Expected Insurer Stock Returns and Systemic Risk Premia

ABSTRACT

In this study, we employ asset pricing models to investigate how investors price the systemic importance of insurance companies. We examine the cross-section of expected stock returns of life and non-life insurers for the time period 1990-2014 and two crisis periods. As potential risk factors, we test the interconnectedness with the banking and insurance sector, size, and the dependence on the CDS market. Our results show that investors receive a premium for holding stocks of highly interconnected insurance companies. Market participants thus appear to assume that insurance companies are not too-interconnected-to-fail to be bailed out by the government in the event of failure. We find that even directly after the bailout of AIG, investors did not view insurance companies as systemically relevant. Furthermore, we find evidence that suggests that an insurer's size does not fully predict the firm's systemic relevance.

Keywords: Asset pricing, interconnectedness, insurance, systemic risk, bail-out guarantees
JEL Classification: G12, G22

1 Introduction

Studying asset pricing models and pricing factors has been an important field of research in the past 50 years. However, financial institutions are mostly excluded from the studies. A few studies exist which specifically examine the cross-section of bank stocks. These studies show that the cross-sectional variation in asset stock returns is different for banks and non-financials. Especially, Gandhi and Lustig (2015) reveal that there is a size anomaly in bank stock returns, concluding that bail-out guarantees given by the government result in large banks taking on tail risk. Since the recent financial crisis and the bailout of AIG, finance literature on the potential systemic relevance of insurance companies increased, but none of these studies links the pricing of insurers' assets to the perception of systemic risk in the insurance sector by market participants.

In this empirical study we use asset pricing models to investigate how investors evaluate the exposure and contribution of insurance companies to systemic risk. We examine the cross-section of 74 life and 189 non-life insurance companies for three different time periods. Literature on potential factors enhancing the systemic relevance of insurers agree that the interconnectedness with the banking sector is the main driver for an insurance company to become systemically relevant (see, e.g., Acharya et al. (2009) and Cummins and Weiss (2014)). In our analysis we therefore focus on this factor, but additionally include the interconnectedness with the insurance sector, the insurers' size and their dependency on the CDS market in our study. Our entire sample period ranges from January 1990 to December 2014. Additionally, we examine the structure of asset prices in subperiods that cover the time of the recent financial crisis and the credit crunch crisis in the early 90s. Following the literature on asset pricing studies we first examine characteristic-sorted portfolios of returns to identify return patterns that cannot be explained by standard asset pricing models. The asset pricing models we employ are the CAPM, the Fama-French 3-factor model by Fama and French (1993) and the Fama-French 5-factor model by Fama and French (2015). Secondly, we run Fama-Macbeth regressions developed by Fama and MacBeth (1973) to determine the premium that is rewarded for a unit exposure to each risk factor.

How market participants evaluate the risk of insurers' assets, three outcomes are possible.

If interconnectedness is not priced into stocks it could indicate that investors neither view the exposure nor the contribution of insurers to systemic risk to be relevant. In this case either systemic risk in the insurance sector does indeed not exist, or investors improperly assessed the situation. Far more interesting is the question how investors view insurance companies if interconnectedness is priced into stocks. Interconnectedness being priced in with a positive risk premium would imply that stocks of insurers with a higher interconnectedness are expected to generate higher returns. It indicates that market participants do not view insurers to be of systemic relevance and assume they would not be bailed out in the event of failure. A third possible outcome is that interconnectedness is priced in with a negative risk premium. In that case, insurers that are higher interconnected with the banking sector are assumed to have a lower risk and therefore expected returns are lower. This would directly imply that highly interconnected insurance companies are expected to be bailed out by the government if necessary.

Our results show that in general, investors receive a premium for holding stocks of highly interconnected insurance companies. This indicates that market participants assume that insurance companies are not too-interconnected-to-fail to be bailed out by the government in the event of failure. On the contrary, we find that both life and non-life insurers that are higher interconnected to the insurance and banking sector have higher expected returns. For the time of the financial crisis, the interconnectedness with insurers is also priced in the cross-section of non-life insurer's expected stock returns. Thus, even directly after AIG has been saved by the government, investors did not view insurance companies as systemically relevant. The insurers' size is neither priced in stock returns over the complete sample period nor during the financial crisis which confirms the argument of Acharya et al. (2009) and Cummins and Weiss (2014) that interconnectedness can be a predictor of systemic relevance, but size is not. Furthermore, we find evidence that the dependency on the CDS market is priced into life insurers' expected stock returns with a negative risk premium for the complete sample period. It indicates that life insurers with a higher connection to the CDS market are viewed as systemically relevant.

The results that we find have important implications for investors and policymakers alike. On the one hand, investors interested in taking up long positions in insurer stocks should carefully price in the unsecured extra risk that stems from the insurer's systemic importance and the exposure to contagion from the banking sector. On the other hand, regulators and policymakers should take notice of the fact that market investors demand a risk premium for an insurer's interconnectedness with banks. First, it shows that a high interconnectedness is viewed critically by investors underlining the notion that interconnectedness could lead to a higher exposure to systemic risk from the banking sector. Second, and more importantly, we find no evidence in support of investors perceiving insurers to be too-interconnected-to-fail. Rather, investors appear to expect insurers to be hit hard by a crisis rather than be bailed-out as they receive a risk premium instead of a discount for holding the stocks of interconnected insurers. Consequently, regulators should expect investors to divest heavily from the stocks of interconnected insurers in case of a downturn of the banking sector.

This article is structured as follows. Section 2 gives an overview about the related literature on the asset pricing of firms, systemic risk in the insurance industry and investor sentiment. Section 3 presents the data and methodology used in the empirical study and describes the risk factors that we test. Section 4 presents the results of our analysis. Concluding remarks are given in Section 5.

2 Literature review

A variety of studies approach the asset pricing of firms. In recent times, Chabi-Yo et al. (2015) capture the crash sensitivity of stocks by their lower tail dependence with the market based on copulas. They employ the one-factor CAPM, the Fama-French 3-factor model and a 4-factor model by Calomiris and Mason (1997). Using the Fama-French 3-factor model and Fama-Macbeth regressions, Cremers et al. (2015) show that aggregate jump and aggregate volatility are significantly priced risk factors in the cross-section of returns. van Oordt and Zhou (2013) test whether systematic tail risk is priced in the cross-section of expected returns of non-financial firms by applying the tail beta. They find no evidence of a premium associated with tail betas. Moreover, Garlappi and Yan (2011) find evidence that the presence of potential shareholder recovery upon financial distress alters the risk structure of equity.

In asset pricing studies, financial firms are mostly excluded. There exist, however, several studies that concentrate only on financial institution. Viale et al. (2009) analyze risk factors that are priced in bank equities. Acharya et al. (2015) find that bondholders of large financial institutions expect that the government will bail them out in the event of failure and, consequently, they do not accurately price risk. A first study that links the analysis of asset pricing with systemic risk in the financial sector is the work by Gandhi and Lustig (2015). They extend the Fama-French 3-factor model by two bond risk factors and find a size effect in U.S. bank stock returns that is different from those documented for non-financials. They conclude that bail-out guarantees given by the government results in large banks taking on tail risk. A few studies exist which exclusively investigate the pricing factors of insurance companies. Cummins and Harrington (1988) were the first to employ the CAPM in the insurance sector. They study the cross-section of property/liability insurance stocks, finding that idiosyncratic risk is correlated with returns. Ben Ammar et al. (2015) analyze the cross-section of stock returns of property/ liability insurers, finding that the book-to-market ratio, short-term reversal, illiquidity, and cashflow volatility are priced in. They use these four factors to develop an insurance-specific model.

Our work is also related to studies that analyze systemic risk of financial institutions. Acharya et al. (2010), Adrian and Brunnermeier (2014), Brownlees and Engle (2012) and Huang et al. (2009) introduce new methods to measure systemic risk. Furthermore, it contributes to the ongoing debate on whether insurance companies pose systemic risk. Some academic literature and other publications argue that there are considerable differences between banks and insurers (see, e.g., Insurance Europe (CEA) (2014), Das et al. (2003) and Harrington (2009)). Traditional insurers do not write a large amount of nontraditional insurance, e.g. catastrophe bonds, credit default swaps, alternative risk transfer arrangements or mortgage insurance, and are less affected by the ups and downs on the financial market. Furthermore, compared to banks insurers have more long-term and less liquid assets which makes ”runs” on insurance companies during financial crises less likely. Thus, it is argued that insurers can be affected by financial crises, but are in general not systemically risky themselves. Chen et al. (2014) empirically confirm that argumentation. In their study on credit default swaps they show that banks create significant systemic risk for insurers but not inversely. Other studies, however, argue that insurers could contribute to the instability of the financial sector under certain circumstances. The main argument is that interlinkages between insurers and banks through trading with non-traditional insurance increased during the last decades. (see, e.g., Baluch et al. (2011), Rule (2001) and Schinasi (2006)). The literature usually names three factors that could lead to an insurer becoming systemically relevant: size, interconnectedness and non-core activities (see, e.g., Geneva Association (2010), IAIS (2012), Acharya et al. (2009), and Cummins and Weiss (2014)).

A question which has not yet been approached in the existing literature is how investors assess the systemic relevance of insurance companies. Several studies show that investor sentiment is an important factor in the pricing of assets and that the media may strongly influence investor behavior (see, e.g., De Long et al. (1990), Da et al. (forthcoming), Baker and Wurgler (2006), Tetlock (2007) and Barber and Odean (2008)). Furthermore, Irresberger et al. (2016) show that during the recent financial crisis investors mainly exited insurer stocks not because of rational assessment of the insurer's actual exposure to the crisis but rather by reason of irrational crisis sentiment. With this study we fill this gap and link the asset pricing of insurers' stocks to the evaluation of systemic risk in the insurance sector.

3 Data and methodology

In the following section we describe the construction of our sample as well as data sources, outline the methodology we employ in the empirical study and define the risk factors we test for being priced into insurer stock returns.

3.1 Sample construction and data sources

To construct our data sample, we select all publicly traded insurance companies with U.S. headquarters listed in CRSP with SIC codes 6311, 6321, 6331, 6351 or 6399. Thus, we include life insurers, accident and health insurers, fire, marine and casualty insurers, surety insurers and other insurance carriers. We explicitly exclude title insurers due to their specialized business model and any type of banks or insurance agents. The definition of life and non-life insurance companies in the company lists of CRSP is not precise in some cases.[1] Therefore, we manually check whether the web pages of the companies in our sample are indicative of a non-insurance nature of the companies' business. Focusing on U.S. insurers ensures that all companies in our study are subject to uniform regulation standards. Share price data are retrieved from CRSP, financial accounting data are obtained from COMPUSTAT. For insurers with missing data in each of the databases we check whether the data is available from Thomson Reuters Financial Datastream. Data on the Fama-French factors and the 1-month Treasury bill rate is downloaded from the Kenneth French's website. Stock price data for the market makers are retrieved from Datastream.

From our initial data sample of 391 insurers, we exclude insurers' stocks which have less than 36 months of consecutive returns data or negative book values. Additionally, we exclude Berkshire Hathaway due to its unusually high stock price. Our sample period ranges from January 1990 to December 2014. Before 1990, both the number of insurance stocks and the availability of accounting data decreases strongly. Our final sample consists of 263 U.S. insurance companies, 74 life and 189 non-life insurers. We perform our analysis separately for life and non-life insurers since there are considerable differences between these lines of insurance. One reason is that they cover different types of risk with different calculation bases. Additionally, there are differences in the magnitudes of several variables which we employ in our analysis, e.g., size, since life insurers are in general larger than non-life insurers. Table I shows the number of companies for which stock price data is available in each year of our sample period.

– insert Table I about here –

[1] For instance, an oil company and a software company are listed as non-life insurers in CRSP's company lists.

On average, data is available for 34 life and 102 non-life insurers per year. The number of life insurers steadily decreases over our sample period which might be an indication that over the past 30 years the size of life insurers increased through mergers and acquisitions.

3.2 Methodology

Literature on asset pricing usually proposes two approaches to analyze the influence of specific factors on stock returns. The first approach is to examine portfolios of returns sorted by several characteristics to identify return patterns that cannot be explained by standard asset pricing models. A second approach is to regress each asset's or portfolio's excess returns against these factors to determine their exposure to the factor. Then, to determine what premium is rewarded for a unit exposure to each factor, the excess returns of each asset or portfolio are regressed against its factor exposures in each time period. The average of the coefficients over time describe the premiums for each factor.

Following the approach in the literature, we first rank all insurer stock returns by each characteristic as of January of each year. The returns are then divided into the three portfolios low (bottom 20%), mid (middle 60%) and high (top 20%). For each portfolio we calculate equally-weighted returns for each month over the next year. We follow Ben Ammar et al. (2015) and use equally weighted returns to ensure the portfolio returns are not biased due to few large insurers in our relatively small sample. For example, in our sample AIG accounts for more than 15% of the entire amount of total assets of non-life insurers in December 2014. Additionally, in the Fama and MacBeth (1973) regressions each independent variable is weighted equally.

We regress monthly excess returns for each characteristic-sorted portfolio on factors of three different asset pricing models from the finance literature. The general setting of the time-series regression for each portfolio i is defined as

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + \epsilon_{i,t},$$

where $R_{i,t}$ is the monthly return on the i-th characteristic-sorted portfolio, $R_{f,t}$ is the risk-free rate, $f_{k,t}$ is the realization of factor k and $\beta_{i,k}$ is the sensitivity of portfolio i to factor k at time t.

The first model we test is the CAPM with the excess return of a stock market index as only risk factor, thus

$$f_t = \begin{bmatrix} MKT \end{bmatrix}.$$

The market factor MKT is calculated using the value-weighted returns of all NYSE, AMEX, and NASDAQ stocks listed in CRSP minus the one-month Treasury bill rate from Ibbotson Associates.

The second model in our analysis is the Fama-French three-factor model by Fama and French (1993) with risk factors

$$f_t = \begin{bmatrix} MKT & SMB & HML \end{bmatrix},$$

where SMB (small minus big) is a zero-investment portfolio between stocks sorted by market capitalization, and HML is a zero-investment portfolio between stocks sorted by book-to-market ratios. Hence, this model extends the CAPM by a size and a value factor.

The third model is the Fama-French five-factor model by Fama and French (2015) with risk factors

$$f_t = \begin{bmatrix} MKT & SMB & HML & RMW & CMA \end{bmatrix},$$

where RMW (robust minus weak) is a zero-investment portfolio with stocks sorted by their operating profitability, and CMA (conservative minus aggressive) is a zero-investment portfolio with stocks sorted by their investment strategy.

As a second step, we employ the Fama-Macbeth two-stage regression methodology developed by Fama and MacBeth (1973). With this methodology the premium rewarded to a particular risk factor exposure can be estimated. The first-stage time-series regressions are similar to those described earlier in this section, but instead of portfolio returns we now regress each asset's excess returns against the potential risk factors to determine the vector of betas β_i for each risk factor:

$$R_{i,t} - R_{f,t} = \alpha_i + \sum_{k=1}^{K} \beta_{i,k} f_{k,t} + \epsilon_{i,t},$$

where $R_{i,t} - R_{f,t}$ is the monthly return on the i-th asset. The second-stage cross-sectional regressions use these beta estimates as independent variables and estimate the following regression at each time period t:

$$R_{i,t} - R_{f,t} = z_t + \sum_{k=1}^{K} \lambda_{k,t} \hat{\beta}_{i,k,t} + \alpha_{i,t},$$

where λ_k is the risk premium of factor k and $\hat{\beta}_{i,k}$ is the beta estimate from a time-series regression. Then, estimates of λ_k and α_i are the averages across time:

$$\lambda_k = \frac{1}{T} \sum_{t=1}^{T} \lambda_{k,t}, \quad \alpha_i = \frac{1}{T} \sum_{t=1}^{T} \alpha_{i,t}.$$

The T second-stage regressions can be substituted by a single cross-sectional regression by taking the means of the excess returns over time:

$$E(R_i^e) = z + \sum_{k=1}^{K} \lambda_k \hat{\beta}_{i,k} + \alpha_i,$$

where $E(R_i^e)$ is the expected excess return of insurance stock i. With the assumption that the betas are constant over time, the coefficients are the same in both cases. However, the standard errors and t-statistics differ, because the α_i in the second approach are in most cases heteroskedastic and autocorrelated. To correct this problem we use Newey-West standard errors with 5 lags. We assume that the exposure to different risk factors varies over time. Therefore, we divide our sample period into sub-periods. We are particularly interested in whether investors tend to evaluate stocks differently in times of crisis and additionally perform the analysis for the periods of two major banking crises that occurred during our sample period. The first crisis we consider is the credit crunch from January 1990 - December 1992, the second crisis is the recent financial crisis. We follow Berger and Bouwman (2013) and define the time of the financial crisis as July 2007 - December 2009. In the following subsection we describe the characteristics we test in our asset pricing study.

3.3 Variables

We examine the exposure of insurance companies to four different risk factors. Table II summarizes these variables and their data sources.

– insert Table II about here –

The first variable we test is the interconnectedness of an insurer with the insurance sector. To calculate the variable Interconnectedness insurer we retrieve stock price data for all U.S. insurance companies listed in CRSP and employ the methodology developed by Billio et al. (2012). This univariate measure is based on a principal component analysis of the stock returns. The IAIS (2012) argues that an insurer may become systemically relevant with an increasing interconnectedness with the financial market. We expect this characteristic to be priced in the stock returns, but have no expectations concerning the tendency of the risk premium. A positive risk premium indicates that investors regard insurers as systemically relevant without a guarantee to be bailed out when facing bankruptcy. If the risk premium is negative, investors would assume that systemically risky insurers will be bailed out in case of failure.   underline that insurers get increasingly interlinked with banks through nontraditional insurance due to which a highly connected insurer could pose a systemic risk to banks. Thus, we also include a variable which measures the interconnectedness of insurance companies with the banking sector. The variable Interconnectedness banks is also computed with the methodology by Billio et al. (2012) and includes all U.S. banks for which stock price data is available in CRSP.

To test whether size anomalies are present in the stock returns of our sample, we include the logarithm of total assets as a proxy for insurer size in our analysis. In their sample of property/liability insurers, Ben Ammar et al. (2015) do not find any size anomalies for the time period 1988 - 2013. Hence, we also expect the size factor to be insignificant in our regressions for non-life insurers for our entire sample period. Since investor sentiment might change during times of crisis, however, size anomalies might exist in the subperiods covering the financial crisis and the credit crunch in the early 90s. For life insurers we do not have any expectations. Gandhi and Lustig

(2015) find that the size of U.S. banks is priced into stock returns with a negative risk premium which indicates that large banks are protected by government guarantees in case of bankruptcy. However, despite AIG being saved from failure by the U.S. government, even large insurance companies might in general not be seen as systemically risky and thus their size might not be priced into their stock returns. Furthermore, in contrast to banks, an insurer's business is largely based on portfolio diversification. If a size anomaly with negative risk premiums exists for insurance companies, it might simply be that larger insurers have a more diversified insurance portfolio and therefore a lower risk exposure. A positive risk premium, however, would be a definite indication that insurers are not considered too-big-to-fail.

As a fourth risk factor, we examine the exposure of insurer stocks to the CDS market. In order to do so, we calculate the beta exposure β_{MM} of insurer stock returns to a value-weighted index of market maker returns. The Federal Reserve Bank of New York provides a list of market makers on their webpage.[2] Stock data is retrieved from Datastream. Harrington (2009) underlines that the subsidiary AIGFP was a primary player in the CDS market in the end of 2007 and that its large losses during the crisis was a major factor for the failure of AIG.

4 Empirical results

In this section we present and interpret our results to answer the question whether insurance companies are regarded as systemically risky by investors. First, we analyze the results of single-sorted portfolios, followed by time-series regressions of the excess returns of each characteristic-sorted portfolio on the different asset pricing model factors. Afterwards we discuss the results obtained from the two-pass regressions of individual stock returns on each characteristic. To get a first impression on potential differences between stocks in the lowest and highest quintile of characteristic-sorted stocks, we plot the time evolution of the bottom and top portfolio returns

[2] We calculate the index including Bank of America, Barclays, BNP Paribas, Credit Suisse Group, Deutsche Bank, Goldman Sachs, HSBC Holdings, JP Morgan Chase, Morgan Stanley, Royal Bank of Scotland, Société Générale, UBS Group and Wells Fargo.

separately for life and non-life insurers in Figure 1 and 2.

– insert Figure 1 and 2 about here –

Firstly, we discuss the illustrations of portfolio returns sorted by the interconnectedness with the insurance and the banking sector, respectively. We notice that life insurers have a similar graphical output for both variables. The return curves of lowest and highest quintiles evolve similarly until the early 2000s, then the returns for the highest quintile decrease sharply. During the time of the recent financial crisis, both the returns of low and high interconnected insurers decrease sharply. Directly after the crisis, the returns of the highest quintile appear to be considerably higher than the returns of the lowest quintile for both variables. This is reversed in the plot showing the evolution of returns of non-life insurers. For both variables the lowest and highest quintile evolve similarly, but after the extreme negative peak in course of the financial crisis, stocks in the lowest quintile appear to generate higher returns than those in the highest quintile.

Now, we turn to the plot of portfolio returns sorted by total assets. The plot indicates that both larger life and non-life insurers had higher losses during the financial crisis, but generated higher returns directly after the negative peak. For the exposure to the CDS market, we do not notice any considerable differences between the lowest and highest quintile of characteristic-sorted returns during the financial crisis. Following Vassalou and Xing (2004) we now analyze the average return spreads between single-sorted portfolios which are presented in Table III.

– insert Table III about here –

For our entire sample period, we do not find a significant effect for the interconnectedness with both insurers and banks of life and non-life insurers. For the time of the financial crisis, the return spread is significant for the stocks sorted by the interconnectedness with banks. For life insurers, the monthly return spread between insurers with low and high interconnectedness is 2.96%. Surprisingly, we find the opposite effect for non-life insurers with a significant negative return spread of -1.83%. For the time of the credit crunch crisis in 1990, we also find the return spread of life insurer stocks sorted by interconnectedness with banks to be significant with an average monthly return of 1.33%. In line with the finding of Ben Ammar et al. (2015), the size of both life and non-life insurers is not significant in our complete sample period. Furthermore, we do not find a significant size effect in the two periods of crisis either. The exposure to the CDS market measured by the beta for an insurer's returns compared to a market maker index is significant for life insurers in our entire sample period, but not in the crisis periods. The spread is significant with an average return of 0.76% per month.

In the next step of our analysis, we examine whether the different asset pricing models can explain the spread differences. In Table IV we present the results from regressions of characteristic-sorted portfolio returns on the different asset pricing model factors.

– insert Table IV about here –

We find that the significant return spread between life insurer stock returns sorted by interconnectedness with the banking sector for both crisis periods can neither be explained by the CAPM nor the Fama-French 3- or 5-factor models. The spread is significant with a positive coefficient in all six regressions. Furthermore, we find that the spread between the returns of life insurers sorted by interconnectedness with the insurance sector enters all regressions for the financial crisis significantly with a positive sign. This result confirms the result from the single-sorted portfolios that high-interconnected life insurers have a higher risk exposure and therefore higher returns. It indicates that market participants did not assess life insurers as too-interconnected-to-fail, i.e. they did not assume that highly interconnected life insurers would be bailed out in the event of failure.

The significant negative spread of non-life insurers' returns for the financial crisis cannot be confirmed in the time-series regressions. All three asset pricing models can explain the spread difference. We find significant negative spread returns for the credit crunch crisis, but only in two out of three regressions. This finding is in line with the literature which argues that life insurers have a higher risk exposure than non-life insurers due to higher leverage, a higher possibility of policyholders withdrawing funds during a crisis, and the increasing number of insurance policies that include variable annuities (see, e.g., Harrington (2009) and Cummins and Weiss (2014)).

The results obtained for life insurers and total assets are confirmed in the regressions, the alpha spread is significant in only one out of nine regressions. For non-life insurers, however, we find a significant size effect in all three regressions for the financial crisis. The spread is positive which is evidence that larger non-life insurers cannot compensate losses through a more diversified portfolio, but instead have a higher risk exposure and thus higher returns. This result is not surprising since larger insurers are at the same time usually more interconnected with the financial sector. For our entire sample period we observe significant return spreads with negative coefficients, but only in two out of three regressions. Regressions on risk factors of asset pricing models do not confirm the positive return spread between the returns of life insurers sorted by β_{MM}. We find a significant spread in the regression with the CAPM, but both the Fama-French 3-factor model and the 5-factor model can explain the difference. For non-life insurers, three out of six regressions have a significant positive alpha spread for the crisis periods. The CAPM, however, can explain the spread difference in both regressions.

Next, we analyze the results from Fama-Macbeth regressions to examine risk premiums rewarded to each risk factor. Table V presents the results.

– insert Table V about here –

The results show that the interconnectedness with the banking sector is significantly priced into stock returns with a positive risk premium for both life and non-life insurers in the complete sample period. Additionally, we find a significant positive risk premium in the regression for non-life insurers which employs the interconnectedness with the insurance sector as independent variable. This indicates that both life and non-life insurers that are highly interconnected are assumed to have a higher risk and therefore higher expected returns. It appears that market participants do not assume that insurance companies would be bailed out in the event of failure. For the time of the financial crisis, the interconnectedness with insurers is also priced in the cross-section of non-life insurer's expected stock returns. Thus, even directly after AIG has been saved by the government, investors did not view insurance companies as systemically relevant. The insurers' size is neither priced in stock returns over the complete sample period nor during the financial crisis. This confirms the argument of Acharya et al. (2009) and Cummins and Weiss (2014) that interconnectedness can be a predictor of systemic relevance, but size is not. Results from regressions covering the credit crunch crisis confirm that investors receive a premium for holding stocks of life insurers that are highly interconnected with the insurance and banking sector. During this crisis size is also priced in with a positive risk premium. This could be evidence that insurer size was a relevant risk factor during that subperiod, but it could also display that higher interconnected insurers are usually also larger. Interestingly, we find evidence that the influence of the CDS market is priced into life insurers' expected stock returns with a negative risk premium for the complete sample period. It implies that life insurers with a higher connection to the CDS market are viewed as systemically relevant.

4.1 Robustness checks

To verify our results we perform several robustness checks. One point of critique could be that our definition of the crisis period is incorrect. Several studies investigating different aspects of the recent financial crisis define the period July 2007 - December 2008 as the time in which the crisis occurred (see, e.g., Acharya et al. (2010), Fahlenbrach et al. (2012) and Beltratti and Stulz (2012)). To investigate the robustness of the results obtained for the financial crisis, we conduct our analysis for this alternative time period. The results remain basically unchanged.

In their study on insurance-specific asset pricing anomalies, Ben Ammar et al. (2015) use market capitalization as a measure of insurer size. Therefore, we employ market capitalization as an alternative measure of firm size, with similar results.

5 Conclusion

Using three established asset pricing models, we investigate how investors evaluate the exposure and contribution of insurance companies to systemic risk in three different time periods. Our results show that in general, the interconnectedness with the banking sector is priced in the cross-section of both life and non-life insurer's expected stock returns with a positive risk premium. Hence, market participants appear to expect insurers to be hit hard by a crisis rather than be bailed-out as they receive a risk premium instead of a discount for holding the stocks of interconnected insurers. Even in the time of the financial crisis and after AIG had been saved by the government, market participants did not assume other highly interconnected insurance companies would be saved. Furthermore, we find no significant size anomaly in insurer stock returns which has been revealed for banks. This confirms the findings of Acharya et al. (2009) and Cummins and Weiss (2014) that size alone is not a predictor for the exposure or contribution to systemic risk in the insurance sector. Finally, we find evidence that the dependency on the CDS market is priced into life insurers' expected stock returns with a negative risk premium. It indicates that investors view life insurers with a high connection to the CDS market as systemically relevant.

Our analysis provides a new perspective to the ongoing discussion on the exposure and contribution of insurance companies to systemic risk and our results have important implications for both investors and policymakers. Firstly, market participants should carefully price in the unsecured extra risk that stems from the insurer's systemic importance and the exposure to contagion from the banking sector. Secondly, regulators and policymakers should take notice of the fact that market investors demand a risk premium for an insurer's interconnectedness with banks. It shows that a high interconnectedness is viewed critically by investors underlining the notion that interconnectedness could lead to a higher exposure to systemic risk from the banking sector. More importantly, we find no evidence in support of investors perceiving insurers to be too-interconnected-to-fail. Rather, investors appear to expect insurers to be hit hard by a crisis rather than be bailed-out as they receive a risk premium instead of a discount for holding the stocks of interconnected insurers. Consequently, regulators should expect investors to divest heavily from the stocks of interconnected insurers in case of a downturn of the banking sector.

Further research projects should examine whether our results hold for a sample of global insurance companies. Furthermore, it would be interesting to analyze how investors' views vary over time by considering further time periods than the two crisis periods analyzed in our study.

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Tables and Figures

Figure 1: Illustration of portfolio returns sorted by interconnectedness with the insurance and banking sector.

The figure presents the graphical output of the average monthly characteristic-sorted portfolio returns separated for life and non-life insurers in % per month. Insurer stocks are ranked with respect to the interconnectedness with the insurer and banking sector, respectively, and divided into the three portfolios Low (bottom 20%), Mid (middle 60%) and High (top 20%).

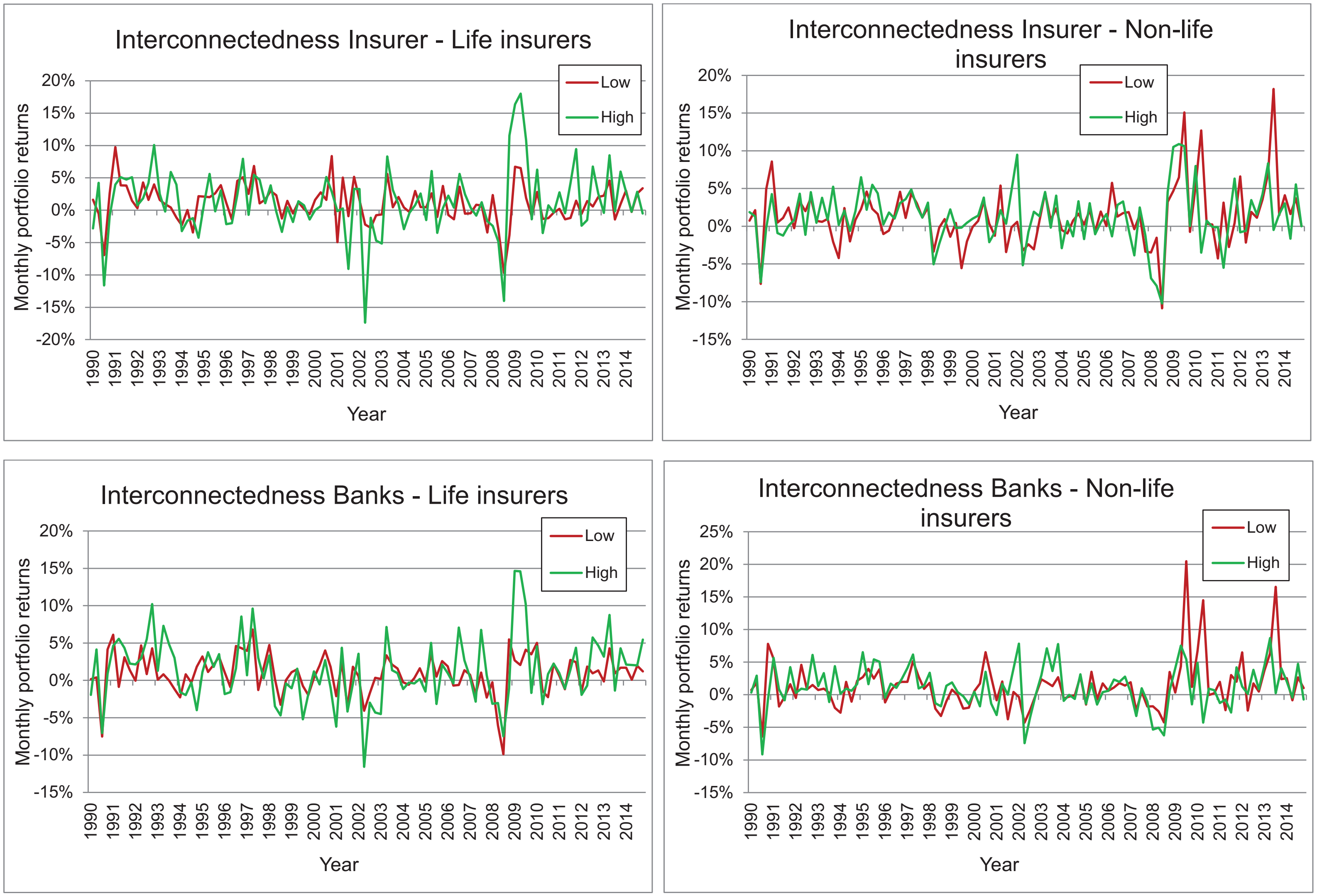

Figure 2: Illustration of portfolio returns sorted by size and dependency on the CDS market.

The figure presents the graphical output of the average monthly characteristic-sorted portfolio returns separated for life and non-life insurers in % per month. Stocks are ranked with respect to the insurers' size and their dependency on the CDS market, and divided into the three portfolios Low (bottom 20%), Mid (middle 60%) and High (top 20%).

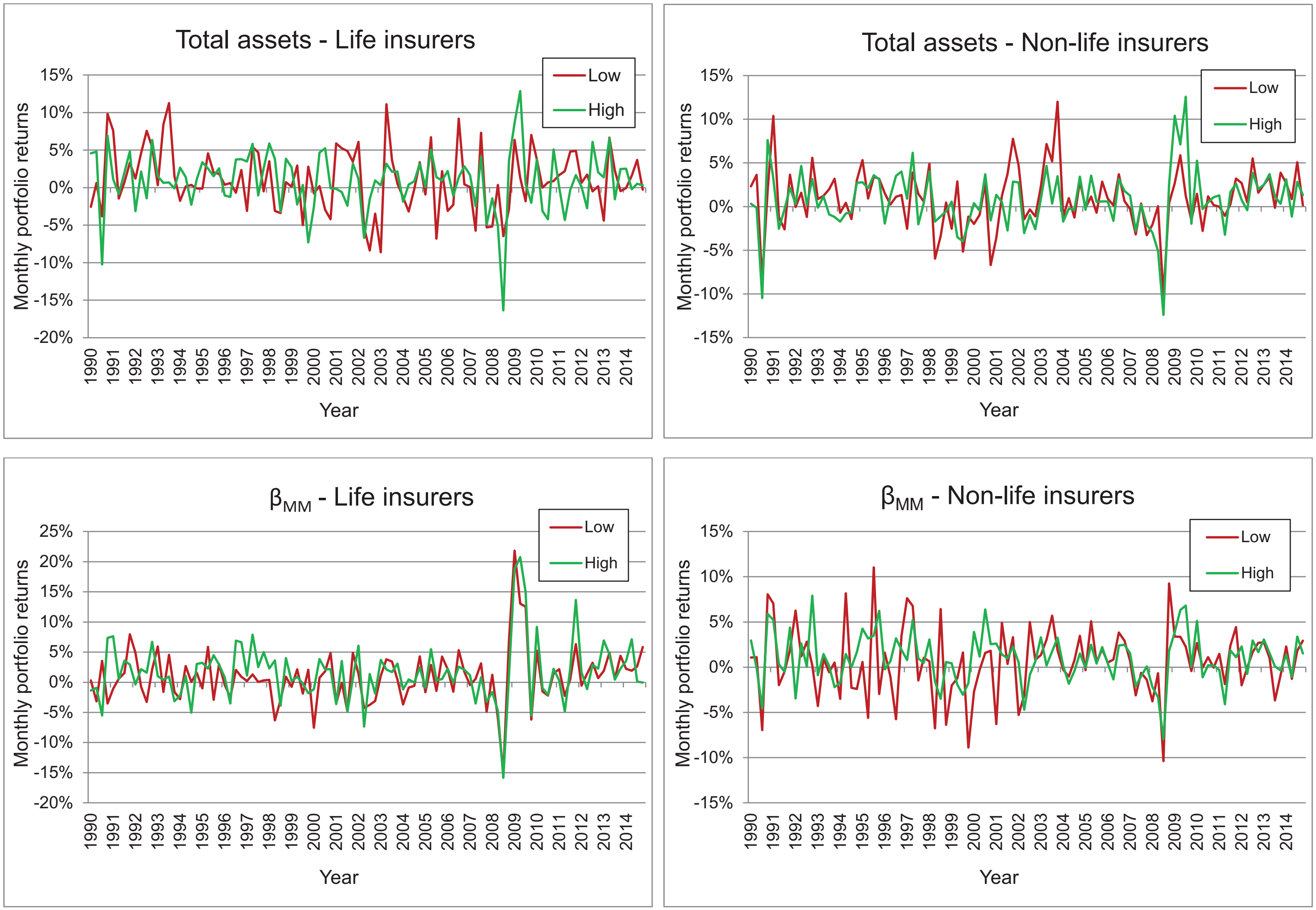

Table I: Sample distribution.

This table shows the number of companies for which stock price data is available in each year from January 1990 to December 2014. The sample consists of 74 life insurers with SIC Code 6311 and 189 non-life insurers with SIC Codes 6321, 6331, 6351, 6361 and 6399. Column 2 reports the number of life insurers per year, column 3 reports the number of non-life insurers per year.

Year	Life insurers	Non-life insurers
1990	42	78
1991	42	83
1992	43	94
1993	45	100
1994	46	107
1995	44	108
1996	40	116
1997	39	115
1998	35	108
1999	33	105
2000	32	99
2001	30	94
2002	30	93
2003	29	97
2004	31	109
2005	30	115
2006	29	119
2007	28	119
2008	26	113
2009	25	108
2010	27	104
2011	26	98
2012	25	93
2013	25	89
2014	25	87

Table II: Variable definitions and data sources.

The table presents definitions and data sources for all dependent and independent variables that are used in the empirical study.

Variable name	**Definition**	**Data source**
Returns	Monthly buy-and-hold returns on an insurer's stock.	CRSP, Datastream
Interconnectedness insurer	Univariate measure of an insurer's interconnectedness with the rest of the insurance sector based on a principal component analysis of the stock returns of a sample of U.S. insurers as defined by Billio et al. (2012).	CRSP
Interconnectedness banks	Univariate measure of an insurer's interconnectedness with the banking sector based on a principal component analysis of the stock returns of a sample of U.S. banks as defined by Billio et al. (2012).	CRSP
Total assets	Natural logarithm of an insurer's total assets.	Compustat
β_{MM}	Beta exposure of insurer stock returns to a value-weighted index of market maker returns.	Datastream, CRSP; own calc.

Table III: Average monthly returns of characteristic-sorted portfolios.

This table presents the average monthly returns of characteristic-sorted portfolios separated for life (74 insurers) and non-life insurers (189 insurers) in % per month. Insurer stocks are ranked regarding each characteristic and divided into the three portfolios Low (bottom 20%), Mid (middle 60%) and High (top 20%). Panel A shows the results for the complete sample period, Panel B reports the results for the time of the recent financial crisis and Panel C shows the results for the time of the Credit Crunch Crisis in 1990-1992. P-values are shown in parantheses and calculated from Newey-West standard errors with lags of 5. ***,**,* indicate statistical significance at the 1%, 5% and 10% level, respectively.

	Life insurers				Non-life insurers			
	Interconnectedness insurer	Interconnectedness banks	Total assets	β_{MM}	Interconnectedness insurer	Interconnectedness banks	Total assets	β_{MM}
Panel A: Complete sample period, January 1990 - December 2014								
Low	1.069	0.856	1.029	0.854	1.265	1.391	0.923	0.563
Mid	0.918	0.986	1.276	0.939	0.715	0.698	0.841	0.893
High	1.291	1.270	0.884	1.616	1.229	1.168	0.733	0.970
Spread (High - Low)	0.222	0.414	-0.145	**0.761****	-0.035	-0.222	-0.189	0.387
	(0.678)	(0.320)	(0.736)	**(0.021)**	(0.930)	(0.605)	(0.604)	(0.255)
Panel B: Financial Crisis, July 2007 - December 2009								
Low	-0.211	-0.141	-0.740	2.943	0.915	1.765	-0.879	-0.137
Mid	0.359	0.438	1.314	-0.042	-0.695	-0.439	-0.122	0.073
High	3.288	2.920	-0.060	2.323	1.255	-0.249	0.625	0.374
Spread (High - Low)	3.620	**2.957****	0.244	-0.281	0.201	**-1.832***	1.379	0.502
	(0.164)	**(0.020)**	(0.860)	(0.818)	(0.862)	**(0.074)**	(0.389)	(0.575)
Panel C: Credit Crunch Crisis, January 1990 - December 1992								
Low	1.910	1.094	2.202	0.352	1.541	1.076	0.684	2.814
Mid	1.181	1.148	1.349	1.378	1.015	0.979	1.416	1.093
High	1.617	2.422	1.058	1.538	-0.232	0.339	0.337	1.423
Spread (High - Low)	-0.293	**1.328***	-1.144	-0.737	1.187	-0.737	-0.348	-0.952
	(0.802)	**(0.076)**	(0.205)	(0.267)	(0.172)	(0.267)	(0.607)	(0.718)

Table IV: Alphas from times-series regressions with different asset pricing models.

This table shows the alphas from time-series regressions in which we regress monthly portfolio returns (in %) on the factors of different asset pricing models. We run the regressions separately for 74 life and 189 non-life insurers. The asset pricing models which we employ are the CAPM, the Fama-French 3-factor model, and the Fama-French 5-factor model. Panel A, D, and G present the results for our entire sample period from January 1990 - December 2014. Panel B, E, and H show the results for the time of the recent financial crisis from July 2007 - December 2009. Panel C, F, and I present the results for the time of the Credit Crunch from January 1990 - December 1992. The first three rows in each panel show the intercepts of regressions for each portfolio from low to high exposure for each variable we test. The fourth row presents the alpha from time-series regressions on the spread between high minus low exposure, respectively. P-values are presented in parentheses and calculated from Newey-West standard errors with lags of 5. ***,**, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Life insurers				Non-life insurers			
	Interconnected -ness insurer	Interconnected -ness banks	Total assets	β_{MM}	Interconnected -ness insurer	Interconnected -ness banks	Total assets	β_{MM}
Panel A: Complete sample period, CAPM								
Low	0.409	0.086	0.325	-0.029	0.653	0.80*	0.262	-0.110
	(0.167)	(0.691)	(0.411)	(0.932)	(0.146)	(0.088)	(0.445)	(0.725)
Mid	-0.022	0.025	0.318	0.156	0.046	-0.043	0.163	0.201
	(0.939)	(0.940)	(0.352)	(0.568)	(0.839)	(0.866)	(0.513)	(0.432)
High	0.230	0.372	-0.155	0.454	0.290	0.333	-0.203	0.173
	(0.624)	(0.359)	(0.612)	(0.177)	(0.465)	(0.229)	(0.515)	(0.577)
Spread (High - Low)	-0.179	0.286	-0.481	**0.483***	-0.363	-0.463	-0.465	0.280
	(0.704)	(0.467)	(0.259)	**(0.095)**	(0.475)	(0.351)	(0.189)	(0.420)
Panel B: Complete sample period, Fama French 3-factor								
Low	0.179	-0.129	0.098	-0.398	0.586	0.695	0.100	-0.303
	(0.372)	(0.358)	(0.793)	(0.227)	(0.227)	(0.167)	(0.743)	(0.319)
Mid	**-0.337***	-0.300	-0.079	-0.086	-0.143	-0.264	-0.028	-0.002
	(0.053)	(0.108)	(0.691)	(0.616)	(0.443)	(0.162)	(0.880)	(0.993)
High	-0.189	-0.017	**-0.442****	0.001	-0.132	0.058	**-0.535****	-0.076
	(0.664)	(0.964)	**(0.033)**	(0.997)	(0.656)	(0.785)	**(0.017)**	(0.726)
Spread (High - Low)	-0.368	0.112	-0.540	0.399	-0.718	-0.637	**-0.635****	0.138
	(0.446)	(0.788)	(0.209)	(0.163)	(0.184)	(0.223)	**(0.037)**	(0.673)
Panel C: Complete sample period, Fama-French 5-factor								
Low	0.073	-0.168	-0.023	-0.343	0.470	0.497	0.069	-0.330
	(0.724)	(0.267)	(0.951)	(0.389)	(0.287)	(0.290)	(0.821)	(0.275)
Mid	**-0.412***	**-0.411***	-0.113	-0.233	**-0.307***	**-0.398****	-0.238	-0.245
	(0.051)	**(0.059)**	(0.702)	(0.212)	**(0.085)**	**(0.023)**	(0.106)	(0.113)
High	-0.078	0.105	**-0.454****	0.070	-0.104	0.080	**-0.557****	-0.206
	(0.870)	(0.823)	**(0.024)**	(0.860)	(0.740)	(0.712)	**(0.038)**	(0.329)
Spread (High - Low)	-0.151	0.273	-0.431	0.413	-0.574	-0.417	**-0.626***	0.017
	(0.743)	(0.529)	(0.318)	(0.147)	(0.222)	(0.377)	**(0.086)**	(0.958)
Panel D: Financial crisis, CAPM								
Low	0.522	0.801	-0.108	**4.541***	1.335	2.116	-0.395	0.390
	(0.451)	(0.471)	(0.876)	**(0.062)**	(0.366)	(0.231)	(0.481)	(0.728)
Mid	1.703	1.838	2.799	0.861	-0.187	0.221	0.339	0.611
	(0.253)	(0.283)	(0.119)	(0.359)	(0.769)	(0.809)	(0.623)	(0.414)
High	**4.983***	**4.257*****	1.421	4.427	2.761	0.577	1.929	1.222
	(0.069)	**(0.009)**	(0.374)	(0.129)	(0.128)	(0.599)	(0.221)	(0.152)
Spread (High - Low)	**4.461***	**3.456*****	1.529	-0.114	1.426	-1.539	**2.324****	0.832
	(0.067)	**(0.004)**	(0.224)	(0.894)	(0.418)	(0.368)	**(0.035)**	(0.168)

Table IV: Alphas from times series regressions with different asset pricing models (continued).

	Life insurers				Non-life insurers			
	Interconnected -ness insurer	Interconnected -ness banks	Total assets	β_{MM}	Interconnected -ness insurer	Interconnected -ness banks	Total assets	β_{MM}
Panel E: Financial crisis, Fama French 3-factor								
Low	0.753	0.400	-0.003	**4.968***	1.250	2.241	**-0.716****	0.061
	(0.369)	(0.503)	(0.997)	**(0.071)**	(0.398)	(0.247)	**(0.050)**	(0.939)
Mid	1.729	1.902	**2.964***	1.042	-0.331	0.051	0.183	0.492
	(0.176)	(0.271)	**(0.080)**	(0.316)	(0.486)	(0.940)	(0.702)	(0.350)
High	**5.290***	**5.091****	1.262	**4.808***	2.712	0.385	2.105	1.273
	(0.070)	**(0.026)**	(0.326)	**(0.086)**	(0.113)	(0.654)	(0.156)	(0.104)
Spread (High - Low)	**4.536***	**4.692****	1.265	-0.160	1.462	-1.856	**2.821****	**1.212*****
	(0.066)	**(0.040)**	(0.195)	(0.824)	(0.304)	(0.313)	**(0.023)**	**(0.000)**
Panel F: Financial crisis, Fama-French 5-factor								
Low	0.444	-0.311	-0.706	3.848	0.170	1.046	-0.631	-0.385
	(0.619)	(0.670)	(0.380)	(0.125)	(0.902)	(0.558)	(0.125)	(0.555)
Mid	1.092	1.101	2.789	0.470	-0.607	-0.128	-0.218	0.025
	(0.373)	(0.476)	(0.126)	(0.540)	(0.232)	(0.855)	(0.527)	(0.955)
High	**4.063***	**4.664****	0.677	**4.361****	**2.854****	0.110	2.092	**1.269****
	(0.093)	**(0.021)**	(0.517)	**(0.046)**	**(0.022)**	(0.839)	(0.123)	**(0.022)**
Spread (High - Low)	**3.619***	**4.975****	**1.383***	0.512	**2.684*****	-0.936	**2.722****	**1.655*****
	(0.059)	**(0.018)**	**(0.082)**	(0.523)	**(0.001)**	(0.617)	**(0.014)**	**(0.000)**
Panel G: Credit crunch crisis, CAPM								
Low	1.134	0.261	**1.338***	-0.149	0.675	0.173	-0.249	**2.581*****
	(0.125)	(0.675)	**(0.067)**	(0.854)	(0.101)	(0.515)	(0.498)	**(0.001)**
Mid	0.139	0.113	0.323	0.551	0.235	-0.009	0.435	0.104
	(0.820)	(0.884)	(0.745)	(0.524)	(0.565)	(0.984)	(0.370)	(0.871)
High	0.873	1.711	-0.001	0.502	**-1.107****	-0.547	-0.677	0.483
	(0.587)	(0.168)	(0.998)	(0.297)	**(0.024)**	(0.351)	(0.300)	(0.213)
Spread (High - Low)	-0.261	**1.450***	-1.339	0.651	**-1.782*****	-0.721	-0.429	-1.744
	(0.823)	**(0.059)**	(0.146)	(0.405)	**(0.001)**	(0.273)	(0.525)	(0.278)
Panel H: Credit crunch crisis, Fama French 3-factor								
Low	**1.105****	0.233	**1.308****	-0.206	**0.671****	0.175	-0.271	**1.783*****
	(0.021)	(0.563)	**(0.021)**	(0.707)	**(0.050)**	(0.540)	(0.434)	**(0.004)**
Mid	0.103	0.079	0.254	0.525	0.218	-0.031	0.429	0.102
	(0.736)	(0.851)	(0.554)	(0.422)	(0.431)	(0.922)	(0.344)	(0.871)
High	0.794	**1.621*****	0.034	0.495	**-1.152****	-0.584	-0.694	0.487
	(0.398)	**(0.006)**	(0.951)	(0.255)	**(0.011)**	(0.135)	(0.226)	(0.350)
Spread (High - Low)	-0.311	**1.388*****	-1.275	0.701	**-1.823*****	**-0.759***	-0.423	-1.200
	(0.724)	**(0.002)**	(0.110)	(0.309)	**(0.003)**	**(0.066)**	(0.560)	(0.353)
Panel I: Credit crunch crisis, Fama-French 5-factor								
Low	**1.068***	0.637	**1.116****	**-1.118****	**1.060*****	0.604	-0.397	-0.799
	(0.059)	(0.222)	**(0.012)**	**(0.047)**	**(0.002)**	(0.137)	(0.449)	(0.159)
Mid	0.305	0.208	0.202	0.788	**0.350****	0.127	0.561	0.314
	(0.370)	(0.656)	(0.712)	(0.190)	**(0.049)**	(0.710)	(0.135)	(0.511)
High	**1.569****	**2.090*****	0.522	0.869	**-1.353*****	**-0.800***	-0.117	0.830
	(0.036)	**(0.000)**	(0.480)	(0.131)	**(0.008)**	**(0.050)**	(0.813)	(0.102)
Spread (High - Low)	0.501	**1.453****	-0.594	**1.987*****	**-2.413*****	**-1.403*****	0.280	**1.512****
	(0.443)	**(0.024)**	(0.526)	**(0.001)**	**(0.000)**	**(0.005)**	(0.721)	**(0.022)**

Table V: Univariate Fama-Macbeth regressions with individual stock returns.

This table presents the results from Fama-Macbeth regressions of individual stock returns in excess of the risk-free rate on the variables described in Section 3.3. We run the regressions separately for life and non-life insurers. Panel A presents the results for our entire sample period from January 1990 - December 2014. Panel B shows the results for the time of the recent financial crisis from July 2007 - December 2009. Panel C presents the results for the time of the Credit Crunch from January 1990 - December 1992. P-values are presented in parentheses. Standard errors are adjusted for heteroscedasticity and autocorrelation using Newey-West standard errors with lags of 5. ***,**, and * denote statistical significance at the 1%, 5% and 10% level, respectively.

	Life insurers				Non-life insurers			
Independent variable	Interconnected -ness insurer	Interconnected -ness banks	Total assets	β_{MM}	Interconnected -ness insurer	Interconnected -ness banks	Total assets	β_{MM}
Panel A: Complete sample period								
Coefficient	0.053	**0.000*** **	0.004	**-0.015*** **	**0.373** **	**0.000** **	0.004	-0.003
	(0.736)	**(0.003)**	(0.520)	**(0.001)**	**(0.068)**	**(0.012)**	(0.752)	(0.850)
Constant (z)	**1.120*** **	**1.055*** **	**1.239*** **	**1.158*** **	**0.639*** **	**0.669*** **	**0.798*** **	**0.717*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
R^2	0.001	0.032	0.008	0.049	0.026	0.023	0.001	0.000
Panel B: Financial crisis								
Coefficient	-0.008	0.000	0.000	-0.004	**0.011** **	0.000	0.001	0.000
	(0.198)	(0.188)	(0.916)	(0.140)	**(0.065)**	(0.550)	(0.277)	(0.764)
Constant (z)	**1.042*** **	**1.050*** **	**1.160*** **	**0.658** **	**0.806*** **	**0.837*** **	**0.818*** **	**0.865*** **
	(0.000)	**(0.000)**	**(0.000)**	**(0.045)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.000)**
R^2	0.008	0.023	0.001	0.062	0.023	0.000	0.004	0.000
Panel C: Credit crunch crisis								
Coefficient	**0.201** **	**0.000*** **	**0.001*** **		-0.037	0.000	0.002	
	(0.081)	**(0.000)**	**(0.000)**		(0.485)	(0.782)	(0.338)	
Constant (z)	**1.131*** **	**1.151*** **	**1.225*** **		**0.873*** **	**0.870*** **	**0.835*** **	
	(0.000)	**(0.000)**	**(0.000)**		**(0.000)**	**(0.000)**	**(0.003)**	
R^2	0.033	0.020	0.142		0.001	0.000	0.004	