Shadow Insurance and Systemic Risk

August 19, 2017

ABSTRACT

This paper investigates whether U.S. life insurers that cede reinsurance to affiliated, unauthorized, and unrated entities, so called "shadow insurers" increase their exposure and relevance to systemic risk in the banking sector. Our findings suggest that shadow insurance activities increase life insurers' exposure to systemic risk stemming from the banking sector as well as life insurers' idiosyncratic risks. Using newly available data on the funding structure of shadow insurance agreements within life insurance groups since 2011, we are able to directly measure life insurers' degree of interconnectedness with the banking sector by determining the exposure to banks via the amount of letters of credit issued and the number of banks involved in each transaction. We observe that banks and life insurers are interconnected through letters of credit financing of shadow entities, which increases life insurers' sensitivity to market movements in the banking sector. The results we find are robust to instrumental variable regressions, a difference-in-difference approach, and fixed effects. We conclude that shadow insurance does pose some interconnectedness risk and theoretically discuss options for regulation.

Keywords: Shadow insurance, capital management, insurance regulation, systemic risk, interconnectedness.

JEL Classification Numbers: G01, G22, G23, G28.

1 Introduction

In response to the adoption of Regulation XXX/AXXX in the early 2000s, life insurers in the United States now make extensive use of alternative reinsurance agreements within the insurance group that involve unauthorized and unrated entities, so called "shadow insurers", which are often captives. These captive reinsurers (captives) or special purpose vehicles (SPV) can be located off-shore or in states with favorable laws that allow for this potential regulatory capital arbitrage. Most prominently, Koijen and Yogo (2016a,b) recognize significant growth of shadow insurance, which now often makes up a large proportion of total reinsurance ceded.[1] One of the main issues with shadow insurance activities is the lack of transparency about the actual risk involved in these transactions. While these non-traditional reinsurance arrangements allow life insurers to reduce prices through lower marginal costs (see Koijen and Yogo, 2016b), they may also carry additional risks that have not been assessed to a satisfactory degree. For example, life insurers are linked to the banking sector via letters of credit (LOC) financing and thus, are dependent on the ability or willingness of banks to renew the LOCs for future funding. At the same time, banks are exposed to the possibility that life insurers or their affiliated shadow insurers are unable to fulfill their financial obligations.[2] Among other risk, using shadow insurance can create *interconnectedness risk*, which has been recognized as one of the main drivers of systemic risk.

In this paper, we investigate the question whether the use of shadow insurance poses risk to and from the financial system. We find that life insurance groups that employ shadow insurance are not necessarily perceived as riskier by investors, but that they are more sensitive to market movements in the banking sector. Our main results suggest that insurance groups are linked to the banking sector via the financing of shadow entities through letters of credit and as a result increase their exposure to respective bank equity market movements. The more insurance groups make use of LOCs to collateralize shadow reinsurance transactions, the more dependent they are on the

[1] Harrington (2014, 2015) provides a detailed overview of the developments in the U.S. life insurance sector regarding shadow insurance.

[2] One commonly used collateral is the LOC with parental guarantee. If the shadow reinsurer defaults and triggers a draw on the LOC, then the parent company will ultimately be forced to reimburse this draw on bankHarrington (2015).

bank counterparty to extend the financing. As a result, we find that life insurers' market beta with respect to U.S. bank equities increases. In the same way, we observe that life insurance groups are more exposed to systemic risk in the banking sector. Thus, we conclude that shadow insurance does pose interconnectedness risk.

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 investors are unable to assess the actual risk involved. However, since 2011, life insurers are required to not only disclose information on the funding structure of transactions with unauthorized reinsurers (e.g., the amount of LOCs used as collateral), but also the names of the respective counterparties, i.e., the banks that provide the collateral (see NAIC, 2010). By viewing this change in disclosure practices of shadow insurance users as a shock on the quality of information provided, we are able to observe respective changes in market-based idiosyncratic and systemic risk measures of the respective life insurance group. Thus, we can compare investors' perception of the insurers' equity risk before and after the release of additional information on shadow insurance activities using a difference-in-difference approach. We hypothesize that due to improved knowledge about the interconnectedness of life insurance groups with the banking sector through LOCs, investors will re-evaluate the sensitivity of life insurer equities towards the banking sector.

In this paper, we further directly measure life insurers' degree of interconnectedness with the banking sector by determining the exposure to banks via the amount of LOCs issued and the number of banks involved in each transaction. This is an advantage over other approaches that involve indirect measurement via equity prices.[3] [4] In 2012, about one third of the shadow insurance ceded was collateralized by LOCs, which builds an additional link between the life insurance and banking sector. Such collateral for shadow insurance translates into approximately $100 billion. This is a non-negligible amount that could impair financial stability if insurers systematically defaulted on

[3]For example, Billio et al. (2012) construct a measure of interconnectedness by applying a principal component analysis to the variance-covariance matrix of a set of financial institutions' stock returns and broadly define interconnectedness via the explanatory power of the principal components. In addition they define another interconnectedness measure by looking at the number of significant Granger causalities among the time-series.

[4]Another example is given in the work of Chen et al. (2014), where interconnectedness within the financial system is measured by using daily stock and credit default swap data.

their obligations (see Schwarcz, 2015). Intuitively, when only one bank provides a large amount of collateral for the shadow insurer, that bank is highly exposed to the well-being of the life insurer and its affiliated reinsurer. Similarly, the insurer is highly dependent on the willingness of that bank to renew the full amount of issued LOCs. However, if several banks are (equally) involved in the shadow insurance transaction, potential risks are distributed among those banks and the life insurer might be more likely to receive a renewal of LOCs. [5] Thus, both the exposure and contribution to systemic risks are reduced in this case. The aim of this paper is therefore to explore the economic consequences of these linkages with regard to financial stability.

We analyze a sample of 35 publicly listed U.S. life insurance groups from 2002 to 2014 and empirically test whether shadow insurance usage is a driver of risk measures. To distinguish between changes in idiosyncratic risk and systemic/systematic risk (with respect to a bank equity index), we use two sets of risk measures as dependent variables. On the one side, we use life insurers' stock volatility, Value-at-Risk, and Expected Shortfall as market measures of individual firm risk. On the other side we employ a firm's beta, Marginal Expected Shortfall (MES) and ΔCoVaR (see Acharya et al., 2016; Adrian and Brunnermeier, 2016) as dependent variables in various regression analyses. We relate these risk measures to shadow insurance usage by life insurance groups using ordinary least squares and instrumental variable regressions as well as a difference-in-difference setting. Afterwards, we restrict our sample to shadow insurance users only and use information on the amount of LOCs used to collateralize the shadow insurance transactions to see whether the funding structure is a determinant of the group's equity risk. Further, we include the concentration of banks involved in shadow insurance transactions as a control variable for evaluating the dependence of life insurers on single banks.

Our study is mostly related to the literature on capital management in life insurance companies (see, e.g., Berry-Stölzle et al., 2014; Niehaus, 2016; Altuntas et al., 2015) and systemic risk in the insurance sector. Studies on the latter topic deal with the determinants of common measures

[5] When a bank decide whether to issue or renew the LOC, it would presumably reason that other banks that chose to issue or renew the LOC had superior information about the financial health of the obligee or guarantor (Schwarcz, 2015). So several banks involved may signal a strong financial condition of the life insurer's parent.

of exposure and contribution to systemic risk of insurance companies (see, e.g., Mühlnickel and Weiß, 2015; Weiß and Mühlnickel, 2014; Bierth et al., 2015), while, e.g., Cummins and Weiss (2014), Schwarcz and Schwarcz (2015), or Eling and Pankoke (2016) give a more comprehensive overview of systemic risk in insurance. Ceding shadow insurance can create systemic risks for insurers to the extent that it increases the *interconnectedness* with the banking sector and that it understates *leverage*, both of which are known factors in determining systemic relevance (see, e.g., IAIS, 2011, 2012; Billio et al., 2012).

The outcomes of this study are relevant for at least two reasons: First, analyzing the riskiness of shadow insurance transactions is important, as most of the life insurers ceding to affiliated shadow insurers are larger companies that can be systemically relevant (see Koijen and Yogo, 2016b). We assess the funding structure of shadow insurers and focus on the issuance of LOCs, which serves as collateral in these transactions. Second, we directly measure the degree of interconnectedness between the banking and the life insurance sector as a result of shadow insurance to assess systemic risks stemming from only these reinsurance agreements.

The remainder of the paper is organized as follows: In the next section, we describe the general structure of shadow insurance agreements and highlight the potential systemic risks associated with these transactions. We further denote the hypotheses we empirically test in this paper. Section 3 develops the empirical methodologies and introduces shadow insurance variables. Section 4 introduces the data and sample used in this study. In Section 5, we elaborate on our empirical results. We then extend the discussion to regulation on shadow insurance spill over effects in section 6. Finally, we conclude in Section 7.

2 Overview and Hypotheses

In this section, we provide a brief overview of shadow reinsurance agreements, their funding structure, and potential risks arising from these transactions. Further, we present some evidence on the interconnectedness of banks and life insurers due to LOC financing of shadow reinsurance agreements. For a more comprehensive overview of the different kinds of agreements and technical details, we refer to the work of Schwarcz (2015).

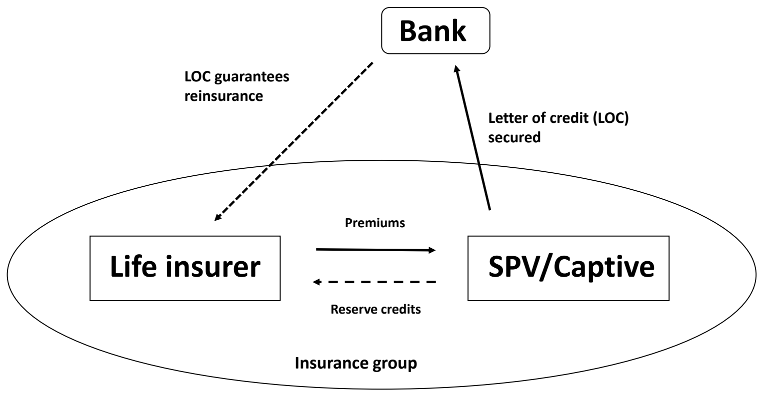
AFFILIATED AND UNAUTHORIZED REINSURANCE AGREEMENTS

Insurance companies cede reinsurance to reduce their exposure to risks (i.e. catastrophic risks), but also to reduce the required amount of capital that they must hold as a buffer for their risky liabilities. Traditionally, the reinsurance counterparty is another, external (re-)insurance company that reports to the *National Association of Insurance Commissioners* (NAIC) and is required to hold regulatory capital in the same way other authorized insurance companies are supposed to. However, when the NAIC proposed changes in statutory capital requirements for certain life insurance products (Regulation XXX/AXXX), U.S. life insurers started to engage in non-traditional reinsurance activities in order to reduce the required amount of risk-based capital that they must hold. Instead of using outside reinsurance companies, which must meet the same (strict) statutory capital standards, life insurers set up affiliated entities within the same insurance group, usually captives or Special Purpose Vehicles (SPV), with the sole purpose of assuming reinsurance from the life insurer. These affiliated entities are not authorized as insurance companies and thus, do not follow the same accounting standards but follow, e.g., the less strict Generally Accepted Accounting Principles (GAAP) when determining reserve requirements. This is possible as several state laws allow life insurers to take reserve credits through this kind of reinsurance agreement if the transaction is *collateralized* through (unconditional) letters of credit (LOC) or a trust fund (usually provided by a bank) (see NAIC, 2011). Reinsurance ceded to affiliated and unauthorized entities is called "shadow insurance" if the entity is not rated by A.M. Best and thus, there is little information about the financial situation of the respective reinsurance counterparty (see Koijen and Yogo, 2016b).

SHADOW INSURANCE FUNDING STRUCTURE

We illustrate the general setting and participants in a shadow reinsurance transaction using LOC financing in Figure 1.[6] The life insurance company cedes reinsurance to an affiliated SPV or

Figure 1: Shadow reinsurance transaction with letters of credit collateral



captive and may take reserve credits in return, which will lower risk-based capital requirements. In order to "authorize"[7] this transaction it is collateralized by a letter of credit. The LOC agreement ensures that the life insurer is still insured in case the affiliated entity is unable to make payments.

Regardless of the type of collateral used to authorize the affiliated reinsurance agreements, we observe that there is an additional link between the life insurance and banking sector via shadow insurance. The aim of this paper is therefore to explore the economic consequences of these linkages with regard to financial stability. Based on this setting, we want to empirically test the following hypotheses:

HYPOTHESIS 1: Life insurance groups that use shadow insurance have higher exposure to systemic and systematic risk from the banking market.

In reverse, because of the linkage through shadow insurance, a distressed life insurance sector could potentially impair the banking sector as well. Thus, another hypothesis investigated is:

[6] Bank issues LOCs to captive; captive is secured by bank.

[7] Note that while the captive or SPV is not an authorized insurance company, the reinsurance transaction itself has to be authorized (see Schwarcz, 2015).

HYPOTHESIS 2: Life insurance groups that use shadow insurance increase their contribution to systemic risk in the banking sector.

While we only know the total amount of shadow insurance ceded and the financing method before 2011, life insurers are now required to report additional information on the source of financing, i.e., the names of the counterparty banks that secure the LOCs or trust agreements. Therefore, investors are now able to take into account more information on the investment grade of the bank that provides the financing of shadow insurance agreements in the life insurance group. This can have a negative effect on market-based risk measures if the respective banks exhibit a lack of financial soundness (and positive effects if they are financially well-off). However, regardless of the riskiness of the shadow insurance agreements, increased knowledge of the interconnectedness of banks and life insurers can result in a re-evaluation of the co-movements of their respective equities. Therefore, we test a third hypothesis:

HYPOTHESIS 3: Life insurance groups' exposure and contribution to bank equity movements changed after the introduction of new disclosure standards of shadow insurance funding structures.

RISKS OF FINANCING SHADOW INSURANCE WITH LETTERS OF CREDIT

If a shadow insurance agreement relies on LOCs, there is a risk that one or more banks involved will not renew the rather short-term LOC[8] contracts.[9] This in turn, would force the life insurers to recapture the reinsurerd business and recalculate its RBC minimum without taking credit for reserve. This recapture of "removed" liabilities would suddenly decrease its capital and increase its regulatory minimum requirement.[10] Therefore, we hypothesize that the reliance on LOC financing can be viewed as riskier than other collateral methods[11] due to the dependence on the banking

[8]Letters of credit generally have a one-year duration, after which they must be renewed. See Cowley and Cummins (2005), p219.

[9]There is substantial risk that a replacement LOC would not be secured(Schwarcz, 2015).

[10]This maturity mismatch in non-traditional insurance activities such as securities lending or Funding-Agreement Backed Securities (FABS) has been recognized as another threat to financial stability in financial markets (see Foley-Fisher et al., 2016b,a).

[11]To receive reserve credit for unauthorized reinsurance, reinsurer's obligations must be collateralized by qualified LOC, funds withheld by ceding insurers, or by placing assets in a trust account. (NAIC, 2001)

sector.

HYPOTHESIS 4: Shadow insurance users that rely heavily on LOC financing are perceived as riskier than other life insurance groups and are more exposed to bank equity market movements.

Due to improved reporting requirements of affiliated, unauthorized reinsurance agreements within life insurance groups since 2011, we are able to not only observe the funding structure of these transactions, but also obtain information on the banks involved in shadow insurance. Besides the amount of LOC received, we hypothesize that the structure of the financing is important for the risk evaluation of life insurance groups. If one bank provides most of the collateral of the shadow insurance agreement, the life insurance group is dependent on this one bank to renew the short-term contracts. These should be less risk when a number of banks are involved in this transaction. We therefore test the following hypothesis for shadow insurance users:

HYPOTHESIS 5: A higher concentration among banks for LOC financing increases life insurers' risk.

SOME EVIDENCE FROM 2014

Below, we provide some descriptive statistics on shadow insurance transactions of selected life insurers and banks.[12] Table 1 shows the amount of LOCs issued to ten life insurers, the number of banks providing LOCs to these insurers, and a concentration index (HHI) based on the magnitude of the issues from each bank.[13] We observe that most of the shadow insurance transactions involve more than 15 different banks and thus, the concentration of the funding is relatively low, although there are some insurers that receive LOCs from a few banks only. On the one hand, this means that when there is financial distress stemming from the life insurance sector, banks should be only mildly affected by losses. On the other hand, the greater number of banks involved allows for more spillovers to the banking sector and thus, there is a higher interconnectedness risk.

In Table 2, we consider the other side of the transactions. The amount of LOCs issued to the

[12]While the figures above are given for individual life insurance companies (and banks), we aggregate respective data to the insurance group level for our analysis of market-based risk measures.

[13]The concentration index is calculated as a Herfindahl-type index which is the sum of the the squared shares of the total LOC amounts each bank/insurer holds.

Table 1: TOP 10 life insurers based on LOC amount in 2014

The table shows descriptive statistics for ten life insurers (or a respective affiliated entity) that received letters of credits from banks in 2014. The first column shows the name of the life insurer and the second column provides the amount of dollars received via LOCs. The third and fourth column indicate the average number of banks that issued LOCs to the insurer and a Herfindahl index based on the amount of dollars received by these banks respectively. The fifth to seventh columns give summary statistics of the amount of shadow insurance and total reinsurance ceded respectively. Dollar figures are given in millions.

Life Insurer	LOC Amount (million $)	No. Banks	HHI_LOC (in %)	Shadow Insurance (million $)	Reins_ceded (million $)	Shadow Ratio (in %)
JOHN HANCOCK LIFE INSURANCE COMPANY (USA)	4,650	35	11.9	37,960	51,980	73.0
THE LINCOLN NATIONAL LIFE INSURANCE COMPANY	3,297	34	24.8	8,219	17,210	47.8
AXA EQUITABLE LIFE INSURANCE COMPANY	3,102	17	8.4	11,490	12,920	88.9
SWISS RE LIFE & HEALTH AMERICA INC.	2,319	9	94.3	7,624	9,786	77.9
TRANSAMERICA LIFE INSURANCE COMPANY	1,643	41	41.5	6,222	31,030	20.1
HANNOVER LIFE REASSURANCE COMPANY OF AMERICA	1,565	15	39.5	20,050	25,090	79.9
TRANSAMERICA PREMIER LIFE INSURANCE COMPANY	1,509	18	58.7	9,427	9,982	94.4
BANNER LIFE INSURANCE COMPANY	1,275	3	98.0	2,464	4,979	49.5
METROPOLITAN LIFE INSURANCE COMPANY	1,259	33	28.7	29,250	46,150	63.4
THE CANADA LIFE ASSURANCE COMPANY (U.S. BUSINESS)	713	5	44.2	4,816	6,504	74.1

Table 2: TOP 10 banks based on amount of LOC issued in 2014

The table shows descriptive statistics for ten banks that issued letters of credits to life insurers (or a respective affiliated entity) in 2014. The first column shows the name of the bank and the second column provides the amount of money issued via LOCs. The third and fourth columns respectively represent the number of life insurers that the banks issued LOCs to and a Herfindahl index based on the amount of dollars issued to these insurers. Dollar figures are given in millions.

Bank name	LOC (million $)	No. Insurers	HHI of LOC issued (in %)
JP MORGAN CHASE BANK, N.A.	5,291	40	27.8
DEUTSCHE BANK AG	3,992	29	64.3
CITIBANK, N.A.	2,114	55	19.8
THE NORTHERN TRUST COMPANY	2,061	13	98.8
MORGAN STANLEY BANK, N.A.	1,959	20	48.4
CREDIT SUISSE AG	1,758	29	43.3
BARCLAYS BANK PLC	1,600	38	43.6
LANDESBANK HESSEN-THURINGEN GIROZENTRALE	1,455	8	22.7
BAYERISCHE LANDESBANK	1,112	2	75.1
THE BANK OF NOVA SCOTIA	1,074	12	32.0

life insurance sector is relatively high, amounts above five billion dollars issued to 40 different life insurers. The banks that issued most of the LOCs in 2014 provided more than $ 22 bn in LOCs. Most of these banks issued LOCs to more than 10 life insurers, again, indicating a degree of interconnectedness between the two sectors.

3 Methodology and Shadow Insurance Measures

How do investors and the market perceive shadow insurance as an alternative to traditional reinsurance? By ceding reinsurance to shadow insurers, life insurers are able to reduce marginal costs by alleviating the stricter Regulation XXX/AXXX reserve requirements. Also, as captives and other SPVs are often used for shadow insurance arrangements, life insurers may free up capital to the overall group. However, the use of letters of credit as a way to collateralize shadow reinsurance interconnects the insurance companies with the broader banking sector. As a result, the financial stability of life insurance companies may be subject to the health of banking counterparties involved in LOC financing agreements. In reverse, the lack of transparency in shadow reinsurers may also hide threats to the stability of both the insurance and banking system. Therefore, we analyze effects of shadow insurance usage on life insurance group's idiosyncratic and systemic risks as perceived by investors.

3.1 OLS regressions

To examine how investors perceive the riskiness of shadow insurance, we perform OLS regressions using several idiosyncratic risk measures as dependent variables. In addition, we include measures of systemic and systematic risk to further explore whether the use of shadow insurance poses an interconnectedness risk. Specifically, we use stock return volatility, Value-at-Risk, and Expected Shortfall as idiosyncratic risk measures. The market beta with respect to a bank equity index is used to measure systematic risk, while Marginal Expected Shortfall and ΔCoVaR are used to measure a life group's exposure and relevance to systemic risk, respectively. The OLS regressions are specified as following:

$$\mathrm{Y}_{i,t} = \nu_i + \mu_t + \gamma \times \text{Shadow Insurance}_{i,t} + \zeta \times \text{Controls}_{i,t-1} + \varepsilon_{i,t},$$

where $\mathrm{Y}_{i,t}$ is one of the risk measures. The independent variable of interest is Shadow Insurance$_{i,t}$, which is measured by either a shadow insurance dummy or a shadow insurance ratio. To correct possible omitted variable bias, we control for both year and group fixed effects. All standard errors are corrected for heteroskedasticity.

3.2 Instrumental variable regressions

The OLS regressions may indicate how shadow insurance is associated with life insurers' risk. However, shadow insurance usage might be endogenous, e.g., due to reversed causality. The fact that life insurers choose to use shadow insurance or decide against it rather than being assigned as "user" or "non-user" makes it hard to directly compare these two groups. Thus, we employ an instrumental variable regression approach to address this potential endogeneity problem. Koijen and Yogo (2016b) instrument a shadow insurance dummy with the insurer's market share in term life insurance in 1999 (interacted with a stock dummy), when relating life insurer ratings to shadow insurance. We follow the idea of using a life insurance group's term life insurance market share in 1999 as an instrument, as it is exogenous to outcomes in 2002 and after. Furthermore, if we view the change in life insurance regulation in 2000 as an exogenous event affecting the life insurance sector, we can infer that the share of the term life insurance market in 1999 exogenously impacts the decision to use shadow insurance.[14]

The first stage of instrumental variable regression is therefore specified as following:

$$\text{Shadow Dummy}_{i,t} = \mu_t + \beta \times \text{Term life market share}_{i,1999} + \Theta \times \text{Controls}_{i,t-1} + \varepsilon_{i,t},$$

[14]New life insurance regulation in 2000 mostly affected the market for term life and universal life insurance. Thus, insurers with higher market shares in term life insurance in 1999 should have a stronger incentive to use shadow insurance.

where $\text{Shadow Dummy}_{i,t}$ is an indicator of shadow insurance usage in a given year and $\text{Term life market share}_{i,1999}$ is a life insurance group's term life insurance market share in the year 1999 (before Regulation XXX became effective). We include a set of lagged group characteristics as control variables. To account for unobserved time-varying factors, we control for year fixed effects which is represented by μ_t. All standard errors are corrected for heteroskedasticity.

The second stage regressions estimate the impact of shadow insurance usage (indicator variable) on our risk measures $\text{Y}_{i,t}$ and are specified as follows:

$$\text{Y}_{i,t} = \mu_t + \gamma \times \text{Shadow Dummy}_{i,t} + \zeta \times \text{Controls}_{i,t-1} + \varepsilon_{i,t},$$

where $\text{Y}_{i,t}$ is one of the risk measures. All standard errors are corrected for heteroskedasticity.

3.3 Difference-in-difference approach

One of the main concern with shadow insurance arrangements is the lack of transparency about the actual risk involved in reinsurance counterparties as well as the quality of collaterals. Since 2011, to facilitate regulators identifying reinsurers who have received letters of credit from a bank, the NAIC discloses information on bank counterparties (see NAIC, 2010). Prior to this disclosure update, the NAIC annual statement reports only the LOC amount for each unauthorized reinsurance transactions, but not the sources of those LOCs. However, under the new reporting standards, regulators or investors can determine which bank or banks are providing collateral and can also evaluate the quality of such third party guarantees, e.g., by evaluating the strength of those banks.

Treating this change in disclosure standards for shadow insurance funding structure as a shock to the quality of information available, we are able to observe corresponding changes in market based risk measures of the respective life insurance groups. Therefore, we compare investors' perception of insurers' equity risk before and after the release of additional information on shadow insurance activities using a difference-in-difference approach. Due to improved knowledge on the interconnectedness of life insurance groups with the banking sector through LOCs, we hypothesize that investors will re-evaluate the sensitivity of life insurer equities towards the banking sector.

Our difference-in-difference analysis is performed by using data from 2006 to 2014. We define year 2011 to year 2014 as the post event period. In order to have a consistent treatment group throughout the whole sample period, we include life insurance groups who used shadow insurance in every year during 2006-2014 into the treatment group. The control group consists of life insurance groups that do not use shadow insurance at all during that period.[15] The regression model is set up as following:

$$\mathrm{Y}_{i,t} = \nu_i + \mu_t + \mathrm{TREAT}_i + \mathrm{TREAT}_i \times \text{Post-2011}_t + \Theta \times \mathrm{Controls}_{i,t-1} + \varepsilon_{i,t},$$

where TREAT_i is an indicator for treated life insurance groups, Post-2011_t is a dummy variable indicating year in the post event period. ν_i represents group fixed effects, and μ_t control for year fixed effects.[16]

3.4 Does shadow insurance funding structure matter?

To test Hypothesis 4, whether dependence on LOC financing is perceived as riskier and makes life groups more exposed to banking system, we perform a set of regressions on risk measures for shadow insurance users only. Our first variable of interest is the LOC ratio, which is the fraction of LOC provided for shadow insurance to the total shadow insurance ceded. Further, we implement another set of OLS regressions to examine our Hypothesis 5, whether a higher dependence on LOC funding sources increases life insurers' risk. We employ LOC HHI, an index that proxies for the concentration of LOC financing among bank counterparties, as a control variable in our subsample regressions. The OLS regressions are performed in the following way:

$$\mathrm{Y}_{i,t} = \mu_t + \mathrm{LOC}_{i,t} + \theta \cdot \mathrm{Controls}_{i,t-1} + \varepsilon_{i,t}$$

[15] Sample description for this difference-in-difference analysis is provided in section 4.

[16] Note that the single term Post-2011_t is subsumed in the year fixed effects. The treatment group dummy is multicollinear to the group fixed effects so that some group dummies are omitted from the regression as well.

where $\mathrm{Y}_{i,t}$ is a set of idiosyncratic/systemic/systematic risk measures and $\mathrm{LOC}_{i,t}$ is either LOC ratio or LOC HHI. All standard errors are corrected for heteroskedasticity. Detailed introduction to variables is given in the following subsections.

3.5 Shadow insurance and Variables

MEASURES OF SHADOW INSURANCE

In this study, reinsurance ceded is defined as the sum of reserve credit taken[17] and modified coinsurance reserve.[18] Life insurers may take reserve credits when they reinsure their risks, by ceding reinsurance to either affiliated licensed/authorized[19] entities or to authorized reinsurers outside of their groups. In the case a reinsurer is not licensed in the ceding insurer's domicile, the ceding insurer may still take reserve credits and reduce balance-sheet liabilities if sufficient collateral is provided (see, e.g., NAIC, 2011). Reserve credit taken captures most of the transferred reinsurance liabilities, but not does not include reserve credits structured under modified-coinsurance. As one of the main types of reinsurance, modified coinsurance is similar to coinsurance funds withheld–for both arrangements, the assets used to pay for reinsurance premiums remain on ceding companys' balance sheet. In modified coinsurance, the ceding insurer not only retains control of its assets, but also the reserves (liabilities) remain on its balance-sheet. Therefore, reserve credit taken does not include reinsurance ceded under modified coinsurance structure. The sum of reserve credit taken and modified coinsurance reserve essentially measures the dollar amount of reinsurance ceded (Koijen and Yogo, 2016).

Following Koijen and Yogo (2016b,a), we define shadow insurers as affiliated and unauthorized reinsurers, which are not rated by A.M. Best.[20] Applying this definition, we create two variables to measure the use of shadow insurance. The first main variable of interest is an indicator

[17] According to statutory accounting procedures, a ceding company is permitted to treat amounts due from reinsurers as reductions from liability, e.g. reserve reduction, given certain conditions are met by the reinsurer. Reserve credit taken specifies the amount of such reserve reduction.

[18] In modified coinsurance, both the assets used to pay for reinsurance premiums and the reserves (liabilities) remain on primary insurers' balance sheet, while specified risks are transfered to reinsurers (See Harrington, 2015).

[19] A reinsurer is authorized if it was licensed or accredited in the ceding company's domicile.

[20] This definition of shadow insurers is stricter than captive reinsurers. Some captives are actually authorized.

coded as one if a life insurance group cedes reinsurance to shadow insurers in a given year and zero otherwise. As shown by Appendix 2, there were about 43% of life insurance groups categorized as a shadow insurance user during 2002 to 2014. The second proxy is the fraction of total shadow insurance ceded by a group to its total reinsurance ceded. Table 3 reports the total amount of shadow insurance ceded by members of ten financial holding companies in 2014 (Top 10 by shadow insurance amount).

By far the highest amount of shadow insurance is ceded by *Manulife Financial Group* with a total amount of $106.50 billion in 2014. Among its total amount of shadow insurance, $101 billion takes the form of modified coinsurance, under which the ceding insurer retains both liability and assets (reinsurance premium) of reinsurance activity. This extensive use of modified coinsurance also explains the relatively small volume of reinsurance premiums ceded. The aggregate amount of shadow insurance used by the ten groups is about $268.36 billion. For most of the groups, shadow insurance makes up more than 50% of total reinsurance ceded revealing that this practice is quite common among the large financial groups.

SHADOW INSURANCE FUNDING STRUCTURE

Since shadow insurance is reinsurance ceded to unauthorized entities, the ceding company receives reserve credit or risk-based capital credit only if the reinsurers' obligations are collateralized. Among other types of collateral, shadow insurers rely on letters of credit from accredited third party banks to back their unauthorized reinsurance transactions. To measure how much shadow insurance is collateralized by letters of credit, we define the *LOC ratio* as the amount of letters of credit provided for shadow insurance to total shadow insurance ceded by a group. As stated in the NAIC (2006), "U.S. regulators verify the LOC issued on behalf of any unauthorized reinsurer **is** an amount at least equal to the amount of annual statement credit taken as respects to reinsurance ceded to that reinsurer." Thus the value of *LOC ratio* could be greater than one. As alternatives to LOCs, unauthorized reinsurers also use other forms of collateral such as trust funds and funds

Table 3: Top 10 Financial Groups by Shadow Insurance Ceded (2014)

This table shows a list of the ten financial groups with the highest amount of shadow insurance ceded by their U.S. subsidiaries in 2014. *Shadow Insurance* is the reinsurance ceded to affiliated, unauthorized, and unrated reinsurers. We report the total amount of shadow insurance ceded by the group and its two components — *shadow reserve credit taken* and *shadow modified coinsurance*. *Reinsurance Ceded* represents the total amount of reserve credits taken and modified coinsurance reserves. *Shadow/ReinsCeded* represents the ratio of shadow insurance to total reinsurance ceded, while *Shadow/Assets* is the ratio of shadow insurance to total assets.

Group Name	**Shadow Insurance** (billion $)	**Shadow Rsvcr** (billion $)	**Shadow Modco** (billion $)	**Reins Ceded** (billion $)	**Shadow/ReinsCeded** (in %)	**Shadow/Assets** (in %)
MANULIFE FINANCIAL GRP	106.50	5.5	101	133.70	79.6	38.8
ATHENE GRP	39.26	1.62	37.64	55.36	70.9	62.8
METROPOLITAN GRP	28.46	1.44	27.02	51.72	55.0	6.8
GREAT LAKES DELTA INS	26.74	13.92	12.82	53.54	49.9	12.7
AXA INSURANCE GRP	12.47	12.47	0	18.27	68.3	7.3
GREAT WEST L ASR	12.12	3.24	8.88	14.00	86.6	19.7
GOLDMAN SACHS GRP	8.79	4.14	4.65	14.25	61.7	24.8
LINCOLN NATIONAL	8.22	8.2	0.02	19.52	42.1	3.6
PRUDENTIAL OF AMERICA	7.81	2.35	5.46	88.47	8.8	1.9
SWISS REINSURANCE	7.62	5.62	2.00	12.31	61.9	52.6

withheld accounts.[21] As a result, the LOC ratios observed in our sample range from zero to values that may be greater than one.

In our sample, as reported by the summary statistics in Appedix 2, the mean value of the LOC ratio is over 35%. On average, over one third of shadow insurance agreements are collateralized via letters of credit, which are provided by third party banks. However, funding via LOCs may expose the life insurance sector to default risk in the banking sector, and vice versa. In addition, collateralization 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. For shadow insurance users, we measure the concentration of an insurance group's LOC sources among bank counterparties, by calculating a Herfindahl-type Index based on the LOC amount (LOC HHI). A higher value can be interpreted as a funding structure in which the LOC amount is concentrated on one bank or a few banks. Thus, an insurance group with a higher LOC concentration is more dependent on the willingness of one or a few banks to renew its LOCs.[22] Similarly, involved banks are exposed to the well-being of the reinsurer and its parent company.[23]

In Table 4, we provide some statistics on the aggregate LOC amount received by insurance groups (Top 10) in 2014.

The *MetLife Insurance Group* and *Manulife Financial Group* have the most LOCs with total amounts of about \$6.49 billion and \$5.15 billion. In these shadow insurance agreements, they receive LOCs from 36 and 28 banks, respectively. Therefore, the concentration of LOC financing is rather low for these two life insurance groups with LOC HHIs of about 40% and 11%, respectively. Other insurance groups such as *Swiss Reinsurance* or *Banner Life Group* have less counterparties for their shadow insurance LOC financing, and the amounts obtained are dependent on only a few banks. The HHIs in this case are above 90%. The ten insurance groups listed above

[21]In a trust account arrangement, a reinsurer places liquid assets in a trust account at a third party bank, with the ceding company named as the beneficiary. Funds withheld is similar to trust account, except that the assets are held on ceding company's balance sheet (Schwarcz, 2015).

[22]If LOCs are not renewed, life insurers will be forced to recapture the reinsured business and recalculate its RBC minimum without taking credit for reserve, which suddenly decreases its capital and increase its regulatory minimum

[23]In the LOC with parental guarantee. If the shadow reinsurer defaults and triggers a draw on the LOC, then the parent company will ultimately be forced to reimburse this draw on bank (Schwarcz, 2015). Thus, banks are exposed to the well-being of both the shadow reinsurer and its parent.

Table 4: Top 10 life insurance groups by letters of credit amounts

This table shows descriptive statistics for ten life insurance groups that obtained letters of credit from banks in 2014. The first column shows the names of the life insurance groups and the second column provides the amount in billions of dollars obtained from LOCs. The third column lists the number of banks that have provided LOCs to the life insurance group in 2014, while the fourth column shows a Herfindahl-type index based on the amount of LOCs issued by these banks. The fifth and sixth column summarize the amount of shadow insurance ceded by each group in billions of dollars and also a ratio of shadow insurance ceded to total reinsurance ceded by the group.

Group name	**LOC** (billion $)	**#Banks**	**HHI of LOC received** (in %)	**Shadow insurance ceded** (billion $)	**Shadow ratio** (in %)
METROPOLITAN LIFE INSURANCE GROUP	6.49	36	39.5	28.46	55.0
MANULIFE FINANCIAL GROUP	5.15	28	11.2	160	79.6
GREAT LAKES DELTA INSURANCE	3.87	28	33.3	26.74	49.9
NETHERLANDS INSURANCE CO	3.92	34	8.2	7.03	63.2
AXA INSURANCE GROUP	3.58	15	8.5	12.47	68.3
LINCOLN NATIONAL	3.28	24	24.8	8.22	42.1
SWISS REINSURANCE	2.27	11	94.2	7.62	61.9
HANNOVER GRP	1.53	14	39.7	17.99	71.7
BANNER LIFE GROUP	1.26	7	93.1	2.83	44.9
SCOR REINS CO	1.16	14	17.9	1.80	17.9

receive a total of $32.51 billion in LOC financing.

IDIOSYNCRATIC RISK MEASURES

Our first set of dependent variables proxy for idiosyncratic risk of insurance groups as perceived by investors. As a standard measure of risk, we employ the annual stock return volatility.It is measured as the standard deviation of a life group's daily stock returns in a given year. Further, we compute two measures of tail risk, the Value-at-Risk (VaR) and the Expected Shortfall (ES). The VaR of a life group is the 5th percentile of its daily stock returns in a given year.[24] For example, the 5% VaR for Metropolitan group in 2014 is 0.024, which means there a 5% chance that its stock will decline in value by more than 2.4% in that year. For our full sample, the mean value of VaR is about 3.6%.

As an alternative measure to the VaR, the Expected Shortfall is more sensitive to the shape of the tail of the loss distribution. Following Acharya et al. (2016), we calculate ES as the expected loss conditional on the daily stock return lower than its 5% quantile. For example, the ES for Metropolitan group in 2014 is 0.032, indicating an expected loss of 3.2% conditional on the stock experiencing its 5% worst cases. The mean value of ES in our sample is 0.054, representing an expected loss of 5.4% conditional on the stock return lower than its 5% quantile.

In Figure 2, we plot the mean values of the three risk measures for shadow insurance users and non-users for the time period 2006-2014 by year. The mean values of the two tail risk measures are roughly the same over the whole time period. However, in 2008, shadow insurance users had on average a 1% lower Value-at-Risk and a 3% lower Expected Shortfall. Except for the year 2008, where shadow insurance users exhibit about twice as high of a mean stock volatility than non-users, the mean values for both groups are almost identical.

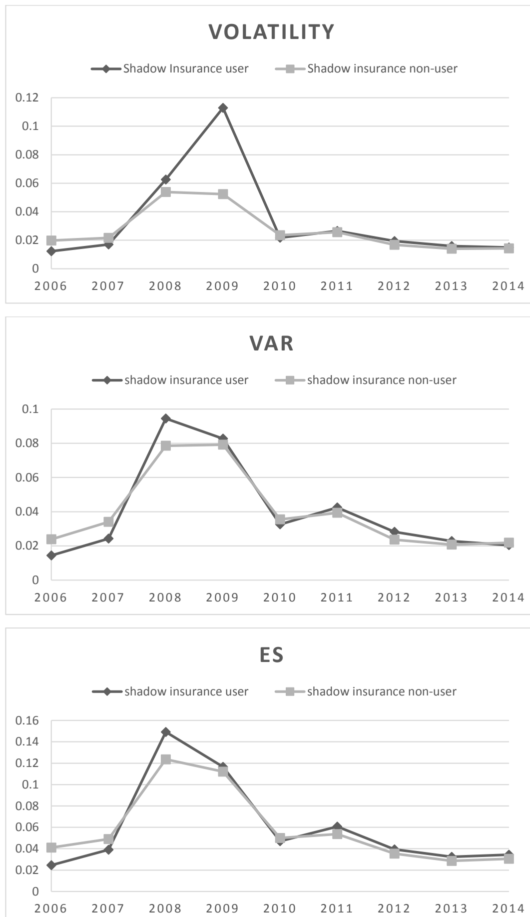
SYSTEMIC AND SYSTEMATIC RISK MEASURES

Another set of dependent variables are systemic and systematic risk measures based on the stock

[24] VaR always represents a loss and thus, we report it as a positive number.

Figure 2: Idiosyncratic Risk Measures (2006-2014)

The figure shows the time evolution of three idiosyncratic risk measures, volatility, Value-at-Risk (VaR), and Expected Shortfall (ES) from 2006 to 2014 for a set of 35 publicly listed insurance groups. We divide the sample into shadow insurance users and non-users and calculate mean values of the respective measure for each year. Variable definitions are given in Appendix 1.



prices of our publicly listed life insurance groups. To measure the sensitivity systematic risk of insurance group's with regard to U.S. bank stock returns, we use the market beta of an insurer's stock with respect to an U.S. bank equity index. In a given year, we compute the beta by dividing the covariance of daily insurer stock returns and the daily returns of the *U.S. Banks Datastream* *equity index* by the variance of the banking market index. By employing the bank equity index as our market index, we are able to measure the sensitivity of the insurance group stocks towards developments in the U.S. banking sector. In our sample, the mean value of U.S. bank-based market beta is 0.726, showing that the life group's stock return is about 27% less volatile than the U.S. bank-based index.

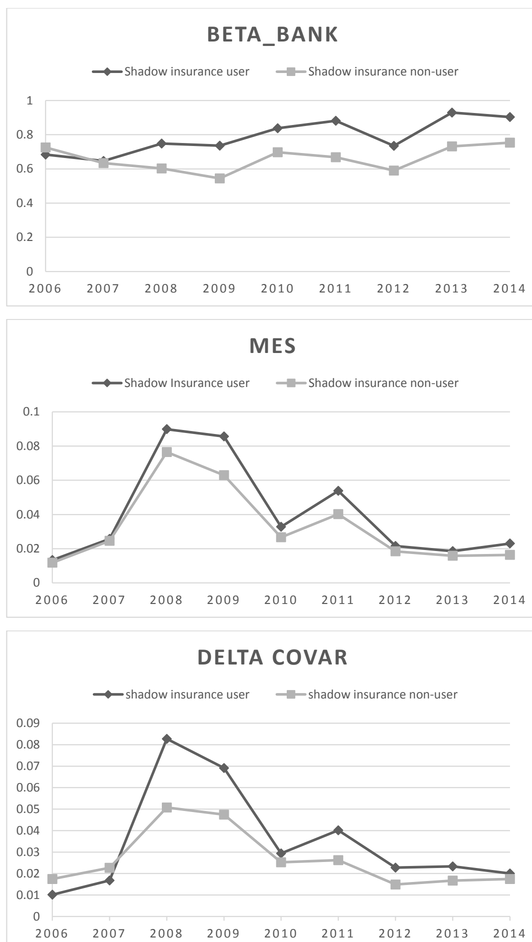
Next, we calculate an insurer's Marginal Expected Shortfall (MES) as defined in Acharya et al. (2016). MES is the (negative) average of the daily stock returns on the days where the market (bank equity index) experiences its 5% worst returns. Benoit et al. (2013) point out that parts of the MES measure are captured by the market beta as well so that we can expect similar results for both of these systemic or systematic risk measures. Thus, coefficient estimates for these dependent variables will be used to test Hypothesis 1 and 3. Specifically, in testing Hypothesis 1, we expect the shadow usage dummy to positively relate to MES. In Hypothesis 3, a positive coefficient on the DID term is expected. According to the summary statistics, the mean value of MES in our sample is 3%, showing that when the banking sector is experiencing its 5% worst cases, an insurance group is expected to decline in value by that percentage.

As our second systemic risk measure, we employ the (unconditional) ΔCoVaR as introduced in Adrian and Brunnermeier (2016). CoVaR of an institution corresponds to the Value-at-Risk of the financial system conditional on this specific institution being in distress. The contribution of an institution to systemic risk (ΔCoVaR) is then measured by the difference between the institution's CoVaR conditional on it being in distress (5% quantile of returns) and its CoVaR conditional on it being in "normal" state (median of returns). ΔCoVaR can be obtained by multiplying the bank-based market beta by the difference in Value-at-Risks conditional on the insurer being in its 95% quantile of losses (5% quantile of returns) and the insurer being in the median returns. We construct CoVaR so that higher values indicate higher contribution of life insurance stocks to bank equity market movements. Figure 3 shows the time evolution of annual mean values of the three systemic/systematic measures from 2006 to 2014.

First, we notice that the average beta is always below one, indicating low sensitivity towards

Figure 3: Systemic/Systematic Risk Measures (2006-2014)

The figure shows the time evolution of three systemic and systematic risk measures, bank-based market beta, Marginal Expected Shortfall (MES), and ΔCoVaR (with respect to the U.S. Banks Datastream equity index) from 2006 to 2014 for a set of 35 publicly listed insurance groups. We divide the sample into shadow insurance users and non-users and calculate mean values of the respective measures for each year. Variable definitions are given in Appendix 1.



the bank equity index. For all three measures, we observe some parallel trends between shadow insurance users and non-users. Shadow insurance users, however, exhibit higher bank-based market betas, higher MES, and higher relevance to systemic risk in the banking sector, as measured by ΔCoVaR. This is especially pronounced during the financial crisis.

OTHER VARIABLES

Several control variables are included in our main regression analyses. To measure the size of a life insurance group, we employ the *natural logarithm of the group's total assets*. IAIS (2011) suggests the size of an institution as a potential source of systemic risks in insurance. Larger insurance group may have a broader range of pooled risks and may gain more diversification benefits than smaller firms. Thus, it is less likely to suffer from cumulative losses. However, larger insurance group could become more systemically relevant due to the larger amount of financial services it provides to the financial system (IAIS, 2013).

The number of group affiliates can have impact on the intra-group commitments and can indicate a complex group structure. A group with more affiliates may gain more intra-group support to the non-traditional or non-insurance activities, which can increase its systemic relevance (IAIS, 2013). In addition, the number of group members can have an impact on the supply of affiliated reinsurance within a group, and thus affect the demand for affiliated reinsurance. Although affiliated reinsurance is less costly, as it internalizes the asymmetric information problem, it fails to transfer risks to the outside and the risks are still retained within the group. We use the *natural logarithm of the number of group affiliates* to control for these effects.

Next, insurance leverage provides an indication of how well an insurer can handle above-average losses. High leverage provides incentive for excessive risk-taking to increase a firm's profitability Bierth et al. (2015). We control for this effect by defining *insurance leverage* as a ratio of a group's net premiums written to its total surplus. A smaller insurance leverage ratio indicates a lower risk position.

According to IAIS (2013), reinsurance can be a proxy for an insurer's counterparty exposure and indicates the degree of interconnectedness with the insurance sector through reinsurance transactions. From another perspective, the use of reinsurance helps life insurers reduce their loss exposure by transferring risk to a reinsurance company or several reinsurers. Reinsurance is also commonly used for the purpose of income smoothing and surplus relief. Thus, we include *reinsurance usage* as a control variable and calculate it by dividing a group's total premiums ceded to the group's total premiums written (includes reinsurance assumed).

As stated by A.M. BEST (2002), companies with higher liquidity are more capable to meet their short- and long-term obligations to policyholders, and are also less likely to default. Therefore, a group's *current liquidity* is included as a control variable in regressions on a firm's risk. We measure current liquidity as the proportion of liabilities covered by unencumbered cash and unaffiliated investments.[25]

4 Data and Sample

4.1 Insurer group sample

Our main analyses are performed at group level, including only listed life insurance groups, for two reasons. First, our market-based (systemic) risk measures are calculated using life insurers' daily stock return data, which are reported at group level and are available for listed groups only. Second, in evaluating the potential risks of shadow insurance, it is more relevant to view all group members as a whole rather than look at individual firms, because the (potential) risks stemming from affiliated reinsurance activities lie within the group. Shadow insurance is ceded by life insurers to their affiliated companies, and such a transaction is often protected via a parental guarantee.[26] As a result, the risks associated with liabilities remain within the insurance group and the correlation of life insurers' and shadow insurers' financial distress is higher than in the usual reinsurance

[25] For a company with lower than 100% current liquidity ratio, its solvency is dependent on the collectibility of premium balances and affiliated investments (A.M. Best).

[26] Under a recourse structure, the LOC entails a "parental guarantee", the LOC provider has recourse against the ceding insurers parent for any draws (Harrington, 2015).

agreements.

We start building our sample by employing all life insurers that report to the NAIC between year 2002 and 2014. We retrieve company level data on reinsurance ceded to affiliated and unaffiliated entities from the NAIC Life annual statement *Schedule S part 3*. Reinsurance ceded to unauthorized entities are retrieved from *Schedule S part 4*. To identify shadow insurance transactions, we merge our reinsurance sample obtained from *Schedule S part 3* and *part 4* with the *Best Key Rating Guide* provided by *A.M. Best Company* to obtain rating data (see Koijen and Yogo, 2016b).

Information on letters of credit are extracted from NAIC Life annual statement *Schedule S part 4*, which provides details on collateral that is used to back up unauthorized reinsurance transactions. Specifically, we are given the dollar amounts of LOCs and other kinds of collateral in each reinsurance transaction. By filtering the reinsurance counterparty relationship,[27] we further observe the amount of LOCs used to support each shadow insurance transaction. Since 2011, the NAIC reports disclose the routing number and name of banks that provided LOCs to reinsurers, including shadow reinsurers. These newly disclosed items enable regulators to identify reinsurers who received LOCs from a bank or banks whose rating is below investment grade. Also, it allows us to identify bank counterparties that are involved in shadow insurance transactions.

Before aggregating our company level data to the group level, we apply several filters to our initial data sample. First, we exclude all firms without any affiliated members from our sample. 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. The company level sample is then aggregated by year and life insurers' group identification. For our dependent variables, we need share price data on the publicly listed insurance

[27]Specifically, we find shadow insurance counterparties by filtering several factors: affiliation with cedants; authorization for doing reinsurance; rated or unrated status. Then we define shadow insurance transactions as reinsurance ceded by life insurers to their unauthorized affiliates who do not have an A.M. Best rating.

groups/holdings. We retrieve insurer stock price data from the CRSP database and match the results with our sample of insurance groups using the CUSIP identifier. In the end, we obtain a sample of 35 publicly listed insurance groups. Summary statistics for the group sample are shown in Appendix 2.

4.2 Sample for difference-in-difference analysis

The difference-in-difference analysis is performed using data from 2006 to 2014. We define 2011-2014 as post event period. To have a consistent treatment group throughout the whole sample period, we include life insurance groups that used shadow insurance in every year during 2006-2014 into the treatment group. Other life insurance groups are assigned into control group. Based on this setting, there are 23 life groups in the treatment group and 202 life groups in the control group. Among the treated groups, 8 are listed. While in the control group, 27 life groups are listed.

5 Empirical Results

5.1 OLS regressions

Table 5 shows the results of our OLS regressions, with evidence in support of Hypothesis 1 and 2. Both shadow insurance usage variables are positively related to the systematic and systemic risk measures. From columns [1]-[3] of both panels we observe that shadow insurance users tend to have a higher VaR and ES as well as higher stock return volatility. However, the coefficient estimates of the shadow usage variables are only significantly different from zero at the 10% level in the case of the former two dependent variables. While this is hardly evidence for a causal relation, the regressions reveal a slightly significant correlation between shadow insurance usage and insurers' idiosyncratic risks.

A statistically significant, positive coefficient estimate for the bank-based market beta suggests that shadow insurance users are more sensitive to market movements in the banking sector, due to their usage of shadow insurance. Numerically, being a shadow insurance user makes the life group 7% more volatile relative to the banking system. Alternatively, increasing the proportion of shadow insurance of total reinsurance by 10% makes the life group 2% more volatile relative to the bank industry. As indicated by the coefficients in column [6] using ΔCoVaR as dependent variable, life insurance groups contribute more to systemic risk of banks when they are involved in shadow insurance activities and thus, pose an interconnectedness risk.

5.2 Instrumental variable regressions

Empirical results from OLS regressions provide some indications of how shadow insurance is associated with life insurers' risk. However, shadow insurance usage might be endogenous, e.g., due to reversed causality. The fact that life insurers choose to use shadow insurance or decide against it rather than being assigned as "user" or "non-user" makes it hard to directly compare these two groups. Thus, we employ an instrumental variable regression approach to address this potential endogeneity problem.

As shown by the first stage result in Table 6, life insurance groups with a larger share in the term life insurance market in 1999 are more likely to cede reinsurance to shadow entities.[28] From the second stage results, we observe a positive and significant relation between shadow insurance usage and a group's VaR. This result indicates an increased tail risk for this subsample of life insurance group. Most importantly, we find that the IV results are consistent with the simple OLS regressions, where an increased exposure to banking market movements is present. Similarly, a positive and significant coefficient of ΔCoVaR suggests an increased contribution to bank industry systemic risk made by shadow insurance users.

5.3 Difference-in-difference approach

Results of the difference-in-difference regressions are given in Table 7. Consistent with Hypothesis

[28] Further, the Kleibergen-Paap test statistics (rank- and F-test) are large and suggest that the instrument is valid.

Table 5: OLS regressions of (systemic) risk measures on shadow insurance usage

This table shows the results of OLS regressions of life insurance groups' risk measures against shadow insurance usage variables from 2002 to 2014. Robust standard errors are reported in parenthesis. The dependent variable in column [1] is the standard deviation of a life insurance group's daily stock return in a given year. The dependent variable in column [2] is an insurer stock's Value-at-Risk at the 95% confidence level. The dependent variable in column [3] is the (negative) expected return when the return is lower than its 5th percentile (a higher ES thus indicates a greater loss). Dependent variable in column [4] is the market beta of an insurers stock in a given year with respect to the U.S. banking sector. The dependent variable in column [5] is the Marginal Expected Shortfall, while dependent variable in column [6] is the (negative) unconditional ΔCoVaR. In Panel A, the main independent variable of interest is a dummy variable coded as one if a life insurance group cedes reinsurance to shadow insurers in a given year and zero otherwise (Shadow dummy). In Panel B, the main variable of interest is the ratio of shadow insurance to total reinsurance ceded (shadow ratio). Group fixed effects and year fixed effects are included. Variable definitions are given in Appendix 1.

	Idiosyncratic Risk			Systemic/Systematic Risk		
Panel A: Shadow dummy	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variable:	Volatility	VaR	ES	Beta	MES	ΔCoVaR
Shadow Dummy	0.0027	0.0035	**0.0069***	**0.0727***	**0.0054****	**0.0082****
	[0.0022]	[0.00232]	**[0.0039]**	**[0.0394]**	**[0.0026]**	**[0.0039]**
N	397	397	397	391	397	391
R^2	0.242	0.797	0.747	0.579	0.759	0.514
Adjusted R^2	0.138	0.769	0.712	0.522	0.726	0.448

	Idiosyncratic Risk			Systemic/Systematic Risk		
Panel B: Shadow Ratio	[1]	[2]	[3]	[4]	[5]	[6]
Dependent variable:	Volatility	VaR	ES	Beta	MES	ΔCoVaR
Shadow ratio	0.0458	**0.0119***	**0.0207***	**0.1850*****	0.0104	**0.0201***
	[0.0395]	**[0.0067]**	**[0.0111]**	**[0.0623]**	[0.0072]	**[0.0113]**
N	387	387	387	381	387	381
R^2	0.257	0.805	0.760	0.605	0.768	0.529
Adjusted R^2	0.152	0.777	0.726	0.549	0.735	0.462
Group FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Table 6: Instrumental variable regressions of (systemic) risk measures on shadow dummy

This table shows results of instrumental variable regressions for the time period from 2002 to 2014 for a sample of 35 U.S. life insurance groups that report to the NAIC. The main variable of interest is a dummy variable that is equal to one if an insurance group uses shadow insurance in a given year. The first column shows the result from the first stage regression and columns [2] to [7] show results of the second stage regressions using one of the six risk measures as dependent variables. Robust standard errors are reported in parenthesis. Variable definitions are given in Appendix 1.

		Idiosyncratic Risk			Systemic/Systematic risk		
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
	Shadow dummy	Volatility	VaR	ES	Beta	MES	ΔCoVaR
Term life share 1999	**6.4110*** **						
	[1.6920]						
Shadow dummy		-0.0396	**0.0200** **	0.0135	**0.5420*** **	0.0113	**0.0296***
		[0.0507]	**[0.0102]**	[0.0164]	**[0.1730]**	[0.0128]	**[0.0167]**
Log(assets)$_{t-1}$	**0.0646*** **	0.00363	**-0.0036*** **	-0.0031	0.0128	**0.0028** **	-0.0007
	[0.0132]	[0.0059]	**[0.0013]**	[0.0019]	[0.0264]	**[0.0013]**	[0.0021]
Log(#affiliates)$_{t-1}$	**0.1740*** **	0.0137	**-0.0054** **	-0.0039	**-0.1280*** **	-0.0028	-0.0064
	[0.0327]	[0.0166]	**[0.0027]**	[0.0045]	**[0.0373]**	[0.0030]	[0.0042]
Insurance leverage$_{t-1}$	0.0004	-0.0026	**-0.0020*** **	**-0.0024*** **	**-0.0227*** **	**-0.0015*** **	**-0.0028*** **
	[0.0078]	[0.0016]	**[0.0005]**	**[0.0008]**	**[0.0087]**	**[0.0005]**	**[0.0007]**
Reinsurange usage$_{t-1}$	**0.9330*** **	0.0242	-0.0169	-0.0143	**-0.6740*** **	-0.0212	**-0.0413** **
	[0.1190]	[0.0375]	[0.0107]	[0.0166]	**[0.2110]**	[0.0137]	**[0.0183]**
Current liquidity$_{t-1}$	**-0.0343***	-0.0020	**0.0017** **	0.0019	0.0014	-0.0001	0.0009
	[0.0208]	[0.0035]	**[0.0008]**	[0.0012]	[0.0158]	[0.0008]	[0.0012]
N	351	329	329	329	324	329	324
Kleibergen-Paap rk LM statistic	-	16.88	16.88	16.88	17.14	16.88	17.14
Kleibergen-Paap rk Wald F statistic	-	20.59	20.59	20.59	20.96	20.59	20.96
Year FE	YES	YES	YES	YES	YES	YES	YES

Table 7: Difference-in-difference Regressions

This table shows the results of difference-in-difference regressions for the period of 2006 to 2014. The event of interest is the information disclosure on bank counterparties involved in LOC transactions since 2011 (see NAIC, 2010). The treatment group is defined as life insurance groups that have used shadow insurance in every year during 2006-2014. Post-2011 is used to identify the post event period, which is a dummy variable that equals one for years 2011-2014 and zero otherwise. Column [1] to [6] shows the regression results using one of the six risk measures as the dependent variable. Robust standard errors are reported in parenthesis. We control for both group and year fixed effects. Variable definitions are given in Appendix 1.

	Idiosyncratic Risk			Systemic/Systematic Risk		
2006-2014	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Volatility	VaR	ES	Beta	MES	ΔCoVaR
TREAT	0.0019	**0.0199***	0.0317	**0.5260*****	**0.0284*****	**0.0527****
	[0.0244]	**[0.0119]**	[0.0210]	**[0.1340]**	**[0.0103]**	**[0.0243]**
TREAT $\times$ Post-2011	-0.0196	-0.0016	-0.0006	**0.0760***	-0.0036	-0.0074
	[0.0201]	[0.0042]	[0.0066]	**[0.0430]**	[0.0045]	[0.0078]
Log(assets)$_{t-1}$	0.0127	0.0051	0.0082	0.0439	0.0051	**0.0114***
	[0.0111]	[0.0038]	[0.0066]	[0.0459]	[0.0038]	**[0.0060]**
Log(#affiliates)$_{t-1}$	0.0151	0.0006	-0.0009	-0.00443	-0.000340	-0.00417
	[0.0192]	[0.0040]	[0.0073]	[0.0441]	[0.00429]	[0.00745]
Insurance leverage$_{t-1}$	**-0.0038***	**-0.0024*****	**-0.0037*****	**-0.0171*****	**-0.00248*****	**-0.00291*****
	[0.0022]	**[0.0004]**	**[0.0008]**	**[0.0045]**	**[0.0005]**	**[0.0007]**
Reinsurance usage$_{t-1}$	-0.0383	0.0094	-0.0041	0.1780	-0.0081	0.0327
	[0.0513]	[0.0177]	[0.0267]	[0.197]	[0.0145]	[0.0368]
Current liquidity$_{t-1}$	-0.0036	-0.0008	-0.0001	-0.0021	0.0000	0.0015
	[0.0039]	[0.0014]	[0.0020]	[0.0199]	[0.0019]	[0.0023]
N	284	284	284	281	284	281
Adjusted R^2	0.140	0.792	0.747	0.661	0.751	0.514
Group FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

3, we find that shadow insurance users became more sensitive to banking sector movement than non-users after the new disclosure practice. As presented in column [4] of Table 7, the coefficient estimate of the interaction term is significantly positive, indicating that insurers in the treatment group experienced an increase in market risk around the shock in information disclosure in 2011. The treatment indicator variable is also significant in the systemic/systematic risk regressions. From the results, we observe that a treated life insurance group generally has a higher beta (see also Figure 3), higher MES, and higher ΔCoVaR, confirming that those life insurance groups, on average, are more sensitive to bank market movement and are more relevant to the potential systemic risk in banking sector.

5.4 Does shadow insurance funding structure matter?

To test Hypothesis 4, whether dependence on LOC financing is perceived as riskier and makes life groups more exposed to banking system, we perform a set of regressions on risk measures for shadow insurance users only. Empirical results are presented in Table 8.

Panel A shows results for the years 2002-2014 using the LOC ratio as the main explanatory variable. We observe that the LOC ratio is positively and significantly related to the bank-based market beta, indicating an increase in systematic risk due to the intensive use of LOCs as a funding method. Other than that, we observe no statistically significant relationship between the LOC ratio and any other risk measures.

In Panel B, where LOC HHI is the main variable of interest, no significant evidence is found to explain the relation between the concentration in funding and life insurers' risk measures. Therefore, no support was found for Hypothesis 5 — a higher concentration among banks for LOC financing increases a life insurer's risk. According to the *Potential Benefits of Lender Monitoring View* by Harrington (2015), "Providers of financial support for captive reinsurance (via LOCs, surplus or credit-linked notes, and so on) evaluate the likelihood that the ceded business could produce draws on such funding, including the use of independent actuarial analysis." Thus, funding providers give an additional source of risk monitoring of captive reinsurance activities and the

Table 8: Shadow insurance funding structure and (systemic/systematic) risk

This table presents the results of shadow insurance funding structure regressions. Only shadow insurance users are included in this analysis. Panel A reports the results from 2002 to 2014, with the LOC ratio as the main independent variable of interest. Panel B shows the results of OLS regressions using the LOC HHI as the main variable of interest, for the period of 2011-2014. The dependent variable in columns (1) to (6) is one of the six risk measures. Robust standard errors are reported in parenthesis. We include year dummies to control for year fixed effects. Variable definitions are given in Appendix 1.

Panel A: LOC ratio (2002-2014)	Idiosyncratic Risk			Systemic/Systematic Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Volatility	VaR	ES	Beta	MES	ΔCoVaR
LOC ratio	0.0031	0.0026	0.0026	**0.0518****	0.0027	0.0037
	[0.0032]	[0.0017]	[0.0028]	**[0.0246]**	[0.0017]	[0.0033]
N	164	164	164	162	164	162
R^2	0.204	0.751	0.724	0.525	0.789	0.523
Adjusted R^2	0.105	0.720	0.690	0.465	0.763	0.463
Panel B: LOC HHI (2011-2014)	Idiosyncratic Risk			Systemic/Systematic Risk		
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Volatility	VaR	ES	Beta	MES	ΔCoVaR
LOC HHI	0.0009	0.0027	0.0026	-0.0372	-0.0004	0.0006
	[0.0019]	[0.0023]	[0.0043]	[0.0728]	[0.0025]	[0.0038]
N	91	91	91	90	91	90
R^2	0.582	0.648	0.630	0.355	0.843	0.453
Adjusted R^2	0.535	0.609	0.589	0.282	0.825	0.391
Year FE	YES	YES	YES	YES	YES	YES
Lagged controls	YES	YES	YES	YES	YES	YES

use of LOCs (as a way for shadow insurance funding) not necessarily create more risk for life insurers. Another possible explanation is the limitation in sample size. We are able to identify bank counterparty relationships involved in LOC only for the years 2011 to 2014. Such a restriction further reduces the size of our shadow insurance user sample. In addition, the period since bank counterparties became identifiable might be not long enough for investors or the market to respond.

6 Regulation of Shadow Insurance Spillover Effects

Our empirical results suggest that shadow insurance usage by life insurance groups significantly increases their sensitivity to bank equity market movements. In reverse, linkages to the banking sector through such reinsurance activities may result in spillover losses for counterparties that help finance or collateralize shadow reinsurance contracts. Some empirical evidence from 2014 in Section 2 suggests that for example the amount of LOC financing of shadow insurance activities is only large for a few life insurance groups. However, there has been an increasing interest in monitoring these activities (which can be seen, e.g., by the disclosure updates in 2011 and following years). Given the potential spillover effects and the increasing amount of shadow insurance ceded by life insurers, regulators have to respond to these developments in the life insurance sector with a proper regulatory framework. In this section, we mostly take the regulator's view and theoretically discuss options for limiting spillover risk to outside of the life insurance sector stemming from shadow insurance activities.

Let A_t and L_t represent an insurer's assets and liabilities in time t, respectively.[29] Also, let $p \in [0,1]$ be the probability that a letter of credit amount of $\mathrm{LOC}_t \geq 0$ will be renewed by an insurer's counterparty. If the LOC is not renewed, the respective amount is added to an insurer's liabilities L_t. In this case, an insurer's statutory capital is reduced. Thus, accounting for this

[29]As in Koijen and Yogo (2016b), we assume that the shadow insurer's equity is equal to zero.

recapture risk, we obtain an expected liability of

$$\mathbb{E}\left[\text{LIAB}\right] = p \cdot \text{L}_t + (1-p) \cdot \left[\text{L}_t + \text{LOC}_t\right] = \text{L}_t + (1-p) \cdot \text{LOC}_t.$$

Consequently, the expected excess capital (statutory capital) is given by

$$\mathbb{E}\left[\text{K}_t\right] = \text{A}_t - (1+\alpha) \cdot \mathbb{E}\left[\text{LIAB}\right] = \text{A}_t - (1+\alpha) \cdot \left[\text{L}_t + (1-p) \cdot \text{LOC}_t\right],$$

where $\alpha > 0$ is the risk charge parameter set by regulators.[30]

Regulators are interested in reducing potential spillover risks stemming from interconnectedness of banks and life insurers through LOCs. For that purpose we follow KUBITZA AND REGELE and model a counterparty's (e.g., a bank's) expected exposure to financial distress of the life insurance company. Assume that the claim $D > 0$ is to be repaid by the insurer to the counterparty in the future. The counterparty will experience a loss if the insurer is not able to meet its obligations in full, i.e., its excess capital is lower than the claim D. The expected loss in this case equals to

$$\mathbb{E}\left[\text{LOSS}\right] = \text{D} - \min\left(\mathbb{E}\left[\text{K}_t\right], \text{D}\right). \tag{1}$$

The regulator's objective is to minimize such spillover from the life insurance sector to the banking sector. There are at least two ways to achieve this: (i) adjusting the risk charge parameter α or (ii) limiting the amount of LOCs used in shadow insurance transactions. For the latter option it is possible to prohibit its use altogether. However, LOCs are a relatively cheap and flexible option for life insurers to collateralize affiliated, unauthorized reinsurance agreements and thus, it is in the interest of life insurers to have a total LOC amount greater than zero.

First, we assume that the regulator wants to minimize the expected loss given in (1) by choosing the appropriate risk charge α and thus, solving the following optimization problem:

$$\min_{\alpha}\{\text{D} - \min\left(\mathbb{E}\left[\text{K}_t\right], \text{D}\right)\}.$$

[30] Higher values of α tighten capital requirements and reduce risk-based capital levels.

When $\mathrm{D} > \mathbb{E}[\mathrm{K}_t]$, then $\mathbb{E}[\mathrm{LOSS}] > 0$. However, if $\mathrm{D} \leq \mathbb{E}[\mathrm{K}_t] = \mathrm{A}_t - (1+\alpha) \cdot [\mathrm{L}_t + (1-p) \cdot \mathrm{LOC}_t]$, i.e., the excess capital is large enough to repay the debt in full, the exposure is zero since $\mathrm{D} - \min(\mathbb{E}[\mathrm{K}_t], \mathrm{D}) = \mathrm{D} - \mathrm{D} = 0$. Rearranging the last inequality above yields

$$1 + \alpha \leq \frac{\mathrm{A}_t - \mathrm{D}}{\mathrm{L}_t + (1-p) \cdot \mathrm{LOC}_t}. \tag{2}$$

If $\hat{\alpha} > 0$ is the risk charge on the liabilities of affiliated shadow reinsurers with $\hat{\alpha} < \alpha$, the inequality in (2) provides an upper bound for the parameter $\alpha^* > 0$ regulators can use to regulate an insurer's statutory capital. The lower bound is given by $\hat{\alpha}$ as any risk charge lower than those for shadow insurers would make the shadow insurance transaction obsolete. Thus, any $\alpha^* > 0$ with

$$1 + \hat{\alpha} < 1 + \alpha^* \leq \frac{\mathrm{A}_t - \mathrm{D}}{\mathrm{L}_t + (1-p) \cdot \mathrm{LOC}_t}$$

can be chosen to minimize spillover risk in the presence of LOC financing.

Instead of tightening the statutory capital requirements, the regulator may limit the amount of LOC used to finance affiliated reinsurance agreements. The easiest way to do this is to allow no LOCs at all. However, keeping in mind the insurers' interests, the LOC amount is likely to be more than zero as it is a cheap financing vehicle. The question then is what the upper limit of LOC should be. Rearranging inequality (2) again yields:

$$\mathrm{LOC}_t \leq \frac{\mathrm{A}_t - (1+\alpha) \cdot \mathrm{L}_t - \mathrm{D}}{(1+\alpha)(1-p)}.$$

If $\alpha > 0$ is fixed, i.e., the regulator does not change the current risk charge on liabilities, the upper limit for LOC usage is given by the right hand side of the inequality above. The difficulty in the implementation is that we do not know the probability p of LOC renewals. If this probability is high, $1 - p$ will be small and the fraction of LOC financing can be higher.

7 Conclusion

In this paper, we provide empirical evidence that U.S. life insurance groups make extensive use of shadow insurance and are therefore highly connected to the banking sector. Due to this interconnectedness, they exhibit a significantly higher sensitivity towards equity movements in the U.S. banking sector, i.e., a higher market beta. Further, we see that not only are life insurers more exposed to risk stemming from the banking sector, but they also contribute to respective bank equity market risks. The main results we find are robust to fixed effects, an instrumental variable approach, and a difference-in-difference setting that exploits changes in the disclosure of shadow insurance agreement funding structures in 2011.

Our findings reveal that not only does a direct link between the life insurance and the banking sector through shadow insurance activities exist, but it is also highly relevant for assessing the stability of the financial system. As one potential driver of this interconnectedness risk, we identify the reliance on letters of credit that are provided as collateral for these transactions. If states authorize shadow insurance agreements conditional on LOCs as collateral, they should also think about the potential systemic risks that is created. This study therefore contributes to the debate about the risks when using shadow insurance as a tool to circumvent regulatory capital requirements.

Appendix 1: Variable definitions

Variable	Definition
Idiosyncratic Risk Measures:	
Volatility	Standard deviation of daily stock returns in a given year.
VaR	Insurer stock's Value at Risk (VaR) at the 95% confidence level calculated as the 5% quantile of daily stock returns in a given year then multiplied by minus one. Higher VaR indicates higher possible loss.
ES	Expected Shortfall (ES) is the expected loss (negative return) during the days when the stock return is less than its 5% quantile.
Systemic/Systematic Risk Measures:	
Beta	The market beta of an insurer's stock in a given year with respect to the U.S. banking sector. Let r_i be an insurer's daily stock return and r_m be the return of the U.S. Banks Datastream equity index. The beta is then calculated by COV$(r_i, r_m)/\sigma^2(r_m)$ using daily returns for the whole year.
MES	Marginal Expected Shortfall (MES) as defined in Acharya et al. (2016). MES is calculated by averaging the daily stock returns of an insurer's stock on the days the U.S. Banks Datastream equity index experienced its worst 5% returns. The average is then multiplied by minus one.
ΔCoVaR	Unconditional ΔCoVaR as defined in Adrian and Brunnermeier (2016). It is calculated as the market beta (with respect to the U.S. Banks Datastream equity index) times the difference in value at risks of the insurer stock at the 95% and 50% percentile. Higher ΔCoVaR means more contribution to systemic risk.
Shadow Insurance Variables:	
Shadow dummy	Indicator variable that is one if an insurance group cedes reinsurance to affiliated, unauthorized, and unrated entities in a given year.
Shadow ratio	Ratio of the amount of shadow insurance ceded to total reinsurance ceded.
LOC ratio	Amount of letters of credit provided for shadow insurance to total shadow insurance ceded by a group.
LOC HHI	Herfindahl-type index the sum of the share each bank provides in an insurance
Other Variables:	
Log(assets)	Natural logarithm of an insurance group's total assets.
Log(#affiliates)	Natural logarithm of the number of affiliated companies within the insurance group.
Insurance leverage	Ratio of a group's net premiums written to its total surplus.
Reinsurance usage	Group's total premiums ceded to the group's total premiums written.
Current liquidity	The ratio of unencumbered cash and unaffiliated investments to total liabilities.

Appendix 2: Summary statistics (2002-2014)

This table shows summary statistics for a sample of 35 U.S. life insurance groups from 2002 to 2014. We report the number of observations, the mean, minimum and maximum value as well as the standard deviation of each variable. The first panel reports summary statistics for life insurance group's idiosyncratic risk measures and systemic/systematic risk measures. Volatility, Value-at-Risk, and Expected Shortfall measure a life group's riskiness based on its daily stock return. Beta_Bank measures how sensitivity of a life group's stocks towards the equity of U.S. banking sector. Marginal Expected Shortfall and ΔCoVaR are two systemic risk measures relating a life group's stock return to the equity index of U.S. banking sector. The second panel reports variables about shadow insurance. Shadow dummy is an indicator of using shadow insurance. Shadow ratio is the percentage of shadow insurance ceded to total reinsurance ceded by a life group. LOC ratio measures the fraction of letters of credit provided for shadow insurance to total shadow insurance ceded and is for shadow insurance users only. LOC concentration has observations only starting from 2011, since when the information of banks that issuing LOCs is disclosed. The third panel reports some characteristics of life insurance groups. Variable definitions are given in Appendix 1.

Variable	**N**	**Mean**	**sd**	**Min**	**Max**
Risk measures					
Volatility	397	0.027	0.049	0.007	0.924
Value-at-Risk (VaR)	397	0.036	0.027	0.008	0.182
Expected Shortfall (ES)	397	0.054	0.041	0.013	0.271
Beta_Bank	391	0.726	0.321	-0.030	2.965
Marginal Expected Shortfall (MES)	397	0.031	0.028	-0.005	0.194
ΔCoVaR	391	0.028	0.031	-0.004	0.284
Shadow insurance variables					
Shadow dummy	397	0.418	0.494	0.000	1.000
Shadow ratio	387	0.142	0.255	0.000	0.949
LOC ratio (shadow users)	166	0.267	0.618	0.000	5.690
LOC concentration (shadow users)	92	0.547	0.296	0.071	1.000
Control variables					
Log(assets)	397	23.694	2.083	16.267	26.759
Log(#affiliates)	397	1.501	0.650	0	3.045
Insurance leverage	396	2.175	2.012	0.009	15.653
Reinsurance usage	397	0.128	0.175	0	0.877
Current liquidity	397	1.655	1.363	0	6.905

References

ACHARYA, V. V., L. H. PEDERSEN, T. PHILIPPON, AND M. RICHARDSON (2016): "Measuring Systemic Risk," *Review of Financial Studies*, forthcoming.

ADRIAN, T. AND M. K. BRUNNERMEIER (2016): "CoVaR," *American Economic Review*, 106, 1705–1741.

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*, 61, 251–271.

A.M. BEST (2002): "A.M. Best's Rating Methodology for Single Parent Captive Insurance Companies," Best's Special Report.

BENOIT, S., G. COLLETAZ, C. HURLIN, AND C. PÉRIGNON (2013): "A Theoretical and Empirical Comparison of Systemic Risk Measures," Working Paper.

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.

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.

ELING, M. AND M. PANKOKE (2016): "Systemic Risk in the Insurance Sector - A Review and Directions for Future Research," *Risk Management and Insurance Review*, forthcoming.

FOLEY-FISHER, N., B. NARAJABAD, AND S. VERANI (2016a): "Securities Lending as Wholesale Funding: Evidence from the U.S. Life Insurance Industry," Working Paper.

——— (2016b): "Self-fulfilling Runs: Evidence from the U.S. Life Insurance Industry," Working Paper.

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

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

IAIS (2011): "Insurance and Financial Stability," Basel.

——— (2012): "Global Systemically Important Insurers: Proposed Assessment Methodology," Basel.

——— (2013): "Global Systemically Important Insurers: Initial Assessment Methodology," Basel.

KOIJEN, R. AND M. YOGO (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*, 84, 1265–1287.

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

NAIC (2006): "U.S. REINSURANCE COLLATERAL WHITE PAPER," NAIC Reinsurance Task Force of the Financial Condition (E) Committee.

——— (2010): "Annual Statements Instructions - Life," NAIC Blanks Working Group.

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

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

SCHWARCZ, D. (2015): "The Risks of Shadow Insurance," *Georgia Law Review*, 50.

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

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