009): "The Financial Crisis, Systemic Risk, and the Future of Insurance Regulation," *Journal of Risk and Insurance*, 76, 785–819.

——— (2014): "The Use of Captive Reinsurance in Life Insurance," Working paper.

——— (2015): "The Economics and Regulation of Captive Reinsurance in Life Insurance," Working paper.

HECKMAN, J. J. (1979): "Sample selection bias as a specification error," *Econometrica*, 47, 153–161.

KADER, H., M. ADAMS, AND K. MOURATIDIS (2013): "Testing for Trade-offs in the Reinsurance Decision of U.K. Life Insurance Firms," *Journal of Accounting, Auditing and Finance*, 25, 491–522.

KOIJEN, R. AND M. YOGO (2015): "The Cost of Financial Frictions for Life Insurers," *American Economic Review*, 105, 445–475.

——— (2016a): "Risks of Life Insurers: Recent Trends and Transmission Mechanisms," *The Economics, Regulation, and Systemic Risk of Insurance Markets, Oxford University Press*, forthcoming.

——— (2016b): "Shadow Insurance," *Econometrica*, forthcoming.

LAWSKY, B. M. (2013): "Shining a Light on Shadow Insurance: A Little-Known Loophole That Puts Insurance Policyholders and Taxpayers at Greater Risk," Working Paper, New York State Department of Financial Services, New York.

LEE, P. M. AND S. WAHAL (2004): "Grandstanding, certification and the underpricing of venture capital backed IPOs," *Journal of Financial Economics*, 73, 375–407.

MAYERS, D. AND C. W. SMITH (1990): "On the Corporate Demand for Insurance: Evidence from the Reinsurance Market," *Journal of Business*, 63, 19–40.

MÜHLNICKEL, J. AND G. WEISS (2015): "Consolidation and Systemic Risk in the International Insurance Industry," *Journal of Financial Stability*, 18, 187–202.

MYERS, S. C. AND N. S. MAJLUF (1984): "Corporate Financing and Investment Decisions When Firms Have Information That Investors Do Not Have," *Journal of Financial Economics*, 13, 187–221.

NAIC (2011): "Accounting Practices and Procedures Manual," Kansas City, MO.

——— (2013): "Captives and Special Purpose Vehicles," National Association of Insurance Commissioners, White paper.

NIEHAUS, G. (2016): "Managing Capital via Internal Capital Market Transactions: The Case of Life Insurers," *Journal of Risk and Insurance*, forthcoming.

POTTIER, S. AND D. W. SOMMER (1997): "Agency Theory and Life Insurer Ownership Structure," *Journal of Risk and Insurance*, 64, 529–543.

POWELL, L. AND D. SOMMER (2007): "Internal Versus External Capital Markets in the Insurance Industry: The Role of Reinsurance," *Journal of Financial Services Research*, 31, 173–188.

SCHWARCZ, D. (2015): "The Risks of Shadow Insurance," *Georgia Law Review*, forthcoming.

SCHWARCZ, D. AND S. L. SCHWARCZ (2015): "Regulating Systemic Risk in Insurance," *The University of Chicago Law Review*, 81, 1569–1640.

STERN, L. (2014): "Captive Reinsurance and Other Innovative Structures," Society of Actuaries Reinsurance Section, New York.

WEISS, G. AND J. MÜHLNICKEL (2014): "Why Do Some Insurers Become Systemically Relevant?" *Journal of Financial Stability*, 13, 95–117.

Figure 1: Profitability of shadow insurance users and non-users

The figure shows the time evolution of profitability measures in the U.S. life insurance sector from 1997 to 2003. Each panel shows mean values of return on assets (ROA), return on equity (ROE), underwriting (UW) ROA, and underwriting (UW) ROE for a group of life insurers that engage in shadow insurance activities in 2002-2014 at least once (users) and those who do not at all (non-users). Shadow insurance is defined as the reinsurance ceded to affiliated, unauthorized, and unrated reinsurers (reserve credit taken plus modified coinsurance). The two vertical lines indicate the introduction of Regulation XXX/AXXX in 2000 and 2003, respectively. Variable definitions are given in Appendix I. All data are winsorized at the 1st and 99th percentiles.

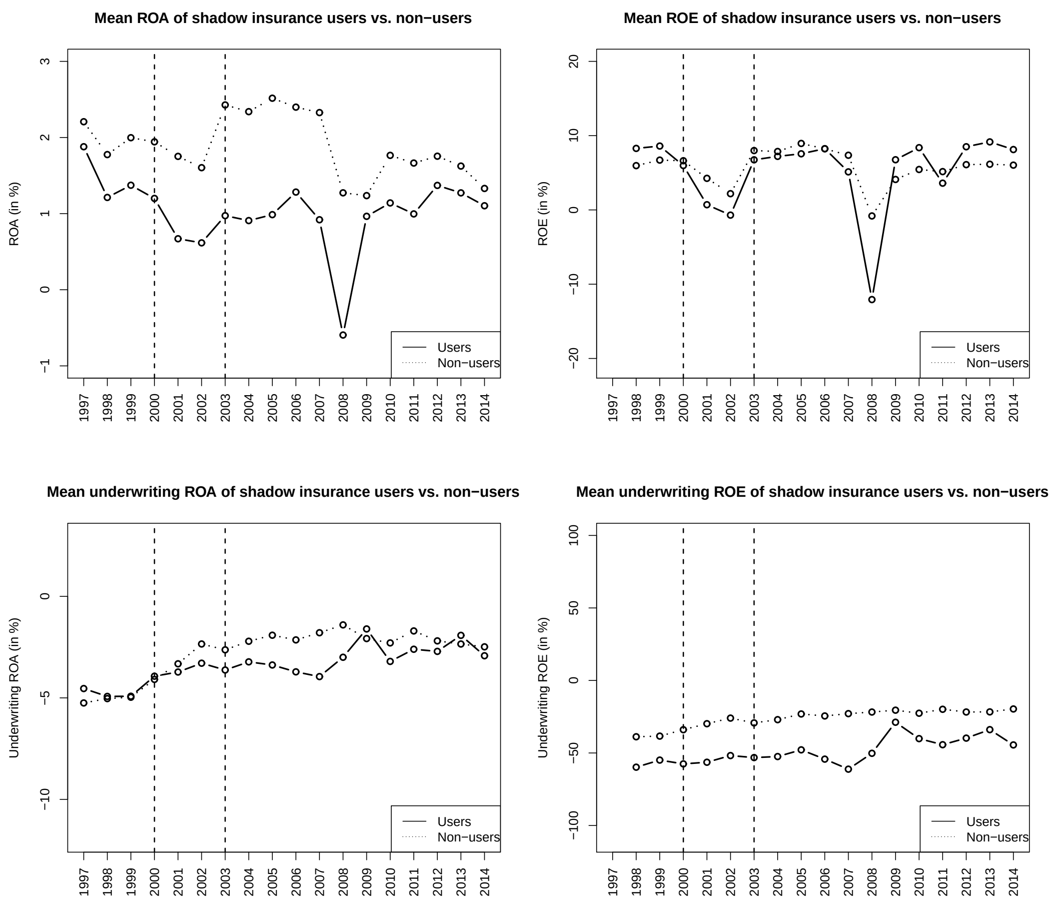

Figure 2: Rating, risk-based capital, and market share of shadow insurance users and non-users

The figure shows the time evolution of A.M. Best ratings, risk-based-capital ratios, and market share based on total premiums written in the U.S. life insurance sector from 1997 to 2014. The first two panel present mean values of the variables for a group of life insurers that engage in shadow insurance activities in 2002-2014 at least once (users) and those who do not at all (non-users). The third panel shows mean values of market share for shadow insurance users only. Shadow insurance is defined as the reinsurance ceded to affiliated, unauthorized, and unrated reinsurers (reserve credit taken plus modified coinsurance). The two vertical lines indicate the introduction of Regulation XXX/AXXX in 2000 and 2003, respectively. Variable definitions are given in Appendix I. All data are winsorized at the 1st and 99th percentiles.

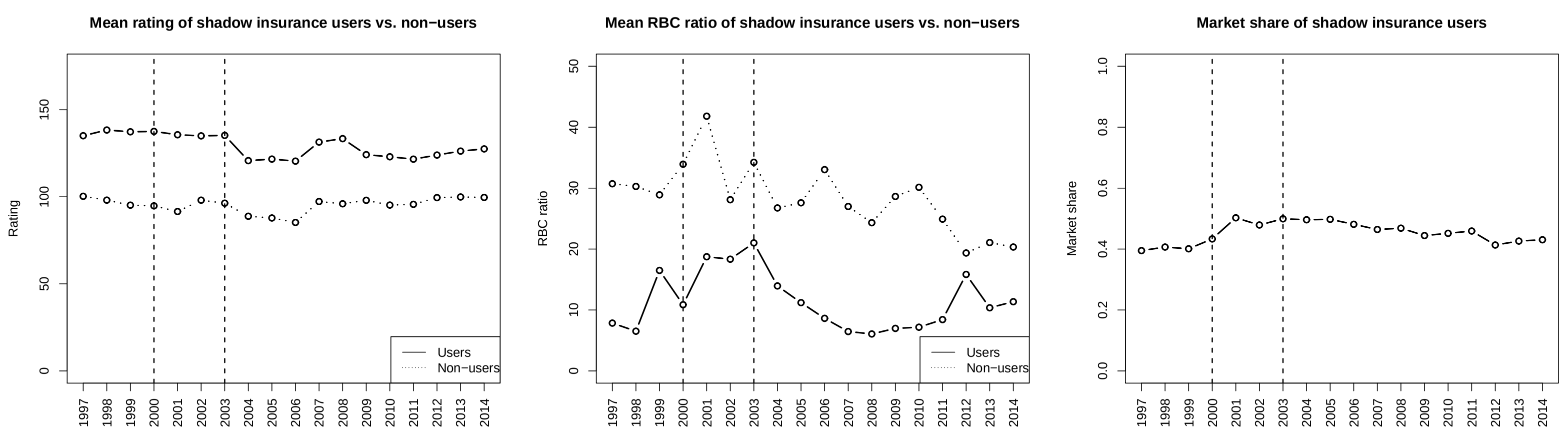

Figure 3: Term life insurance ratios

The figure shows the time evolution of term life insurance ratios in the U.S. life insurance sector from 1997 to 2003. The solid and dotted lines are mean values of *affected* and *unaffected* life insurers' face value of term life insurance in force over total insurance in force each year, respectively. *Affected life insurers* are defined as insurers with a term life insurance ratio above 25%, 33%, 50%, or 75% in the year 1999, respectively. The chosen threshold for the definition of affected life insurers using term life insurance ratios is indicated by the dashed line in each panel below.

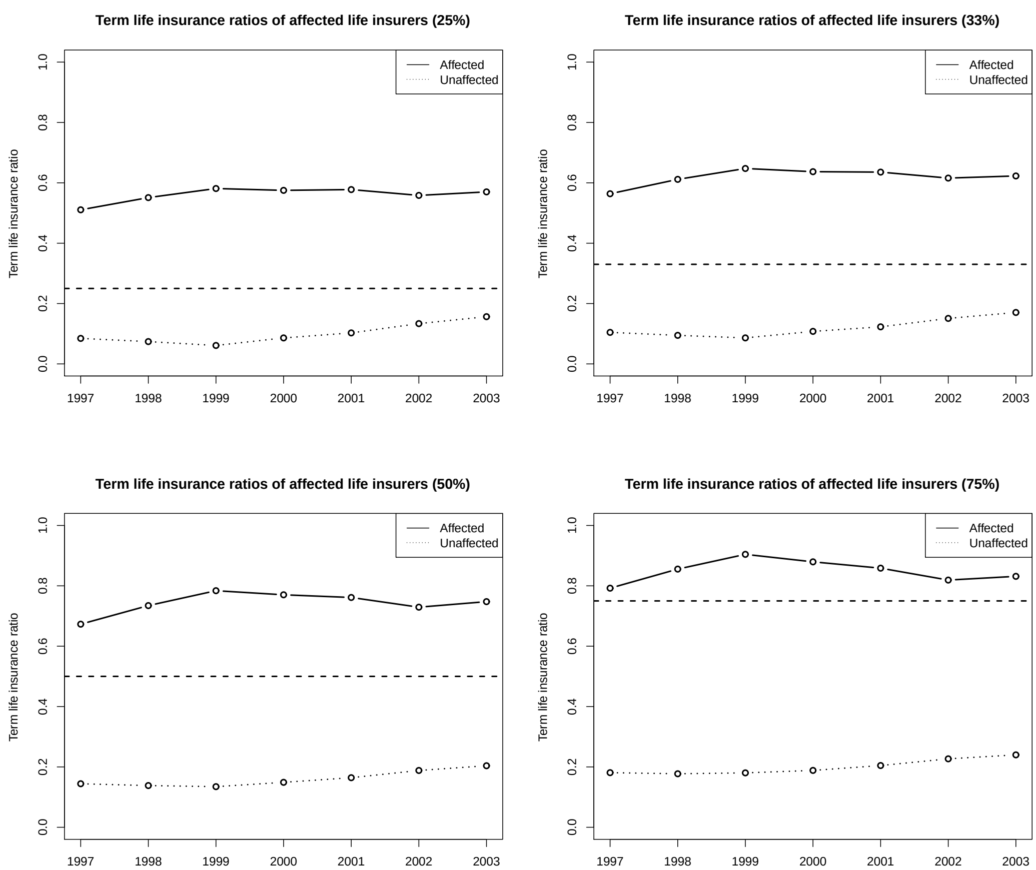

Figure 4: Profitability of affected life insurers

The figure shows the time evolution of profitability measures in the U.S. life insurance sector from 1997 to 2003. The solid and dotted lines are mean values of *affected* and *unaffected* life insurers' profitability measured by its ROA, ROE, underwriting ROA, or underwriting ROE. *Affected life insurers* are defined as insurers with a term life insurance ratio above 25% in 1999. The vertical dashed line indicates the introduction of Regulation XXX in 2000.

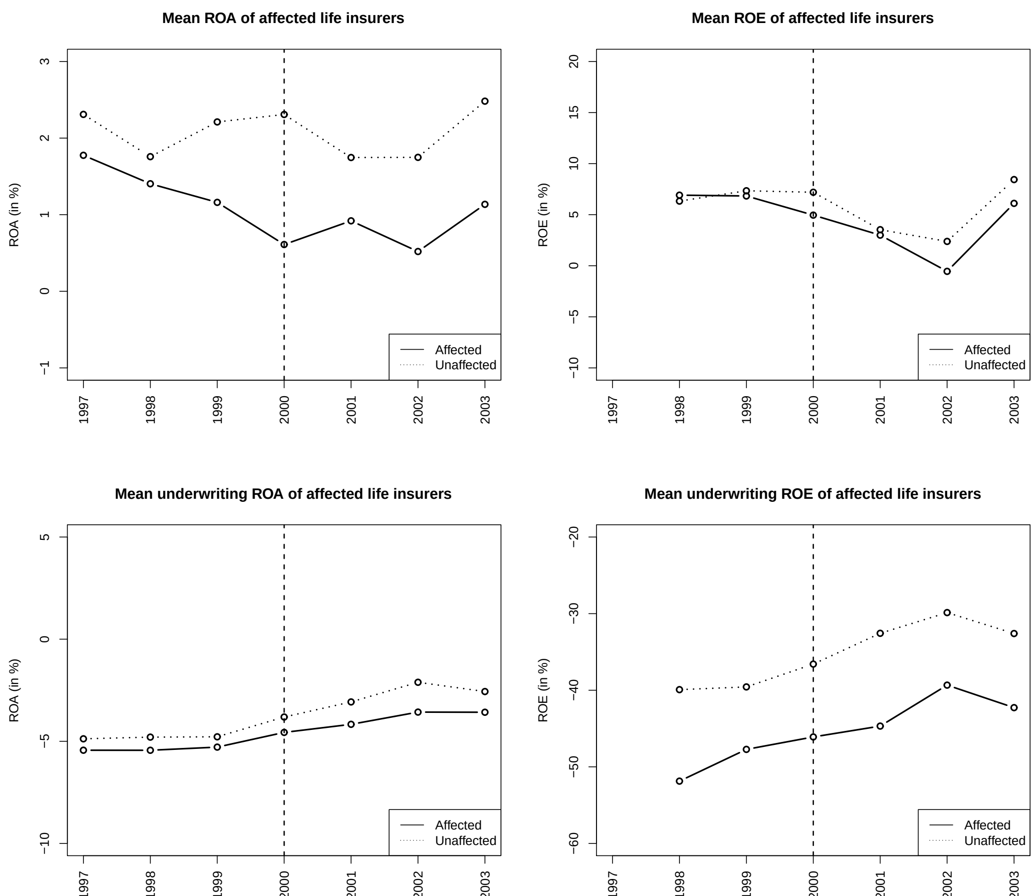

Table 1: Descriptive statistics

This table provides summary statistics for variables used in our empirical study. We report the number of observations, mean values, standard deviations as well as the minimum and maximum values of each variable. Statistics are shown for the full sample and for sub-samples of shadow insurance users and non-users. Shadow insurance users are life insurers that cede reinsurance to affiliated, unauthorized, and unrated reinsurers. Variable definitions are given in Appendix I. The sample consists of all life insurers reporting to the NAIC in the time period from 1997 to 2014. Observations with negative total assets, negative liabilities, negative surplus, or negative premiums written are removed from the sample. Life insurers that report a ratio of premiums ceded to total premiums written with a value above one or below zero in a specific year are excluded. Only companies with total assets above $1 million are included. All variables are winsorized at the 1st and 99th percentiles. T-values indicate statistics of a two-sided t-test on equality of the means for shadow insurance users and non-users in the respective variable.

	Full sample					Users					Non-users						
	Obs.	Min	Mean	Max	St. Dev.	Obs.	Min	Mean	Max	St. Dev.	Obs.	Min	Mean	Max	St. Dev.	t-value	p
ROA	11441	-0.2098	0.0167	0.2518	0.0533	1248	-0.2098	0.0063	0.2518	0.0370	10193	-0.2098	0.0180	0.2518	0.0548	-9.94	0.000
ROE	10604	-0.8761	0.0569	0.6743	0.2028	1233	-0.8761	0.0434	0.6743	0.2527	9371	-0.8761	0.0587	0.6743	0.1952	-2.04	0.041
Underwriting profit (assets)	11441	-0.5374	-0.0308	0.2366	0.0799	1248	-0.5374	-0.0369	0.2366	0.0594	10193	-0.5374	-0.0301	0.2366	0.0820	-3.65	0.000
Underwriting profit (equity)	10604	-2.7413	-0.3283	0.6174	0.4995	1233	-2.7413	-0.5597	0.6174	0.5782	9371	-2.7413	-0.2979	0.6174	0.4801	-15.23	0.000
Rating (card.)	11490	0.0000	104.2933	175.0000	62.9773	1251	0.0000	133.7130	175.0000	48.8150	10239	0.0000	100.6988	175.0000	63.5700	21.77	0.000
RBC ratio	11490	0.8477	24.4744	904.3033	95.5621	1251	0.8477	6.3147	569.5649	20.8620	10239	0.8477	26.6932	904.3033	100.7454	-17.61	0.000
Market share	11490	0.0000	0.0013	0.0187	0.0032	1251	0.0000	0.0038	0.0187	0.0051	10239	0.0000	0.0010	0.0187	0.0028	19.25	0.000
Financial size	11490	0.0000	7.2897	15.0000	4.9085	1251	0.0000	10.7242	15.0000	4.9268	10239	0.0000	6.8701	15.0000	4.7388	26.23	0.000
Term life insurance ratio	10251	0.0000	0.3075	1.0000	0.3269	1239	0.0000	0.4834	1.0000	0.3417	9012	0.0000	0.2833	1.0000	0.3173	19.49	0.000
Annuity ratio (DPW)	10381	0.0000	0.2040	1.0000	0.3254	1110	0.0000	0.3242	1.0000	0.3484	9271	0.0000	0.1896	1.0000	0.3195	12.27	0.000
Surplus ratio	11490	0.0099	0.2607	0.9378	0.2368	1251	0.0099	0.1246	0.8760	0.1362	10239	0.0099	0.2773	0.9378	0.2411	-33.72	0.000
Leverage	11490	0.0016	0.6653	0.9769	0.2948	1251	0.0156	0.8408	0.9769	0.1688	10239	0.0016	0.6439	0.9769	0.2997	35.06	0.000
Current liquidity	10762	0.2340	2.0588	9.9990	2.5578	1180	0.2340	1.0422	9.9990	1.0142	9582	0.2340	2.1840	9.9990	2.6605	-28.45	0.000
Total assets (in bn $)	11490	0.0010	5.4714	103.3813	16.5760	1251	0.0024	18.5557	103.3813	28.8571	10239	0.0010	3.8728	103.3813	13.5349	17.76	0.000
Total liabilities (in bn $)	11475	0.0000	5.0407	97.5968	15.6576	1251	0.0001	17.3518	97.5968	27.3419	10224	0.0000	3.5343	97.5968	12.7646	17.64	0.000
Group leverage	11488	0.0222	0.7745	0.9699	0.2112	1251	0.0729	0.8699	0.9699	0.1294	10237	0.0222	0.7628	0.9699	0.2163	25.27	0.000
Group RBC ratio	11488	1.1614	7.6810	260.9738	24.7639	1251	1.1614	4.6701	260.9738	8.9550	10237	1.1614	8.0489	260.9738	26.0223	-9.36	0.000
Group ROA	11481	-0.1178	0.0159	0.1894	0.0387	1251	-0.1178	0.0060	0.1894	0.0234	10230	-0.1178	0.0171	0.1894	0.0400	-14.39	0.000
Group ROE	11481	-0.9054	0.0841	0.8311	0.2079	1251	-0.9054	0.0635	0.8311	0.1991	10230	-0.9054	0.0866	0.8311	0.2089	-3.86	0.000
Group liabilities (in bn $)	11475	0.0000	5.0407	97.5968	15.6576	1251	0.0001	17.3518	97.5968	27.3419	10224	0.0000	3.5343	97.5968	12.7646	17.64	0.000
Company to group size	11488	0.0001	0.4049	1.0000	0.4103	1251	0.0002	0.4202	1.0000	0.3883	10237	0.0001	0.4030	1.0000	0.4129	1.46	0.143
#Affiliates	11488	1.0000	4.7404	19.0000	4.0861	1251	1.0000	6.4972	19.0000	4.9108	10237	1.0000	4.5257	19.0000	3.9202	13.68	0.000

Table 2: Did Regulation XXX affect life insurers? Profitability

This table shows results of difference-in-difference analyses for the time period from 1997 to 2003 for a sample of U.S. life insurers that report to the NAIC. Regressions are performed by OLS estimation with standard errors clustered on the firm level and are of the following form:

$$\text{PROFITABILITY}_{i,t} = \alpha_i + \mu_t + \beta \cdot \text{AFFECTED}_i + \gamma \cdot (\text{AFFECTED}_i \times \text{POST-XXX}_t) + \varepsilon_{i,t}.$$

The variable POST-XXX$_t$ is one in the years 2000 to 2003 and is interacted with our treatment group dummy variable AFFECTED$_i$. AFFECTED$_i \cdot$POST-XXX$_t$ is the difference-in-difference term, where AFFECTED$_i$ is one if a life insurer's term life insurance ratio is above 25%, 33%, 50% or 75% in 1999 and zero otherwise. PROFITABILITY$_{i,t}$ is either return on assets (ROA), return on equity (ROE), underwriting ROA or underwriting ROE. Variable definitions are given in Appendix I. P-values are given in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. Regressions include insurer fixed effects and year dummies. Adj. R^2 is the average adjusted R^2 of the four regressions for each dependent variable. Coefficients of constants and dummies are suppressed for brevity.

	(1)	(2)	(3)	(4)
Dependent variable:	ROA	ROE	Underwriting ROA	Underwriting ROE
AFFECTED$_i$ × POST-XXX$_t$ (25%)	**-0.0060****	-0.0076	-0.0064	0.0032
	(0.042)	(0.554)	(0.165)	(0.899)
AFFECTED$_i$ × POST-XXX$_t$ (33%)	**-0.0081*****	-0.0157	**-0.0092****	-0.0100
	(0.009)	(0.247)	**(0.042)**	(0.700)
AFFECTED$_i$ × POST-XXX$_t$ (50%)	**-0.0067***	0.0098	**-0.0099****	-0.0067
	(0.075)	(0.553)	**(0.046)**	(0.817)
AFFECTED$_i$ × POST-XXX$_t$ (75%)	-0.0017	0.0231	-0.0047	0.0265
	(0.728)	(0.336)	(0.467)	(0.492)
Year FE	x	x	x	x
Insurer FE	x	x	x	x
N	4,463	3,680	4,463	3,680
Adj. R^2	0.003	0.022	0.023	0.017

Table 3: Did Regulation XXX affect life insurers? Rating, risk-based capital, and market share.

This table shows results of difference-in-difference analyses for the time period from 1997 to 2003 for a sample of U.S. life insurers that report to the NAIC. Regressions are performed by OLS estimation with standard errors clustered on the firm level and are of the following form:

$$\mathrm{Y}_{i,t} = \alpha_i + \mu_t + \beta \cdot \text{AFFECTED}_i + \gamma \cdot (\text{AFFECTED}_i \times \text{POST-XXX}_t) + \varepsilon_{i,t}.$$

The variable POST-XXX$_t$ is one in the years 2000 to 2003 and is interacted with our treatment group dummy variable AFFECTED$_i$. AFFECTED$_i \cdot$POST-XXX$_t$ is the difference-in-difference term, where AFFECTED$_i$ is one if a life insurer's term life insurance ratio is above 25%, 33%, 50% or 75% in 1999 and zero otherwise. Y$_{i,t}$ is rating (cardinal measure), risk-based capital ratio, or market share. Variable definitions are given in Appendix I. P-values are given in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. Regressions include insurer fixed effects and year dummies. Adj. R^2 is the average adjusted R^2 of the four regressions for each dependent variable. Coefficients of constants and dummies are suppressed for brevity.

	(1)	(2)	(3)
Dependent variable:	Rating	RBC ratio	Market share
AFFECTED$_i$ × POST-XXX$_t$ (25%)	**3.6090****	**-9.9060****	0.0001
	(0.039)	**(0.012)**	(0.269)
AFFECTED$_i$ × POST-XXX$_t$ (33%)	**3.1170***	**-10.3600****	0.0001
	(0.086)	**(0.014)**	(0.384)
AFFECTED$_i$ × POST-XXX$_t$ (50%)	**4.3050***	**-12.5400****	-0.0001
	(0.074)	**(0.026)**	(0.327)
AFFECTED$_i$ × POST-XXX$_t$ (75%)	2.8750	**-14.5000***	**-0.0002***
	(0.382)	**(0.091)**	**(0.057)**
Year FE	x	x	x
Insurer FE	x	x	x
N	4,512	4,512	4,512
Adj. R^2	0.002	0.001	0.001

Table 4: Which life insurers use shadow insurance? Logit and Tobit regressions.

This table shows the results of logit and tobit regressions with robust standard errors of shadow insurance usage variables on life insurer (group) characteristics. Model (1) to (4) employ explanatory variables from 1999 and (5) to (8) are from 2001. Model (9) and (10) use mean values of explanatory variables from 2002-2014. The first dependent variable is USER$_i$, which is a dummy variable that is one if a life insurer cedes reinsurance to shadow insurers in 2002-2014 (treatment group) and zero otherwise (control group). In model (10), the dependent variable is the mean ratio of shadow insurance to total reinsurance ceded in 2002-2014. Variable definitions are given in Appendix I. All data are winsorized at the 1st and 99th percentiles.

	Logit 1999				Logit 2001				Logit (2002-2014)	Tobit (2002-2014)
Dependent variable:	USER$_i$				USER$_i$				USER$_i$	Mean SHADOW/REINSURANCE$_i$
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Rating (card.)	0.0054		**0.0055***		0.0034		0.0037			
	(0.106)		**(0.095)**		(0.274)		(0.266)			
RBC ratio		**0.0052*****		**0.0056*****		**0.0045***		**0.0056****		
		(0.002)		**(0.001)**		**(0.058)**		**(0.031)**		
Current liquidity	-0.1020	**-0.1570***	-0.0943	-0.1480	0.0044	-0.0299	-0.0108	-0.0520	0.0901	0.0608
	(0.233)	**(0.061)**	(0.311)	(0.121)	(0.953)	(0.701)	(0.897)	(0.557)	(0.326)	(0.105)
Term life insurance ratio	**0.8000****	**0.8820*****	**0.8820****	**1.0040*****	**0.8290****	**0.8290****	**0.9320*****	**0.9500*****	**1.3870*****	**0.3890*****
	(0.018)	**(0.010)**	**(0.012)**	**(0.005)**	**(0.014)**	**(0.013)**	**(0.007)**	**(0.006)**	**(0.000)**	**(0.000)**
Leverage	0.5710	**1.0350***	0.6880	**1.3970****	0.9910	**1.2560****	**1.3700***	**1.8280*****	0.4610	-0.0860
	(0.375)	**(0.095)**	(0.334)	**(0.035)**	(0.127)	**(0.040)**	**(0.052)**	**(0.005)**	(0.537)	(0.773)
ROE	-0.0762	-0.0811	-0.5730	-0.5630	-0.7120	-0.6990	**-1.0910****	**-1.1660****	0.4280	-0.2510
	(0.884)	(0.878)	(0.317)	(0.316)	(0.118)	(0.127)	**(0.033)**	**(0.023)**	(0.652)	(0.413)
Size	0.1320	0.1160	0.1080	0.0968	**0.1800****	**0.1820****	0.1080	0.1170	**0.2930*****	**0.1090*****
	(0.150)	(0.207)	(0.319)	(0.384)	**(0.025)**	(0.023)	(0.254)	(0.215)	**(0.000)**	**(0.000)**
Group Leverage			-0.3380	-1.0100			-0.2750	-0.8010	-0.6390	0.0510
			(0.748)	(0.322)			(0.779)	(0.408)	(0.526)	(0.903)
Group RBC ratio			-0.0017	-0.0051			0.0295	0.0252	0.0076	0.0012
			(0.934)	(0.755)			(0.173)	(0.252)	(0.272)	(0.646)
Group ROE			1.3460	1.3920			0.4510	0.6500	**-1.9900***	-0.1680
			(0.159)	(0.146)			(0.509)	(0.295)	**(0.054)**	(0.568)
Company to group size			0.0345	-0.0300			0.5720	0.5230	0.1000	0.1740
			(0.938)	(0.946)			(0.212)	(0.252)	(0.818)	(0.188)
Log(#Affiliates)			**0.2980***	0.2770			**0.5010*****	**0.4780*****	**0.5400****	**0.1900*****
			(0.097)	(0.128)			**(0.008)**	**(0.010)**	**(0.018)**	**(0.005)**
Constant	**-4.2650****	**-3.4080***	**-4.2430****	-3.0200	**-5.5260*****	**-5.2100*****	**-5.2780*****	**-4.7240****	**-7.8740*****	**-3.1080*****
	(0.025)	**(0.069)**	**(0.046)**	(0.155)	**(0.001)**	**(0.002)**	**(0.004)**	**(0.012)**	**(0.000)**	**(0.000)**
Financial size FE	x	x	x	x	x	x	x	x	-	-
N	648	648	648	648	607	607	607	607	681	605
Pseudo R^2	0.155	0.158	0.168	0.172	0.165	0.166	0.180	0.182	0.184	0.177
AIC	685.6	682.9	685.5	682.8	656.0	655.2	655.0	653.6	675.5	615.3
BIC	775.0	772.4	797.4	794.6	744.2	743.4	765.2	763.8	725.3	668.2

Table 5: Does shadow insurance provide a competitive advantage? Difference-in-difference.

This table shows results of difference-in-difference analyses for the time period from 1997 to 2014 for a sample of U.S. life insurers that report to the NAIC. Regressions are performed by OLS estimation with standard errors corrected for clustering on the firm level and are of the following form:

$$\mathrm{Y}_{i,t} = \alpha_i + \mu_t + \beta \cdot (\mathrm{TREAT}_i \times \text{POST-XXX}_t) + \gamma \cdot (\mathrm{TREAT}_i \times \text{POST-AXXX}_t) + \varepsilon_{i,t}.$$

The variable POST-XXX$_t$ is one in the years 2000 and after and is interacted with our treatment group dummy variable TREAT$_i$. Similarly, POST-AXXX$_t$ is one in the years 2003 and after. TREAT$_i$ · POST-XXX$_t$ or TREAT$_i$ · POST-AXXX$_t$ are the difference-in-difference terms, where TREAT$_i$ is one if a life insurer cedes reinsurance to affiliated, unauthorized, and unrated reinsurers in 2002-2014 (treatment group). Y$_{i,t}$ is either return on assets (ROA), return on equity (ROE), underwriting (UW) ROA, underwriting (UW) ROE, rating, risk-based capital ratio (RBC), or market share (MSHARE) based on total premiums written. Variable definitions are given in Appendix I. P-values are given in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. Regressions include insurer fixed effects and year dummies. Adj. R^2 is the adjusted R^2. Coefficients of constants and dummies are suppressed for brevity.

Dependent variable:	(1) ROA	(2) ROA	(3) ROE	(4) ROE	(5) UW ROA	(6) UW ROA	(7) UW ROE	(8) UW ROE	(9) RATING	(10) RATING	(11) RBC	(12) RBC	(13) MSHARE	(14) MSHARE
SHADOW$_i$ × POST-XXX$_t$	**-0.0079*****	**-0.0047***	**-0.0362*****	**-0.0450*****	**-0.0169*****	**-0.0089****	**-0.0554***	**-0.0662****	-1.6780	0.6440	4.7380	**6.3990***	**0.0006*****	**0.0005*****
	(0.003)	**(0.085)**	**(0.005)**	**(0.003)**	**(0.000)**	**(0.043)**	**(0.069)**	**(0.028)**	(0.487)	(0.715)	(0.135)	**(0.097)**	**(0.002)**	(0.001)
SHADOW$_i$ × POST-AXXX$_t$		**-0.0047***		0.0130		**-0.0116*****		0.0160		-3.3920		-2.4270		0.0002
		(0.099)		(0.398)		**(0.005)**		(0.599)		(0.182)		(0.543)		(0.132)
Current liquidiy	**-0.0023****	**-0.0023****	**-0.0078****	**-0.0077****	-0.0006	-0.0006	**-0.0273*****	**-0.0273*****	**-2.6810*****	**-2.6850*****	**14.0400*****	**14.0400*****	**0.00003****	**0.00003****
	(0.020)	**(0.019)**	**(0.016)**	**(0.016)**	(0.678)	(0.670)	**(0.000)**	**(0.000)**	**(0.001)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.021)**	**(0.021)**
Leverage	-0.0191	-0.0199	-0.0996	-0.0974	**-0.1020*****	**-0.1030*****	**-0.4980*****	**-0.4950*****	20.5700	20.0400	**-53.1900****	**-53.5700****	**-0.0011*****	**-0.0011*****
	(0.373)	(0.354)	(0.122)	(0.132)	**(0.002)**	**(0.001)**	**(0.000)**	**(0.000)**	(0.133)	(0.144)	**(0.042)**	**(0.040)**	**(0.002)**	**(0.003)**
Surplus ratio	**0.0834*****	**0.0829*****	**0.1800*****	**0.1810*****	-0.0177	-0.0188	**0.3720*****	**0.3740*****	**28.3800****	**28.0600****	**-51.5300****	**-51.7600****	**-0.0005****	**-0.0005****
	(0.000)	**(0.000)**	**(0.003)**	**(0.003)**	(0.602)	(0.579)	**(0.001)**	**(0.001)**	**(0.017)**	**(0.018)**	**(0.040)**	**(0.040)**	**(0.030)**	**(0.036)**
Log(assets)	**0.0038****	**0.0039****	**0.0172****	**0.0167****	**0.0092*****	**0.0096*****	**-0.0620*****	**-0.0626*****	**7.0730*****	**7.1760*****	-7.5610	-7.4880	**0.0005*****	**0.0005*****
	(0.040)	**(0.034)**	**(0.015)**	**(0.018)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.000)**	**(0.000)**	(0.134)	(0.134)	**(0.000)**	**(0.000)**
Company to group size	0.0108	0.0105	0.0366	0.0377	0.0139	0.0130	-0.0127	-0.0113	-9.8500	-10.0900	3.1710	2.9960	**0.0005****	**0.0006****
	(0.191)	(0.205)	(0.218)	(0.204)	(0.235)	(0.263)	(0.806)	(0.827)	(0.119)	(0.110)	(0.796)	(0.806)	**(0.023)**	**(0.020)**
Log(#Affiliates)	-0.0006	-0.0008	0.0059	0.0065	-0.0019	-0.0024	-0.0239	-0.0232	0.1810	0.0398	-2.0130	-2.1140	-0.00003	-0.00002
	(0.821)	(0.760)	(0.559)	(0.519)	(0.574)	(0.484)	(0.291)	(0.306)	(0.930)	(0.985)	(0.563)	(0.550)	(0.764)	(0.831)
Log(Group liabilities)	**0.0044****	**0.0043****	0.0099	0.0099	**0.0086*****	**0.0085*****	**0.0249****	**0.0250****	2.2070	2.1990	-1.3250	-1.3300	**0.0001****	**0.0001****
	(0.026)	**(0.026)**	(0.105)	(0.104)	**(0.001)**	**(0.001)**	**(0.022)**	**(0.022)**	(0.177)	(0.179)	(0.769)	(0.768)	**(0.019)**	**(0.018)**
Group leverage	**-0.0366****	**-0.0364****	-0.0813	-0.0819	**-0.0645*****	**-0.0640*****	**-0.3080*****	**-0.3080*****	**-44.0700*****	**-43.9400*****	21.5200	21.6200	-0.0004	-0.0004
	(0.044)	**(0.045)**	(0.202)	(0.199)	**(0.006)**	**(0.007)**	**(0.005)**	**(0.004)**	**(0.001)**	**(0.001)**	(0.391)	(0.388)	(0.162)	(0.153)
Year FE	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Insurer FE	x	x	x	x	x	x	x	x	x	x	x	x	x	x
N	10,718	10,718	9,915	9,915	10,718	10,718	9,915	9,915	10,759	10,759	10,759	10,759	10,759	10,759
Adj. R^2	0.054	0.054	0.050	0.050	0.054	0.055	0.105	0.105	0.089	0.090	0.137	0.137	0.067	0.068

Table 6: Does shadow insurance provide a competitive advantage? Panel-IV regressions (Term life insurance market share 1999)

This table shows results of instrumental variable analyses for the time period from 1999 to 2014 for a sample of U.S. life insurers that report to the NAIC. The main variable of interest is $\text{SHADOW}_{i,t}$ which is a dummy variable that is equal to one in year t, if an insurer uses shadow insurance in that year. $\text{SHADOW}_{i,t}$ is instrumented in a first stage regression using the interaction of TREAT_i and a time-dummy POST-2001_t that is one after 2001. TREAT_i is one for life insurers that are in the top tercile of term life insurance market share in 1999 and zero if the life insurers is in the bottom tercile. The first stage regressions are of the following form:

$$\text{SHADOW}_{i,t} = \beta \cdot \text{TREAT}_i \times \text{POST-2001}_t + \Theta \cdot \text{CONTROLS}_{i,t} + \mu_t + u_{i,t},$$

Regressions are performed by OLS estimation including year dummies, the term life insurance ratio, and other control variables. Control variables include an insurer's current liquidity, leverage, log of total assets, surplus ratio, company to group size, log of the number of affiliates in the insurance group, log of its group's liabilities, and group leverage. The second stage regressions are of the following form:

$$\text{Y}_{i,t} = \alpha_i + \mu_t + \beta \cdot \text{SHADOW}_{i,t} + \Theta \cdot \text{CONTROLS}_{i,t} + \varepsilon_{i,t},$$

where $\text{Y}_{i,t}$ is either return on assets (ROA), return on equity (ROE), underwriting (UW) ROA, underwriting (UW) ROE, rating, risk-based capital ratio (RBC), or market share (MSHARE) based on total premiums written. Variable definitions are given in Appendix I. P-values are given in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. Regressions include insurer fixed effects and year dummies. Adj. R^2 is the adjusted R^2. Coefficients of constants and dummies are suppressed for brevity. The first column shows results from the first stage regression and columns (1) to (7) show results of the second stage regressions using one of the seven outcome variables as dependent variables.

Dependent variable:	First stage SHADOW	(1) ROA	(2) ROE	(3) UW ROA	(4) UW ROE	(5) RATING	(6) RBC	(7) MSHARE
$\text{TREAT}_i \cdot \text{POST-2001}_t$	**0.2057*****							
	(0.000)							
Term life insurance ratio	**0.1524*****							
	(0.000)							
SHADOW (dummy)		**-0.0369*****	**-0.1570****	**-0.0731*****	**0.2230***	**-22.8400*****	2.1050	-0.0004
		(0.009)	**(0.020)**	**(0.001)**	**(0.088)**	**(0.003)**	(0.834)	(0.534)
Current liquidity	-0.0001	**-0.0021****	-0.0056	**0.0033****	**-0.0232*****	**-1.6270*****	9.6910***	0.00002
	(0.992)	**(0.020)**	(0.195)	**(0.020)**	**(0.006)**	**(0.001)**	**(0.000)**	(0.667)
Leverage	**-0.2313****	**-0.0406****	**-0.2010****	**-0.0955*****	**-0.5200*****	1.4730	-0.5540	**-0.0028*****
	(0.040)	**(0.015)**	**(0.011)**	**(0.000)**	**(0.001)**	(0.871)	(0.963)	**(0.000)**
Log(assets)	**0.0583*****	**0.0045****	**0.0303*****	**0.0104*****	**-0.1070*****	**9.2080*****	**-6.2580*****	**0.0009*****
	(0.000)	**(0.021)**	**(0.001)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
Surplus ratio	-0.0975	**0.0483*****	0.0007	-0.0364	**0.3670*****	**23.6500*****	-9.9550	**-0.0015****
	(0.342)	**(0.001)**	(0.992)	(0.113)	**(0.008)**	**(0.004)**	(0.352)	**(0.020)**
Company to group size	-0.0709	-0.0019	-0.0017	-0.0070	0.0344	-0.9600	**11.2500****	**0.0008*****
	(0.128)	(0.784)	(0.960)	(0.508)	(0.591)	(0.798)	**(0.022)**	**(0.006)**
Log(#Affiliates)	**-0.0392****	-0.0019	-0.0019	-0.0045	**-0.0391***	-0.6170	-1.7060	-0.00002
	(0.016)	(0.443)	(0.870)	(0.241)	**(0.090)**	(0.647)	(0.336)	(0.818)
Log(group liabilities)	0.0054	**0.0036****	0.0027	**0.0075*****	**0.0313****	**4.0760*****	**3.129*****	**0.0001****
	(0.632)	**(0.027)**	(0.728)	**(0.003)**	**(0.039)**	**(0.000)**	**(0.007)**	**(0.036)**
Group leverage	-0.1290	-0.0477***	-0.0237	-0.0817***	-0.3620***	-34.2200***	-24.2400**	-0.000492
	(0.190)	**(0.001)**	(0.730)	**(0.000)**	**(0.007)**	**(0.000)**	**(0.018)**	(0.418)
Year FE	x	x	x	x	x	x	x	x
Insurer FE	-	x	x	x	x	x	x	x
N	4,297	4,297	4,294	4,297	4,294	4,310	4,310	4,310

Table 7: Does shadow insurance provide a competitive advantage? Panel-IV regressions (Adjusted risk-based capital 2001)

This table shows results of instrumental variable analyses for the time period from 2001 to 2014 for a sample of U.S. life insurers that report to the NAIC. The main variable of interest is $\text{SHADOW}_{i,t}$ which is a dummy variable that is equal to one in year t, if an insurer uses shadow insurance in that year. $\text{SHADOW}_{i,t}$ is instrumented in a first stage regression using the interaction of $\text{RBC}_{i,2001} - \widehat{\text{RBC}}_{i,t,2001}$ and a time-dummy POST-2001_t that is one after 2001. $\text{RBC}_{i,2001} - \widehat{\text{RBC}}_{i,t,2001}$ is the difference of the actual and the adjusted RBC ratio in 2001 (adjusted by multiplying liabilities over the sum of liabilities and total shadow insurance of a life insurer in year t). The first stage regressions are of the following form:

$$\left(\frac{\text{SHADOW}}{\text{REINSURANCE}}\right)_{i,t} = \beta \cdot \left(\left[\text{RBC}_{i,2001} - \widehat{\text{RBC}}_{i,t,2001}\right] \times \text{POST-2001}_t\right) + \Theta \times \text{CONTROLS}_{i,t} + \mu_t + u_{i,t},$$

Regressions are performed by OLS estimation including year dummies, the term life insurance ratio, and other control variables. Control variables include an insurer's current liquidity, leverage, log of total assets, surplus ratio, company to group size, log of the number of affiliates in the insurance group, log of its group's liabilities, and group leverage. The second stage regressions are of the following form:

$$\text{Y}_{i,t} = \alpha_i + \mu_t + \beta \cdot \text{SHADOW}_{i,t} + \Theta \cdot \text{CONTROLS}_{i,t} + \varepsilon_{i,t},$$

where $\text{Y}_{i,t}$ is either return on assets (ROA), return on equity (ROE), underwriting (UW) ROA, underwriting (UW) ROE, rating, risk-based capital ratio (RBC), or market share (MSHARE) based on total premiums written. Variable definitions are given in Appendix I. P-values are given in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. Regressions include insurer fixed effects and year dummies. Adj. R^2 is the adjusted R^2. Coefficients of constants and dummies are suppressed for brevity. The first column shows results from the first stage regression and columns (1) to (7) show results of the second stage regressions using one of the seven outcome variables as dependent variables.

Dependent variable:	First stage SHADOW/REINSURANCE	(1) ROA	(2) ROE	(3) UW ROA	(4) UW ROE	(5) RATING	(6) RBC	(7) MSHARE
$\left[\text{RBC}_{i,2001} - \widehat{\text{RBC}}_{i,t,2001}\right] \times \text{POST-2001}_t$	**0.0001***							
	(0.078)							
Term life insurance ratio	-0.0112							
	(0.493)							
SHADOW/REINSURANCE		**-0.8070***	**-2.8100***	0.1020	1.2970	111.3000	10.5200	-0.0057
		(0.067)	**(0.084)**	(0.662)	(0.392)	(0.219)	(0.888)	(0.276)
Current liquidity		-0.0033	-0.0072	-0.0001	**-0.0272*****	**-1.8430*****	**3.6720*****	0.00001
		(0.149)	(0.394)	(0.911)	**(0.001)**	**(0.000)**	**(0.000)**	(0.727)
Leverage		-0.0736	-0.2640	**-0.1380*****	**-0.7430*****	-7.1690	**-16.2700***	**-0.0027*****
		(0.161)	(0.173)	**(0.000)**	**(0.000)**	(0.506)	**(0.067)**	**(0.000)**
Log(assets)		**0.0135***	**0.0596****	**0.00768***	-0.0268	**4.349*****	0.238	0.000843***
		(0.090)	**(0.042)**	**(0.068)**	(0.326)	**(0.008)**	(0.859)	**(0.000)**
Surplus Ratio		**0.0678***	0.1060	**-0.0649*****	0.1080	6.9310	3.0650	**-0.0012****
		(0.091)	(0.473)	**(0.002)**	(0.433)	(0.401)	(0.652)	**(0.011)**
Company to group size		-0.0008	0.0082	**0.0197***	-0.0428	-3.1720	**6.0880***	0.0002
		(0.970)	(0.912)	**(0.065)**	(0.537)	(0.443)	**(0.074)**	(0.433)
Log(#Affiliates)		-0.0149	-0.0444	0.0015	0.0006	2.1760	0.6560	-0.0001
		(0.140)	(0.234)	(0.786)	(0.986)	(0.294)	(0.701)	(0.622)
Log(Group liabilities)		0.0061	0.0228	**0.0060****	0.0058	0.9790	-0.9320	0.0001
		(0.190)	(0.182)	**(0.014)**	(0.716)	(0.302)	(0.233)	(0.167)
Group leverage		-0.0592	-0.2140	**-0.0643*****	-0.1860	**-22.3700*****	4.6210	-0.0005
		(0.146)	(0.157)	**(0.003)**	(0.187)	**(0.008)**	(0.503)	(0.334)
N	5,056	5,056	5,052	5,056	5,052	5,056	5,056	5,056
Year FE	x	x	x	x	x	x	x	x
Insurer FE	-	x	x	x	x	x	x	x

Table 8: Heckman two-stage selection model.

The table shows the results of a Heckman two-stage procedure. The selection dummy is one if a life insurer engages in shadow insurance activities in a given year. First, we estimate a probit model in which we explain the selection dummy with the interaction of TREAT_i and a time-dummy POST-2001_t that is one after 2001, term life insurance ratios, and other control variables. TREAT_i is one for life insurers that are in the top tercile of term life insurance market share in 1999 and zero if the life insurers is in the bottom tercile. Control variables include an insurer's current liquidity, leverage, log of total assets, surplus ratio, company to group size, log of the number of affiliates in the insurance group, log of its group's liabilities, and group leverage. Predicted value of the estimated probit model are used to calculate the inverse Mills ratio, which is included in the second stage regression. The second stage of the Heckman procedure is an OLS regression of the following form:

$$\text{Y}_{i,t} = \alpha_i + \mu_t + \beta \times \text{INVERSE MILLS RATIO}_{i,t} + \gamma \times \text{SHADOW}_{i,t} + \delta \times \text{CONTROLS}_{i,t} + \varepsilon_{i,t},$$

where $\text{Y}_{i,t}$ is either return on assets (ROA), return on equity (ROE), underwriting (UW) ROA, underwriting (UW) ROE, rating, risk-based capital ratio (RBC), or market share (MSHARE) based on total premiums written. Panel A and B show results for the time periods from 1999 to 2014 and 2002 to 2014, respectively. Variable definitions are given in Appendix I. P-values are given in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. Regressions include insurer fixed effects and year dummies. Adj. R^2 is the adjusted R^2. Coefficients of constants, dummies, and control variables are suppressed for brevity. The first column shows results from the first stage regression and columns (1) to (7) show results of the second stage regressions using one of the seven outcome variables as dependent variables.

Panel A: 1999-2014	Selection	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	SHADOW	ROA	ROE	UW ROA	UW ROE	RATING	RBC	MSHARE
SHADOW		**-0.0050***	-0.0162	**-0.0147*****	-0.0410	-2.0210	1.8590	-0.0004
		(0.060)	(0.300)	**(0.000)**	(0.169)	(0.323)	(0.315)	(0.148)
Inverse Mills ratio		0.0091	0.0339	0.0134	0.0138	**-20.6400*****	21.9300	-0.0003
		(0.146)	(0.126)	(0.103)	(0.753)	**(0.002)**	(0.156)	(0.202)
$\text{TREAT}_i \times \text{POST-2001}_t$	0.0439							
	(0.636)							
Term life insurance ratio	**0.7360*****							
	(0.000)							
N	3,205	3,574	3,572	3,574	3,572	3,575	3,575	3,575
Pseudo/Adj. R^2	0.180	0.049	0.074	0.046	0.101	0.104	0.121	0.085
Panel B: 2002-2014	Selection	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	SHADOW	ROA	ROE	UW ROA	UW ROE	RATING	RBC	MSHARE
SHADOW		**-0.0062****	-0.0223	**-0.0143*****	-0.0293	-1.3100	1.6410	**-0.0007****
		(0.045)	(0.219)	**(0.001)**	(0.373)	(0.522)	(0.312)	**(0.019)**
Inverse Mills ratio		0.0115	0.0323	**0.0165***	0.0463	**-24.9700*****	26.7600	-0.0003
		(0.113)	(0.229)	**(0.056)**	(0.345)	**(0.002)**	(0.185)	(0.163)
$\text{TREAT}_i \times \text{POST-2001}_t$	0.0439							
	(0.636)							
Term life insurance ratio	**0.7360*****							
	(0.000)							
Control variables	x	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x	x
Insurer FE	-	x	x	x	x	x	x	x
Financial size FE	x	-	-	-	-	-	-	-
N	3,205	3,205	3,205	3,205	3,205	3,205	3,205	3,205
Pseudo/Adj. R^2	0.180	0.056	0.078	0.035	0.084	0.104	0.079	0.096

Table 9: Does shadow insurance provide a competitive advantage? Balanced sample

This table shows results of OLS and two-stage least squares regressions for the time period from 1999 to 2014 for a balanced sample of U.S. life insurers that report to the NAIC. The balanced sample consists of matched pairs of life insurers using propensity score matching with replacement (nearest neighbor). Users of shadow insurance (in 2002-2014) are matched to non-users based on their company to group size, number of affiliates in the group, (log) group liabilities, and group leverage in 2001. Regressions are performed by OLS estimation with standard errors clustered on the firm level and are of the following form:

$$\mathrm{Y}_{i,t} = \alpha_j + \mu_t + \beta \times \mathrm{SHADOW}_{i,t} + \varepsilon_{i,t},$$

The main variable of interest is $\mathrm{SHADOW}_{i,t}$ which is either a dummy variable that is equal to one in year t, if an insurer uses shadow insurance in that year or the ratio of shadow insurance and total reinsurance ceded. The $\mathrm{SHADOW}_{i,t}$ dummy is instrumented in a first stage regression using the interaction of TREAT_i and a time-dummy POST-2001_t that is one after 2001. TREAT_i is one for life insurers that are in the top tercile of term life insurance market share in 1999 and zero if the life insurers is in the bottom tercile. The ratio is instrumented with the difference of the actual and adjusted RBC ratio in 2001 (adjusted by the respective amount each year). All control variables in the main regression and the term life insurance ratio are also included in the first stage regression. $\mathrm{Y}_{i,t}$ is either return on assets (ROA), return on equity (ROE), underwriting (UW) ROA, underwriting (UW) ROE, rating, risk-based capital ratio (RBC), or market share (MSHARE) based on total premiums written. Variable definitions are given in Appendix I. P-values are given in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. Regressions include financial size fixed effects and year dummies. Adj. R^2 is the adjusted R^2 of the OLS regression. Coefficients of control variables and dummies are suppressed for brevity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	ROA	ROE	UW ROA	UW ROE	RATING	RBC	MSHARE
SHADOW dummy (2SLS)	**-0.0846****	**-0.3750****	**-0.0900***	0.3680	**43.0600****	3.9340	**-0.0091***
	(0.035)	**(0.025)**	**(0.088)**	(0.448)	**(0.030)**	(0.544)	**(0.062)**
N	2301	2299	2301	2299	2311	2311	2311
Adj. R^2	0.151	0.092	0.108	0.305	0.834	0.239	0.606
SHADOW/REINSURANCE (2SLS)	**-0.0859****	**-0.5100****	**-0.1160****	-0.0723	**70.6600****	8.2810	-0.0072
	(0.014)	**(0.013)**	**(0.022)**	(0.875)	**(0.014)**	(0.487)	(0.274)
N	2,797	2,797	2,797	2,797	2,797	2,797	2,797
Adj. R^2	0.163	0.089	0.111	0.291	0.814	0.257	0.620
Control variables	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x
Financial size FE	x	x	x	x	x	x	x

Table 10: What explains the differences between shadow insurance users and non-users?

This table shows the results of regressions of the difference in firm outcomes on differences in insurer firm of matched shadow insurance users and non-users from 2001 to 2014. Shadow insurance users are life insurers that cede reinsurance to affiliated, unauthorized, and unrated reinsurers. Dependent variables are differences in either return on assets (ROA), return on equity (ROE), underwriting (UW) ROA, underwriting (UW) ROE, rating, risk-based capital ratio (RBC), or market share (MSHARE) based on total premiums written. Life insurers are matched using the nearest neighbor propensity score matching method (with replacement) based on the group variables group liabilities and leverage, log of the number of affiliated firms, and company to group size in 2001. Variable definitions are given in Appendix I. We estimate pooled OLS regressions with year-fixed effects and bootstrapped standard errors. Adj. R^2 is adjusted R^2.

Dependent variable:	(1) ΔROA	(2) ΔROE	(3) ΔUW ROA	(4) ΔUW ROE	(5) ΔRATING	(6) ΔRBC	(7) ΔMSHARE
ΔCurrent liquidity	0.0024	**0.0173*****	**0.0097*****	0.0088	**2.0830***	**6.3510*****	**-0.0003*****
	(0.125)	**(0.008)**	**(0.001)**	(0.551)	**(0.083)**	**(0.000)**	**(0.008)**
ΔLeverage	0.0121	0.0197	-0.0284	**-0.5940****	18.5900	6.3210	**-0.0117*****
	(0.748)	(0.898)	(0.490)	**(0.026)**	(0.403)	(0.457)	**(0.000)**
ΔTerm life insurance ratio	**-0.0113*****	**-0.0454****	**-0.0174*****	0.0322	**6.1780*****	**2.7100****	**0.0010*****
	(0.000)	**(0.011)**	**(0.000)**	(0.369)	**(0.001)**	**(0.016)**	**(0.000)**
ΔLog(assets)	**0.0029****	0.0066	0.0036	-0.0229	**6.0290*****	**-1.2270****	**0.0015*****
	(0.030)	(0.384)	(0.110)	(0.167)	**(0.000)**	**(0.013)**	**(0.000)**
ΔSurplus ratio	**0.1130*****	0.1410	0.0627	**0.8410*****	**85.7200*****	-0.0783	**-0.0073*****
	(0.009)	(0.380)	(0.123)	**(0.008)**	**(0.001)**	(0.993)	**(0.000)**
ΔAnnuity ratio (DPW)	**-0.0094*****	**-0.0983*****	**-0.0076****	**-0.3570*****	0.4940	1.2040	-0.0003
	(0.000)	**(0.000)**	**(0.049)**	**(0.000)**	(0.813)	(0.181)	(0.130)
Constant	0.0014	**-0.0329***	0.0101	-0.0675	**6.4970***	0.1780	0.0001
	(0.683)	**(0.060)**	(0.102)	(0.142)	**(0.093)**	(0.842)	(0.608)
Year FE	x	x	x	x	x	x	x
N	1,131	1,131	1,131	1,131	1,141	1,141	1,141
Adj. R^2	0.151	0.044	0.095	0.244	0.130	0.178	0.177

Table 11: Shadow insurance during the financial crisis

This table shows results of OLS panel regressions of life insurer characteristics on shadow insurance usage for the time period from 2002 to 2014 for a sample of U.S. life insurers that report to the NAIC. Regressions are performed by OLS estimation with robust standard errors and fixed effects and are of the following form:

$$\mathrm{Y}_{i,t} = \alpha_i + \mu_t + \beta \cdot \mathrm{SHADOW}_{i,t} + \gamma \cdot (\mathrm{SHADOW}_{i,t} \times \mathrm{CRISIS}_t) + \delta \cdot (\mathrm{SHADOW}_{i,t} \times \mathrm{POST\text{-}CRISIS}_t) + \Theta \cdot \mathrm{CONTROLS}_{i,t} + \varepsilon_{i,t}.$$

The main variable of interest is $\mathrm{SHADOW}_{i,t}$ which is either a dummy variable that is equal to one in year t, if an insurer uses shadow insurance in that year or the ratio of shadow insurance and total reinsurance ceded. $\mathrm{SHADOW}_{i,t}$ is interacted with dummy variables CRISIS_t and $\mathrm{POST\text{-}CRISIS}_t$ which are one if an observation is in year 2007-2009 and 2010-2014, respectively. $\mathrm{Y}_{i,t}$ is either return on assets (ROA), return on equity (ROE), underwriting (UW) ROA, underwriting (UW) ROE, rating, risk-based capital ratio (RBC), or market share (MSHARE) based on total premiums written. Variable definitions are given in Appendix I. P-values are given in parentheses and ***, **, and * indicate statistical significance at the 1%, 5%, and 10% level. Adj. R^2 is the adjusted R^2 of the OLS regression. Coefficients of control variables and dummies are suppressed for brevity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable:	ROA	ROE	UW ROA	UW ROE	RATING	RBC	MSHARE
SHADOW (dummy)	**-0.0076****	**-0.0458****	**-0.0142****	**-0.1070****	1.3480	**-10.0800*****	**-0.0006****
	(0.048)	**(0.038)**	**(0.021)**	**(0.011)**	(0.567)	**(0.007)**	**(0.038)**
$\mathrm{SHADOW}_{i,t} \times \mathrm{CRISIS}_t$	-0.0017	-0.0293	-0.0051	0.0116	-1.3200	2.7110	0.0003
	(0.632)	(0.138)	(0.384)	(0.808)	(0.371)	(0.409)	(0.265)
$\mathrm{SHADOW}_{i,t} \times \mathrm{POST\text{-}CRISIS}_t$	**0.0081****	**0.0500****	0.0004	**0.1170****	**-5.4360****	**8.7320****	0.0001
	(0.030)	**(0.038)**	(0.960)	**(0.036)**	**(0.011)**	**(0.027)**	(0.722)
N	7,052	7,014	7,052	7,014	7,052	7,052	7,052
Adj. R^2	0.055	0.065	0.034	0.073	0.070	0.101	0.069
SHADOW/REINSURANCE	**-0.0188***	-0.0745	**-0.0250***	-0.1430	0.0401	-5.3650	-0.0006
	(0.054)	(0.201)	**(0.064)**	(0.136)	(0.988)	(0.130)	(0.228)
$\mathrm{SHADOW}_{i,t} \times \mathrm{CRISIS}_t$	0.0008	0.0083	-0.0136	-0.0393	-0.7710	-3.6540	0.0001
	(0.926)	(0.858)	(0.321)	(0.671)	(0.635)	(0.379)	(0.822)
$\mathrm{SHADOW}_{i,t} \times \mathrm{POST\text{-}CRISIS}_t$	**0.0162***	**0.1260****	-0.0108	0.0367	-1.3710	0.3710	-0.0001
	(0.089)	**(0.043)**	(0.573)	(0.769)	(0.630)	(0.886)	(0.716)
N	5,626	5,620	5,626	5,620	5,626	5,626	5,626
Adj. R^2	0.057	0.074	0.044	0.069	0.038	0.130	0.071
Control variables	x	x	x	x	x	x	x
Year FE	x	x	x	x	x	x	x
Insurer FE	x	x	x	x	x	x	x