Essays on Risk Management and Systemic Risk in Insurance

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Introduction

1.1 Motivation

In July 2010, the government of the United States of America passed the *Dodd-Frank Wall Street Reform and Consumer Protection Act* as a reaction to the recent financial crisis. Since insurance companies and banks unexpectedly had to be bailed out by the government, confidence in the stability of the financial system had to be rebuild. The reform contained changes in regulation of the financial system in the United States and affected all federal financial regulatory agencies, banks, and the insurance industry. Similar to the United States, the European Union created several programs to manage and regulate the financial health such as the *Basel III* framework for the banking sector as well as *Solvency II* in the insurance industry. The inclusion of the insurance sector into these regulatory requirements for financial stability underlines its increasing importance for regulators and academics alike.

The core business of insurance companies involves underwriting risks of policyholders, which is usually assessed and managed via well-understood actuarial methods. Other business operations, however, might be prone to market and exogenous risks that arise from the environment an insurer exists in. For example, insurers that are more involved in financial markets and thus, may focus on non-traditional business areas, are exposed to financial distress in those markets. Also, the more vital an insurer is for an entire market, the more it contributes to the well-being or distress of its participants. Consequently, speaking in terms of possible government interventions, these insurers have a higher probability to be bailed out. Before the recent financial crisis, this appeared to be a phenomenon restricted to the banking sector only, but since the near collapse of *American International Group* (AIG), discussions about systemic risk are not limited to the banking sector anymore. Even the German finance supervision *Bundesanstalt für Finanzdienstleistungsaufsicht* (BaFin) actively seeks the dialogue with the insurance industry, discussing new approaches for requirements preventing default of insurance companies as well as a collapse of the whole insurance sector.

Theoretically, there are several channels through which insurance firms might be exposed or even contribute to financial instability. Insurers have to deal with elementary risks such as market risk, liquidity risk or default risk of financial institutions. While these risks are of huge interest, it is vital to also understand the interplay of these variables when combining these risks. Therefore, risk managers in financial institutions are interested in and require adequate tools for capturing dependence and interactions between these risks. Measures like the *Value-at-Risk*, which only focus on a single effect of each risk, neglecting the dependence structure, are included in regulatory frameworks and are heavily used by a wide range of institutions to manage risks.

Further, the asset side of insurers' balance-sheets corresponds to several parties that destabilize the company's system. The risk in using derivatives like futures, options, and other financial instruments lies in the fact that the market value, instead of the limited maturity, varies over time. Further, in case of over-the-counter transactions especially swap constructions have to capture the rating of the corresponding trading partner and the counterparty risk has to be limited. Insurance companies are not only faced with the respective individual event of default, but also, with the event of a financial market collapse. The chief executive officer (CEO) and the corresponding management group of each insurance company anticipate the consequence of the corporate policy and the management decision for capturing and controlling the personal default risk, the contribution to financial instability of the operating market as well as the avoidance of possible nomination as systemic important financial institution (SIFI).

"SIFIs are financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity."[1] The *Financial Stability Board* (FSB) published a list with *Global Systemically Important Insurers* (G-SIIs) with a methodology proposed by the *International Association of Insurance Supervisors* (IAIS). The details of the implementation are higher requirements on loss absorbency and are supposed to be implemented until 2019.

Economists, risk managers, and regulators around the world are longing for measures and methods to preserve financial stability in the future and detect possible financial risks before they lead to another near-collapsed financial sector. Regarding this, it is questionable if the statement "Systemically important insurers have to hold more capital reserves and are subject to tighter monitoring" is proved to be true. Therefore, it is important to evaluate the actions that have been taken to restore financial stability as well as to question common methodologies that are used by economists and regulators.

The dissertation contributes to the discussion on risk management, financial stability, and the corresponding regulation of insurance companies in the form of five independent articles that empirically assess different aspects of risk management and financial default risk of insurers.

The first article, building the second chapter, studies extreme dependence structures in equity markets as well as cross-dependences between credit derivatives and equities. The dynamic linear and extreme dependence in equity, liquidity, and credit risk is characterized by modeling the joint distribution of the stock returns, bid-ask spreads, and default probabilities. More precisely, the respective stock liquidity is modeled by the bid-ask spread and credit risk is measured by the default probability extracted from the respective credit default swaps contracts.

This empirical study first documents the existence of significant time-varying tail

[1]IAIS (2013): Policy Measures to Address Systemically Important Financial Institutions, 4 November 2011.

dependence between the stock returns, stock liquidity, and the respective firm's default intensities and subsequently introduces a liquidity- and credit-adjusted Value-at-Risk measure that enables risk managers to reliably forecast the total risk exposure of a stock investment. The proposed dynamic vine copula model is found to capture time-varying tail dependence significantly better than static copula or dynamic correlation-based models. However, no study so far has investigated the dependence between equity returns, credit risk, and stock liquidity of individual firms.

Further, this paper proposes a liquidity- and credit-adjusted Value-at-Risk (LC-VaR) does not only account for market price risk, but also for sudden peaks in illiquidity and default probabilities. Using a portfolio of six companies listed in the S&P 500, the study illustrates with a forecast of the portfolio's LC-VaR, employing the dynamic R-vine copula model, that not only LC-VaR forecasts capture downside risk adequately. Additionally, the dynamic R-vine copula model significantly outperforms than the static vine copula or dynamic correlation-based models. Although, the empirical study primarily deals with risk forecasting which is not only limited to the field of risk management.

The following two studies, chapter three and four, examine the issue of systemic risk in the insurance sector. More precise, the empirical investigations explore the methodology of regulators to identify systemically important insurers. Before the recent financial crises and the near collapse of the insurer AIG, neither economists nor regulators originating that insurance companies can be systemically relevant or even contribute to it. Especially, this opinion is substantiated by the differences in the core business actvities of banks and insurers. Fundamental differences are that insurers are not as exposed to runs or liquidity shortages as banks are, and are also smaller in size and less interconnected.

The third chapter is the first empirical study that empirically explores the contribution and exposure to systemic risk for an international panel of insurers over a long time horizon. The study uses the three most prominent systemic risk measures suggested in the literature, the *Marginal Expected Shortfall* (MES) proposed by

Acharya et al. (2010), ΔCoVaR by Adrian and Brunnermeier (2015), and *SRISK* by Brownlees and Engle (2015) as dependent variables in a panel regression approach in order to measure systemic risk. The main variables in this study are the size and the leverage of an insurer as well as a measure of interconnectedness introduced in Billio et al. (2012).

The key finding of this study is that systemic risk in the international insurance sector is small in comparison to precious findings in the literature analyzing the banking sector. Further, during the financial crisis, however, insurers did contribute significantly to the instability of the financial sector. Moreover, systemic risk of insurers is determined by various factors including an insurer's interconnectedness and leverage, the magnitudes and significances of these effects, however, differ depending on the systemic risk measure used and the insurer line and geographic region analyzed.

The empirical study in chapter four explores the determinants of the systemic importance of banks and insurers during the financial crisis. In more detail, the empirical analysis investigates the methodology of regulators to identify global systemically important financial institutions.

The study uses the following empirical methodology in order to measure systemic risk in the banking and insurance sector. The sample exists of the largest 148 banks and 98 insurers in the world, combining a cross-sectional approach with two popular measures of systemic risk, MES and ΔCoVaR.

One result of this analysis is that MES and ΔCoVaR as two common measures of systemic risk produce inconclusive results of financial institutions during the crisis. Furthermore, there is little to no evidence that higher leverage and interconnectedness increase the exposure or contribution of individual institutions to systemic risk. Surprisingly, despite the methodologies published by regulators themselves, global systemically important institutions are clearly identifiable by a quick glance at the total assets in their balance-sheets.

The fifth chapter of this dissertation is dedicated to the solvency regulation and its effect on the idiosyncratic risks of insurers. In the light of recent discussions, the study of idiosyncratic default risk and its determinants in the insurance sector is important and of high relevance to regulators. Especially the interplay of required solvency capital and the default risk of institutions is of great interest to both, regulators and managers.

Although higher capital requirements are the most favorite tools for regulators to support financial stability, they are also viewed by managers as being counterproductive as they reduce profits, subsequently increasing financial instability. However, the effects of higher solvency of insurers is also of great importance to policyholders since they could be affected by increases in insurance premia or could demand more protection from the contract's issuer. Based on an international sample of 308 non-life insurers, this study finds that long-term solvency significantly reduces default risk across all countries. Short-term solvency does not play a significant role in most of the regressions.

Capital requirements related to an insurer's long-term solvency are well suited for increasing the financial soundness of insurers. Another important result is that the regulatory environment of insurers is more important for reducing the default risk of non-life insurers. The main result of this analysis is that long-term capital is significantly negatively related to the default risk of insurers.

The final chapter of this dissertation empirically investigates the impact of derivatives usage by U.S. insurers on the insurers' respective default risk and its exposure to systemic risk. More precisely, the insurers' 10-K filings of U.S. insurance companies are evaluated in order to obtain information on the firms' disclosed derivative usage. Further, this is the first study which analyzes the insurers' intentions to use derivative contracts and describes the variety of derivatives used in insurers' risk management. This analysis is based on a large panel of U.S. insurers for the period from 1999 to 2014 and employs panel regressions of insurers' default risk estimates on proxies of derivative use.

Financial and non-financial companies employ derivative instruments for a variety of reasons. Obviously, companies use derivatives for hedging risky positions on their balance sheet. In contrast, companies could also use financial derivatives for other reasons like lowering their expected costs of default, lowering tax payments, or reducing the volatility of executive compensations (see, e.g., Smith and Stulz, 1985, Froot et al., 1993, DeMarzo and Duffie, 1995). The allegedly adverse effect of derivatives usage on an insurer's firm risk, however, is not as obvious as regulators sometimes claim it to be.

While derivatives trading for risk-taking should obviously increase firm risk, the use of derivatives for hedging purposes should have a decreasing effect on an insurer's default risk. Insurers often employ derivatives to hedge various risks stemming from both sides of the balance sheet.

The main result of the empirical study is that insurers employing financial derivatives have a significantly lower probability of default than matched non-users. However, when insurers use derivatives for risk-taking and non-hedging purposes, derivatives usage has an increasing effect on default risk. Another finding is that derivatives usage is positively correlated with an insurer's exposure to systemic market shocks. The results corroborate current views by insurance regulators that derivatives usage for trading negatively affects financial stability. However, the main findings also underline the risk-reducing and thereby stabilizing effect of using derivatives for hedging purposes.

This dissertation empirically discusses and investigates the impact of regulation, monitoring, and supervision of insurance companies on financial stability and the respective financial distress. Further, it investigates a new approach to capture the dependence between price, liquidity and default risk.

1.2 Publication details

Paper I (Chapter 2):

Dynamic Dependence in Equity Returns, Liquidity, and Credit Risk

Authors:

Hendrik Supper, Christopher Bierth, Gregor Weiß

Abstract:

We characterize the dynamic linear and extreme dependence in equity, liquidity, and credit risk by modeling the joint distribution of the stock returns, bid-ask spreads, and default probabilities of a multivariate stock portfolio at the security-level. We employ dynamic vine copulas and document the existence of significant time-varying and persistent asymmetric tail dependence between the stock returns, stock liquidity, and the respective firms' default intensities. The usefulness of our findings is illustrated in a risk management setting in which we propose a liquidity- and credit-adjusted Value-at-Risk that takes into account the documented extreme dependence. We show that our adjusted Value-at-Risk enables risk managers to reliably forecast the total risk exposure of a stock investment.

Publication details:

Working paper.

Paper II (Chapter 3):

Systemic Risk of Insurers Around the Globe

Authors:

Christopher Bierth, Felix Irresberger, Gregor Weiß

Abstract:

We study the exposure and contribution of 253 international life and non-life insurers to systemic risk between 2000 and 2012. For our full sample period, we find systemic risk in the international insurance sector to be small. In contrast, the contribution of insurers to the fragility of the financial system peaked during the recent financial crisis. In our panel regressions, we find the interconnectedness of large insurers with the insurance sector to be a significant driver of the insurers' exposure to systemic risk. In contrast, the contribution of insurers to systemic risk appears to be primarily driven by the insurers' leverage.

Publication details:

Published in the *Journal of Banking and Finance*.

Paper III (Chapter 4):

Size is Everything: Explaining SIFI Designations

Authors:

Felix Irresberger, Christopher Bierth, Gregor Weiß

Abstract:

In this paper, we study the determinants of the systemic importance of banks and insurers during the financial crisis. We investigate the methodology of regulators to identify global systemically important financial institutions and find that firm size is the only significant predictor of the decision of regulators to designate a financial institution as systemically important. Further, using a cross-sectional quantile regression approach, we find that Marginal Expected Shortfall and ΔCoVaR as two common measures of systemic risk produce inconclusive results concerning the systemic relevance of banks and insurers during the crisis.

Publication details:

Under review in the *Review of Financial Economics*.

Paper IV (Chapter 5):

Non-life Insurer Solvency and Default Risk

Authors:

Christopher Bierth

Abstract:

We investigate the determinants of default risk for an international sample of non-life insurers for the time period from 2000 to 2013. In particular, we address the question whether higher capital leads to a significantly improved financial soundness of insurers. As our main result, we show that the default risk of non-life insurers is lower for those companies that possess more long-term solvency, have more efficient operations, and maintain a higher quality of their risk portfolio. In addition, we observe that most of the variation in the default risk of non-life insurers is driven by country effects rather than idiosyncratic factors.

Publication details:

Working paper.

Paper V (Chapter 6):

Derivatives Usage and Default Risk in the U.S. Insurance Sector

Author:

Christopher Bierth

Abstract:

This paper studies the effect of derivatives usage by U.S. insurers on the insurers' respective default risk. We first document that insurers that employ financial derivatives have a significantly lower risk of defaulting than matched non-using insurers. We then find empirical evidence that the decreasing effect of derivatives usage on default risk is reversed in case insurers use derivatives for risk-taking and non-hedging purposes. Moreover, we find derivatives usage to be positively correlated with an insurer's exposure to systemic market shocks. Our results corroborate current views by insurance regulators that derivatives usage for trading negatively affects financial stability.

Publication details:

Working paper.

Chapter 2

Dynamic Dependence in Equity Returns, Liquidity, and Credit Risk

2.1 Introduction

The analysis and characterization of the extreme dependence between financial time series has gained considerable attention in risk and portfolio management. With the recent financial crisis marking a historic tail event, risk managers and financial economists alike have become more and more interested in analyzing the (potentially time-varying) non-linear nature of dependence between financial assets. In this respect, several recent studies have found dependence in equity (see, e.g., Christoffersen et al., 2012) and credit risk (see, e.g., Christoffersen et al., 2014) to be highly non-linear and asymmetric with the level of asymmetry being time-varying. However, no study so far has investigated the dependence between equity returns, credit risk, and stock liquidity of individual firms.

In this paper, we characterize the dynamic linear and extreme dependence in equity, liquidity, and credit risk by modeling the joint distribution of the stock returns, bid-ask spreads, and default probabilities of a multivariate stock portfolio at the security-level. We employ dynamic vine copulas and document the existence of significant time-varying and persistent asymmetric tail dependence between the stock returns, stock liquidity, and the respective firms' default intensities. To be precise, we model the stock returns, bid-ask spreads, and default intensities of firms in a multivariate portfolio using dynamic regular vine (R-vine) copulas. We then propose and forecast a liquidity- and credit-adjusted Value-at-Risk (VaR) that is in the spirit of the liquidity-adjusted VaR of Berkowitz (2000), Bangia et al. (2002), and Weiß and Supper (2013) but that additionally incorporates information on the credit risk of the underlying securities.[2] Confirming several predictions from the financial economics literature (see, e.g., Bekaert et al., 2007, Friewald et al., 2014, Boehmer et al., 2015), this paper is the first to document the existence of significant tail dependence between the stock returns, stock liquidity, and default intensities of companies. We then illustrate the usefulness of our findings in a risk management setting in which we propose a liquidity- and credit-adjusted Value-at-Risk that takes into account the documented extreme dependence. We show that adjusting the standard Value-at-Risk for liquidity and credit risk enables risk managers to reliably forecast the total risk exposure of a stock investment. Finally, we show that our dynamic vine copula model captures time-varying tail dependence significantly better than static copula or dynamic correlation-based models.

In our econometric framework, we aim to model the joint distribution of stock returns, bid-ask spreads, and default intensities (extracted from credit default swap premia) of a stock portfolio. We use a dynamic vine copula model to capture the time-varying dependences in the portfolio and to reproduce the potentially intricate spillover effects and interactions between stock markets, stock liquidity, and credit markets. More precisely, in our model, we consider the dependence between (1) a stock's return and its liquidity, (2) a stock's return and the default intensity of the underlying firm, (3) stock liquidity and the default intensity of a given firm, and (4) all relevant cross-dependences (e.g., between a stock's return and the liquidity of another stock).[3] Our

[2] One could question the idea to incorporate estimates of a firm's default probability into a forecast of a stock investment's Value-at-Risk as a firm's default risk should already be priced in its equity. However, considerable empirical evidence on the so-called "distress puzzle" suggests that equity returns do not fully reflect a firm's default risk (see, e.g., Friewald et al., 2014).

[3] Note that as we use an R-vine copula for dependence modeling, we are also capable of specifying the conditional dependence structure of the joint distribution. See Section 2.2 for details.

state-of-the-art copula approach is motivated by a substantial body of literature on how the concept of stock liquidity is related to stock returns and credit default swap premia (CDS spreads hereafter) and how stock and credit markets are interconnected.

Starting with the relation between stock returns and liquidity, the seminal work by Amihud and Mendelson (1986) finds that market-observed average returns are an increasing function of the bid-ask spread. Further, stocks with higher sensitivities to market liquidity exhibit higher expected returns (Pastor and Stambaugh, 2003), liquidity predicts future returns (Bekaert et al., 2007), and expected stock excess returns reflect compensation for expected market illiquidity (Amihud, 2002). Acharya and Pedersen (2005) provide a theoretical asset pricing model with liquidity risk that helps explain these empirical findings and in which required returns depend on expected liquidity. Since liquidity exhibits commonalities and is characterized by strong temporal variation (Watanabe and Watanabe, 2008, Hasbrouck and Seppi, 2001, Chordia et al., 2000), our dynamic modeling approach is especially appropriate for capturing the potentially time-varying nature of the dependences in our multivariate portfolio.

Regarding the dependence between stock returns and default intensities (i.e., credit risk), the theoretical basis is given by the structural model of Merton (1974). In his model, equity can be viewed as a call option on the firm's assets with a strike price equal to the value of the firm's debt, which suggests a precise pricing relationship between equity- and debt-linked securities (Boehmer et al., 2015). Further, as stated in Friewald et al. (2014), risk premia in equity and credit markets must be related because Merton's (1974) model implies that the market price of risk must be the same for all contingent claims written on a firm's assets. The empirical evidence on the relation of stock returns and credit risk, however, is mixed. Some studies document a positive relation (Vassalou and Xing, 2004, Chava and Purnanandam, 2010), whereas various other papers find a negative relation between stock returns and credit risk (Dichev, 1998, Campbell et al., 2008). Moreover, an increasing branch of literature investigates the interconnectedness of equity and CDS markets and provides empirical evidence on the relation between CDS spreads and stock returns (see, e.g., Acharya and Johnson, 2007, Han and Zhou, 2011).

Finally, modeling the dependence of stock liquidity and default intensities is economically relevant due to the relation between CDS and stock markets.[4] The theoretical and empirical motivation is given in Boehmer et al. (2015), who investigate the effect of CDS markets on equity market quality, that is, liquidity and market efficiency. From a theoretical point of view, the authors discuss two potential channels by which CDS markets could affect liquidity in equity markets, risk sharing and trader-driven information spillovers. Risk sharing might be based on dynamic delta hedging strategies by informed traders and is expected to reduce market liquidity. Trader-driven information spillovers, on the other hand, result from informed speculators' trading on private information which causes all securities to be priced more efficiently and increases market liquidity. While the theoretical effect of CDS markets on equity market liquidity is ambiguous, the empirical study in Boehmer et al. (2015) documents this effect to be adverse. That is, empirically, CDS trading is associated with significant declines in equity market liquidity. Although not giving any evidence on the particular relation between stock liquidity and CDS spreads, the study of Boehmer et al. (2015) indicates that bid-ask spreads and default intensities must somehow be related, thereby providing further motivation for our multivariate modeling approach.[5]

Our paper is related to several studies in the literature but complements these studies by making several major contributions. First, this paper is the first to document strong time-varying tail dependence at the individual security-level between stock returns and default intensities, as well as between stock liquidity and default intensities. While previous studies have documented extreme dependence in stock returns (see, e.g., Poon et al., 2004, Bollerslev and Todorov, 2011, Christoffersen et al., 2012), credit risk (see, e.g., Christoffersen et al., 2014), and between stock returns and liquidity (Ruenzi et al., 2013, Weiß and Supper, 2013), our study provides the first empirical evidence of significant tail dependence across equity and CDS markets. The variant

[4] Note that we extract default intensities from CDS spreads.

[5] Note that we explore this relation in more detail in Section 2.4, where we provide anecdotal evidence on both linear and non-linear dependences between bid-ask spreads and default intensities.

of the standard VaR that we propose is closely related to the liquidity-adjusted VaR of Berkowitz (2000) and Bangia et al. (2002). In contrast to their work, however, we propose a VaR that together with market and liquidity risk additionally incorporates credit risk. The idea to use copulas for modeling different risk factors of a single security is closely related to the work of Nolte (2008) and Weiß and Supper (2013). However, we do not consider a multivariate transaction process model like it is done in the former study, but directly model the stock returns and bid-ask spreads of multiple stocks in a portfolio. In comparison to the latter study, we additionally address the question whether equity returns and liquidity also depend non-linearly on default risk. Finally, our paper builds on several previous studies on the use of vine copulas (see, e.g., Aas et al., 2009, Min and Czado, 2010, Dißmann et al., 2013) and dynamic copula models (see, e.g., Patton, 2006, Christoffersen et al., 2012, Oh and Patton, 2015) in financial econometrics. To the best of our knowledge, we present the first empirical study that employs dynamic R-vine copulas and show that a dynamic vine is indeed significantly better suited to capture the time-varying dependence in the returns, liquidity, and default intensities of our sample firms than competing linear or static models.[6]

The rest of this paper is organized as follows. In Section 2.2, we present the marginal and multivariate models we employ in our study. The data used in the empirical study are presented and discussed in Section 2.3, while Section 2.4 contains a discussion of our empirical results. Section 2.5 concludes.

2.2 Econometric methodology

We now turn to the econometric models for the marginal distributions and the multivariate dependence structure. Our modeling strategy consists of two steps. In a first step, we model the marginal densities of stock returns, bid-ask spreads, and default intensities. In a second step, we then employ a dynamic R-vine copula model to capture

[6]Note that Heinen et al. (2009) also propose a dynamization approach of vine copulas. The authors, however, restrict their study to the specific case of canonical vines (C-vines) and use a dynamic conditional correlation specification to account for time-varying dependence. In contrast, we make use of the more general class of R-vines and follow Patton (2006) to incorporate dynamics into standard copulas.

the time-varying dependences between the marginals.

2.2.1 Univariate models for returns, bid-ask spreads, and default intensities

To apply copula theory and consistently estimate the dependence structure between returns, spreads, and intensities, our univariate modeling approach must be capable of generating white-noise residuals. The univariate filtering techniques should therefore be able to pick up most of the first- and second-moment dependence inherent in the time-series data. To this purpose, we first model mean dynamics using autoregressive (AR) processes and then capture variance dynamics by employing GARCH (Generalized Autoregressive Heteroskedastic) processes as introduced by Bollerslev (1986).

2.2.1.1 Mean dynamics

In the financial econometrics literature, it has now become a stylized fact that stock returns are characterized by significant autocorrelation (see, e.g., Summers, 1986, Amihud and Mendelson, 1987, Fama and French, 1988, for early empirical evidence). Furthermore, as found in Groß-Klußmann and Hautsch (2013), bid-ask spreads exhibit strong long-range dependence.[7] Regarding CDS spreads and default intensities, Oh and Patton (2015) find that CDS spreads are characterized by strong autocorrelation and, more precisely, that daily log-differences of CDS spreads exhibit more autocorrelation than is commonly found for stock returns. Christoffersen et al. (2014) provide support for this finding and show that log-differences of CDS spreads and default intensities are strongly autocorrelated.

In modeling mean dynamics, Christoffersen et al. (2012) use an AR model of order two (denoted as AR(2)), whereas Oh and Patton (2015) use an AR(5) model and find the first three lags to be strongly significant. We therefore include three lags in our AR specification to capture first-moment dependence.

[7] Note that much of this long-range dependence is eliminated by log-differencing. The remaining short-run dependence, however, needs to be filtered by appropriate AR processes.

Formally, with $R_i = \{R_{i,t}\}_{t=1}^{T}$, $i = 1, 2, 3$, denoting the log-differenced time series of stock prices, bid-ask spreads, and default intensities, respectively, the AR(3) process is estimated as

$$R_{i,t} = \mu + \phi_{1,i} R_{i,t-1} + \phi_{2,i} R_{i,t-2} + \phi_{3,i} R_{i,t-3} + e_{i,t}, \qquad (2.1)$$

where estimation is conducted via conditional least squares. The conditional mean, $\mu_{i,t}$, thus evolves according to the following dynamics

$$\mu_{i,t} = \mu + \phi_{1,i} R_{i,t-1} + \phi_{2,i} R_{i,t-2} + \phi_{3,i} R_{i,t-3}, \qquad (2.2)$$

leaving the residuals $e_{i,t} = R_{i,t} - \mu_{i,t}$ for GARCH-filtering in the next step.[8]

2.2.1.2 Variance dynamics

A critical issue in capturing second-moment dependence is time-varying and asymmetric volatility. Asymmetry in volatility is commonly referred to as the leverage effect and is well investigated in the econometrics literature (see, e.g., Christie, 1982, Nelson, 1991). The leverage effect arises from asymmetric volatility responses to bad and good news on a firm and is based on the finding that the upward revision of conditional volatility due to bad news is more pronounced than the downward revision due to good news. In case of stock returns, bad news comes in the form of a negative AR residual (that is, $e_{i,t} < 0$). In case of bid-ask spreads and default intensities, on the other hand, bad news is associated with a positive AR residual (i.e., $e_{i,t} > 0$).

Another critical issue is the specification of an adequate distributional model for the margins. As stated in existing studies, skewness and fat tails might lead to misspecified marginal distributions and, consequently, to biased estimates for the parameters of the dependence model.[9]

Christoffersen et al. (2014) and Oh and Patton (2015) find that stock returns and

[8]In our empirical study in Section 2.4, we show that our AR(3) model for conditional mean dynamics passes the standard specification tests.

[9]See McNeil et al. (2005) and Kim et al. (2007) for details.

log-differences of CDS spreads and default intensities are characterized by asymmetry in volatility as well as by skewness and fat tails. Therefore, we follow Oh and Patton (2015) and employ the GJR-GARCH model as proposed by Glosten et al. (1993) to capture asymmetric volatility, where we use the skewed t distribution of Fernandez and Steel (1998) to additionally account for skewness and fat tails in the marginal distributions. More precisely, we fit a GJR-GARCH(1,1) model to the AR residuals, $e_{i,t}$, so that conditional volatility evolves according to the following dynamics

$$\begin{aligned} e_{i,t} &= \sigma_{i,t}\varepsilon_{i,t}, \qquad \varepsilon_{i,t}|\mathcal{F}_{i,t-1} \sim iid\ skt(\nu_i, \gamma_i) \\ \sigma^2_{i,t} &= \omega_i + \beta_i\sigma^2_{i,t-1} + \alpha_i e^2_{i,t-1} + \delta_i e^2_{i,t-1}\mathbf{1}_{(-\infty,0)}(e_{i,t-1}) \end{aligned} \tag{2.3}$$

where the parameters in the conditional variance equation are constrained to be positive, $\mathcal{F}_{i,t}$ denotes the set of information available on series R_i up to and including time t, $\mathbf{1}_{[\cdot,\cdot]}(\cdot)$ is the indicator function, and $skt(\nu_i, \gamma_i)$ denotes the skewed t distribution as proposed by Fernandez and Steel (1998) with degrees of freedom parameter $\nu_i \in (2, \infty)$ and skewness parameter $\gamma_i \in (0, \infty)$. With f_t denoting the probability density function (pdf) of a univariate standard t distribution, the pdf of $skt(\nu_i, \gamma_i)$, f_{skt}, is given by

$$f_{skt}(\varepsilon; \nu_i, \gamma_i) = \frac{2}{\gamma_i + \frac{1}{\gamma_i}}\left[f_t\left(\frac{\varepsilon}{\gamma_i}\right)\mathbf{1}_{[0,\infty)}(\varepsilon) + f_t(\gamma_i\varepsilon)\mathbf{1}_{(-\infty,0)}(\varepsilon)\right] \tag{2.4}$$

As becomes apparent from (2.4), the γ_i parameter controls the allocation of mass to each side of the mode, and $skt(\nu_i, \gamma_i)$ nests the standard t distribution in case of $\gamma_i = 1$. That is, $\gamma_i \neq 1$ indicates skewness in the marginal time series, R_i, $i = 1, 2, 3$.[10]

Note that the distribution of the return shocks, $e_{i,t}$, differs across the individual time series, R_i, but is constant over time, whereas the distribution of R_i does vary through time due to the conditional mean and variance dynamics discussed above. The GJR-GARCH(1,1) model in (2.3) is straightforwardly estimated via maximum likelihood.

[10] We refer to Fernandez and Steel (1998) for a detailed discussion on the statistical properties of $skt(\nu_i, \gamma_i)$.

2.2.2 Dependence modeling with dynamic R-vine copulas

We now turn to the task of modeling the joint distribution of stock returns, bid-ask spreads, and default intensities of multiple firms. To capture both linear dependences and potential non-linearities in the dependence structure, we rely on copulas in our modeling approach. More precisely, we employ dynamic R-vine copulas which provide us with a powerful tool to model high-dimensional distributions and to capture complex and time-varying dependences in an extremely flexible way. Subsequently, we discuss R-vine copulas and present our dynamization approach. We start with a brief review on copulas and pair-copula constructions.

2.2.2.1 Copulas and pair-copula constructions

Generally speaking, a d-dimensional copula function is a multivariate distribution function on the unit cube $[0,1]^d$ with standard uniform margins. More precisely, a copula specifies the link between a multivariate distribution and its one-dimensional marginal distributions (see Nelsen, 2006). Formally, with $(X_1,...,X_d)$ denoting a d-dimensional random vector with joint density $\boldsymbol{f} = (f_1,...,f_d)$ and distribution function $\boldsymbol{F} = (F_1,...,F_d)$, the copula $\boldsymbol{C}$ of the distribution $\boldsymbol{F}$ is given by

$$\boldsymbol{C}(u_1,...,u_d) = \boldsymbol{F}(F_1^{-1}(u_1),...,F_d^{-1}(u_d)), \tag{2.5}$$

where F_i^{-1} is the generalized inverse of F_i and $u_i \in [0,1]$, $i = 1,...,d$. The theoretical framework of copulas goes back to Sklar (1959) who shows that, under certain conditions, every copula is a joint distribution function and vice versa (see Nelsen, 2006, for a detailed discussion). Using (2.5), the joint density, $\boldsymbol{f}$, can be expressed as

$$\boldsymbol{f}(x_1,...,x_d) = \boldsymbol{c}(F_1(x_1),...,F_d(x_d)) \prod_{i=1}^{d} f_i(x_i), \tag{2.6}$$

where $\boldsymbol{c}$ denotes the density of $\boldsymbol{C}$. Hence, we can separate the dependence structure from the marginal structure and thus model the joint distribution by first modeling the marginal distributions and then specifying a model for the dependence structure.[11]

In case of bivariate data (i.e., $d = 2$), there is a wide range of Archimedean and elliptical copulas available that allow for flexible dependence modeling.[12] In case of multivariate data sets (that is, $d > 2$), however, this becomes much more difficult so that existing studies in the econometrics and statistics literature emphasize the need for flexible copula models in high dimensions (see Chollete et al., 2009, Aas et al., 2009, Dißmann et al., 2013).[13] While some papers attempt to construct multivariate extensions of (bivariate) Archimedean copulas (Embrechts et al., 2003, Savu and Trede, 2010, Hofert, 2011), another strand in the literature aims to construct flexible multivariate dependence models by splitting up the copula density, $\boldsymbol{c}$, into a cascade of bivariate (unconditional and conditional) copulas.[14] The resulting expression is called a pair-copula construction (PCC hereafter) and can be derived as follows.

Let $f_{j|k} = f_{j|k}(x_j|x_k)$, $F_{j|k} = F_{j|k}(x_j|x_k)$, $c_{ij|k} = c_{ij|k}(F_{i|k}, F_{j|k})$, and be η a $(d-1)$-dimensional vector satisfying $\eta_\ell \in \{1, ..., d\} \setminus \{i\}$ and $\eta_{\ell_1} \neq \eta_{\ell_2}$ for $\ell_1 \neq \ell_2$. Then, we can decompose the multivariate density, $\boldsymbol{f}$, in the following way

$$\boldsymbol{f} = f_d \prod_{i=1}^{d-1} f_{d-i|d-i+1,...,d}. \tag{2.7}$$

Further, as stated in Aas et al. (2009), the conditional density, $f_{j|\eta}$, can be factorized as

$$f_{j|\eta} = \boldsymbol{c}_{j\eta_m|\eta_{-m}} f_{j|\eta_{-m}}, \tag{2.8}$$

where η_m is an arbitrarily chosen component of η and η_{-m} results from removing η_m from η, $m \in \{1, ..., d-1\}$. Combining the two factorizations in (2.7) and (2.8) then

[11] Note that the expression in (2.6) provides the theoretical basis for our modeling strategy since we first model the marginal densities using GARCH processes and then model the dependence structure with R-vine copulas.

[12] See Nelsen (2006) for a detailed overview.

[13] Note that, in high dimensions, the choice of copulas is virtually reduced to elliptical copulas such as the normal and the *t* copula which are only useful if the assumption of elliptical dependence is valid.

[14] For further details, see the seminal works by Joe (1997), Bedford and Cooke (2001, 2002), Whelan (2004).

yields the following expression for a PCC

$$\boldsymbol{f} = \prod_{k=1}^{d} f_k \prod_{h=1}^{d-1} \prod_{i=1}^{d-h} \boldsymbol{c}_{i\eta_m|\eta_{-m}}, \tag{2.9}$$

where $h = \dim(\eta)$ and $m = m(h, i) \in \{1, ..., h\}$ is arbitrarily chosen.[15]

Based on the pioneering works by Joe (1996, 1997) and Bedford and Cooke (2001, 2002), Aas et al. (2009) introduced the concept of pair-copulas to the finance literature and spurred a surge in empirical applications of PCCs (see, e.g., Heinen et al., 2009, Aas and Berg, 2009, Chollete et al., 2009, Min and Czado, 2010, 2011). For our modeling framework, the use of PCCs is especially appropriate in many respects. First, splitting up the multivariate density according to (2.9) results in a computationally feasible density for likelihood estimation and, therefore, enables us to handle the high dimensionality of our modeling approach. Moreover, PCCs provide us with an extremely flexible tool to capture the presumably intricate dependences between stock returns, bid-ask spreads, and default intensities. Using PCCs, we are able to choose each pair-copula from a different parametric copula family and, further, PCCs permit the modeling of not only the pairs of the original variables but also pairs of conditional distributions of recomputed variables (see Weiß and Supper, 2013).[16] Since we follow Patton (2006) and estimate dynamic processes for the parameters of the pair-copulas, the dynamic PCCs are also capable of accounting for potentially time-varying patterns in the dependence structure.

2.2.2.2 Regular vines

As can be seen from the expression in (2.9), there exist many different PCCs for a given multivariate distribution, $\boldsymbol{F}$.[17] To select a particular PCC and to determine the way in which the marginals are to be coupled, Bedford and Cooke (2001, 2002) introduce so-called (regular) vines. Vines are convenient tools with a graphical representation that

[15] We use the convention $i\eta_m|\emptyset = i\eta_m$. Thus, $h = 1$ yields unconditional pair-copulas $\boldsymbol{c}_{i\eta_m}$, $i = 1, ..., d-1$.

[16] That is, we are capable of specifying the conditional dependence structure for the joint distribution.

[17] This results from the fact that η_m is arbitrarily chosen.

facilitate the description of the conditional specifications made for the joint distribution, $\boldsymbol{F}$. More precisely, an R-vine is a graphical tree model that is based on a nested set of trees satisfying certain conditions.

To formally describe the concept of R-vines, we label the components of $\boldsymbol{X}$ from 1 to d and recall that a tree, $T = \{N, E\}$, is an acyclical graph, where $N \subset \mathbb{N}$ and $E \subset \binom{N}{2}$ denote the set of nodes and edges, respectively. Bedford and Cooke (2002) define a regular vine on d elements, $\mathcal{V}$, as a nested set of trees, $\mathcal{V} = \{T_1, ..., T_{d-1}\}$, that satisfies the following conditions

(c1) T_1 is a tree with nodes $N_1 = \{1, ..., d\}$ and a set of edges denoted E_1.

(c2) For $i = 2, ..., d$, T_i is a tree with nodes $N_i = E_{i-1}$ and $|N_i| = i + 1$.

(c3) For $i = 2, ..., d-1$ and $\{a, b\} \in E_i$, it must hold that $|a \cap b| = 1$.

To derive the PCC induced by $\mathcal{V}$, each edge in T_i is associated with a bivariate (un-)conditional copula, $i = 1, ..., d-1$. The edges of the R-vine trees are computed according to (c1)-(c3) and on the basis of set operations on so-called conditioning and conditioned sets, which are given as follows.[18] With U_{e_i} denoting the set of all indices contained in $e_i = \{a, b\} \in E_i$, the conditioning set, D_{e_i}, is given by $D_{e_i} = U_a \cap U_b$, and the conditioned set, C_{e_i}, is defined to be $C_{e_i} = U_a \Delta U_b$, with Δ denoting the symmetric difference operator.[19]

As shown in Bedford and Cooke (2001, 2002), there is a unique PCC associated with $\mathcal{V}$, which can be expressed as

$$\boldsymbol{f} = \prod_{k=1}^{d} f_k \prod_{h=1}^{d-1} \prod_{e \in E_h} \boldsymbol{c}_{C_e|D_e}. \tag{2.10}$$

Hence, R-vine copulas as used in our modeling approach are particular PCCs, i.e. PCCs with a particular decomposition (2.9), which are determined according to the combinatorial rules presented above.[20]

[18]We follow the presentation in Dißmann et al. (2013).

[19]Note that $|C_{e_i}| = 2$ and $C_{e_i} \cap D_{e_i} = \varnothing$.

[20]A detailed description on the construction of R-vines and R-vine copulas as well as examples and illustrations can be found in Bedford and Cooke (2001, 2002), Aas et al. (2009), Dißmann et al. (2013).

2.2.2.3 Fitting an R-vine copula

Fitting an R-vine copula can be organized into three steps: (1) Selection of R-vine structure, (2) Selection of bivariate copula families, and (3) Estimation of copula parameters. These steps are accomplished following the sequential method as proposed in Dißmann et al. (2013) and Hobæk Haff (2013), which exploits the tree-by-tree structure of vines and under which selection and estimation are performed treewise, conditioning on the precedingly selected trees and estimated copula parameters.[21] More precisely, for a given tree, $T_i \in \mathcal{V}$, we first calculate the empirical Kendall's tau, $\hat{\tau}_{j,k}$, for all possible variable pairs, $\{j,k\}$, $j,k = 1,...,d$, and determine the edges of T_i by selecting the spanning tree that maximizes the sum of absolute empirical taus.[22] Then, each of the resulting edges is associated with a bivariate (un-)conditional copula, which is selected according to the Akaike information criterion (AIC).[23] We calculate the AIC for each copula family considered and choose the copula with the minimum AIC.[24] Using the fitted copulas in tree T_i, we now compute the transformed variables by means of the corresponding h-functions and repeat the above procedure until we reach tree T_{d-1} (see Dißmann et al., 2013, for details), resulting in a total of $d(d-1)/2$ dynamic (un-)conditional pair-copulas.

Since we need standard uniform data to consistently estimate copulas, fitting the R-vine copula in our econometric approach should be based on white-noise time series. Assuming that the GARCH processes discussed above correctly specify the marginal densities, we apply the R-vine copula to the corresponding GARCH residuals, $\varepsilon_{i,t}$. The pseudo-observations used for estimation, u_i, are then computed as the ranks of the residuals, i.e. $u_i = F_i(\varepsilon_i)$.

[21] Note that this method does not necessarily lead to a global optimum. Most of the dependence is, however, captured in the first tree so that the model fit is considerably influenced by the fit of the copulas in the first tree.

[22] Actually, we use Prim's (1957) algorithm and calculate the minimum spanning tree with weights $-\hat{\tau}_{j,k}$.

[23] As found in Manner (2007), the AIC provides a reliable criterion, especially when compared to alternative criteria such as copula goodness-of-fit tests.

[24] We include dynamic extensions of the normal, t, (rotated) Clayton, (rotated) Gumbel, and (rotated) Joe copula. Details can be found in Appendix A.

2.3 Data

This section presents the data used in our empirical study and provides descriptive statistics. Starting with a description of the data sources, we also discuss the procedure applied to extract default intensities from CDS spreads.

2.3.1 Data sources

To implement our econometric modeling strategy discussed in the preceding section, we need to collect data on stock prices, bid-ask spreads, and default intensities. In our empirical study, we focus on S&P 500 constituents, and obtain the corresponding mid, bid, and ask quotes from *Thomson Reuters Datastream*. More precisely, we collect daily quotes of all constituents in the S&P 500 index as reported by *Datastream* from January 2008 to December 2013. Bid-ask spreads are then calculated as the difference between ask and bid quotes to proxy for the liquidity of the underlying stock.

Further, since default intensities are not observable in the market, we follow Christoffersen et al. (2014) and extract default intensities from CDS spreads (see below). Daily CDS spreads are retrieved from *Datastream*, where we start with an initial sample of all constituents of the S&P 500 index between January 2008 and December 2013. Since we need to restrict our sample to companies with traded CDS contracts, we apply the following screening procedures to identify these companies. First, we match *Datastream*'s equity codes with CDS codes.[25] If there is no match according to this criterion, we additionally perform a search using the 'related series' function in *Datastream* to confirm that there is no corresponding CDS spread to the respective company's name as it appears in the S&P 500 constituents list. Moreover, we focus on dollar-denominated CDS contracts with a five-year maturity and a modified restructuring clause, since these are the most frequently traded contracts in the U.S. market and,

[25]The corresponding *Datastream* CDS codes are constructed as follows. First, we decompose each firm's Mnemonics (*Datastream* code) into its general (i.e., 'U' and '@') and firm-specific component. To each three- or four-digit firm-specific component, we add the dollar sign to specify the currency. Finally, we complement the CDS Mnemonic with the two-digit string 'MR' to specify the restructuring clause.

consequently, unlikely to be distorted from low levels of liquidity. These restrictions reduce the initial sample to a total of 209 companies. For increased transparency, we list the names of all sample firms in Appendix A.1.

Finally, as discussed in the next section, extracting default intensities from CDS spreads relies on the valuation of CDS contracts and, therefore, requires the construction of spot rate curves to derive discount rates. We follow existing studies in the literature and use the bootstrapping procedure suggested by Longstaff et al. (2001) to compute spot rate curves with maturities reaching from one day up to five years for each trading day between January 2008 and December 2013 (see, e.g., Jarrow et al., 2007, Longstaff and Rajan, 2008).[26] Using *Datastream*, we collect daily observations for the overnight, one-week, one-month, three-month, six-month, and one-year LIBOR rates as well as for the midmarket two-year, three-year, four-year, and five-year par swap rates. As in Longstaff et al. (2001), we then use a standard cubic spline algorithm to interpolate the par curve at semi-annual intervals, and compute spot rates by bootstrapping the interpolated par curve. The resulting semi-annual spot rates, in turn, are interpolated employing cubic splines and are used to compute the discount factors required in the CDS valuation formula.

2.3.2 Extracting default intensities from CDS spreads

A credit default swap is essentially an insurance contract that provides protection against credit loss due to default. The buyer of a CDS contract makes periodic payments (referred to as premiums) to the seller of the contract and, in exchange, receives a payoff from the seller if the reference entity defaults on a loan or a bond prior to the maturity date of the contract. The periodic amount that the protection buyer pays the protection seller is quoted in terms of a spread, which is commonly measured in basis points and can be converted into a dollar amount by multiplying with the contract size (i.e., the notional principal).[27]

[26] That is, the five-year spot rate curve contains daily spot rates and is updated each day.
[27] See, e.g., Duffie and Singleton (2003) for details.

There now exists a substantial body of literature on CDS contracts. As stated in Oh and Patton (2015), the pronounced interest is largely driven by the close relation between CDS spreads and the market perception of default probabilities. For instance, CDS spreads are higher for entities which the market perceives to have higher default probabilities or higher losses given default (see Creal et al., 2014). Since we require default probabilities for our empirical study in Section 2.4, we shall exploit this relation and subsequently show how default probabilities (or rather, default intensities) can be extracted from CDS spreads.[28]

We follow Christoffersen et al. (2014) and Hull and White (2003) in our presentation and denote the periodic payments from the protection buyer to the seller as the premium payment leg of the CDS contract, and the compensating payoff from the protection seller to the buyer in case of default as the payoff leg of the CDS. Further, we assume that the CDS contract has quarterly payment dates $T = \{t_i | i = 1, ..., N\}$ (with t_N denoting the maturity of the contract), spread S_t, and notional 1, where the payment dates fall on the 20th of March, June, September and December, and $N = 20$ (corresponding to a maturity of five years). If default occurs, the reference entity recovers a certain percentage, r, of the notional where the (risk-neutral) probability that the entity defaults before time t is given by $P(t) = \Pr[\tau \leqslant t]$, with τ denoting the time of default.[29] The corresponding default intensity, h, is defined by $h(t)\mathrm{d}t = \Pr[\tau \in \mathrm{d}t | \tau > t]$ and can be computed according to

$$P(t) = 1 - \exp\left(-\int_0^t h(s)\mathrm{d}s\right). \tag{2.11}$$

Finally, let $v(t, T_i)$ denote the discount factors calculated from the spot rate curve, and let $\Delta_i = t_i - t_{i-1}$ be the time period between two payment dates. With $q(s,t)$, $s < t$, being the risk-neutral survival probability, the value of the premium payment leg, V_{prem},

[28]See (2.11) for the formal link between default intensities and probabilities.

[29]Consequently, in case of default the protection buyer receives a payoff equal to the difference between the notional of the contract and the recovered value, i.e. $1 - r$.

can then be calculated according to

$$V_{\text{prem}}(t,T,S_t) = S_t \sum_{i=1}^{N} v(t,t_i)\left[\Delta_i q(t,t_i) + \int_{t_{i-1}}^{t_i} (s-t_{i-1})\, P(\mathrm{d}s)\right], \tag{2.12}$$

where the integral accounts for the accrual payment the protection buyer has to make for the time frame from the last payment date to the time of default.[30] The value of the payoff leg, V_{pay}, is given by

$$V_{\text{pay}}(t,T,S_t) = (1-r)\int_{t}^{t_N} v(t,s)P(\mathrm{d}s). \tag{2.13}$$

Following Christoffersen et al. (2014), we compute the integrals in (2.12) and (2.13) by numerical approximations and, for this purpose, define a grid of daily maturities, $\{s_i | i = 0, ..., m\}$, where $s_0 = t$ and $s_m = t_N$. Furthermore, we assume default intensities to be constant, i.e. $h(t) \equiv h$. The integrals can then be approximated as follows

$$\begin{aligned}\int_{t_{i-1}}^{t_i} (s-t_{i-1})\, P(\mathrm{d}s) &\approx \sum_{\{j | s_j \in (t_{i-1}, t_i]\}} (s_j - t_{i-1})\left(\exp\left(ht_{i-1}\right) - \exp\left(ht_i\right)\right),\\ \int_{t}^{t_N} v(t,s)P(\mathrm{d}s) &\approx \sum_{\{j | s_j \in (t_{i-1}, t_i]\}} v(t_{i-1}, s_j)\left(\exp\left(ht_{i-1}\right) - \exp\left(ht_i\right)\right)\end{aligned} \tag{2.14}$$

In a final step, the equation $V_{\text{pay}}(t,T,S_t) - V_{\text{prem}}(t,T,S_t) = 0$ is solved numerically to obtain the default intensity, h. The default probability, $P(t)$, can now be calculated using (2.11).

2.3.3 Descriptive statistics

In our empirical study, we use monthly log-differences of daily mid prices, bid-ask spreads, and default intensities to estimate the marginal and dependence parameters, and employ monthly default probabilities to incorporate credit risk into conventional VaR. More precisely, for each trading day, t, between January 2008 and December 2013, monthly log-differences are calculated using the mid prices, bid-ask spreads,

[30] Note that $q(s,t) = 1 - [P(t) - P(s)]$.

and default intensities at days t and $t-30$. Daily bid-ask spreads are computed as the difference between daily ask and bid quotes, and daily default intensities are extracted from daily CDS spreads as discussed in the preceding section using a fixed recovery rate of 30% (i.e., $r = 0.3$).[31] Monthly default probabilities are derived employing (2.11) adjusted for a monthly horizon, that is

$$P(t) = 1 - \exp\left(\frac{30}{360}h\right) \tag{2.15}$$

As a simple first step, we start our empirical investigation by analyzing the cross-sectional variation in our data. Table 2.1 presents descriptive statistics on the cross-sectional distribution of daily mid prices, bid-ask spreads, default intensities, and default probabilities for the period from January 2008 to December 2013.

[31] Note that holding the recovery percentage at a constant level is fairly standard in existing studies involving CDS or (defaultable) bond valuation (see, e.g., Duffie, 1999, Duffie and Singleton, 1999, Longstaff et al., 2005, Christoffersen et al., 2014). As stated by Hull and White (2000), the fixed recovery rate assumption has little impact on CDS valuation when the expected recovery rate is in the 0% to 50% range.

Table 2.1: Summary statistics for mid prices, bid-ask spreads, and default intensities/probabilities.

The table reports descriptive statistics on the cross-sectional distribution of daily mid prices, bid-ask spreads, default intensities, and default probabilities for the period from January 2008 to December 2013. The sample consists of the 209 companies listed in Appendix A.1. We first calculate the time-series percentiles and moments for each firm in the sample, and then compute the cross-sectional percentiles and mean in a second step. That is, the columns present the percentiles and mean from the cross-sectional distribution of the measures listed in the rows. Mid prices and bid-ask spreads are denominated in U.S. dollar, where the latter are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 2.3 and have a horizon of one year. Default probabilities are derived from the intensities using the formula in (2.15) and thus have a horizon of one month.

		Percentiles						
	Min	5th	25th	Median	75th	95th	Max	Mean
Panel A: Mid prices								
Percentiles								
- Min	0.8400	3.6280	9.9300	17.0900	26.9000	45.8640	89.0900	20.2645
- 1st	1.2760	5.0117	11.8050	19.9050	31.0920	50.2999	105.5355	23.3106
- 5th	2.3325	6.3485	14.8925	23.3652	36.7150	55.4575	115.3875	27.0530
- 25th	6.0900	11.2805	20.2625	32.3463	47.9500	76.1260	150.8350	36.2797
- Median	7.4300	14.0420	24.8525	37.8950	55.8950	84.1910	255.6450	43.6447
- 75th	9.9475	17.5680	31.5783	45.5750	65.0250	103.7060	368.5473	52.3385
- 95th	12.8400	23.6085	42.0950	57.4525	82.7050	138.7835	736.6686	70.1802
- 99th	13.5535	25.9969	44.8700	63.3770	89.6535	153.0323	921.4764	76.6626
- Max	14.1100	26.8480	46.4800	67.4800	92.1000	161.2720	993.9536	80.0887
Moments								
- Mean	8.2180	14.9015	26.7132	40.0617	57.8519	88.2465	258.5393	45.1288
- St. Dev.	1.8085	4.0083	6.8227	10.1979	14.3946	28.3231	208.9269	13.0255
- Skewness	-1.2140	-0.5642	-0.0150	0.3789	0.7668	1.5137	2.8058	0.4088
- Exc. Kurt.	-1.5268	-1.2267	-0.6563	-0.1856	0.3355	1.9105	6.5508	0.0611
- AC(1)	0.9834	0.9891	0.9931	0.9949	0.9963	0.9976	0.9983	0.9943
Panel B: Bid-ask spreads								
Percentiles								
- Min	0.0025	0.0050	0.0100	0.0100	0.0100	0.0100	0.0100	0.0094
- 1st	0.0025	0.0050	0.0100	0.0100	0.0100	0.0100	0.0100	0.0094
- 5th	0.0025	0.0054	0.0100	0.0100	0.0100	0.0100	0.0100	0.0096
- 25th	0.0025	0.0088	0.0100	0.0100	0.0100	0.0100	0.0600	0.0104
- Median	0.0075	0.0100	0.0100	0.0200	0.0200	0.0300	0.1200	0.0180
- 75th	0.0100	0.0200	0.0200	0.0300	0.0400	0.0760	0.1899	0.0369
- 95th	0.0200	0.0300	0.0500	0.0700	0.1090	0.1900	1.0056	0.0908
- 99th	0.0300	0.0600	0.1272	0.1800	0.3044	0.6206	4.5000	0.2715
- Max	0.0900	0.6300	3.0000	6.0500	10.5475	55.4340	194.0000	12.2525
Moments								
- Mean	0.0126	0.0179	0.0280	0.0383	0.0550	0.1087	0.3186	0.0494
- St. Dev.	0.0061	0.0352	0.1090	0.2156	0.3732	1.7631	4.9038	0.4049
- Skewness	3.6236	8.0310	17.6093	21.9631	26.4984	36.6845	39.4965	22.2276
- Exc. Kurt.	24.0800	114.8145	337.4985	529.0167	775.7203	1398.1281	1558.6459	616.4122
- AC(1)	-0.0011	0.0172	0.0941	0.2140	0.3463	0.4755	0.6675	0.2255

Table 2.1: Summary statistics for mid prices, bid-ask spreads, and default intensities/probabilities (continued).

		Percentiles						
	Min	5th	25th	Median	75th	95th	Max	Mean
Panel C: Default intensities								
Percentiles								
- Min	0.0015	0.0023	0.0039	0.0056	0.0092	0.0229	0.0452	0.0080
- 1st	0.0020	0.0027	0.0045	0.0068	0.0102	0.0256	0.0453	0.0090
- 5th	0.0020	0.0036	0.0053	0.0081	0.0120	0.0292	0.0484	0.0105
- 25th	0.0030	0.0047	0.0071	0.0113	0.0163	0.0359	0.1205	0.0145
- Median	0.0037	0.0056	0.0085	0.0135	0.0209	0.0462	0.1474	0.0179
- 75th	0.0052	0.0067	0.0105	0.0178	0.0285	0.0606	0.5800	0.0256
- 95th	0.0062	0.0101	0.0154	0.0299	0.0530	0.1153	1.2542	0.0486
- 99th	0.0067	0.0114	0.0183	0.0362	0.0658	0.1626	1.2552	0.0619
- Max	0.0082	0.0122	0.0201	0.0409	0.0720	0.1949	1.2618	0.0718
Moments								
- Mean	0.0044	0.0062	0.0094	0.0146	0.0249	0.0530	0.4055	0.0219
- St. Dev.	0.0003	0.0012	0.0030	0.0057	0.0125	0.0327	0.4631	0.0124
- Skewness	-10.1455	-0.8015	0.6270	1.4298	2.1049	3.0180	11.0968	1.3137
- Exc. Kurt.	-1.6157	-0.7029	0.3303	2.4236	4.8407	10.7446	172.9344	4.8357
- AC(1)	0.5482	0.9604	0.9904	0.9938	0.9960	0.9979	0.9986	0.9835
Panel D: Monthly default probabilities								
Percentiles								
- Min	0.0001	0.0002	0.0003	0.0005	0.0008	0.0019	0.0038	0.0007
- 1st	0.0002	0.0002	0.0004	0.0006	0.0009	0.0021	0.0038	0.0007
- 5th	0.0002	0.0003	0.0004	0.0007	0.0010	0.0024	0.0040	0.0009
- 25th	0.0003	0.0004	0.0006	0.0009	0.0014	0.0030	0.0100	0.0012
- Median	0.0003	0.0005	0.0007	0.0011	0.0017	0.0038	0.0122	0.0015
- 75th	0.0004	0.0006	0.0009	0.0015	0.0024	0.0050	0.0472	0.0021
- 95th	0.0005	0.0008	0.0013	0.0025	0.0044	0.0096	0.0992	0.0040
- 99th	0.0006	0.0009	0.0015	0.0030	0.0055	0.0135	0.0993	0.0051
- Max	0.0007	0.0010	0.0017	0.0034	0.0060	0.0161	0.0998	0.0059
Moments								
- Mean	0.0004	0.0005	0.0008	0.0012	0.0021	0.0044	0.0325	0.0018
- St. Dev.	0.0000	0.0001	0.0002	0.0005	0.0010	0.0027	0.0365	0.0010
- Skewness	-10.1516	-0.8023	0.6249	1.4276	2.1030	3.0159	11.0892	1.3107
- Exc. Kurt.	-1.6162	-0.7069	0.3297	2.4192	4.8266	10.5930	172.7859	4.8158
- AC(1)	0.5482	0.9604	0.9904	0.9938	0.9960	0.9979	0.9986	0.9836

Panel (A) of Table 2.1 reports descriptive statistics for the mid prices of the 209 sample firms. As indicated by the statistics on the time-series means, our sample is characterized by strong cross-sectional variation of mid prices, with the time-series means ranging from 8.23 U.S. dollars (USD hereafter) to 258.54 USD and being 45.13 USD on average. Further, mid prices are positively skewed and weakly leptokurtic on average, with an average skewness and excess kurtosis of 0.4088 and 0.0611, respectively. Not surprisingly, mid prices exhibit significant autocorrelation with the average first-order autocorrelation being about 99.43%.

Turning to the bid-ask spreads in Panel (B), we find the average bid-ask spread to be 0.05 USD. Again, our panel data exhibit considerable cross-sectional variation with the time-series means ranging from 0.01 USD to 0.31 USD. This finding is further supported by the statistics on the percentiles of the cross-sectional distribution. As we employ the bid-ask spreads of the companies as a proxy for stock liquidity, these results indicate that the trading costs associated with immediately trading the shares of a particular firm differ remarkably across our sample. Thus, in view of the substantial variation in bid-ask spreads, incorporating liquidity risk into conventional VaR appears to be economically essential to adequately capture losses from potential liquidity shocks. Finally, the time-series distributions of bid-ask spreads are heavily skewed and leptokurtic on average.

In Panels (C) and (D) of Table 2.1, we present descriptive statistics for the default intensities and default probabilities extracted from the CDS spreads of our sample firms. Regarding the latter, the average time-series mean is at a comparatively modest level of 0.18%, whereas the minimum and maximum time-series means are given by 0.04% and 3.25%, respectively, indicating that default risk varies considerably across our sample firms. Of particular note is the substantial amount of default risk of some S&P 500 constituents in our sample during the period from January 2008 to December 2013. To be precise, as follows from the statistics on the time-series maxima, the monthly default probabilities amount to a maximum of about 10%. Consequently, the significant variation and serious amounts of default risk further motivate our approach of adjusting standard VaR for credit risk. Turning to the higher-order moments, we find that default probabilities are positively skewed, leptokurtic, and significantly autocorrelated on average.

In addition to the summary statistics on stock prices, bid-ask spreads, and default intensities, we also present corresponding statistics for all data in differences. The descriptive statistics for the log-differences of mid prices, bid-ask spreads, and default intensities are presented in Table 2.2.

Table 2.2: Summary statistics for log-differences of mid prices, bid-ask spreads, and default intensities.

The table reports descriptive statistics on the cross-sectional distribution of monthly log-differences of mid prices, bid-ask spreads, and default intensities for the period from January 2008 to December 2013. For each trading day, t, log-differences are calculated using the prices, spreads, and intensities at days t and $t-30$. The sample consists of the 209 companies listed in Appendix A.1. We first calculate the time-series percentiles and moments for each firm in the sample, and then compute the cross-sectional percentiles and mean in a second step. That is, the columns present the percentiles and mean from the cross-sectional distribution of the measures listed in the rows. Bid-ask spreads are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 2.3 and have a horizon of one year.

		Percentiles						
	Min	5th	25th	Median	75th	95th	Max	Mean
Panel A: Stock returns								
Percentiles								
- Min	-2.4172	-1.1086	-0.6718	-0.5019	-0.3763	-0.2487	-0.1456	-0.5646
- 1st	-1.7198	-0.6902	-0.4206	-0.3245	-0.2442	-0.1524	-0.1105	-0.3612
- 5th	-0.5608	-0.2909	-0.2092	-0.1570	-0.1182	-0.0799	-0.0660	-0.1698
- 25th	-0.1242	-0.0795	-0.0534	-0.0392	-0.0278	-0.0188	-0.0113	-0.0427
- Median	-0.0129	0.0013	0.0090	0.0130	0.0191	0.0271	0.0411	0.0137
- 75th	0.0274	0.0373	0.0500	0.0622	0.0735	0.0945	0.1195	0.0630
- 95th	0.0656	0.0785	0.1110	0.1412	0.1737	0.2530	0.3481	0.1492
- 99th	0.0882	0.1116	0.1705	0.2237	0.2995	0.4728	0.9937	0.2549
- Max	0.1155	0.1534	0.2532	0.3534	0.4798	0.8391	1.3251	0.4010
Moments								
- Mean	-0.0436	-0.0089	0.0003	0.0051	0.0091	0.0159	0.0217	0.0044
- St. Dev.	0.0438	0.0546	0.0744	0.0978	0.1231	0.1801	0.3478	0.1059
- Skewness	-2.8099	-1.8866	-1.2889	-0.8675	-0.5818	-0.1877	0.7702	-0.9438
- Exc. Kurt.	0.4175	0.9385	2.1253	3.6449	5.4871	9.6011	15.1429	4.2101
- AC(1)	0.8984	0.9172	0.9360	0.9447	0.9537	0.9626	0.9698	0.9437
Panel B: Log-differences of bid-ask spreads								
Percentiles								
- Min	-9.8730	-8.4583	-6.7719	-6.2832	-5.5984	-3.5666	-1.6094	-6.1205
- 1st	-3.7483	-2.8421	-2.3979	-2.1846	-1.9459	-1.6094	-1.0986	-2.1828
- 5th	-2.3988	-1.5593	-1.3863	-1.0986	-1.0986	-0.6931	-0.6931	-1.1752
- 25th	-0.7215	-0.6931	-0.4700	-0.4055	-0.2231	0.0000	0.0000	-0.3449
- Median	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
- 75th	0.0000	0.0000	0.0000	0.2877	0.4055	0.5596	0.6948	0.2473
- 95th	0.6931	0.6931	1.0986	1.0986	1.2528	1.4642	2.6378	1.1241
- 99th	1.0986	1.4390	1.9459	2.1972	2.4965	2.8916	3.7677	2.1941
- Max	1.7918	3.6687	5.6168	6.2766	6.7719	8.4841	9.8730	6.1533
Moments								
- Mean	-0.0710	-0.0328	-0.0255	-0.0216	-0.0166	-0.0098	0.0014	-0.0213
- St. Dev.	0.3300	0.6064	0.7596	0.8368	0.9172	1.0662	1.4616	0.8384
- Skewness	-0.2592	-0.1267	-0.0086	0.0444	0.1147	0.2441	0.3778	0.0518
- Exc. Kurt.	0.7405	2.9375	8.2886	12.5335	16.6561	23.5607	58.6048	12.8523
- AC(1)	0.0381	0.1510	0.2237	0.2635	0.2989	0.3522	0.4762	0.2586

Table 2.2: Summary statistics for log-differences of mid prices, bid-ask spreads, and default intensities (continued).

		Percentiles						
	Min	5th	25th	Median	75th	95th	Max	Mean
Panel C: Log-differences of default intensities								
Percentiles								
- Min	-1.9458	-0.6973	-0.3701	-0.2705	-0.2120	-0.1338	-0.0512	-0.3332
- 1st	-0.2704	-0.1347	-0.1030	-0.0883	-0.0784	-0.0542	-0.0423	-0.0918
- 5th	-0.0730	-0.0592	-0.0482	-0.0395	-0.0285	-0.0017	-0.0015	-0.0354
- 25th	-0.0210	-0.0119	-0.0053	-0.0016	-0.0012	-0.0006	-0.0004	-0.0038
- Median	-0.0007	-0.0005	-0.0005	-0.0005	-0.0005	-0.0005	-0.0001	-0.0005
- 75th	-0.0005	-0.0005	-0.0003	0.0000	0.0006	0.0082	0.0211	0.0013
- 95th	-0.0004	0.0004	0.0285	0.0433	0.0535	0.0660	0.0825	0.0389
- 99th	0.0922	0.0973	0.1023	0.1083	0.1192	0.1553	0.2137	0.1148
- Max	0.0937	0.1603	0.2518	0.3338	0.4543	0.8304	2.1231	0.4007
Moments								
- Mean	-0.0015	-0.0008	-0.0003	0.0001	0.0003	0.0008	0.0023	0.0001
- St. Dev.	0.0131	0.0225	0.0294	0.0334	0.0364	0.0533	0.1565	0.0351
- Skewness	-19.3336	-1.1683	0.4377	1.0662	1.9198	6.2680	23.9300	1.3678
- Exc. Kurt.	5.4259	9.1788	14.2182	27.1295	48.2334	217.8431	622.8101	57.0487
- AC(1)	-0.4265	-0.2422	-0.0711	0.0611	0.1297	0.1805	0.2660	0.0183

Panel (A) of Table 2.2 reports summary statistics on the cross-sectional distribution of stock returns. As can be seen from the panel, the stock returns of our sample firms exhibit the usual stylized facts of a negligible mean of 0.44%, pronounced negative skewness, and significant leptokurtosis on average. The average autocorrelation of stock returns is around 94% and thus slightly smaller than that of mid prices. As expected, given the fact that our sample period partly comprises the financial crisis, the stock returns are characterized by considerable time-series variation, with the average time-series minimum and maximum being given by about -56% and 40%, respectively. Further, as indicated by the statistics on the percentiles and the time-series means, the stock returns also vary considerably in the cross-section.

Turning to the cross-sectional statistics on log-differenced bid-ask spreads in Panel (B), we find that the time-series means of log-differences vary from approximately -7% to 0.14% and are -2% on average. Interestingly, as in the case of stock returns, bid-ask spread changes exhibit strong time-series variation, as indicated by, e.g., the average interquartile range which reaches from about -34% to 25% and, therefore, implies considerable dispersion in the time-series distributions of log-differenced bid-ask spreads. That is, our sample period is characterized by substantial changes in the stock liquidity of the average sample firm. Finally, the log-differences are slightly skewed and considerably autocorrelated on average.

Regarding the log-differences of default intensities in Panel (C) of Table 2.2, we find that the corresponding time-series means vary from -0.15% to 0.23% and are 0.01% on average, implying only slight cross-sectional variation. Turning to the time-series variation, however, we can see from the panel that changes in the default intensities of the sample firms vary considerably from -33% to 40% on average, indicating fundamental changes in the market perception of default risk during the sample period. Furthermore, log-differences of default intensities are heavily skewed and only slightly autocorrelated, so that log-differencing already eliminates most of the serial dependence in default intensities.

Figure 2.1 illustrates the temporal variation in the cross-section of our data. More precisely, the figure plots the time evolution of daily mid prices, bid-ask spreads, and default intensities, as well as of the corresponding log-differences, where we calculate the cross-sectional average across all 209 sample firms for each trading day between January 2008 and December 2013.

Panels (a) and (b) show the time evolution of average mid prices and stock returns, respectively. As can be seen from Panel (a), stock prices experienced sharp declines during the financial crisis and decreased significantly from more than 50 USD in 2008 to approximately 20 USD in 2009. The post-crisis years as of the second quarter in 2009 are characterized by a strong and stable upward trend, with the mid prices rising to pre-crisis levels. Turning to the time evolution of monthly stock returns, we find that the temporal variation of average returns is as expected. The time period comprising the financial crisis is characterized by substantial price changes and pronounced volatility, with stock returns ranging from -50% to 50%. In the post-crisis period, however, volatility of average returns declines remarkably and returns stay relatively flat, varying between -20% and 20%.

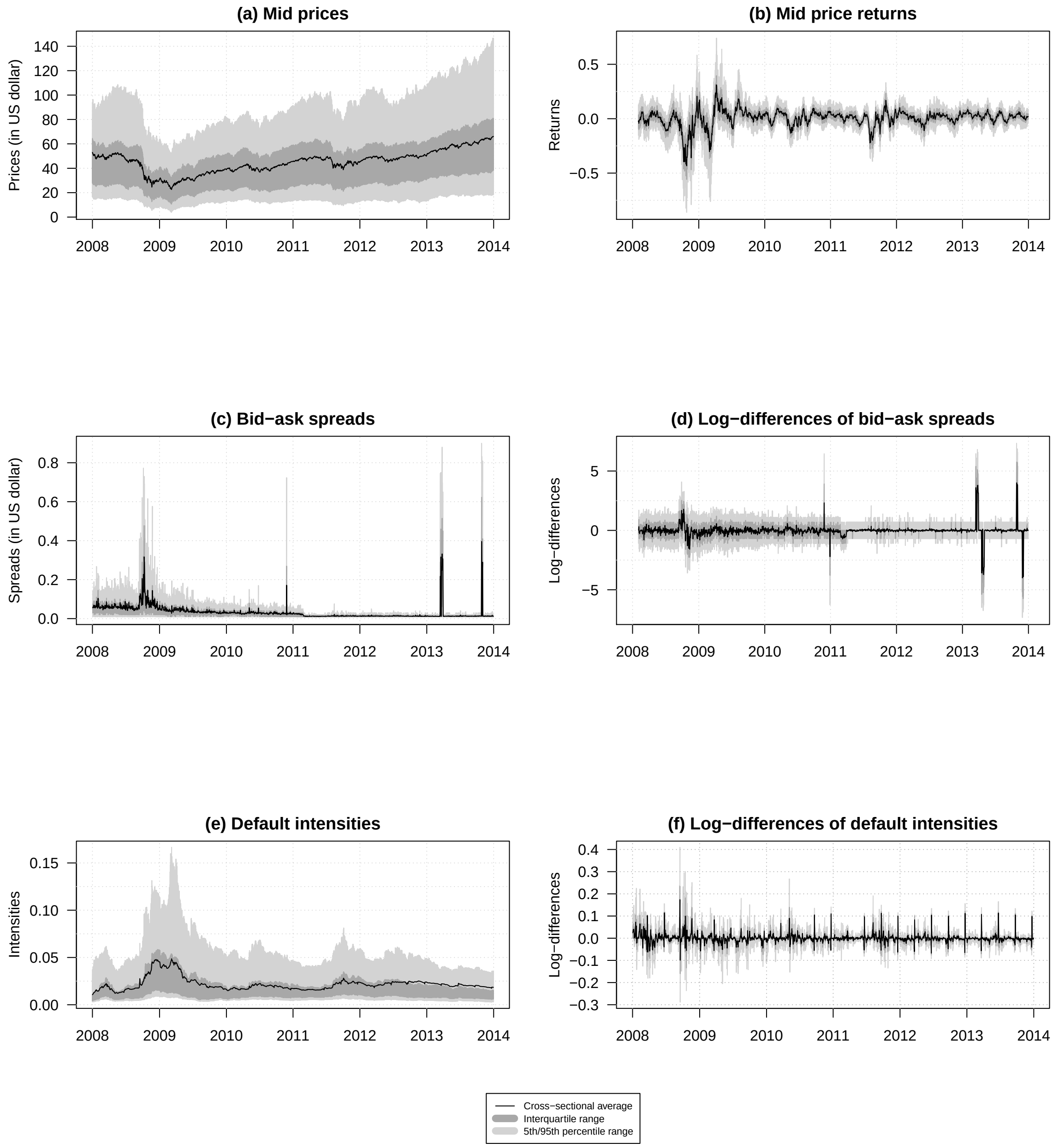
Panels (c) and (d) of Figure 2.1 present the time evolution of average daily bid-ask spreads and the corresponding monthly log-differences. Not surprisingly, average bid-ask spreads increased steeply during the financial crisis, indicating a severe deterioration of stock liquidity and, consequently, implying increased trading costs for the stocks of the average sample firm. The increased log-differences in Panel (b) in the second half of 2008 result from the temporary surge in (average) bid-ask spreads and reflect the considerable changes in the stock liquidity of the sample firms. In subsequent years, bid-ask spreads and the corresponding log-differences return to low levels and stay relatively flat, indicating that liquidity restores and trading costs decline to pre-crisis levels.[32]

Finally, Panels (e) and (f) show the time evolution of average default intensities and the corresponding log-differences. The temporal variation of default intensities is as expected and shows that default risk significantly increased during the financial crisis. Average default intensities increased from approximately 1% in 2008 to nearly 5% in 2009 and returned to pre-crisis levels in the following years. Interestingly, as indicated by the 5th to 95th percentile range and as discussed above, the sample is characterized by strong cross-sectional variation, with the average 95th percentile default intensity peaking at about 15% in 2009. Turning to the log-differences, we find that the increased intensities during the financial crisis coincide with increased log-differences and increased volatility of log-differences.

[32] Note that the surges in bid-ask spreads and log-differences in the post-crisis period are predominantly driven by outliers lacking any economic relevance. In our empirical study, however, we remove spurious outliers by winsorising to assure the validity of our results.

Figure 2.1: Time evolution of cross-sectional data.

The figure shows the time evolution of daily mid prices, bid-ask spreads and default intensities, as well as of the corresponding monthly log-differences for the period from January 2008 to December 2013. The sample consists of the 209 companies listed in Appendix A.1. For each day of the sample period, we calculate the cross-sectional average (black line) as well as the cross-sectional interquartile (dark-gray shaded area) and 5th/95th percentile range (light-gray shaded area). Mid prices and bid-ask spreads are denominated in US dollar, where the latter are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 2.3 and have a horizon of one year. Monthly log-differences are calculated for each day in the sample period using the prices, spreads, and intensities at days t and $t - 30$.



2.4 Empirical study

In this section, we first characterize the dynamic linear and extreme dependence in equity, liquidity, and credit risk. We then implement our econometric modeling approach and illustrate the usefulness of our previous findings in a risk management setting by investigating the performance of our newly proposed VaR-model in a comprehensive simulation study.

2.4.1 Anecdotal evidence

As a simple first step, we start our empirical study by reporting anecdotal evidence on the relation between stock returns, bid-ask spreads, and default intensities, providing further motivation for our risk management application in the next section. Taking returns, spreads, and intensities as proxies for market price, liquidity, and credit risk, we are especially interested in the dynamic dependence of these risk types and shall document linear dependences as well as potential non-linearities in the dependence structure. To this purpose, we implement the following simple econometric modeling strategy. First, for each trading day between January 2008 and December 2013 and for each of the 209 firms in the sample, we calculate monthly log-differences of mid prices, bid-ask spreads, and default intensities (extracted from daily CDS spreads, see Section 2.3), resulting in the respective time series $\left\{R^j_{i,t}\right\}_{t=1}^{T}$, $i = 1, 2, 3$; $j = 1, ..., 209$, where $T = 1542$. To filter the time series and compute white-noise residuals, we then apply standard AR(3)-GARCH(1,1) processes with normally distributed innovations to the log-differenced time series, capturing most of the first- and second-moment dependence.[33] That is

$$\begin{aligned}
R_{i,t} &= \mu_{i,t} + e_{i,t} = \mu_{i,t} + \sigma_{i,t}\varepsilon_{i,t}, \quad \varepsilon_{i,t}|\mathcal{F}_{i,t-1} \sim iid\ \mathcal{N}(0,1), \\
\mu_{i,t} &= \mu_i + \phi_{1,i}R_{i,t-1} + \phi_{2,i}R_{i,t-2} + \phi_{3,i}R_{i,t-3}, \\
\sigma^2_{i,t} &= \omega_i + \alpha_i e^2_{i,t-1} + \beta_i\sigma^2_{i,t-1},
\end{aligned} \tag{2.16}$$

where the subscript denoting the respective firm, j, is omitted for convenience. Pseudo-observations, u_i, are then obtained by calculating the corresponding ranks, i.e. $u_i = F_i(\varepsilon_i)$.

In a next step, we then calculate dynamic correlations and tail dependences between the stock returns, bid-ask spreads, and default intensities of the *same* firm.[34] The former are computed using the Dynamic Conditional Correlation (DCC) model as proposed by Engle (2002).[35] The DCC model uses the residuals from the univariate GARCH processes as building blocks and assumes that the dynamics in the correlation matrix, R_t, are driven by some autoregressive term and the cross-product of return shocks, i.e.

$$\begin{aligned}
R^j_t &= \mathrm{diag}(Q^j_t)^{-1}Q^j_t\ \mathrm{diag}(Q^j_t)^{-1}, \\
Q^j_t &= (1-\psi^j_1-\psi^j_2)Q^j + \psi^j_2 Q^j_{t-1} + \psi^j_1\tilde{\varepsilon}^j_{t-1}\tilde{\varepsilon}^{j\top}_{t-1},
\end{aligned} \tag{2.17}$$

where ψ^j_1 and ψ^j_2 are non-negative parameters, Q^j is the unconditional correlation matrix, and $\tilde{\varepsilon}^j_t = \left(\tilde{\varepsilon}^j_{1,t}, \tilde{\varepsilon}^j_{2,t}, \tilde{\varepsilon}^j_{3,t}\right)^\top$ with $\tilde{\varepsilon}^j_{i,t}$ given by $\varepsilon^j_{i,t}\sqrt{Q^j_{ii,t}}$, $j = 1, ..., 209$ (see Aielli, 2013, for details).

Dynamic tail dependences, on the other hand, are calculated using Patton's (2006) dynamic t copula, which is outlined in Appendix A. Copula estimation is conducted

[33] Note that we merely aim to provide first evidence on the time-varying linear and non-linear dependences between stock returns, bid-ask spreads, and default intensities. Due to computational feasibility, in this section, we therefore neglect such issues as asymmetry in volatility and fat tails as well as skewness in the marginal distributions. These issues are however addressed in our risk management application in the next section.

[34] This restriction is necessary to ensure computational feasibility. Note, however, that the model approach discussed in Section 2.2 and employed in the next section, accounts for all relevant cross-dependences.

[35] In fact, we use the modified DCC model according to Aielli (2013).

for each of the three possible pairs of returns, spreads, and intensities on the basis of the corresponding pseudo-observations, (u_{i_1}, u_{i_2}), where $i_1, i_2 = 1, 2, 3$; $i_1 \neq i_2$.

Table 2.3 reports the cross-sectional distribution of estimates for the marginal and dependence parameters.

The former are captured in Panel (A) and presented separately for stock returns, bid-ask spreads, and default intensities. The estimation results for stock returns are fairly standard. We find the first two AR lags to be strongly significant, capturing the autocorrelation evidenced in Section 2.3. Further, the conditional variance models reveal an only mild effect of lagged return shocks on current volatility, as indicated by the α parameter being around 0.05 on average. The autoregressive β parameter is, however, dominating with the cross-sectional average being around 0.94. As is commonly found in the literature, volatility persistence is quite high (0.99 on average).[36]

Turning to the marginal parameters of bid-ask spreads, we find all three AR lags to be strongly significant. Moreover, as in the case of stock returns, the variance parameters indicate low values for the estimates of the news-arrival parameter, α, (0.08 on average) and high values for the autoregressive β parameter (0.89 on average). As above, volatility persistence is high at 0.97 on average.

Regarding default intensities, we can see from the marginal parameter estimates that the first two AR lags turn out to be significant. Interestingly, the α parameter is around 0.29 on average and, thus, considerably higher for default intensities than for stock returns and bid-ask spreads, indicating that news arrival affects volatility of default intensities to a greater extent than volatility of stock returns and bid-ask spreads. At the same time, the autoregressive β parameter is much smaller and about 0.53 on average. Volatility persistence, on the other hand, remains high at 0.82 on average, but appears to be relatively low when compared to volatility persistence of stock returns and bid-ask spreads.

Turning to the DCC parameter estimates in Panel (B) of Table 2.3, we find the autoregressive ψ_2 parameter to be clearly dominating (0.90 on average). Further, the

[36] See, e.g., Christoffersen et al. (2012) and Engle (2002).

Table 2.3: Cross-sectional distribution of parameter estimates.

The table shows summary statistics of the parameter estimates for the marginal distributions as well as the correlation and copula models used to report first evidence on the dependence of prices, liquidity, and credit risk. The marginals are modeled as AR(3)-GARCH(1,1) processes with standard normally distributed innovations, and correlations are computed from Engle's (2002) Dynamic Conditional Correlation (DCC) model (using the Aielli (2013) modification). The copula models are based on Patton's (2006) dynamic t copula as discussed in Appendix A. For each of the 209 firms in the sample (see Appendix A.1), the models are estimated on monthly log-differences of the mid prices, bid-ask spreads, and default intensities of the *same* firm for the period from January 2008 to December 2013, where estimation of the DCC and the t copula models is based on the corresponding AR-GARCH residuals. Descriptive statistics are then calculated cross-sectionally across all sample firms. Persistence for the marginal and DCC models is computed as $\alpha + \beta$ and $\psi_1 + \psi_2$, respectively.

	Cross-sectional distribution												
		Percentiles								Moments			
	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
Panel A: Parameter estimates for AR-GARCH processes													
Stock returns													
μ	0.7099	0.7521	0.8032	0.9053	0.9425	0.9778	1.0150	1.0698	1.1261	0.9345	0.0664	-0.7963	1.2636
ϕ_1	-0.1705	-0.1231	-0.0948	-0.0385	-0.0050	0.0448	0.1369	0.1982	0.2309	0.0062	0.0721	0.5639	0.1035
ϕ_2	-0.1733	-0.1218	-0.0897	-0.0247	0.0093	0.0396	0.0753	0.1100	0.1170	0.0046	0.0510	-0.5435	0.4564
ϕ_3	-0.0017	-0.0008	-0.0004	0.0001	0.0003	0.0006	0.0011	0.0017	0.0018	0.0003	0.0005	-0.0800	2.0703
ω	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	2.8841	14.0772
α	0.0000	0.0232	0.0291	0.0420	0.0527	0.0611	0.0789	0.0956	0.0994	0.0527	0.0155	0.2690	0.4786
β	0.8946	0.9025	0.9114	0.9289	0.9398	0.9484	0.9638	0.9718	0.9994	0.9391	0.0157	-0.0100	0.7668
Persistence	0.9560	0.9747	0.9825	0.9890	0.9929	0.9953	0.9993	1.0016	1.0024	0.9918	0.0056	-1.9519	8.6149
Bid-ask spreads													
μ	0.0376	0.0857	0.1265	0.1774	0.2127	0.2455	0.3084	0.3869	0.4848	0.2137	0.0592	0.6655	2.5100
ϕ_1	-0.1078	-0.0498	0.0262	0.0723	0.1049	0.1377	0.1879	0.2141	0.2590	0.1037	0.0545	-0.3384	1.1941
ϕ_2	-0.0469	-0.0264	0.0513	0.0979	0.1311	0.1585	0.1980	0.2612	0.2888	0.1276	0.0502	-0.2115	1.3672
ϕ_3	-0.0381	-0.0241	-0.0204	-0.0142	-0.0113	-0.0083	-0.0015	0.0014	0.0045	-0.0113	0.0056	-0.2702	2.2573
ω	0.0000	0.0003	0.0017	0.0093	0.0140	0.0216	0.0403	0.1652	0.3870	0.0201	0.0350	7.6350	68.2337
α	0.0304	0.0325	0.0442	0.0635	0.0784	0.1013	0.1409	0.1917	0.2919	0.0849	0.0341	1.8250	6.6965
β	0.4415	0.5391	0.8387	0.8796	0.8991	0.9139	0.9411	0.9639	0.9644	0.8881	0.0622	-4.4872	24.6484
Persistence	0.6417	0.7072	0.9461	0.9664	0.9785	0.9897	1.0040	1.0181	1.0680	0.9729	0.0440	-5.4572	36.1846
Default intensities													
μ	-0.5321	-0.5137	-0.2581	-0.0644	0.0550	0.1216	0.1766	0.2091	0.2701	0.0119	0.1473	-1.2988	2.0961
ϕ_1	-0.4508	-0.2737	-0.1172	-0.0047	0.0394	0.0712	0.1100	0.1263	0.1474	0.0196	0.0823	-2.3825	8.6786
ϕ_2	-0.1694	-0.1162	-0.0739	-0.0159	0.0132	0.0392	0.0816	0.1273	0.1492	0.0106	0.0480	-0.3077	1.0732
ϕ_3	-0.0017	-0.0010	-0.0007	-0.0003	0.0000	0.0003	0.0009	0.0020	0.0022	0.0000	0.0005	0.7591	3.5747
ω	0.0000	0.0000	0.0000	0.0001	0.0002	0.0004	0.0008	0.0012	0.0014	0.0003	0.0003	1.4110	1.8542
α	0.0000	0.0002	0.0112	0.1114	0.2326	0.3815	0.7161	1.0000	1.0000	0.2901	0.2326	1.2397	1.4225
β	0.0000	0.0000	0.0000	0.2441	0.6017	0.8359	0.9722	0.9915	0.9998	0.5326	0.3304	-0.2887	-1.3085
Persistence	0.0374	0.0930	0.3301	0.6327	0.9123	0.9927	1.1087	1.4202	1.5210	0.8227	0.2647	-0.5796	0.4133

Table 2.3: Cross-sectional distribution of parameter estimates (continued).

	Cross-sectional distribution												
		Percentiles								Moments			
	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.
Panel B: Parameter estimates for DCC models													
ψ_1	0.0000	0.0000	0.0002	0.0007	0.0031	0.0073	0.0164	0.0237	0.0320	0.0051	0.0056	1.7866	3.7179
ψ_2	0.0007	0.0494	0.2750	0.9447	0.9636	0.9776	0.9895	0.9940	0.9955	0.8950	0.2076	-3.0676	8.4476
Persistence	0.0207	0.0515	0.2758	0.9504	0.9681	0.9815	0.9926	0.9962	0.9966	0.9000	0.2065	-3.0832	8.5102
Panel C: Parameter estimates for copula models													
Stock returns - Bid-ask spreads													
c	-0.3755	-0.2286	-0.1579	-0.0086	0.0048	0.0416	0.1881	0.2938	0.3214	0.0148	0.0963	-0.0505	2.5971
b	-2.0121	-2.0086	-1.9593	-1.3570	-0.0164	1.5862	1.9352	1.9700	2.0356	0.0850	1.4664	-0.0645	-1.5590
a	-0.7829	-0.7021	-0.4633	-0.1025	0.0233	0.0994	0.3801	0.5293	0.7382	-0.0162	0.2460	-0.4087	1.1521
ν	6.1908	8.9543	12.1979	20.7282	37.5850	63.6554	93.8263	99.9548	99.9995	44.4172	26.0986	0.4750	-0.9234
Stock returns - Default intensities													
c	-0.1870	-0.1385	-0.0333	0.0086	0.0693	0.2590	0.6596	0.8174	1.1433	0.1653	0.2209	1.5093	2.2150
b	-2.1471	-2.0622	-2.0168	-1.3190	0.3870	1.6951	1.9810	2.0028	2.0363	0.1837	1.4668	-0.2149	-1.4834
a	-0.6104	-0.4915	-0.3039	-0.0615	0.0224	0.1072	0.4002	0.6315	0.9743	0.0318	0.2025	0.6263	3.0254
ν	8.2157	8.6381	10.4262	15.3369	24.2336	44.4626	79.4284	99.6542	99.9992	32.7019	22.9692	1.2417	0.8157
Bid-ask spreads - Default intensities													
c	-0.3462	-0.2171	-0.1323	-0.0437	-0.0066	0.0086	0.0994	0.2263	0.2777	-0.0167	0.0752	-0.1227	3.8508
b	-2.0353	-2.0130	-1.9991	-1.7140	-0.2303	1.1646	1.8970	2.0045	2.0118	-0.2421	1.4562	0.1702	-1.5744
a	-0.8831	-0.6167	-0.3822	-0.1680	-0.0132	0.1279	0.3330	0.4137	0.4695	-0.0202	0.2216	-0.4639	0.6792
ν	8.6169	9.5970	14.3452	31.5501	54.2957	78.5693	99.9412	99.9996	99.9999	56.0324	27.7647	0.0326	-1.2075

estimates indicate considerable persistence in the conditional correlation of stock returns, bid-ask spreads, and default intensities of the *same* firm.

Panel (C) reports the parameter estimates for the dynamic *t* copulas and, on the one hand, shows that there is substantial cross-sectional variation in the dependence between stock returns, bid-ask spreads, and default intensities. On the other hand, the estimates reveal that the dependence between returns and spreads, returns and intensities, and between spreads and intensities differ considerably, indicating that each pair of returns, spreads, and intensities is characterized by specific patterns in dependence.

The temporal variation of correlations and tail dependences is depicted in Figure 2.2.

Panel (a) plots the corresponding correlations and shows that correlations exhibit considerable time variation and differ materially across the three pairs of returns, spreads, and intensities. While dynamic correlations between returns and spreads and between returns and intensities range from approximately -40% up to 50%, correlations between spreads and intensities stay at comparatively moderate levels and vary in the range of -30% to 25%. These patterns can also be found for the dynamic tail dependences in Panel (b). To be precise, dynamic tail dependences also exhibit considerable variation across time as well as across the three pairs of returns, spreads, and intensities. With the tail dependences between returns and spreads and between returns and intensities varying between 0% and 15% and between 0% and 20%, respectively, the tail dependence between spreads and intensities is somewhat less pronounced and remains in the 0% to 2.5% range.

Figure 2.2: Dynamic correlations and tail dependences.

The figure shows the minimum/maximum range of dynamic correlations and tail dependences of stock returns, bid-ask spreads, and default intensities. For each trading day between January 2008 and December 2013 and for each of the 209 firms in the sample (see Appendix A.1), we calculate dynamic correlations and tail dependences between the returns, spreads, and intensities of the *same* firm, resulting in a total of each 627 correlation and tail dependence coefficients per firm and day. We then calculate cross-sectional minimum and maximum values for each day. Dynamic correlations are computed from Engle's (2002) Dynamic Conditional Correlation (DCC) model (using the Aielli (2013) modification), and dynamic tail dependence coefficients from Patton's (2006) dynamic *t* copula (see Appendix A). The models are estimated on the basis of the residuals from AR(3)-GARCH(1,1) processes applied to monthly log-differences of mid prices, bid-ask spreads, and default intensities.

(a) Dynamic correlations

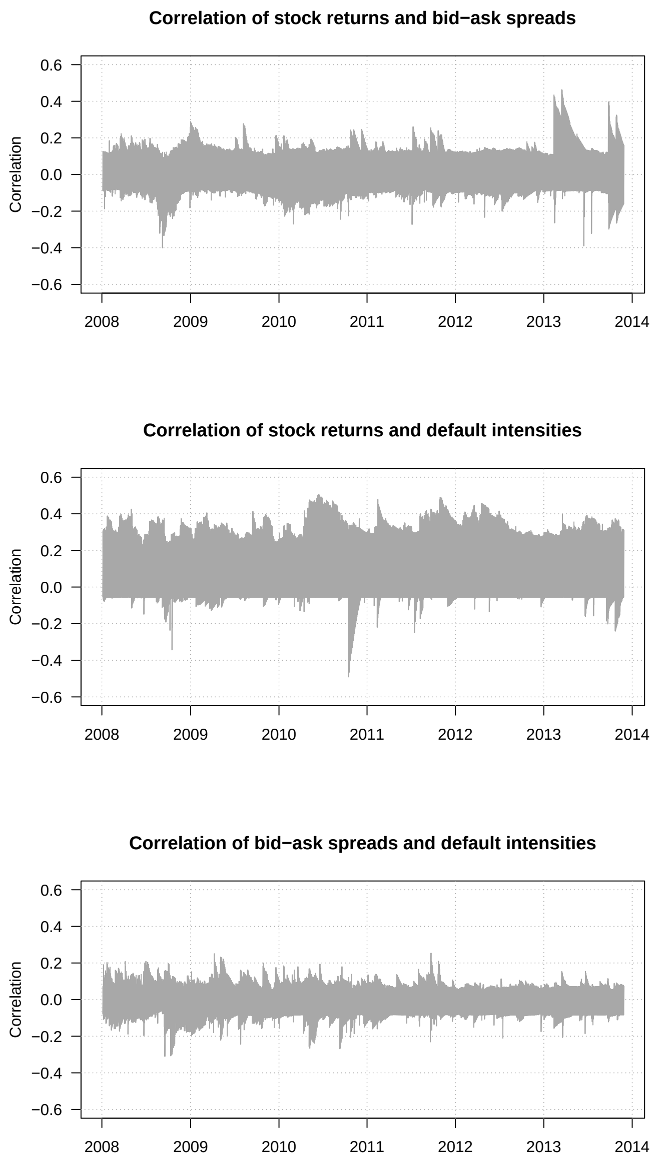
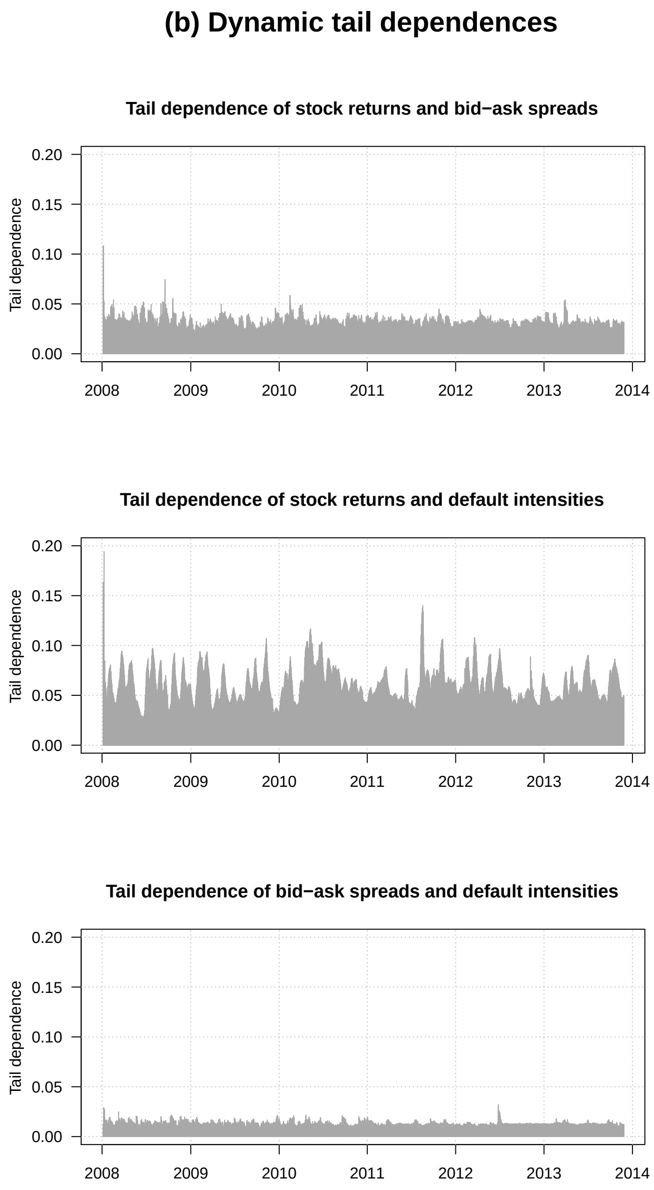


Figure 2.2: Dynamic correlations and tail dependences (continued).



2.4.2 Forecasting Liquidity- and Credit-Adjusted Value-at-Risk

We now turn to our VaR simulation study, which applies the dynamic vine copula model discussed in Section 2.2 to forecasting liquidity- and credit-adjusted VaR. We first discuss our approach to incorporate liquidity and credit risk into the standard VaR framework and present the simulation design. We then discuss the simulation and forecasting results and compare the performance of competing dependence models.

2.4.2.1 Simulation design

The onset of the VaR concept as a de-facto industry standard has spurred a surge in theoretical and empirical VaR studies in the risk management literature. Since then, a recurring topic has been the incorporation of liquidity risk into the standard VaR framework which only accounts for market price risk. Being subject of an intense and controversial debate in the literature, much effort has been spent on the incorporation of liquidity risk into standard VaR and many different extensions have been proposed in existing studies (see, e.g., Berkowitz, 2000, Bangia et al., 2002, Qi and Ng, 2009). The incorporation of credit risk, on the other hand, has also been widely discussed in the literature (see Crouhy et al., 2000, for an overview), but has so far been restricted to portfolios of credit-linked securities, i.e., bond portfolios (Andersson et al., 2001) and portfolios of derivatives with defaultable counterparties or borrowers (Duffie and Pan, 2001). Following the notion of stockholders as the residual claimants on a firm's assets (Vassalou and Xing, 2004), we argue that VaR measures of stock portfolios as well need to be modified by considering potential future losses from credit events since stock portfolios are subject to credit risk and might suffer severe losses in case of the underlying firm being in financial distress. Because a firm defaults when it fails to service its debt obligations and equity, in turn, is serviced subordinately to debt, credit losses might be passed to stockholders causing stock values to suffer sharp declines and forcing stockholders to significantly write off their portfolios.

To formally describe our liquidity- and credit-adjusted VaR (subsequently denoted as LC-VaR) as well as the simulation design, we adopt the notation introduced in the preceding sections and, in the first step, estimate the AR(3)-GJR-GARCH(1,1) processes for the marginal time series of log-differences, $\left\{R_{i,t}^j\right\}$, with $i = 1, 2, 3$ denoting the type of series (returns, spreads, intensities) and $j = 1, ..., d$ denoting the corresponding firm. The resulting residuals, $\left\{\hat{\varepsilon}_{i,t}^j\right\}$, are then used to compute pseudo-observations (i.e., copula data), $\left\{\hat{u}_{i,t}^j\right\}$, by calculating the corresponding ranks via the transformation $\hat{u}_i^j = \hat{F}_i^j(\hat{\varepsilon}_i^j)$, with $\hat{F}_i^j$ denoting the empirical distribution function. In the next step, we estimate the dynamic R-vine copula model as discussed in Section 2.2, where estimation is based on the copula data, $\left\{\hat{u}_{i,t}^j\right\}$. Note that, for each day t in the estimation period, there are three observations for each of the d firms, resulting in a $3d$-dimensional random vector given as

$$\left(\hat{u}_{1,t}^1, \hat{u}_{2,t}^1, \hat{u}_{3,t}^1, ..., \hat{u}_{1,t}^d, \hat{u}_{2,t}^d, \hat{u}_{3,t}^d\right)^\top. \tag{2.18}$$

Having estimated the R-vine copula, we employ the sampling algorithm as discussed in Dißmann et al. (2013) and simulate $K = 500$ independent observations, $\left\{{}_k\breve{u}_{i,t+1}^j\right\}_{k=1}^K$, from the specified copula model.[37] The simulated (or rather, forecasted) copula data can then be converted to simulated log-differences of mid prices, bid-ask spreads, and default intensities in the following way. With $q_{skt}(\,\cdot\,; \nu_i^j, \gamma_i^j)$ denoting the quantile function of the skewed t distribution of Fernandez and Steel (1998), the simulated time series can be calculated as

$$\begin{aligned} {}_k\breve{R}_{i,t+1}^j &= \breve{\mu}_{i,t+1}^j + \breve{e}_{i,t+1}^j = \breve{\mu}_{i,t+1}^j + \breve{\sigma}_{i,t+1}^j \breve{\varepsilon}_{i,t+1}^j, \\ \breve{\varepsilon}_{i,t+1}^j &= q_{skt}({}_k\breve{u}_{i,t+1}^j; \hat{\nu}_i^j, \hat{\gamma}_i^j), \end{aligned} \tag{2.19}$$

where $\breve{\mu}_{i,t+1}^j$ and $\breve{\sigma}_{i,t+1}^j$ are computed by inserting the estimated AR-GJR-GARCH parameters into equations (2.2) and (2.3), respectively. The forecasted mid prices,

[37] This results in 500 vectors of the form as in (2.18). Note that, as indicated by the time subscript, we identify these vectors as the forecasted pseudo-observations for day $t + 1$.

$\left\{{}_k\check{m}^j_{t+1}\right\}$, bid-ask spreads, $\left\{{}_k\check{s}^j_{t+1}\right\}$, and default intensities, $\left\{{}_k\check{h}^j_{t+1}\right\}$, are given by

$$ {}_k\check{m}^j_{t+1} = m^j_t \exp\left({}_k\check{R}^j_{1,t+1}\right), \quad {}_k\check{s}^j_{t+1} = s^j_t \exp\left({}_k\check{R}^j_{2,t+1}\right), \quad {}_k\check{h}^j_{t+1} = h^j_t \exp\left({}_k\check{R}^j_{3,t+1}\right), \tag{2.20} $$

where the forecasted monthly default probabilities, $\left\{{}_k\check{p}^j_{t+1}\right\}$, can be calculated according to (2.15) as follows

$$ {}_k\check{p}^j_{t+1} = 1 - \exp\left(\frac{30}{360}\,{}_k\check{h}^j_{t+1}\right). \tag{2.21} $$

Computing LC-VaR forecasts, $\widetilde{\text{LC-VaR}}^j_{t+1}(\theta)$, now essentially reduces to calculating empirical quantiles of forecasted mid price returns, bid-ask spreads, and default probabilities, where θ denotes the corresponding confidence level. More precisely, with $rs^j_t = s^j_t/m^j_t$ being the relative spread and b^j_t denoting the bid price, LC-VaR forecasts are calculated according to

$$ \widetilde{\text{LC-VaR}}^j_{t+1}(\theta) = \widetilde{\text{VaR}}^j_{t+1}(\theta) + \widetilde{\text{L-VaR}}^j_{t+1}(\theta) + \widetilde{\text{C-VaR}}^j_{t+1}(\theta), \tag{2.22} $$

where

$$ \widetilde{\text{VaR}}^j_{t+1}(\theta) = m^j_t\left(1 - \exp\left(\hat{q}\left(\left\{{}_k\check{R}^j_{1,t+1}\right\};\theta\right)\right)\right) \tag{2.23} $$

is the standard VaR and

$$ \widetilde{\text{L-VaR}}^j_{t+1}(\theta) = \frac{1}{2}m^j_t\hat{q}\left(\left\{{}_k\check{rs}^j_{t+1}\right\};1-\theta\right), \quad \widetilde{\text{C-VaR}}^j_{t+1}(\theta) = b^j_t\hat{q}\left(\left\{{}_k\check{p}^j_{t+1}\right\};1-\theta\right) \tag{2.24} $$

denote the liquidity- and credit-adjustment, respectively, with $\hat{q}(\,\cdot\,;\theta)$ denoting the empirical quantile function evaluated at probability θ.

The liquidity-adjustment in (2.24) is proposed by Bangia et al. (2002) and accounts for the exogenous liquidity risk of the underlying stock. Exogenous liquidity risk is proxied by the bid-ask spread and refers to the cost of immediate trading, which results from the liquidity suppliers' purchasing at the bid and selling at the ask price (see Kyle, 1985, Amihud and Mendelson, 1986). Further, C-VaR$_t^j$ denotes the credit-adjustment we propose to account for default risk of the underlying firm. The idea of incorporating credit risk into VaR calculation is based on the fact that stockholders are serviced subordinately to debt holders in case of financial distress and might bear a large portion of the credit losses when default occurs. Note that we base the calculation of C-VaR$_t^j$ on the simplifying assumption that stockholders loose all of their capital invested in a particular firm in the event of default, i.e. they suffer a loss equal to the bid price of the corresponding stock.[38] Thus, we define C-VaR$_t^j$ to be the maximum (expected) credit loss over the next month that will not be exceeded with probability $1 - \theta$.

2.4.2.2 Forecasting LC-VaR: The baseline approach

In our baseline approach, we estimate and forecast portfolio LC-VaR based on a portfolio consisting of six firms from the S&P 500, resulting in an 18-dimensional vector of prices, bid-ask spreads, and default intensities for each trading day in the sample period.[39] The firms included in LC-VaR forecasting are printed in bold type in Appendix A.1 and comprise *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. Portfolio LC-VaR is calculated at a monthly time horizon with a confidence level of 95% (i.e., $\theta = 0.95$). Formally, portfolio LC-VaR forecasts are derived by replacing m_t^j, ${}_k\check{R}_{1,t+1}^j$, ${}_k\check{rs}_{t+1}^j$, b_t^j, and ${}_k\check{p}_{t+1}^j$ in (2.23) and (2.24) with the corresponding portfolio prices, returns, spreads, and intensities calculated using cross-sectional equally-weighted averages.

The marginal models and the dependence model are estimated on an in-sample com-

[38] Note, however, that the potential recovery for stockholders in the event of default is a result from renegotiation between claim holders and depends on the degree of shareholder advantage (see Garlappi et al., 2008). To make C-VaR computation feasible for our purposes, we rely on the assumption of zero stockholder recovery.

[39] That is, we set $d = 6$ and obtain vectors of the form as in (2.18) for each day t.

prising monthly log-differences of prices, bid-ask spreads, and default intensities for the 261 trading days in 2010. The estimated models are then used to forecast LC-VaR numbers for the trading days in January 2011. The in- and out-of-samples are subsequently shifted forward one month and the models are re-estimated based on the period from February 1st, 2010 to February 1st, 2011, where forecasting is now conducted for February 2011. We repeat this procedure ten times, resulting in 230 LC-VaR forecasts for the 230 trading days following January 1st, 2011. The marginal models are re-estimated every day, whereas the dynamic R-vine copula model is re-estimated every month due to computational complexity.

Descriptive statistics on the sample firms' stock prices, bid-ask spreads, and default intensities in levels and log-differences are provided in the Appendix in Tables A.2 and A.3, respectively. The time evolution of the stock returns, bid-ask spreads, and default intensities of the six companies are plotted in Figure 2.3.

The different panels of Figure 2.3 highlight that all six companies in our sample are characterized by volatile stock returns and increasing liquidity. For several sample companies, default intensities exhibit a U-shaped time evolution with default risk reaching its minimum at the start of 2011 and increasing through most of 2011. Furthermore, almost all time series exhibit extreme data points underlining the need to account for the non-linear dependence structure in our data. For example, the shares of *3M Company* plummeted by more than 40% on one day in August 2011 with *American Express*, *Hewlett-Packard*, and *Textron* experiencing losses of similar magnitude on their equity. Quite similarly, the illiquidity of our sample firms' stocks spiked as well during the sample period (see, e.g., the bid-ask spreads of *3M Company* and *Hewlett-Packard* in 2010). Finally, the time series of default intensities are expectedly less volatile than the companies' stock returns but are also characterized by few extreme observations.

Figure 2.3: Time evolution of stock returns, bid-ask spreads, and default intensities of firms included in the Value-at-Risk study.

The figure plots the time series of stock returns, bid-ask spreads, and default intensities for the six firms included in the Value-at-Risk (VaR) study. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The plots refer to the in- and out-of-sample time periods in the VaR study, which cover the period from January 2010 to November 2011. For each day, t, in the sample period, stock returns are calculated using the mid prices at days t and $t-30$. Bid-ask spreads are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 2.3 and have a horizon of one year.

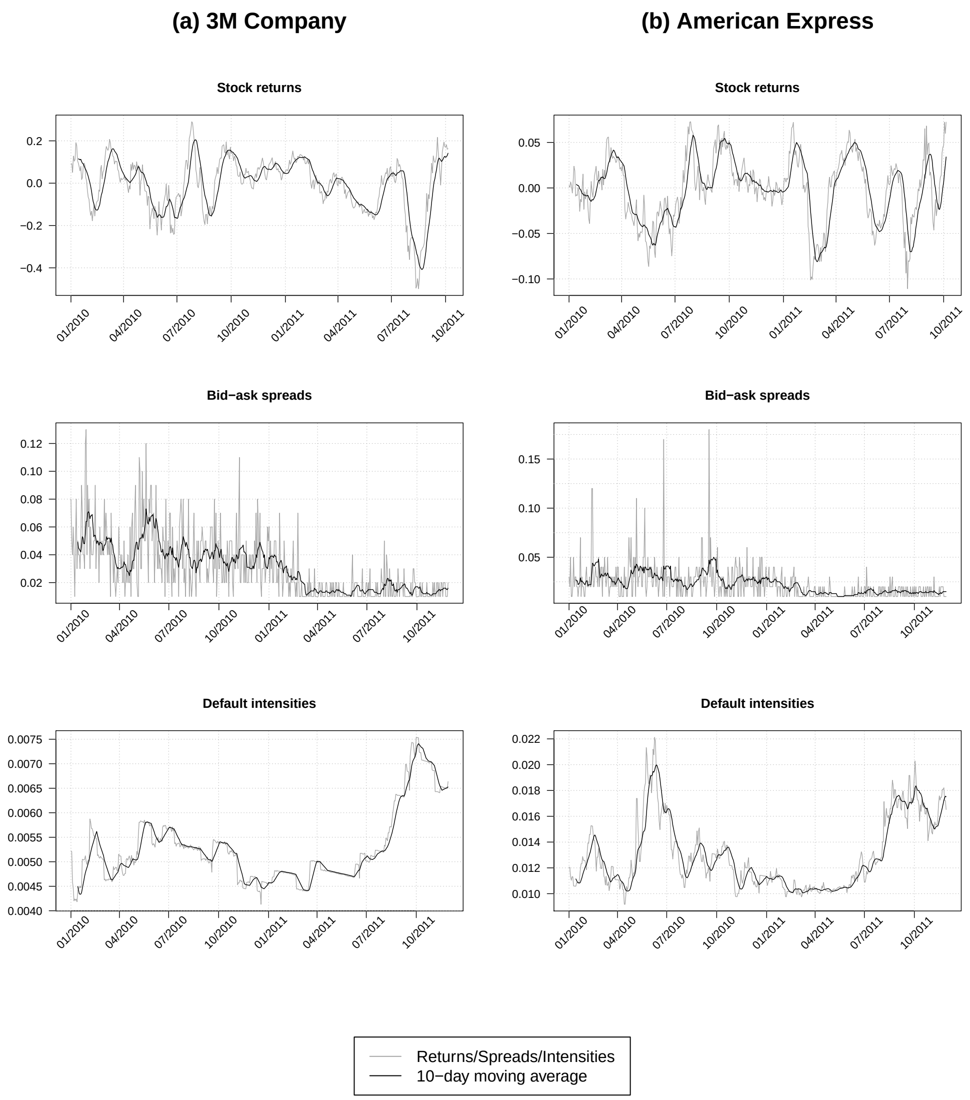


Figure 2.3: Time evolution of stock returns, bid-ask spreads, and default intensities of firms included in the Value-at-Risk study (continued).

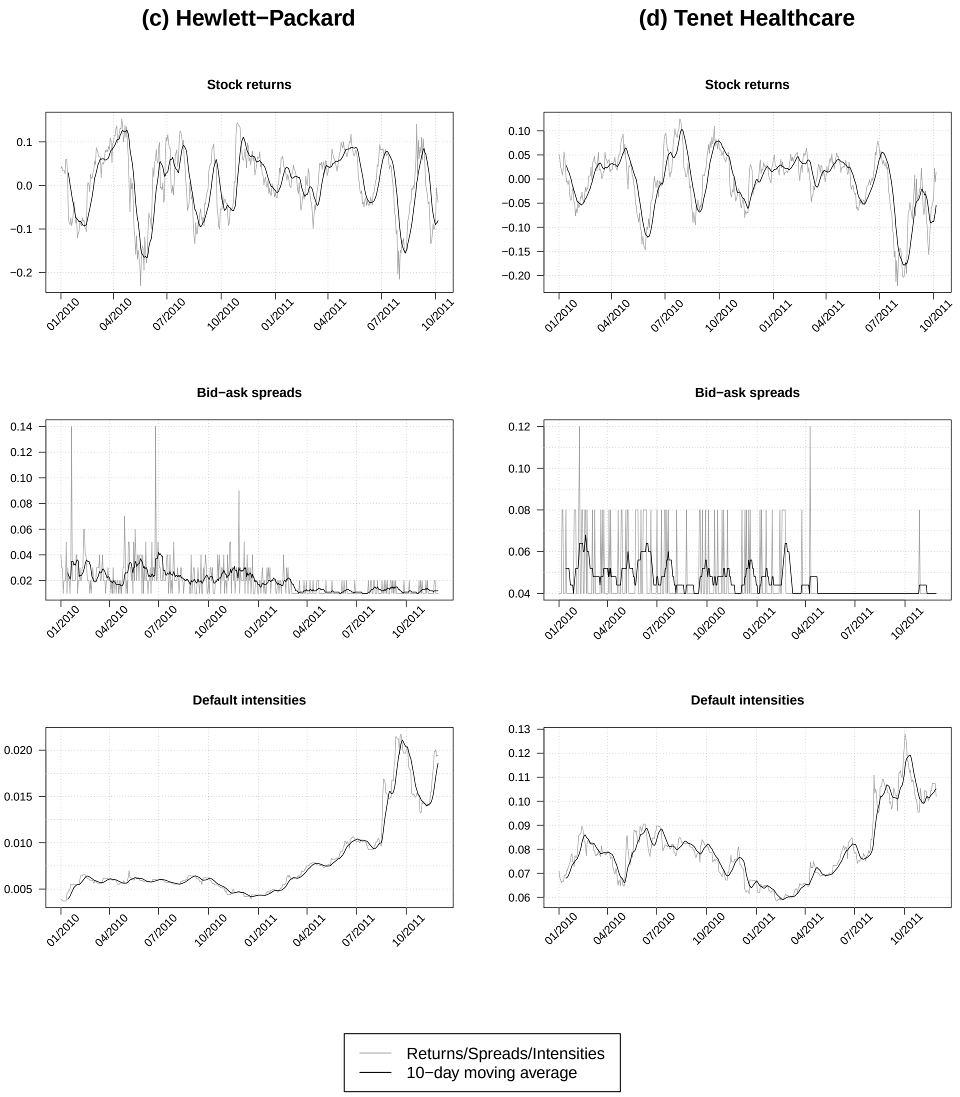
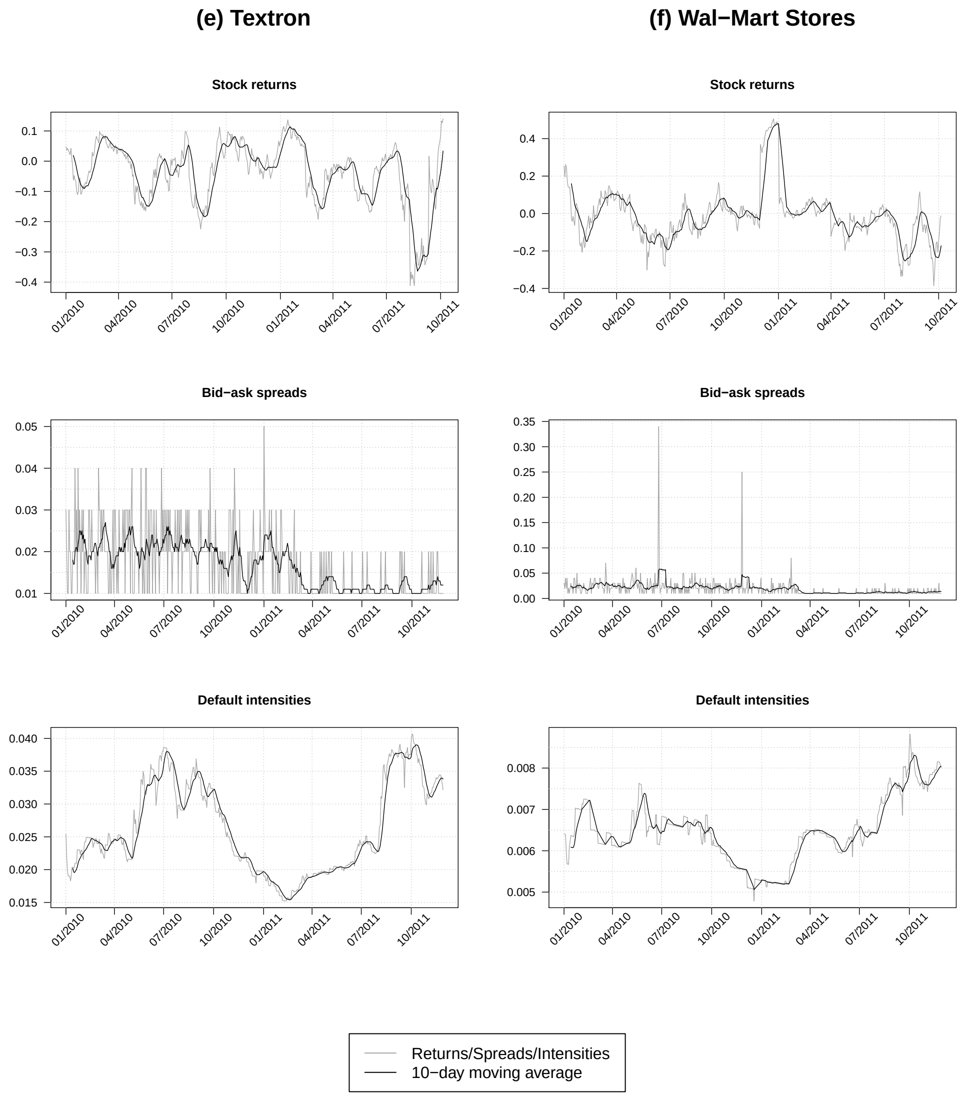


Figure 2.3: Time evolution of stock returns, bid-ask spreads, and default intensities of firms included in the Value-at-Risk study (continued).



In the next step, we shortly comment on the parameter estimates for the marginal models of the six sample companies in our Value-at-Risk study. Average parameter estimates for the marginal distributions of monthly log-differences on daily mid prices, bid-ask spreads, and default intensities are presented in Table 2.4.

The parameter estimates for the mean dynamics show that at least the first two AR lags are strongly significant for stock returns, bid-ask spreads, and default intensities. The results on the Ljung-Box test up to ten lags (denoted as LB(10) test) further indicate that the AR(3) processes are successful in capturing the serial dependence evidenced in Section 2.3. The estimation results for the variance dynamics, on the other hand, are fairly standard. Of particular note are the estimates for the δ parameter which captures asymmetry in volatility. While the δ estimates for stock returns and bid-ask spreads predominantly reveal only mild statistical evidence of asymmetry in volatility, volatility of default intensities appears to be characterized by strong asymmetry across all six firms.[40] Further, the estimates for the skewed t distribution indicate fat tails and slight skewness for the returns, spreads, and intensities of most firms. Finally, to check the adequacy of the variance models, we apply the LB(10) test to the squared standardized GARCH residuals. Impressively, the GJR-GARCH models are able to pick up most of the second-moment dependence inherent in the time-series data, as indicated by the low number of rejections for the LB(10) test. We conclude from Table 2.4 that the marginal AR-GJR-GARCH models are capable of delivering the white-noise residuals required to obtain unbiased estimates for the dependence parameters of our dynamic R-vine copula model.

To get a better understanding of our model's ability to account for non-linear dependences in market price, liquidity, and credit risk, we quickly review the temporal variation in the selected parametric pair-copulas in our dynamic R-vine copula. The percentages of selected parametric bivariate pair-copulas are shown in Table 2.5.

[40] Note, however, that the estimated values for the δ parameter of default intensities are positive throughout the sample firms, which is somewhat counterintuitive since negative AR residuals are associated with good news (see Section 2.2). That is, the positive values imply an upward revision of volatility in response to good news.

Table 2.4: Average parameter estimates for marginal distributions.

The table reports average parameter estimates for the marginal distributions of monthly log-differences on daily mid prices, bid-ask spreads, and default intensities for the six firms investigated in our Value-at-Risk (VaR) study. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The marginal distributions are modeled using AR(3)-GJR-GARCH(1,1) processes with skewed-*t* distributed innovations as discussed in Section 2.2. Starting with an in-sample comprising the 261 trading days in 2010, the estimation period for the marginal models is subsequently shifted forward one day after each VaR forecast, resulting in 230 re-estimations. The parameter estimates shown in the table result from averaging across the re-estimations. Variance persistence (denoted Var. Pers. in the table) is calculated as $\beta + \alpha + \frac{1}{2}\delta$. The last two columns show the number of rejections (at the 0.01 level) across all 230 re-estimations from Ljung-Box tests for serial correlation up to 10 lags as applied to the standardized and squared standardized residuals.

	Mean dynamics				Variance dynamics							#Rej. of LB(10) test	
	μ	ϕ_1	ϕ_2	ϕ_3	ω	β	α	δ	Var. Pers.	ν	γ	Resid.	Sq. Resid.
Panel A: Stock returns													
3M Company	0.9980	0.0238	-0.0762	0.0006	0.0000	0.9190	0.0550	0.0239	0.9859	17.5909	0.8578	0	0
American Express	0.9460	0.0292	-0.0317	0.0001	0.0000	0.9097	0.0305	0.0176	0.9490	11.4982	0.8934	0	7
Hewlett-Packard	0.9328	0.0993	-0.1152	0.0011	0.0000	0.9252	0.0157	0.0599	0.9709	6.6431	0.9982	9	0
Tenet Healthcare	0.9501	0.1252	-0.1455	0.0004	0.0000	0.9620	0.0143	0.0126	0.9826	9.8417	0.8842	2	16
Textron	1.0466	0.0071	-0.1040	-0.0013	0.0000	0.9307	0.0015	0.0801	0.9722	5.2423	1.0024	0	0
Wal-Mart Stores	0.8942	0.0459	0.0090	0.0009	0.0000	0.9931	0.0051	-0.0204	0.9880	3.2150	0.9207	0	0
Panel B: Log-differences of bid-ask spreads													
3M Company	-0.0131	-0.0665	-0.0448	-0.0457	0.0018	0.9807	0.0347	-0.0515	0.9896	3.3627	0.9713	1	0
American Express	0.0189	0.0745	0.1175	-0.0390	0.0029	0.8766	0.0652	0.1195	1.0015	5.5385	0.9406	0	0
Hewlett-Packard	0.1082	-0.0116	-0.0103	-0.0467	0.0092	0.9862	0.0281	-0.0576	0.9855	29.9999	1.0737	0	0
Tenet Healthcare	0.0317	0.0119	0.0467	-0.0763	0.0046	0.9963	0.0055	-0.0196	0.9920	8.9658	1.0573	0	0
Textron	-0.0532	0.0741	0.0498	-0.0490	0.0066	0.9910	0.0249	-0.0637	0.9841	29.8826	1.0429	9	0
Wal-Mart Stores	0.0055	0.0357	-0.1111	-0.0123	0.0568	0.8016	0.2413	-0.1613	0.9623	2.1100	0.8096	0	0
Panel C: Log-differences of default intensities													
3M Company	-0.0545	0.0511	0.0244	0.0005	0.0000	0.8921	0.0035	0.1667	0.9790	3.8639	1.0657	0	0
American Express	-0.2948	-0.1048	0.0061	0.0001	0.0001	0.4055	0.1286	0.3970	0.7326	2.9294	0.9821	0	61
Hewlett-Packard	-0.1336	0.0266	-0.0025	0.0006	0.0001	0.6981	0.0082	0.2532	0.8330	4.0834	1.0327	0	42
Tenet Healthcare	-0.1938	-0.0026	-0.0125	0.0002	0.0001	0.5834	0.0612	0.3558	0.8225	3.0183	0.9840	0	0
Textron	-0.0668	0.0419	0.0231	-0.0011	0.0001	0.7984	0.0000	0.2218	0.9093	3.1483	0.9319	0	0
Wal-Mart Stores	-0.0910	-0.0142	0.0034	0.0008	0.0000	0.9336	0.0025	0.1194	0.9958	2.9655	1.1106	0	0

Table 2.5: Temporal variation of selected parametric pair-copulas.

The table reports results on the selected bivariate parametric pair-copulas in our dynamic R-vine copula model for each estimation period included in our Value-at-Risk (VaR) study. The R-vine copula model is estimated on pseudo-observations of standardized log-differences of mid prices, bid-ask spreads, and default intensities for six firms from the S&P 500, resulting in 153 ($= 18 \cdot 17/2$) parametric pair-copulas that need to be specified and estimated for each R-vine copula estimation. The results in the table show the number of a particular parametric copula family being selected as a percentage of the number of pair-copulas to be specified in each R-vine copula estimation (that is, 153). The candidate copulas include dynamic versions of the standard normal, *t*, (rotated) Clayton, (rotated) Gumbel, and (rotated) Joe copula, where we follow the dynamization approach suggested by Patton (2006) (as outlined in Appendix A). The selection of the bivariate pair-copulas is based on the sequential method as proposed by Dißmann et al. (2013) and conducted using Akaike's Information Criterion (AIC) as the selection criterion to be minimized.

Estimation period	Parametric copula families (in %)							
	Normal	*t*	Clayton	Rotated Clayton	Gumbel	Rotated Gumbel	Joe	Rotated Joe
01/2010 - 01/2011	51.63	12.42	1.31	2.61	8.50	14.38	2.61	6.54
02/2010 - 02/2011	55.56	5.88	1.96	3.92	5.88	9.15	12.42	5.23
03/2010 - 03/2011	51.63	5.88	2.61	0.65	7.84	15.69	3.27	12.42
04/2010 - 04/2011	56.21	11.76	3.27	3.92	5.23	9.80	5.23	4.58
05/2010 - 05/2011	56.21	12.42	1.96	1.96	8.50	11.76	3.92	3.27
06/2010 - 06/2011	57.52	11.11	3.27	5.23	3.27	7.84	5.88	5.88
07/2010 - 07/2011	54.25	7.84	0.00	4.58	9.15	16.99	2.61	4.58
08/2010 - 08/2011	56.21	8.50	3.27	2.61	5.23	13.73	5.23	5.23
09/2010 - 09/2011	48.37	6.54	2.61	3.27	13.73	14.38	7.19	3.92
10/2010 - 10/2011	49.02	8.50	3.27	2.61	11.76	15.03	3.27	6.54

The percentages given in Table 2.5 show that for around 50% of the bivariate pair-copulas, the tail independent normal copula is selected. Between 5.88% to 12.42% of the pair-copulas are modeled using the symmetrically tail dependent Student's *t* copula. Conversely, 30% up to 45% of the pair-copulas are modeled using either upper- or lower-tail dependent copulas underlining the notion that the dependence structure of our data is indeed significantly non-linear and asymmetric. Furthermore, the percentages for several parametric copulas vary considerably during the course of our sample period thus confirming the need to employ time-varying copulas. For example, the upper-tail dependent Gumbel copula is chosen for 8.50% of the pair-copulas for the first of our estimation periods with this percentage plummeting to 3.27% for the period of June 2010 to June 2011 and increasing again to 13.73% for the period of September 2010 to September 2011.

The results so far emphasize that, while much of the dependence inherent in market price, liquidity, and credit risk can be adequately modeled using tail independent normal copulas, the dependence structure of our data is also characterized by significant asymmetric tail dependence. However, our particular estimation approach for the R-vine copulas specifically tries to capture as much dependence as possible in the upper trees of the vine structure. As a consequence, it could be that most of the unconditional dependence in our data is actually linear while the tail dependent parametric copulas are only selected in lower (less important) trees in which the conditional dependence is modeled. To answer this question, Table 2.6 presents corresponding percentages of selected parametric pair-copulas separately by the respective tree in the R-vine model.

The results of Table 2.6 show an opposite picture. The normal copula is selected for only 35.88% of the pair-copulas in the first tree while the vast majority of bivariate (unconditional) data pairs are modeled using tail dependent parametric copulas.[41] In the lower trees of the R-vines, the percentage for the normal copula increases up to 65% while several of the tail dependent parametric copulas are no longer selected.

[41] In Table A.4 in the Appendix, we additionally tabulate the selected parametric pair-copulas in the first R-vine tree for all bivariate data pairs.

Table 2.6: Treewise selection of parametric pair-copulas.

The table reports average results on the treewise selection of bivariate parametric pair-copulas in our dynamic R-vine copula model across the estimation periods included in our Value-at-Risk (VaR) study. The R-vine copula model is estimated on pseudo-observations of standardized log-differences of mid prices, bid-ask spreads, and default intensities for six firms from the S&P 500, resulting in 153 ($= 18 \cdot 17/2$) parametric pair-copulas that need to be specified and estimated for each R-vine copula estimation. The 18-dimensional R-vine copula is composed of 17 trees, where copula selection is based on the sequential method as proposed by Dißmann et al. (2013) and conducted using Akaike's Information Criterion (AIC) as the selection criterion to be minimized. Each tree, i, requires the selection and estimation of $18 - i$ bivariate parametric pair-copulas. The results in the table show the number of a particular parametric copula family being selected in tree i, $i = 1, ..., 17$, as a percentage of the total number of pair-copulas to be specified in tree i (that is, $18 - i$). The resulting percentages are averaged across all ten re-estimations conducted in our VaR study (see Section 2.4). The candidate copulas include dynamic versions of the standard normal, t, (rotated) Clayton, (rotated) Gumbel, and (rotated) Joe copula, where we follow the dynamization approach suggested by Patton (2006) (as outlined in Appendix A).

Tree	Parametric copula families (in %)							
	Normal	t	Clayton	Rotated Clayton	Gumbel	Rotated Gumbel	Joe	Rotated Joe
1	35.88	18.82	0.59	1.18	7.06	22.94	1.76	11.76
2	46.88	5.00	5.00	2.50	11.25	12.50	6.88	10.00
3	57.33	8.00	0.00	9.33	10.00	10.00	2.67	2.67
4	47.14	15.00	3.57	2.86	5.71	17.86	4.29	3.57
5	52.31	11.54	3.85	0.77	9.23	13.85	1.54	6.92
6	55.00	9.17	1.67	1.67	9.17	10.00	8.33	5.00
7	56.36	10.00	4.55	3.64	6.36	8.18	5.45	5.45
8	62.00	9.00	1.00	6.00	3.00	9.00	6.00	4.00
9	64.44	7.78	1.11	3.33	7.78	6.67	5.56	3.33
10	62.50	1.25	5.00	1.25	3.75	11.25	10.00	5.00
11	61.43	7.14	1.43	0.00	11.43	11.43	4.29	2.86
12	61.67	1.67	0.00	1.67	6.67	13.33	8.33	6.67
13	52.00	6.00	4.00	4.00	8.00	12.00	10.00	4.00
14	65.00	5.00	0.00	2.50	10.00	10.00	5.00	2.50
15	56.67	3.33	3.33	3.33	10.00	13.33	3.33	6.67
16	65.00	0.00	0.00	5.00	5.00	15.00	5.00	5.00
17	50.00	0.00	0.00	10.00	10.00	20.00	10.00	0.00

These results further underline our finding that our data indeed exhibit strong non-linear dependence.

We now turn to the main results of our VaR study in which we intend to calculate LC-VaR forecasts for the portfolio profits and losses (P/L) at time t, $\mathrm{PL}_t^{\mathrm{pf}}$. The portfolio P/L are calculated according to

$$\mathrm{PL}_t^{\mathrm{pf}} = b_t - a_{t-1}, \tag{2.25}$$

where b_t and a_t denote the portfolio bid and ask price, respectively. The actual portfolio P/L are then compared to the LC-VaR forecasts estimated at a confidence level of $\theta = 0.95$ using monthly log-differences of mid prices, bid-ask spreads, and default intensities. In Figure 2.4, we plot the realized out-of-sample portfolio P/L against the corresponding LC-VaR forecasts calculated from our dynamic R-vine copula model.

In Panel (a) of Figure 2.4, we first plot the realized portfolio P/L against the estimated LC-VaR forecasts for the out-of-sample period that covers the full year 2011. The plot shows that our LC-VaR forecasts stay relatively close to the realized P/L throughout the out-of-sample. Even more importantly, the LC-VaR estimates appear to capture the downward movements of the portfolio P/L quite adequately without underestimating portfolio risk. This last finding is emphasized by the plot in Panel (b) in which we illustrate the distance between the realized portfolio P/L and the LC-VaR forecasts as well as the LC-VaR exceedances. First, we note that the distances between the P/L and the LC-VaR in case the LC-VaR is not exceeded are relatively small throughout the out-of-sample. Consequently, companies employing the LC-VaR based on our dynamic R-vine copula model are able to limit their excess regulatory capital derived from the LC-VaR forecasts. At the same time, the distances are also small to non-existent in case the portfolio losses exceeded the LC-VaR. Our model thus appears to produce small Expected Shortfall estimates as well. Second, our R-vine model also seems to forecast portfolio P/L quite adequately based on the number of times the portfolio losses exceed the respective daily LC-VaR forecast. This second finding is highlighted in Panel (c) of Figure 2.4 in which we only plot the losses that exceed the LC-VaR forecasts.

Our analysis so far has shown that the LC-VaR forecasts from our dynamic R-vine copula model adequately predict portfolio losses. Consequently, our results support the notion that integrating information on the dependence between market price, liquidity, and credit risk into a VaR model is vital for accurate risk forecasting. However, we cannot rule out the possibility that the LC-VaR forecasts we estimate solely capture market price risk and that the effect of liquidity and credit risk is negligible. If this were the case, the good fit of our LC-VaR model would simply be due to chance as it simply forecasts market price risk employing a significant amount of redundant information on liquidity and credit risk. Figure 2.5 shows that the opposite is true.

In Figure 2.5, we decompose the LC-VaR forecasts into their market price (VaR), liquidity risk (L-VaR) and credit risk component (C-VaR) and plot the time evolution of the three components. The upper Panel (a) of Figure 2.5 compares the time evolution of the standard market price VaR of our stock portfolio to the LC-VaR forecasts. As expected, the LC-VaR forecasts predominantly consist of the standard VaR with the market price component. However, a significant part of the LC-VaR forecasts (1% to 5%) are due to the liquidity and/or credit components. The plot for the liquidity component given in Panel (b) shows that liquidity risk plays a significant role in the forecasting of LC-VaR as the liquidity component accounts for up to 2.5% of the LC-VaR forecasts. Furthermore, the percentage of the liquidity component of the LC-VaR shows only little time variation and decreases during the course of our out-of-sample.[42] Finally, Panel (c) of Figure 2.5 shows that up to 2% of the absolute LC-VaR forecasts are due to credit risk. More importantly, the relative weight of the credit component in the LC-VaR forecasts varies significantly during our sample period, thus again underlining the need to account for the time dynamics in market price and credit risk.

[42]This finding again reflects the increase in the overall liquidity of stocks during our sample period as shown in Figure 2.3.

Figure 2.4: Realized portfolio losses and Value-at-Risk forecasts.

The figure shows the realized out-of-sample portfolio profits and losses (P/L) on our sample portfolio as well as the forecasts of liquidity- and credit-adjusted Value-at-Risk (LC-VaR) calculated from our dynamic R-vine copula model. The portfolio P/L at time t, $\mathrm{PL}_t^{\mathrm{pf}}$, is calculated according to $\mathrm{PL}_t^{\mathrm{pf}} = b_t - a_{t-1}$, where b_t and a_t denote the portfolio bid and ask price, respectively. The sample portfolio is composed of six firms from the S&P 500 including *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The forecasting period covers the 230 trading days following January 1st, 2011. Starting with an in-sample comprising the 261 trading days in 2010 and an out-of-sample covering January 2011, the in- and out-of-samples are shifted forward one month with the R-vine copula model being re-estimated. LC-VaR forecasts are calculated at a confidence level of $\theta = 0.95$ based on monthly log-differences of mid prices, bid-ask spreads, and default intensities.

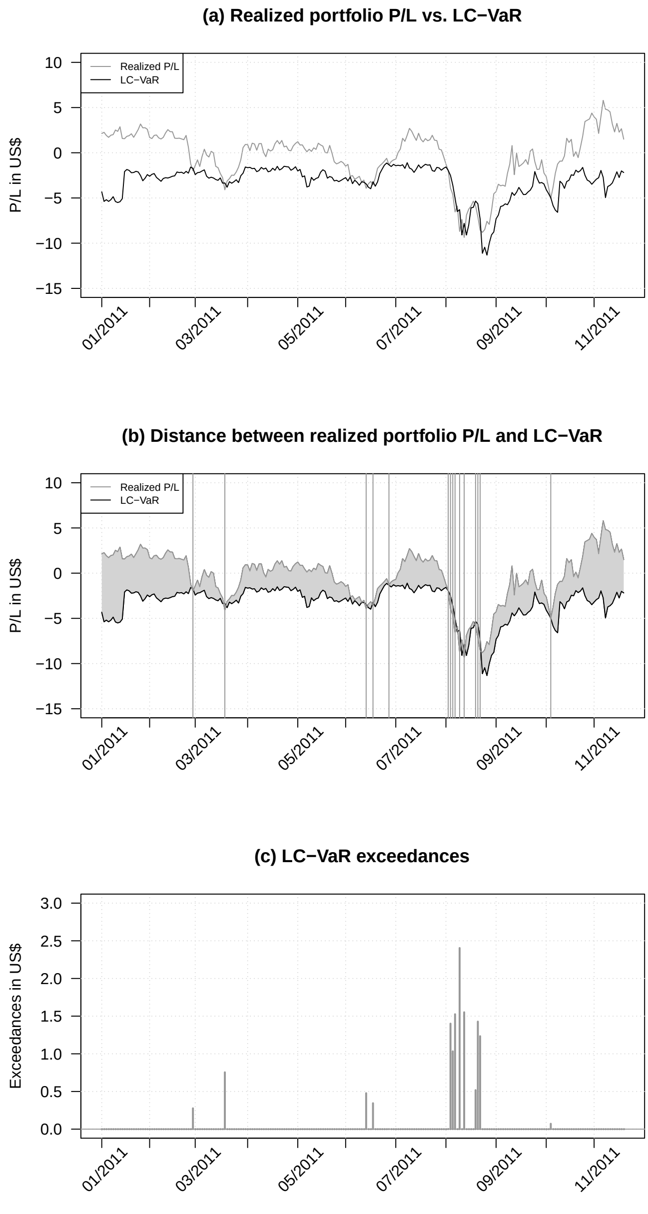
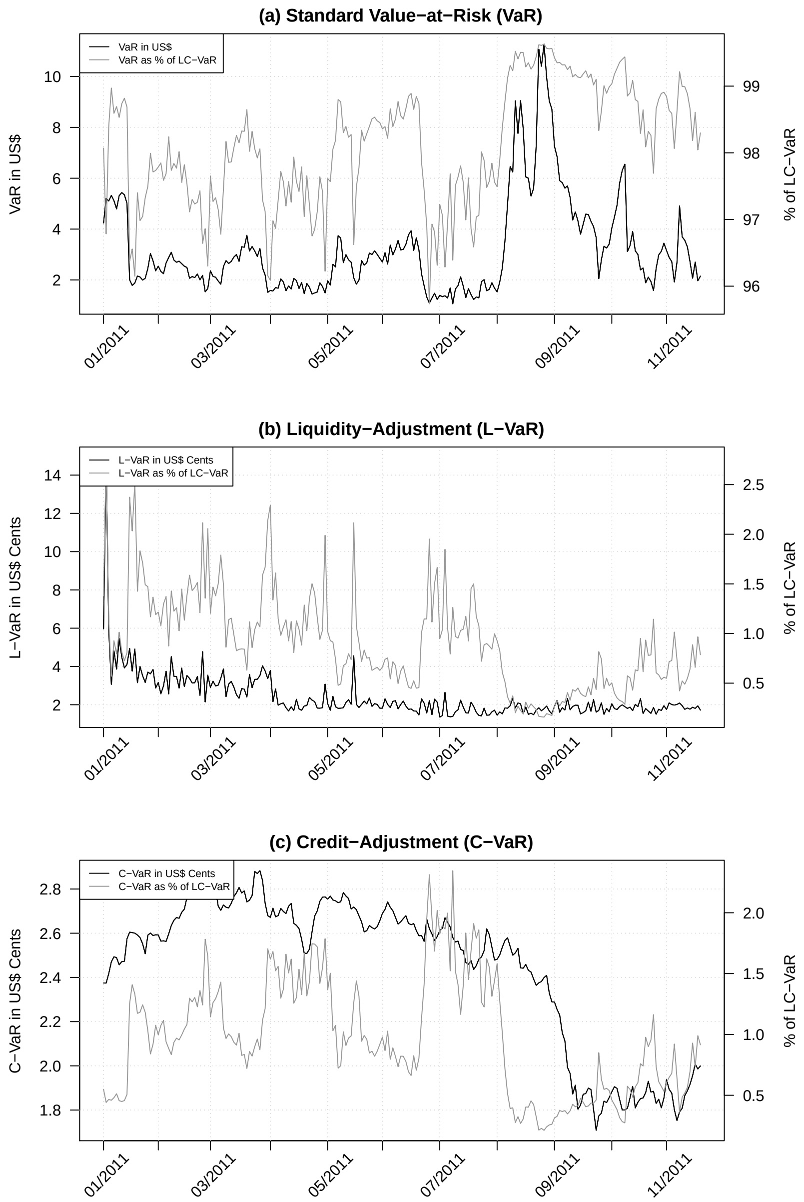


Figure 2.5: Decomposing liquidity- and credit-adjusted Value-at-Risk.

The figure presents the time evolution for the market price (VaR), liquidity (L-VaR), and credit component (C-VaR) of liquidity- and credit-adjusted Value-at-Risk (LC-VaR) forecasts. LC-VaR forecasts are computed from the our dynamic R-vine copula model at a confidence level of $\theta = 0.95$ based on monthly log-differences of mid prices, bid-ask spreads, and default intensities for the six firms in our sample portfolio. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The forecasting period covers the 230 trading days following January 1st, 2011. Starting with an in-sample comprising the 261 trading days in 2010 and an out-of-sample covering January 2011, the in- and out-of-samples are shifted forward one month with the R-vine copula model being re-estimated.



2.4.2.3 Neglecting dynamics and non-linearities in dependence

In the last part of our empirical study, we address the question whether the additional flexibility of using (a) a dynamic instead of a static model and (b) a copula instead of a correlation-based model is indeed necessary for accurate risk forecasting. To this end, we compare the forecasting accuracy of our proposed dynamic R-vine copula model to that of a static R-vine model as well as Engle's (2002) DCC model.

As a first step, we compare the realized out-of-sample portfolio profits and losses on our sample portfolio with the forecasts of the LC-VaR calculated from the respective dependence model. Here, we are especially interested in documenting the differences of both dependence models relating to the portfolio profits and losses in our sample. The results of this comparison are presented in Figure 2.6.

The upper parts of Panels (a) and (b) of Figure 2.6 plot the realized profits and losses of our portfolio against the LC-VaR forecasts estimated from our static R-vine copula and DCC model, respectively. The plots show that for both models, the LC-VaR forecasts stay relatively close to the realized portfolio losses. This finding is confirmed by the middle plots in both panels in which we illustrate the distances between the realized portfolio P/L and the LC-VaR forecasts. Compared to the corresponding plots for our dynamic R-vine copula model, however, both models appear to be more conservative as both the distances between the realized P/L and the LC-VaR forecasts are larger and the number of VaR-exceedances are (unnecessarily) smaller.[43] This finding is confirmed in a direct comparison of the different models. The results of this comparison are plotted in Figure 2.7.

The plots presented in Figure 2.7 clearly show that both the static vine copula and the DCC model overestimate portfolio risk to a significant degree. While both models yield LC-VaR forecasts that are exceeded on only few trading days, our dynamic R-vine copula model produces forecasts that not only adequately capture extreme losses

[43] In untabulated results, we further check the forecasting accuracy of all three models by performing tests of the models' conditional coverage (see Christoffersen and Pelletier, 2004). The results of these tests show that none of the models is rejected.

but also limit the use of (regulatory) capital. Neglecting the time dynamics and non-linearities in the dependence structure between market price, liquidity, and credit risk thus leads to an excessive allocation of capital that is not needed and that ultimately leads to unnecessarily high capital costs. In fact, the cumulative difference between our dynamic R-vine copula and the static R-vine alternative increases to more than 200 USD at the end of our out-of-sample period showing the economically highly significant potential to limit capital costs. Furthermore, as evidenced by Panel (c) of Figure 2.7, accounting for time variation in the dependence structure of the three LC-VaR components seems to be more important than accounting for non-linear dependence.

Figure 2.6: Realized portfolio losses and Value-at-Risk forecasts from alternative dependence models.

The figure shows the realized out-of-sample portfolio profits and losses (P/L) on our sample portfolio as well as the forecasts of liquidity- and credit-adjusted Value-at-Risk (LC-VaR) calculated from alternative dependence models. The alternative dependence models include a static R-vine copula model as well as Engle's (2002) Dynamic Conditional Correlation (DCC) model. The portfolio P/L at time t, $\mathrm{PL}_t^{\mathrm{pf}}$, is calculated according to $\mathrm{PL}_t^{\mathrm{pf}} = b_t - a_{t-1}$, where b_t and a_t denote the portfolio bid and ask price, respectively. The sample portfolio is composed of six firms from the S&P 500 including *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The forecasting period covers the 230 trading days following January 1st, 2011. Starting with an in-sample comprising the 261 trading days in 2010 and an out-of-sample covering January 2011, the in- and out-of-samples are shifted forward one month with the dependence models being re-estimated every day. LC-VaR forecasts are calculated at a confidence level of $\theta = 0.95$ based on monthly log-differences of mid prices, bid-ask spreads, and default intensities.

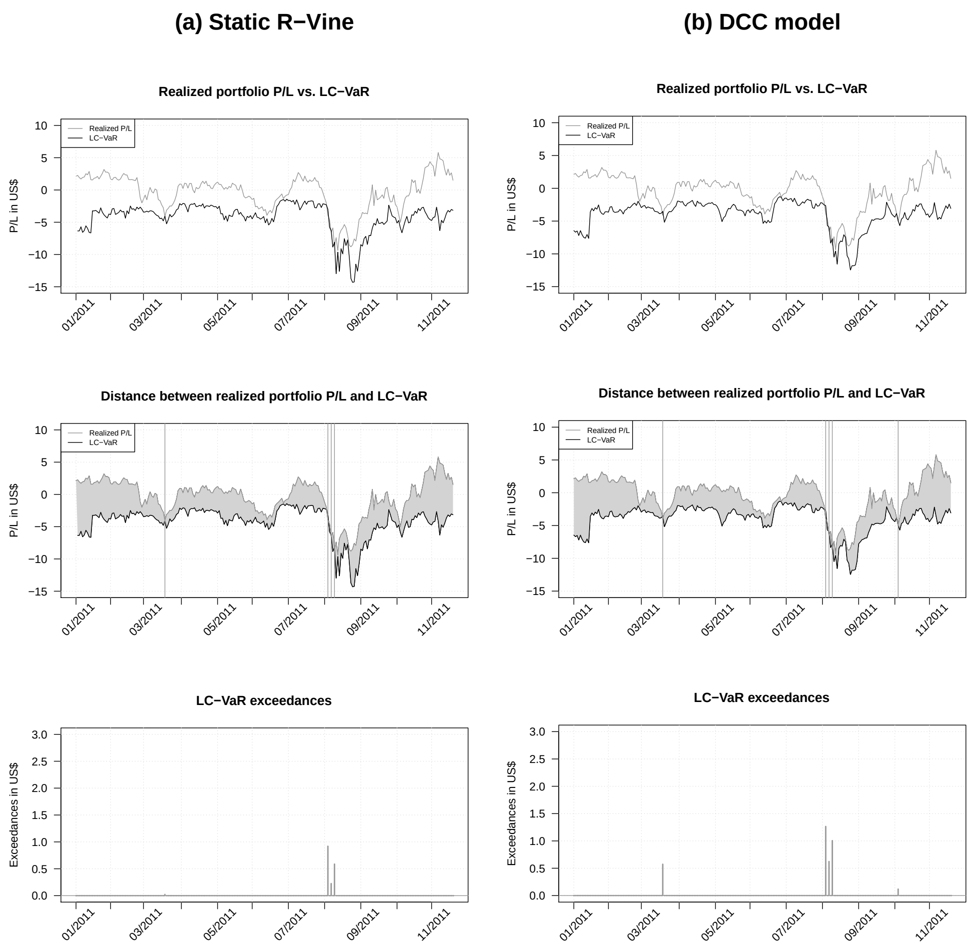


Figure 2.7: Dynamic R-vine copula model versus alternative dependence models.

The figure compares the liquidity- and credit-adjusted Value-at-Risk (LC-VaR) forecasts from the dynamic R-vine copula model to the LC-VaR forecasts from the static R-vine copula model and Engle's (2002) Dynamic Conditional Correlation (DCC) model. LC-VaR forecasts are calculated at a confidence level of $\theta = 0.95$ based on monthly log-differences of mid prices, bid-ask spreads, and default intensities of six firms from the S&P 500 including *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The forecasting period covers the 230 trading days following January 1st, 2011. Starting with an in-sample comprising the 261 trading days in 2010 and an out-of-sample covering January 2011, the in- and out-of-samples are shifted forward one month with the dynamic R-vine model and the alternative dependence models being re-estimated every month and every day, respectively. Portfolio profits and losses (P/L) at time t, $\mathrm{PL}_t^{\mathrm{pf}}$, are calculated according to $\mathrm{PL}_t^{\mathrm{pf}} = b_t - a_{t-1}$, where b_t and a_t denote the portfolio bid and ask price, respectively.

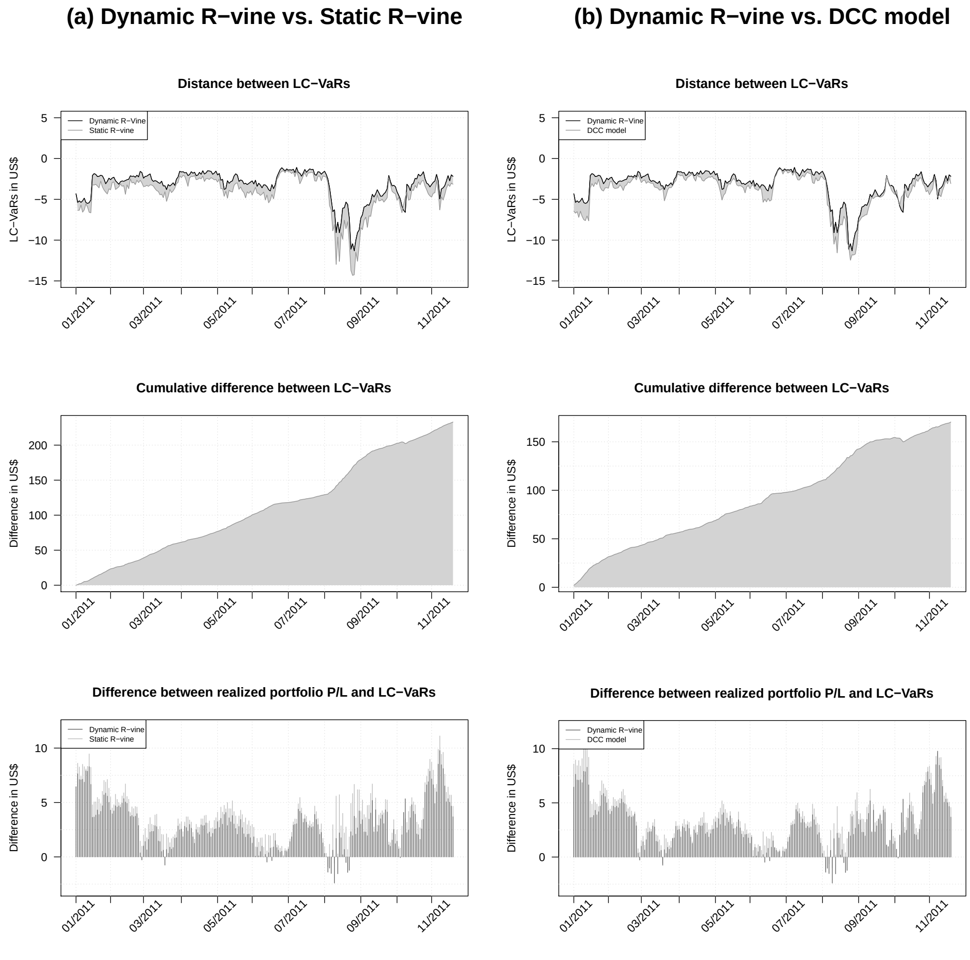
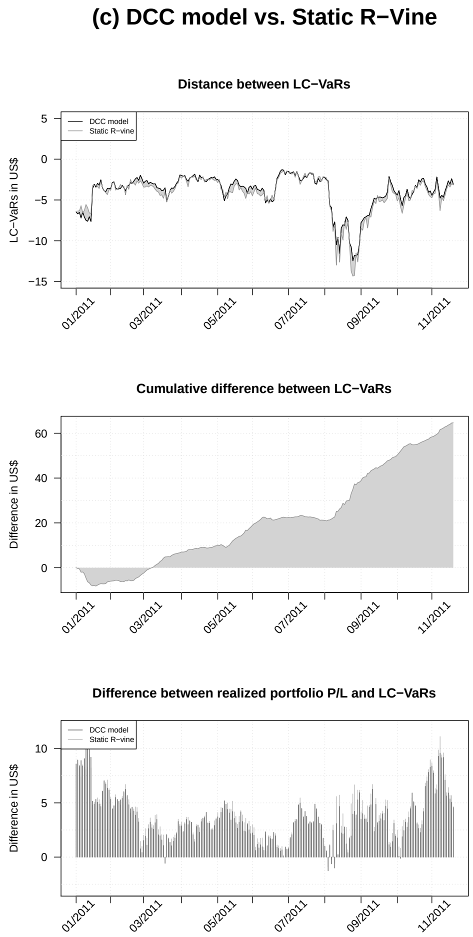


Figure 2.7: Dynamic R-vine copula model versus alternative dependence models (continued).



2.5 Conclusion

In this paper, we present first empirical evidence of persistent and time-varying asymmetric extreme dependence in equity prices, liquidity, and credit risk. We propose to use dynamic R-vine copulas to model the joint distribution of the market price, liquidity, and credit risk of a multivariate stock portfolio at the security-level. Our model is extremely flexible yet at the same time still tractable even for high-dimensional multivariate distributions and accounts for possible time variation in a distribution's linear and non-linear dependence structure. Using the dynamic R-vine copula model, we document the existence of significant time-varying tail dependence between the returns, the liquidity, and the default intensities of companies listed in the S&P 500. While non-linear dependence has been shown to exist in stock returns and between individual stock and market liquidity, this paper is the first to confirm that the joint distribution of equity returns, liquidity, and default risk is characterized by strong tail dependence as well.

We then propose a liquidity- and credit-adjusted Value-at-Risk (LC-VaR) that not only accounts for market price risk, but also for sudden peaks in illiquidity and default probabilities. Using a portfolio of six companies from the S&P 500, we forecast the portfolio's LC-VaR with the help of our dynamic R-vine copula model. Not only do we find the LC-VaR forecasts to adequately capture downside risk, we also find our dynamic R-vine copula model to significantly outperform static vine copula or dynamic correlation-based models. While both benchmarks overestimate portfolio risk, our dynamic R-vine model significantly saves on risk capital while at the same time yielding an acceptable number of VaR-violations.

Although our empirical study primarily deals with risk forecasting, our main finding is not limited to the field of risk management. In fact, our proposed dynamic R-vine copula model can be used in any context in financial economics in which one wishes to model the dynamic tail dependence in a high-dimensional data set. Consequently, future research should address the question whether dynamic R-vines are (economically) significantly superior to static or correlation-based models in other application like, e.g., asset pricing studies in the spirit of Ruenzi et al. (2013), Ruenzi and Weigert (2013), and Meine et al. (2015).

Chapter 3

Systemic Risk of Insurers Around the Globe

"SIFIs are financial institutions whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity."

Financial Stability Board, 11/04/2011

3.1 Introduction

At the climax of the financial crisis of 2007-2009, American International Group (AIG) became the first example of an insurance company that required (and received) a bailout due to it being regarded as systemically important. Not only did AIG's near-collapse come to the surprise of most economists who considered systemic risk to be confined to the banking sector, but it also spurred a realignment of insurance regulation towards a macroprudential supervision of so-called global systemically important insurers (G-SIIs). As a consequence, the Financial Stability Board (FSB) together with the International Association of Insurance Supervisors (IAIS) recently published a list of nine G-SIIs which will ultimately face higher capital and loss absorbency requirements. In their methodology, insurers are deemed to be of systemic relevance to the global financial sector, if they are of such size and global interconnectedness that their default would cause severe disruptions in the financial sector and subsequently the real economy.

However, the (heavily criticized)[44] methodology proposed by the IAIS has only undergone limited empirical scrutiny so far. Most importantly, the relation between the interconnectedness and systemic risk of insurers has not been analyzed before. In this paper, we intend to fill this gap in the literature by investigating whether the interconnectedness of insurers with the global financial sector in addition to their size increased the insurers' individual contribution to systemic risk. As the main result of our analysis of a panel of global insurers from 2000 to 2012, we find that interconnectedness only increases the systemic vulnerability of large life and non-life insurers. In contrast, the impact of an insurer's interconnectedness on its contribution to systemic risk is much less clear.

Economists have long neglected the potential of the insurance sector to destabilize the whole financial system. In contrast to banks, insurers are not subject to depositor runs and thus do not face the risk of a sudden liquidity drain,[45] hold more capital (see Harrington, 2009) and are less interconnected horizontally with the rest of the financial sector. However, the case of American International Group (AIG) showed that insurers can become systemically important nonetheless if they engage too heavily in business activities outside the traditional insurance sector. As a consequence, the Financial Stability Board urged the IAIS to identify G-SIIs that could potentially destabilize the global financial sector and to implement new regulation for these insurers. Building on the experiences made during the AIG case, the IAIS (2013) recently published a proposal for a methodology for identifying G-SIIs that cites non-core and non-insurance activities, insurer size and interconnectedness as the major drivers of systemic risk in

[44] For example, the Secretary General of the Geneva Association, John Fitzpatrick, criticized the IAIS indicators for penalizing risk diversification.

[45] Although one could possibly think of an "insurer run" on life insurance policies, this possibility appears to be highly unlikely as insurance customers are often protected by guarantees and as cancelling a long-term life insurance policy often implies the realization of severe losses. Consequently, there exists no example of a default of an insurer in the past that caused significant contagion effects (see, e.g., Eling and Pankoke, 2014).

the insurance industry.

Both the question whether insurers can actually become systemically important and the question whether the IAIS's proposed methodology is suitable for identifying G-SIIs remain relatively unanswered in the literature. Early treatments of the topic of systemic risk in insurance include the works by Acharya et al. (2009), Harrington (2009) and Cummins and Weiss (2014).[46] In the latter, it is hypothesized that non-core activities and high degrees of interconnectedness are the primary causes of insurers' systemic relevance. The interconnectedness of insurers is also empirically analyzed by Billio et al. (2012) who argue that illiquid assets of insurers could create systemic risks in times of financial crisis. In a related study, Baluch et al. (2011) conclude that systemic risks exist in the insurance sector even though they are smaller than in banking. More importantly, systemic risk in insurance appears to have grown partly as a consequence to the increasing interconnectedness of insurers and their activities outside the traditional insurance business. Chen et al. (2014) put a special emphasis on the insurance sector but find in their analysis of credit default swap and intraday stock price data that the insurance sector is exposed but does not contribute to systemic risks in the banking sector. While the former two studies are only concerned with the interconnectedness of banks and insurers, Weiß and Mühlnickel (2014) also study the impact of size, leverage and other idiosyncratic characteristics included in the IAIS methodology on the systemic risk exposure and contribution of U.S. insurers during the financial crisis.[47] Most importantly, they find that insurer size seems to have been a major driver of the systemic risk exposure and contribution of U.S. insurers. Several of the IAIS indicators (like, e.g., geographical diversification), however, do not appear to be significantly related to the systemic risk of insurers. Finally, Weiß and Mühlnickel (2015) support the too-big-to-fail conjecture for insurers by showing that insurer mergers tend to increase the systemic risk of the acquiring insurers.

[46] Other analyses of systemic risk in insurance include the works of Eling and Schmeiser (2010), Lehmann and Hofmann (2010) and van Lelyveld et al. (2011).

[47] In a related study, Cummins and Weiss (2014) analyze the characteristics of U.S. insurers that are systemically important based on the insurers' SRISK (see Acharya et al., 2012).

We complement the existing empirical literature on systemic risk in insurance by performing the first panel regression analysis of the systemic risk exposure and contribution of international insurers. In particular, we test hypotheses that size and interconnectedness could drive the systemic importance of international insurers. To measure an insurer's exposure and contribution to the fragility of the financial sector, we follow Anginer et al. (2014b,a) and Weiß and Mühlnickel (2015, 2014) and employ the Marginal Expected Shortfall (MES) of Acharya et al. (2010) and ΔCoVaR methodology of Adrian and Brunnermeier (2015), respectively. We then estimate these measures for a sample of 253 international life and non-life insurers for the period from 2000 to 2012 and perform panel regressions of the quarterly MES and ΔCoVaR estimates. As independent variables, we use insurer-specific and macroeconomic variables that have been discussed in the literature as potential drivers of systemic risk. Most importantly, we employ the measure of interconnectedness proposed by Billio et al. (2012) which is based on a principal component analysis of the stock returns of financial institutions.[48]

Based on a sample of 253 life and non-life insurers, we find systemic risk in the international insurance sector to be small in comparison to previous findings in the literature for banks. However, confirming the results of Baluch et al. (2011), we find a strong upward trend in both the exposure and contribution of insurers to the fragility of the global financial system during the financial crisis. In our panel regressions, we find the interconnectedness of large insurers with the financial sector to be a significant driver of the insurers' exposure to systemic risk. In contrast, the contribution of insurers to systemic risk appears to be primarily driven by the insurers' size and leverage.

The remainder of this article is structured as follows. Section 3.2 introduces the data and the methodology used in our empirical study. Section 3.3 presents the results of our investigation into the determinants of systemic risk in the insurance industry.

[48] Other potential measures of the interconnectedness of financial institutions include the measures proposed by Billio et al. (2012) and Chen et al. (2014) which are both based on Granger causality tests.

Concluding remarks are given in Section 3.4.

3.2 Data

This section describes the construction of our sample and presents the choice of our main independent variables as well as descriptive statistics of our data.

3.2.1 Sample construction

We construct our data sample by first selecting all publicly listed international insurers from the dead and active firm lists in *Thomson Reuters Financial Datastream*. For reasons of relevance, we concentrate on insurance firms with total assets in excess of $ 1 billion at the end of 2000. We then omit all firms for which stock price data are unavailable in *Datastream*. Next, we exclude all secondary listings and nonprimary issues from our sample. Further, we exclude Berkshire Hathaway which is listed as an insurance company in *Datastream* due to its unusually high stock price. Balance-sheet and income statement data are retrieved from the *Thomson Worldscope* database and all stock market and accounting data are collected in U.S. dollars to minimize a possible bias in our results stemming from currency risk.

Finally, we split our data sample into life and non-life insurers. The definition of life and non-life insurance companies in the company lists of *Datastream* is somewhat fuzzy.[49] Therefore, the industry classification of *Datastream* is cross-checked with the firms' SIC code (Worldscope data item WC07021, SIC codes 6311, 6321, 6331) and the Industry Classification Benchmark (ICB) code (Worldscope data item WC07040, ICB supersector 8500) to exclude firms which cannot be clearly classified as life or non-life insurance companies.[50] Additionally, all company names are manually screened for words suggesting a non-insurance nature of the companies' business and the respective companies being excluded from the sample. In total, we end up with

[49]For example, several medical service plans and medical wholesale companies are listed as life insurance companies in *Datastream*'s company lists.

[50]Consequently, HMO, managed care and title insurance companies are not included in the final sample.

an international sample of 253 insurers, containing 112 life insurers and 141 non-life insurers. For increased transparency, the names of all insurers in our sample are listed in Appendix B.1.

In the following subsections, we define and discuss the different dependent and independent variables we use in our empirical study. An overview of all variables and data sources is given in Appendix B.2.

3.2.2 Systemic risk measures

Our analysis focuses on the exposure and contribution of individual insurers to the systemic risk of the global financial sector during the period 2000 through 2012. Consequently, we employ an insurer's Marginal Expected Shortfall (MES), Systemic Risk Index/Capital Shortfall (SRISK) and ΔCoVaR as main dependent variables in our regression analyses. We estimate the three measures of systemic risk for each quarter in our sample using daily stock market data for our sample insurers. Our choice of these systemic risk measures is motivated by the fact that these measures have been extensively discussed in the literature and are also used by regulators and central banks for monitoring financial stability (see Benoit et al., 2013).[51] As our first measure of systemic risk, we use the quarterly Marginal Expected Shortfall which is a static structural form approach to measure an individual insurers' *exposure* to systemic risk. It is defined by Acharya et al. (2010) as the negative average return on an individual insurer's stock on the days a market index experienced its 5% worst outcomes. As a proxy for the market's return, we use the World Datastream Bank Index in our main analysis.

Next, we implement the ΔCoVaR method proposed by Adrian and Brunnermeier (2015), which is based on the tail covariation between the returns of individual financial institutions and the financial system. We use ΔCoVaR as an additional measure of an insurer's *contribution* to systemic risk as Adrian and Brunnermeier (2015) criticize

[51] All three systemic risk measures we employ share the property that they are all based on economic theory and capture different aspects of systemic risk. Since the recent financial crisis, several other measures of systemic risk have been proposed in the literature. Further examples for such measures apart from those used in this study are due to De Jonghe (2010), Huang et al. (2012), Schwaab et al. (2011), Hautsch et al. (2015), Hovakimian et al. (2012) and White et al. (2015).

the MES measure for not being able to adequately address the procyclicality that arises from contemporaneous risk measurement.[52] While the unconditional ΔCoVaR estimates are constant over time, the conditional ΔCoVaR is time-varying and estimated using a set of state variables that capture the evolution of tail risk dependence over time. However, since we calculate ΔCoVaR based on stock prices for a given quarter, the standard state variables used for estimating the conditional CoVaR show almost no time-variation. Consequently, we focus on estimating the unconditional version of ΔCoVaR in our analysis. An insurer's contribution to systemic risk is then measured as the difference between CoVaR conditional on the insurer being under distress and the CoVaR in the median state of the institution. A lower value of ΔCoVaR indicates a higher contribution to systemic risk, while a positive MES indicates an exposure to systemic risk rather than a stabilizing effect.

As our third systemic risk measure, we use SRISK which attempts to measure the expected capital shortfall of a firm. SRISK is given as the average quarterly estimate of the Systemic Risk Index as proposed by Acharya et al. (2012) and Brownlees and Engle (2015). An insurer's SRISK is estimated by the insurer's book value of debt weighted with a regulatory capital ratio (set to 8%) plus the weighted long run Marginal Expected Shortfall multiplied by the insurer's market value of equity.

3.2.3 Explanatory variables

In this subsection, we characterize the main independent variables we use in our panel regressions and robustness checks later on. In our analysis we attempt to capture the key features that make insurers become systemically relevant. We thus concentrate on the factors that have recently been suggested by the IAIS (2011, 2013) as potential sources of systemic risk in insurance. We therefore include in our regressions proxies for an insurer's size, its capital structure, non-core activities, and interconnectedness with the financial system.

[52]Conversely, Acharya et al. (2010) criticize the ΔCoVaR measure as being based on a non-coherent risk measure.

To proxy for the latter, we make use of the measure of interconnectedness of a financial institution proposed by Billio et al. (2012). Let Z_i be the standardized stock returns of the ith institutions and $G = Cov(Z_i, Z_j)_{ij}$ be the covariance matrix of the institutions's daily stock returns. Using principal component analysis, we are able to decompose this matrix into a matrix Λ, which is a diagonal matrix of the eigenvalues $\lambda_1, \ldots, \lambda_N$ of G, and a matrix $L = (L_{ik})_{ik}$ that contains the eigenvectors of the returns' correlation matrix. Billio et al. (2012) then define the system's variance as

$$\sigma_S^2 = \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{l=1}^{N} \sigma_i \sigma_j L_{ik} L_{jk} \lambda_k.$$

In their work, Billio et al. (2012) argue that the more interconnected a system is, the less eigenvalues are necessary to explain a proportion of H of the system's variance σ_S^2.[53] A univariate measure of an institution's interconnectedness with the system of N financial institutions is then given by

$$PCAS_{i,n} := \sum_{k=1}^{n} \frac{\sigma_i^2}{\sigma_S^2} L_{ik}^2 \lambda_k \bigg|_{h_n > H},$$

where $PCAS_{i,n}$ is the contribution of institution i to the risk of the system, and h_n is $\frac{\sum_{k=1}^{n} \lambda_k}{\sum_{k=1}^{N} \lambda_k}$ with a prescribed threshold H.[54]

The more interconnected an insurer is with the rest of the financial sector, the higher its systemic relevance will be. We therefore expect our proxy for interconnectedness to enter our regressions of ΔCoVaR with a significant negative sign. Similarly, we expect interconnectedness to have a positive effect on both MES and SRISK, since being more interconnected with the financial system exposes insurers to contagion risks from other banks and insurers.

To proxy for the size of an insurer, we use the natural logarithm of an insurer's total

[53] Following a suggestion in Billio et al. (2012), we set $H = 0.33$.

[54] We calculate the proxy for interconnectedness using data on insurers and banks. To be precise, we employ data on all insurance companies in our sample as well as data on all banks available from *Datastream* with total assets in excess of $ 1 billion at the end of 2000. The total sample used for estimating the interconnectedness of individual insurers comprises 1,491 banks and 253 insurers.

assets.[55] We expect insurer size to be an economically significant driver of systemic risk. On the one hand, a larger company is less likely to suffer from cumulative losses due to its broader range of pooled risks and better risk diversification. On the other hand, an insurer could become more systemically relevant by being too-big-to-fail and too-complex-to-fail (see IAIS, 2013).

Another important explanatory variable in our regressions is an insurer's leverage ratio. We follow Acharya et al. (2010) and Fahlenbrach et al. (2012) and approximate an insurer's leverage as the book value of assets minus book value of equity plus market value of equity, divided by market value of equity. We have no prediction for the sign of the coefficient on leverage in our regression. High leverage is a factor that incentivizes managers into excessive risk-taking to increase a firm's profitability.[56] In contrast, Vallascas and Hagendorff (2011) argue that managers of companies with high leverage could feel pressured by investors to provide enough liquid assets to cover the payment of interests. Consequently, a higher leverage could exert a disciplining function on managers leading to a decrease in an insurer's total risk.

Furthermore, we employ several other insurer- and country-specific characteristics as control variables. We include the variable debt maturity which is defined as the ratio of total long term debt to total debt. There exists a wide consensus among economists and regulators that the dependence of certain banks and insurers on short-term funding exposed these institutions to liquidity risks during the financial crisis and ultimately led to significant systemic risks (see Brunnermeier and Pedersen, 2009, Cummins and Weiss, 2014, Fahlenbrach et al., 2012). Consequently, the IAIS has included the ratio of the absolute sum of short-term borrowing and total assets in its methodology as a key indicator of systemic relevance. We adopt their line of thought but use total long-term debt instead of short term debt.

To include a proxy for an insurer's investment success in our panel regression, we

[55] In our robustness checks, we use net revenues, given as the log value of an insurer's total operating revenue, as an alternative proxy for firm size.

[56] Support for this view is found by Acharya et al. (2010), Fahlenbrach et al. (2012) and Hovakimian et al. (2012) who present empirical evidence that banks with low leverage during the crisis performed better and had a smaller contribution to systemic risk.

use the ratio of investment income to net revenues. It is defined as the ratio of an insurer's absolute investment income to the sum of absolute investment income and absolute earned premiums. To characterize the quality of the insurance portfolio, in our analysis we compute the insurer's loss ratio, constructed by adding claim and loss expenses plus long term insurance reserves and dividing by premiums earned. We expect insurers with higher loss ratios to contribute more to systemic risk. In our regressions, we also use an insurer's market-to-book ratio, defined as the market value of common equity divided by the book value of common equity.

Next, we employ the insurers' operating expense ratio, given by the ratio of operating expenses to total assets, to control for the quality of management.[57] Furthermore, we follow the reasoning of the IAIS (2013) and control for the degree to which an insurer engages in non-traditional and non-insurance activities. We use the variable Other income defined as other pre-tax income and expenses besides operating income. If an insurer operates more outside the traditional insurance business, e.g., by mimicking banks or becoming a central counterparty for credit derivatives, the more will it be exposed to systemic risks from the financial sector as its interrelations with other financial institutions increase. Therefore, we expect a positive correlation between other income and systemic risk.

Another variable that captures the non-core activities of insurers is non-policyholder liabilities, which is given by the total on balance-sheet liabilities divided by total insurance reserves. We suspect a positive correlation of non-policyholder liabilities and systemic risk as policyholder liabilities are indicative of traditional insurance activities (see IAIS, 2013). To proxy for an insurer's profitability and past performance in our regressions, we use the standard measures Return on Equity (ROE) and Return on Assets (ROA). Higher profits can act as a buffer against future losses thus shielding an insurer against adverse effects spilling over from the financial sector. Additionally, we employ the quarterly buy-and-hold returns on an insurer's stock as an independent variable. It

[57] In our robustness checks, we also compute the operating expense ratio by dividing operating expenses by earned premiums.

is very likely that insurers that performed well in the past will continue to perform well over time. However, institutions that took on too many risks in the past could also stick to their culture of risk-taking (see Fahlenbrach et al., 2012) and increase their exposure and contribution to systemic risk. We therefore expect this measure to have a positive impact on the systemic risk of insurers.

Finally, we also consider macroeconomic and country-specific variables like the GDP growth rate (in %) and the log of the annual change of the GDP deflator. Moreover, we employ a country's stock market turnover defined as the total value of shares traded in a given country divided by the average market capitalization to proxy for the development of a country's equity market (see, e.g., Levine and Zervos, 1998, Bartram et al., 2012).

3.2.4 Descriptive statistics

Table 3.1 presents descriptive statistics for the dependent and explanatory variables we use in our analysis.

For our full sample of life and non-life insurers, we only find limited evidence of a systemic importance of insurers. Although weakly economically significant, insurers had mean estimates of MES and ΔCoVaR of only 1% during our full sample period. The summary statistics on SRISK also underline the finding that the majority of insurers did not significantly contribute to the instability of the financial sector. However, the minimum estimate of ΔCoVaR and the maximum SRISK estimate show that at least some insurers contributed significantly to systemic risk at some point during our sample period. Intuitively, we would expect insurers to have experienced the extreme values of systemic relevance during the financial crisis. This intuition is proven in Figure 3.1 in which we plot the time evolution of the three systemic risk measures we use over the course of our complete sample period.

We can see from Figure 3.1 that the mean MES is relatively constant over time, showing a significant peak during the financial crisis. The exposure to systemic risk

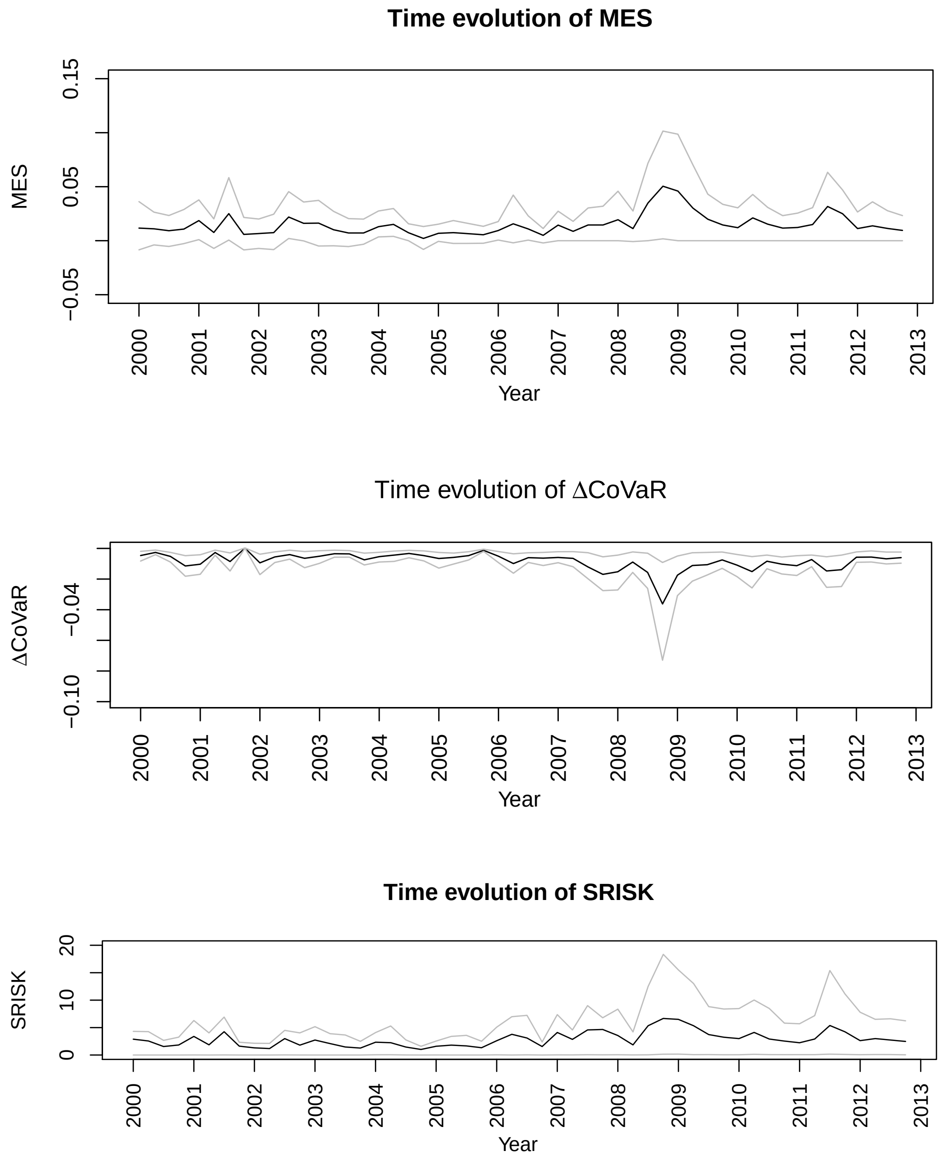
Table 3.1: Descriptive statistics.

The table presents descriptive statistics of the quarterly estimates of different systemic risk measures for a sample of 253 international insurers. The sample period runs from Q1 2000 to Q4 2012. Additionally, the table presents descriptive statistics for our set of explanatory variables. We report the number of observations, minimum and maximum values, percentiles and moments. All variables and data sources are defined in Appendix B.2.

			Percentiles							Moments			
	Obs	Min	1th	5th	20th	80th	95th	99th	Max	Mean	St. Dev.	Skewness	Kurtosis
MES	12,808	-0.11	-0.02	-0.01	0.00	0.02	0.05	0.09	0.45	0.01	0.02	3.44	35.53
ΔCoVaR	4,893	-0.12	-0.04	-0.02	-0.01	0.00	0.00	0.00	0.00	-0.01	0.01	-3.90	29.98
SRISK (in billions)	8,997	0.00	0.00	0.00	0.07	2.46	12.30	42.09	166.22	2.80	8.50	7.56	81.36
Interconnectedness	11,361	0.00	0.00	0.00	0.00	0.16	2.37	123.99	399,010.80	386.98	8,929.08	29.26	982.91
Total assets (in billions)	10,998	0.02	0.59	1.18	29.03	61.37	331.62	865.13	2,076.19	65.63	165.79	5.40	38.05
Leverage	12,066	1.01	1.32	1.77	3.10	13.37	30.41	86.80	44,180.69	30.27	819.12	52.16	2,796.82
Debt maturity	11,104	0.00	0.00	0.00	0.58	1.00	1.00	1.00	1.00	0.78	0.32	-1.45	0.78
Foreign sales	7,131	-63.41	0.00	0.00	0.00	50.42	82.85	109.82	202.64	23.63	30.11	1.23	1.26
Investment success	12,065	-22.10	0.04	0.23	0.59	0.89	0.95	1.03	4.13	0.71	0.49	-34.67	1,614.19
Loss ratio	11,994	-1,717.91	3.39	38.53	64.26	109.65	196.19	770.70	8,439.29	107.48	211.37	20.09	681.64
Market-to-book	12,038	-14.10	0.26	0.55	0.91	2.27	4.16	7.49	45.12	1.78	1.67	8.32	167.10
Non-policyholder liabilities	12,025	0.56	1.01	1.05	1.12	1.70	4.78	35.67	1,144.63	4.03	35.51	21.25	524.18
Operating expenses	12,510	-0.18	0.01	0.05	0.11	0.32	0.54	0.78	1.39	0.23	0.16	2.06	7.81
Other income (in millions)	12,669	-4.87	-0.93	-0.10	-0.00	0.01	0.17	1.19	17.95	0.02	0.53	0.00	0.00
ROA	12,423	-30.22	-5.56	-1.09	0.39	3.44	6.94	10.90	38.08	1.88	3.22	1.30	30.09
Performance	12,744	-0.91	-0.43	-0.25	-0.09	0.12	0.30	0.57	10.64	0.02	0.21	11.83	559.55
Net Revenues (in billions)	10,954	0.00	0.08	0.26	0.73	11.40	44.61	105.30	172.37	9.70	19.15	3.95	18.57
ROE	9,853	-77.86	-66.22	-6.84	5.66	16.29	25.82	34.29	36.69	10.16	12.84	-3.39	19.27
GDP Growth	12,598	-8.54	-5.49	-3.11	0.81	4.10	5.54	9.30	14.78	2.21	2.57	-0.45	2.25
Inflation	12,598	-14.45	-2.22	-1.20	0.88	3.12	6.01	8.86	27.57	2.15	2.16	1.49	12.38
Stock market turnover	12,648	0.15	1.99	6.80	63.14	189.07	348.58	404.07	404.07	130.21	85.64	1.17	1.78

Figure 3.1: Time evolution of the systemic risk measures for the period from 2000 to 2012.

This figure plots the evolution of the systemic risk measures Marginal Expected Shortfalls (MES), SRISK, and ΔCoVaR over our full sample period from 2000 to 2012. The sample consists of 253 international life and non-life insurers. In each plot, the mean of the respective risk measure (black line) is plotted against the corresponding 10% and 90% percent quantiles (grey lines). All variables and data sources are defined in Appendix B.2.



during this peak, however, is highly economically significant with insurers, on average, suffering losses of 5% on their stocks on those days the market plummeted. Some insurers were hit even harder with MES estimates of up to 10%. The second plot for our estimates of the insurers' ΔCoVaR shows a similar picture. The contribution to systemic risk by insurers was low to non-existent until 2007 when both mean and minimum ΔCoVaR estimates decreased dramatically. After the crisis, the average ΔCoVaR of insurers increased again showing that the average contribution of insurers to systemic risk was again limited. This result is corroborated by the plot of the insurers' SRISK estimates.[58]

Although the summary statistics for our full sample yield some instructive information on our sample, some of our variables differ significantly for life and non-life insurers. To get a better understanding of the composition of our sample, we therefore split our sample into life and non-life insurers and compare selected summary statistics across both lines of business. The resulting summary statistics and tests of the equality of sample means are presented in Table 3.2. Summary statistics are given separately for our full sample period in Panel A and for the sub-sample of the quarters during the financial crisis in Panel B.

In Panel A of Table 3.2, we compare the values of the systemic risk measures together with the three main (presumed) determinants of systemic risk (size, leverage, and interconnectedness) for the life and non-life insurers in our sample.

We can see from both Table 3.2 that the means of the variables differ substantially for life and non-life insurers. First, both the mean estimates of MES and ΔCoVaR are higher for life insurers than for non-life insurers. In contrast, on average, non-life insurers have significantly higher SRISK estimates than life insurers. These differences are statistically significant although the absolute levels of the average contribution and exposure to systemic risk are again not economically significant (at least not across our full panel).[59]

Concerning the potential drivers of systemic risk in insurance, the univariate analysis

[58] Further summary statistics for our explanatory variables given in Table 3.1 show that the average interconnectedness of the insurers in our sample is limited. Some insurers, however, are strongly interconnected with the rest of the global insurance sector. Most notably, AIG, AON, AXA, Genworth, and MunichRe are above the 99% quantile of our interconnectedness variable. The average size of a sample insurer is ca. \$ 65 billion. Note that our sample includes both very small (5% quantile: \$ 1.2 billion) and very large insurers (95% quantile: \$ 331.6 billion).

[59] Furthermore, the differences in the mean SRISK and ΔCoVaR estimates are most likely due to the different sizes of the samples for which both measures can be computed.

Table 3.2: Descriptive statistics for main variables of interest: life and non-life insurer.

The table compares the characteristics of insurers in the life insurance sector relative to those in the non-life sector. Our sample consists of 253 international insurers (listed in Appendix B.1) and covers the period from Q1 2000 to Q4 2012 (Panel A) and from Q3 2008 to Q2 2009 (Panel B). We report the minimum, maximum, mean, 5%- and 95%-quantiles, and the standard deviation of the variables. The equality of means of the different variables is tested using Welch's t test for unequal sample sizes and possibly unequal variances of the two samples. All variables and data sources are defined in Appendix B.2. ***,**,* denote estimates that are significant at the 1%, 5%, and 10% level, respectively.

	Non-life							Life							
	No. obs.	Min	25%	Mean	75%	Max	St. dev.	No. obs.	Min	25%	Mean	75%	Max	St. dev.	t-statistic
Panel A: Q1 2000 - Q4 2012															
MES	6,386	-0.082	0.003	0.014	0.019	0.452	0.020	4,991	-0.047	0.004	0.016	0.023	0.304	0.020	-7.274***
ΔCoVaR	2,272	-0.119	-0.009	-0.007	-0.003	0.001	0.010	1,582	-0.089	-0.010	-0.008	-0.003	0.001	0.010	2.331**
SRISK (in billions)	5,150	0.000	0.103	3.210	1.718	1.662	10.280	3,847	0.000	0.108	2.242	1.836	79.23	5.190	5.842***
Interconnectedness	6,462	0.000	0.000	679.690	0.100	399,010.800	11,831.450	4,899	0.000	0.000	0.879	0.095	350.900	9.680	4.612***
Total assets (in billions)	6,180	0.02	2.75	43.00	24.13	1,483.00	134.65	4,818	0.11	7.22	94.66	93.28	2,076.00	194.91	-15.71***
Leverage	5,974	1.01	2.89	16.01	8.61	7,100.00	200.04	4,588	1.25	6.25	56.52	16.22	44,180.00	1,308.26	-2.08**
Panel B: Q3 2008 - Q2 2009															
MES	520	-0.032	0.012	0.034	0.049	0.195	0.031	388	-0.032	0.009	0.040	0.059	0.227	0.039	-2.591***
ΔCoVaR	109	-0.100	-0.021	-0.018	-0.006	-0.001	0.017	84	-0.089	-0.024	-0.020	-0.009	-0.003	0.019	0.957
SRISK (in millions)	369	0.000	0.440	5.988	4.863	88.650	13.040	262	0.000	0.376	4.970	5.156	79.230	9.330	1.144
Interconnectedness	529	0.000	0.000	773.100	0.070	294,900.000	13,698.390	405	0.000	0.000	0.001	1.205	0.098	202.800	10.710
Total assets (in billions)	443	0.16	3.63	47.89	27.45	1476.00	143.59	328	0.73	12.38	126.30	125.90	2,076.00	248.28	-5.12***
Leverage	443	1.32	3.02	11.67	9.88	210.60	23.42	322	1.50	7.18	297.00	22.93	44,180.00	3,475.01	-1.47

given in Table 3.2 shows that non-life insurers are, on average, slightly more interconnected but are significantly smaller and less levered than life insurers. Non-life insurers have mean total assets of $ 43 billion while life insurers are significantly larger with mean total assets of $ 94.66 billion. The leverage of the average non-life insurer is 16 whereas the average life insurer has a leverage 56. Although the mean estimates are again distorted in part by the presence of few extreme outliers, the quantiles presented in Table 3.2 underline the finding that life insurer are significantly larger and more levered.

Before turning to our panel regression analysis of the systemic relevance of global insurers, we shortly comment on the subset of nine Global Systemically Important Insurers (G-SIIs) as identified by the Financial Stability Board in July 2013. In Table 3.3, we repeat our analysis of the summary statistics of our systemic risk measures and selected explanatory variables for the nine G-SIIs.

Table 3.3: Descriptive statistics for main variables of interest: Global Systemically Important Insurers.

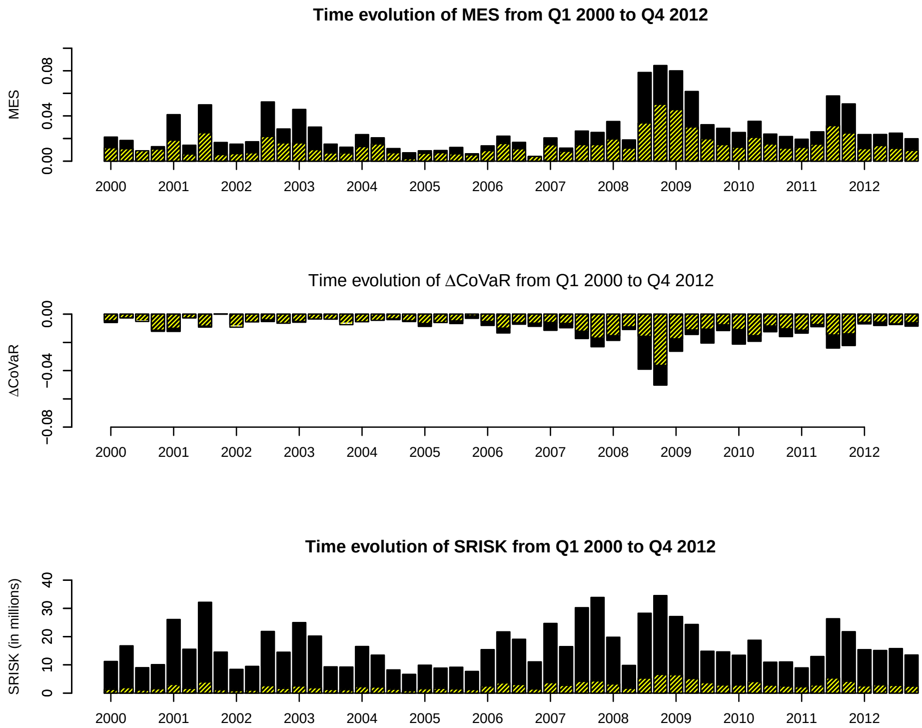
This table shows the respective descriptive statistics for the nine global systemically important insurers (G-SIIs) as defined by the international association of insurance supervisors (IAIS) in the period from Q1 2000 to Q4 2012 (Panel A) and from Q3 2008 to Q2 2009 (Panel B). The nine G-SIIs are Allianz, American International Group, Assicurazioni Generali, Aviva, Axa, MetLife, Ping An Insurance (Group) Company of China, Prudential Financial and Prudential. All variables and data sources are defined in Appendix B.2.

	G-SIIs						
	No. obs.	Min	25%	Mean	75%	Max	St. dev.
Panel A: Q1 2000 - Q4 2012							
MES	434	-0.001	0.011	0.028	0.035	0.452	0.031
ΔCoVaR	249	-0.119	-0.014	-0.011	-0.004	0.000	0.012
SRISK (in billions)	378	0.000	2.065	18.209	27.387	125.494	21.956
Interconnectedness	460	0.000	0.000	0.352	0.094	30.800	1.785
Total assets (in billions)	424	24.55	293.00	521.20	730.90	1483.00	315.38
Leverage	416	1.36	3.71	10.69	14.67	55.08	10.76
Panel B: Q3 2008 - Q2 2009							
MES	36	0.000	0.035	0.065	0.090	0.169	0.042
ΔCoVaR	20	-0.100	-0.039	-0.028	-0.012	-0.008	0.025
SRISK (in billions)	28	0.037	6.544	25.198	36.902	79.229	24.351
Interconnectedness	32	0.000	0.000	0.113	0.037	0.850	0.239
Total assets (in billions)	32	107.80	438.20	615.00	844.80	1476.20	330.19
Leverage	32	2.918	16.909	42.930	32.141	210.612	62.609

During our full sample period, the nine G-SIIs had average MES and ΔCoVaR estimates that did not significantly differ from those of insurers that were not deemed to be systemically important by the Financial Stability Board. However, global systemically important insurers had a significantly higher mean SRISK than insurers in our full sample. Most importantly, however, average estimates for the three systemic risk measures of G-SIIs increased significantly during the financial crisis as shown in Figure 3.2.

Figure 3.2: Time evolution of systemic risk measures for (systemically relevant) insurers for the period from 2000 to 2012.

This figure plots the evolution of the systemic risk measures Marginal Expected Shortfalls (MES), SRISK, and ΔCoVaR over a sample period from 2000 to 2012. The sample consists of 253 international life and non-life insurers. In each plot, the mean of the respective risk measure in each quarter is given for a sample of 253 international insurers (yellow shaded area) and for the nine insurers identified as global systemically important by the IAIS (2013) (black bars). All data are winsorized at the 1% level. Variables and data sources are defined in Appendix B.2.



As expected, G-SIIs, on average also had significantly higher total assets and were more interconnected. Interestingly, the mean leverage of the nine G-SIIs was lower than the leverage of both the average life and non-life insurer in our full sample. Not surprisingly, all variables are on average significantly higher during the crisis than in our full sample. Again, however, these univariate results for our full sample period do not take into account the (possibly strong) correlations between size, interconnectedness, and leverage.

3.3 The determinants of systemic risk of insurers

In this section, we investigate the question which factors determine an insurer's contribution and exposure to systemic risk. First, we comment on the results of our baseline panel regressions. Afterwards, we report and comment the results of various robustness checks.

3.3.1 Panel regressions

Based on the findings from our univariate analysis, we now perform a multivariate panel regression analysis of our sample of international insurers. In particular, we intend to test the hypothesis that systemic risk in insurance is predominantly driven by an insurer's size, its leverage, and its interconnectedness with the rest of the insurance sector. In our baseline setting, we perform several panel regressions with the three systemic risk measures introduced in Section 3.2 as our dependent variables. The set of independent variables includes both the set of key features of systemic relevance as proposed by the IAIS (2013) and various control variables as outlined in Section 3.2.3 and Table B.2. The econometric strategy we use is illustrated below.

$$\begin{aligned} SystemicRisk_{i,t} = \ & \beta_0 \ + \ \beta_1 \cdot Interconnectedness_{i,t-1} + \ \beta_2 \cdot Leverage_{i,t-2} \\ & + \ \beta_3 \cdot Total\ assets_{i,t-2} \ + \Omega \cdot Insurer\ controls_{i,t-2} \\ & + \ \Theta \cdot Country\ controls_{i,t-1} \ + \varepsilon_{i,t}, \end{aligned} \tag{3.1}$$

where $SystemicRisk_{i,t}$ is the value of one of the three systemic risk measures for insurer i in quarter t and $Insurer\ controls_{i,t-2}$ as well as $Country\ controls_{i,t-1}$ are various firm-specific and country-specific control variables, respectively. To mitigate the possibility of reverse causality between our dependent and explanatory variables driving our results, we lag all explanatory variables based on accounting statements by two quarters. The interconnectedness measure and country controls are lagged by one quarter. Furthermore, we perform separate regressions for life and non-life insurers to account for systematic differences in accounting in different lines of insurance business. In addition, we estimate all panel regressions with clustered standard errors on the country level and with insurer- and time-fixed effects to account for unobserved heterogeneity. The results of our baseline regressions are presented in Table 3.4.

Starting with regressions (1) and (2) of the insurers' ΔCoVaR, we can see that neither the life insurers' interconnectedness nor their size is a significant driver of the contribution to systemic risk. This first finding is in striking contrast to the hypotheses formulated by the IAIS on the pivotal role of size and interconnectedness for an insurer's systemic importance. For the leverage of a firm, we find that leverage enters the regressions with a negative sign. Our results suggest that the more levered a life insurer is, the more it contributes to the system's fragility. This result is statistically significant at the 10%- and 1% level, respectively. Furthermore, the effect is also economically significant. For life insurers, an increase in leverage by one standard deviation leads to a decrease of -13% in ΔCoVaR (1308.26 $\times$ -0.0001) whereas for non-life insurers, such an increase is associated with an increase in the contribution to systemic risk by 4% (200.04 $\times$ -0.0002). Our result implies that the use of high leverage in the insurance business therefore decreases the value of ΔCoVaR and consequently increases a non-life insurer's contribution to systemic risk.

Next, we report the results of our regressions (3) and (4) of the insurers' Marginal Expected Shortfall as the dependent variable. Interestingly, we find a positive relation between the interconnectedness of a non-life insurer and its exposure to systemic risk spilling over from the insurance sector. We thus conclude that being highly interconnected does not necessarily lead to a significantly higher contribution to systemic fragility, but rather to a higher exposure to adverse spillover effects. Additionally, leverage enters both regressions for life and non-life insurers with a statistically and

Table 3.4: Baseline panel regressions.

This table shows the results of panel regressions of quarterly estimates of three systemic risk measures for a sample of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with clustered standard errors on the country level. The estimated model is:

$$SystemicRisk_{i,t} = \beta_0 + \beta_1 \cdot Interconnectedness_{i,t-1} + \beta_2 \cdot Leverage_{i,t-2} + \beta_3 \cdot Total\ assets_{i,t-2} + \Omega \cdot Insurer\ controls_{i,t-2} + \Theta \cdot Country\ controls_{i,t-1} + \varepsilon_{i,t},$$

where $SystemicRisk_{i,t}$ is the value of one of the three systemic risk measures for insurer i in quarter t and $Insurer\ controls_{i,t-2}$ as well as $Country\ controls_{i,t-1}$ are various firm-specific and country-specific control variables. The sample includes insurer-quarter observations of 112 international life insurers and 141 international non-life insurers over the time period Q1 2000 to Q4 2012. P-values are reported in parentheses. All insurer characteristics based on accounting statements are lagged by two quarters and Interconnectedness and country control are lagged by one quarter. Variable definitions and data sources are provided in Table B.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable:	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK
Sample:	Life	Non-Life	Life	Non-Life	Life	Non-Life
	(1)	(2)	(3)	(4)	(5)	(6)
Interconnectedness	11.6000	2.6100***	-11.7000	0.0078**	-2132.9000	7.0100**
	(0.728)	(0.002)	(0.308)	(0.011)	(0.556)	(0.047)
Total assets	-0.0030	0.0005	0.0049*	-0.0004	1.0075*	5.5704**
	(0.216)	(0.568)	(0.051)	(0.820)	(0.094)	(0.016)
Leverage	-0.0001*	-0.0002***	0.0002*	0.0004***	-0.0072	-0.1228***
	(0.056)	(0.000)	(0.094)	(0.000)	(0.443)	(0.000)
Debt maturity	-0.0011	-0.0006	0.0019	0.0009	0.0754	-3.1216*
	(0.403)	(0.485)	(0.309)	(0.580)	(0.837)	(0.097)
Investment success	0.0008	-0.0067	-0.0049***	0.0091	-0.4141	-2.1429
	(0.652)	(0.281)	(0.004)	(0.221)	(0.434)	(0.484)
Loss ratio	-0.0057	0.0462*	-0.0018	0.0006	0.0544	-1.5115
	(0.183)	(0.067)	(0.128)	(0.898)	(0.666)	(0.156)
Market-to-book ratio	0.0005*	0.0004	-0.0006	0.0002	0.1047	0.0943
	(0.096)	(0.348)	(0.177)	(0.155)	(0.176)	(0.486)
Non-policyholder liabilities	-0.1759**	0.1890**	-0.0022	-0.0424	-4.2576***	14.8805
	(0.030)	(0.035)	(0.637)	(0.376)	(0.003)	(0.611)
Operating expenses	-0.0291**	-0.0041	0.0253**	0.0155*	-1.9027	14.5905
	(0.034)	(0.304)	(0.022)	(0.050)	(0.437)	(0.101)
Other income	-0.6770	0.0184	1.4500	-0.0290	267.000	523.000
	(0.226)	(0.875)	(0.441)	(0.947)	(0.521)	(0.461)
ROA	0.2000	0.0405	0.1811	0.0467	15.8181	156.7285
	(0.649)	(0.802)	(0.512)	(0.820)	(0.693)	(0.147)
Performance	-0.0012	0.0011	-0.0027	-0.0001	-0.3072	0.1843
	(0.409)	(0.471)	(0.158)	(0.966)	(0.165)	(0.726)
GDP growth	0.0003	0.0002	-0.0002	0.0002	-0.0796	-0.0908
	(0.150)	(0.365)	(0.516)	(0.499)	(0.150)	(0.424)
Inflation	-0.0001	-0.0001	-0.0004*	-0.0011***	-0.0269	-0.2008*
	(0.397)	(0.750)	(0.074)	(0.002)	(0.648)	(0.051)
Stock market turnover	0.0023	-0.0108	0.0460***	0.0452***	1.9347	26.7704***
	(0.801)	(0.225)	(0.008)	(0.003)	(0.520)	(0.000)
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	925	1,333	2,658	3,569	2,508	3,426
Adj. R^2	0.5865	0.5752	0.4422	0.4225	0.2040	0.1412

economically significant positive sign. In our regressions, a one standard deviation increase in the leverage of life insurers is associated with a 26.1% higher MES and therefore an increase of an insurer's exposure to systemic risk (1308.26 $\times$ 0.0002). For comparison, a one standard deviation increase in the leverage of a non-life insurer is associated with an 8% increase in MES (200.04 $\times$ 0.0004). In line with our expectation, higher leverage thus appears to significantly increase an insurer's exposure to systemic risk. Higher operating to total assets ratios are associated with a higher MES of insurers.

Finally, in model specifications (5) and (6), we employ the insurers' SRISK as the dependent variable. Underlining our previous findings from the regressions of ΔCoVaR, we find no evidence for the hypothesis that the contribution of insurers to systemic risk is significantly affected by the interconnectedness of an individual life insurer within financial system. For non-life insurers, we again find leverage to have a mitigating effect on systemic risk with the effect being both statistically and economically significant. However, in contrast to our previous regressions, insurer size is now statistically and economically significantly related to the SRISK of insurers. For the life insurers in our sample, we find an increase of total assets to be associated with an increase in SRISK of approx. 196 million (194.91 $\times$ 1.0075). For non-life insurers, we find the economic significance of size to be even larger with a one standard deviation increase in size being associated with an increase in SRISK by approx. 750 million (134.65 $\times$ 5.5704). These findings for SRISK have to be taken with careful consideration, however, since the adjusted R-squared in the regressions of SRISK is considerably lower than in the regressions of MES and ΔCoVaR.

3.3.2 Additional analyses

The results of our baseline regressions have produced only weak evidence that size, interconnectedness, and leverage are fundamental drivers of systemic risk in insurance. To get a deeper understanding of the relation between idiosyncratic insurer characteristics and systemic risk, we perform several additional analyses in this subsection.

First, we examine the question whether the exposure and contribution of large insurers to systemic risk are driven by different factors than the systemic risk measures of insurers in our full sample. To this end, we restrict our sample to insurer-quarter observations of institutions in the top 75% quantile of total assets. The motivation behind our analysis is that the relation between some of our explanatory variables and the systemic risk of an insurer might be mitigated or exacerbated by the insurer's size. The results for the regression using insurers in the top total assets quartile only are presented in Table 3.5.

Several of the results from our baseline regressions carry over to our analysis of large insurers. For example, the inferences for the insurers' leverage remain more or less unchanged. Higher leverage increases both the contribution and the exposure of large life and non-life insurers to systemic risk. While leverage is positively related to the purely equity-based measures of systemic risk, we find a significant negative correlation between leverage and SRISK as our third measure of systemic risk. However, in regression (2) in Table 3.5 we find one striking difference. In contrast to our baseline regressions, the interconnectedness of an insurer is now positively related to its contribution to systemic risk. An increased interconnectedness of large insurers induces more contribution to overall systemic risk. This is intuitive, since an interconnected insurance company could possibly contribute to systemic risk, but only if it is relevant or large enough to have devastating effects through a default. Similarly to the analysis of our full sample, insurer size is significant in the regression of the SRISK of non-life insurers. Furthermore, and in line with our expectation, we find higher loss ratios to be positively associated with the contribution of large insurers to systemic risk.

Next, we address the question whether the drivers of systemic risk in insurance differ across countries. In fact, it is very possible that insurance companies and even whole sectors function in a different way than their counterparts in foreign countries. Even more importantly, insurance regulation differs substantially from country to country. Although we control for these systematic differences by the use of country-fixed ef-

Table 3.5: Panel regressions - Large insurers.

This table shows the results of panel regressions of quarterly estimates of three systemic risk measures for a sample of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with clustered standard errors on the country level. The estimated model is:

$$SystemicRisk_{i,t} = \beta_0 + \beta_1 \cdot Interconnectedness_{i,t-1} + \beta_2 \cdot Leverage_{i,t-2} + \beta_3 \cdot Total\ assets_{i,t-2} + \Omega \cdot Insurer\ controls_{i,t-2} + \Theta \cdot Country\ controls_{i,t-1} + \varepsilon_{i,t},$$

where $SystemicRisk_{i,t}$ is the value of one of the three systemic risk measures for insurer i in quarter t and $Insurer\ controls_{i,t-2}$ as well as $Country\ controls_{i,t-1}$ are various firm-specific and country-specific control variables. The sample includes insurer-quarter observations of 112 international life insurers and 141 international non-life insurers over the time period Q1 2000 to Q4 2012. In contrast to our baseline setting, in these regressions, we only use insurer-quarters of insurers in the top total assets quartile. P-values are reported in parantheses. All insurer characteristics based on accounting statements are lagged by two quarters and Interconnectedness and country control are lagged by one quarter. Variable definitions and data sources are provided in Table B.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable:	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK
Sample:	Life	Non-Life	Life	Non-Life	Life	Non-Life
	(1)	(2)	(3)	(4)	(5)	(6)
Interconnectedness	1.1058	-0.2942**	0.0017	0.4796	0.3641	-205.6195
	(0.179)	(0.023)	(0.120)	(0.112)	(0.337)	(0.500)
Total assets	-0.0008	-0.0037	0.0016	-0.0026	4.6792	11.8426***
	(0.885)	(0.117)	(0.626)	(0.415)	(0.122)	(0.000)
Leverage	0.0001	-0.0001***	0.0004***	0.0003***	-0.0616	-0.0758**
	(0.297)	(0.001)	(0.003)	(0.000)	(0.242)	(0.047)
Debt maturity	-0.0032	0.0032	-0.0007	-0.0082	-1.3610	-19.8851
	(0.243)	(0.292)	(0.867)	(0.208)	(0.330)	(0.105)
Investment success	-0.0114	-0.0347**	0.0174	0.0232	3.8998	-20.3975**
	(0.212)	(0.032)	(0.147)	(0.418)	(0.380)	(0.023)
Loss ratio	-0.1341**	-0.0751*	-0.0090**	0.0359	0.0280	1.9320
	(0.022)	(0.097)	(0.028)	(0.362)	(0.987)	(0.892)
Market-to-book ratio	0.0026**	-0.0013	0.0004	0.0021	-0.4833	8.5890*
	(0.011)	(0.447)	(0.605)	(0.547)	(0.294)	(0.065)
Non-policyholder liabilities	0.4520	-0.9806	0.0398	-0.1975	10.0329	-59.2137
	(0.685)	(0.306)	(0.341)	(0.800)	(0.367)	(0.877)
Operating expenses	0.0220	-0.0730***	0.0331**	0.0722	14.8526	79.9298*
	(0.482)	(0.004)	(0.025)	(0.119)	(0.165)	(0.056)
Other income	3.4200***	0.0539	0.4310	0.1690	3670.0000***	-504.0000
	(0.003)	(0.767)	(0.872)	(0.774)	(0.004)	(0.306)
ROA	-0.6000*	-0.7000	0.5000*	2.0000*	167.0000	993.2000**
	(0.078)	(0.183)	(0.099)	(0.070)	(0.290)	(0.038)
Performance	-0.0046**	0.0047**	-0.0081**	-0.0147***	-0.9752	-2.4596
	(0.037)	(0.024)	(0.013)	(0.005)	(0.132)	(0.298)
GDP growth	0.0000	0.0003	-0.0006	0.0002	-0.2241	-0.6056
	(0.984)	(0.421)	(0.233)	(0.837)	(0.115)	(0.337)
Inflation	-0.0004	-0.0011	0.0005	0.0007	0.6069**	0.7485
	(0.465)	(0.120)	(0.415)	(0.670)	(0.019)	(0.494)
Stock market turnover	-0.0184	-0.0392**	0.0194	0.0629*	-8.2560	68.5784***
	(0.167)	(0.027)	(0.315)	(0.055)	(0.185)	(0.002)
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	377	296	858	560	843	554
Adj. R^2	0.630	0.840	0.556	0.512	0.300	0.395

fects in our robustness checks, it is nevertheless instructive to analyze these country differences in the relation between systemic risk and the insurers' idiosyncratic characteristics in more detail. Our sample is composed of 95 insurers with headquarters located in the United States and 158 insurers from other countries. To analyze the differential drivers of systemic risk, we estimate separate panel regressions for U.S. and non-U.S. insurers. The results are given in Table 3.6.

For U.S. non-based life insurers, interconnectedness enters the regression of ΔCoVaR with a positive coefficient that is statistically significant at the 1% level while for non-U.S. insurers it is significant for both lines of business. On the other hand, interconnectedness seems to slightly increase the values of SRISK for non-life insurers in the U.S. and for life insurers outside the United States. These mixed findings indicate no clear trend on the impact of our interconnectedness measure on the contribution of insurers to systemic risk. With the exception of the regressions of the SRISK estimates of non-life insurers outside the U.S., total assets is not a statistically significant determinant of systemic risk. In contrast, leverage is significantly related to the exposure to systemic risk of non-life insurers (U.S. and non-U.S.) and life insurers (only non-U.S.). Our results suggest that the impact of leverage on the exposure and contribution of systemic risk does not vary across countries or lines of business.

Finally, we investigate the question whether our results change significantly if we restrict our sample to the time period of the financial crisis. In particular, we hypothesize that size, interconnectedness, and leverage might only have been key drivers of systemic risk in insurance during the financial crisis. To this end, in Table 3.7, we repeat our previous baseline regressions but restrict our sample to a smaller time period covering the period from Q1 2006 to Q4 2010 (i.e., the time around and during the financial crisis).

This time, we find no statistically significant impact of interconnectedness on any of the systemic risk measures. Again, insurer size does not appear to be systematically related to systemic risk of insurers except for SRISK of non-life insurers where we, again, find a positive relation. While the signs of the coefficients for leverage remain

Table 3.6: Panel regressions for U.S. and non-U.S. insurers.

This table shows the results of panel regressions of quarterly estimates of three systemic risk measures for a sample of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with clustered standard errors on the country level. The estimated model is:

$$\begin{aligned} SystemicRisk_{i,t} = \; & \beta_0 \; + \; \beta_1 \cdot Interconnectedness_{i,t-1} + \; \beta_2 \cdot Leverage_{i,t-2} \; + \; \beta_3 \cdot Total\ assets_{i,t-2} \\ & + \; \Omega \cdot Insurer\ controls_{i,t-2} \; + \; \Theta \cdot Country\ controls_{i,t-1} \; + \varepsilon_{i,t}, \end{aligned}$$

where $SystemicRisk_{i,t}$ is the value of one of the three systemic risk measures for insurer i in quarter t and $Insurer\ controls_{i,t-2}$ as well as $Country\ controls_{i,t-1}$ are various firm-specific and country-specific control variables. The samples include insurer-quarter observations of 95 U.S. and 158 non-U.S. insurers over the time period Q1 2000 to Q4 2012. P-values are reported in parentheses. All insurer characteristics based on accounting statements are lagged by two quarters and Interconnectedness and country control are lagged by one quarter. Variable definitions and data sources are provided in Table B.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

	US						Non-US					
Dependent variable:	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK	ΔCoVaR	ΔCoVaR	MES	MES	SRISK	SRISK
Sample:	Life	Non-Life	Life	Non-Life	Life	Non-Life	Life	Non-Life	Life	Non-Life	Life	Non-Life
Interconnectedness	34.3000	2.8900***	-129.6	0.0072*	645.1000	5.4200*	2.8900***	-6.1100**	0.0072*	0.6020	5.4200*	-142.4000
	(0.470)	(0.000)	(0.295)	(0.085)	(0.810)	(0.064)	(0.000)	(0.041)	(0.085)	(0.771)	(0.064)	(0.833)
Total assets	0.0005	0.0026	0.0070	-0.0021	0.9090	1.6734	0.0026	0.0002	-0.0021	-0.0012	1.6734	6.1613**
	(0.952)	(0.126)	(0.105)	(0.340)	(0.272)	(0.124)	(0.126)	(0.919)	(0.340)	(0.555)	(0.124)	(0.021)
Leverage	0.0002	-0.0002***	0.0001	0.0004***	0.0020	-0.1180***	-0.0002***	-0.0002**	0.0004***	0.0006**	-0.1180***	0.0368
	(0.545)	(0.000)	(0.537)	(0.000)	(0.822)	(0.000)	(0.000)	(0.046)	(0.000)	(0.016)	(0.000)	(0.573)
Other control varialbes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	258	812	723	1,917	678	1,807	812	521	1,917	1,652	1,807	1,619
Adj. R^2	0.589	0.574	0.452	0.540	0.379	0.221	0.574	0.689	0.540	0.377	0.221	0.195

Table 3.7: Panel regressions for the crisis period.

This table shows the results of panel regressions of quarterly systemic risk of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with clustered standard errors country level. The conceptual approach is the following:

$$SystemicRisk_{i,t} = \beta_0 + \beta_1 \cdot Interconnectedness_{i,t-1} + \beta_2 \cdot Leverage_{i,t-2} + \beta_3 \cdot Total\ assets_{i,t-2} + \Omega \cdot Insurer\ controls_{i,t-2} + \Theta \cdot Country\ controls_{i,t-1} + \varepsilon_{i,t},$$

The sample includes insurer-quarter observations of 253 international insurers over the time period Q1 2006 to Q4 2010. P-values are reported in parantheses. All insurer characteristics based on accounting statements are lagged by two quarters and Interconnectedness and country control are lagged by one quarter. Variable definitions and data sources are provided in Table B.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Adj. R^2 is adjusted R-squared.

Dependent variable: **Sample:**	ΔCoVaR Life (1)	ΔCoVaR Non-Life (2)	MES Life (3)	MES Non-Life (4)	SRISK Life (5)	SRISK Non-Life (6)
Interconnectedness	0.6409	0.0405	-0.0316	-0.0316	29.8448	-2.2579
	(0.252)	(0.920)	(0.962)	(0.377)	(0.833)	(0.851)
Total assets	-0.0192	0.0042	-0.0001	-0.0072	3.9042	6.9138**
	(0.269)	(0.539)	(0.994)	(0.537)	(0.214)	(0.016)
Leverage	0.0002	-0.0003***	0.0005	0.0006***	0.2112	-0.0841***
	(0.480)	(0.000)	(0.254)	(0.000)	(0.180)	(0.000)
Debt maturity	-0.0146	-0.0049	0.0015	0.0061	-2.0916	1.1335
	(0.226)	(0.274)	(0.774)	(0.251)	(0.547)	(0.684)
Investment success	-0.0281	-0.0585**	-0.0127	-0.0016	-6.1390	-0.5964
	(0.316)	(0.020)	(0.555)	(0.722)	(0.439)	(0.581)
Loss ratio	-0.0595	0.0016	0.0342	0.0004	-9.6110*	-1.0701*
	(0.432)	(0.979)	(0.298)	(0.941)	(0.062)	(0.057)
Market-to-book ratio	0.0011	-0.0003	-0.0002	0.0000	-1.4385	-0.0573
	(0.686)	(0.732)	(0.930)	(0.754)	(0.305)	(0.471)
Non-policyholder liabilities	-10.8000***	-1.7117	0.5478	-0.1793	-702.6164	13.0993
	(0.001)	(0.233)	(0.764)	(0.340)	(0.370)	(0.787)
Operating expenses	0.0157***	-0.0061	0.0031	0.0187	5.1510	-1.1348
	(0.005)	(0.476)	(0.820)	(0.316)	(0.538)	(0.796)
Other income	14.3000	1.8100	-15.8000	0.2190	-130.0000	60.0000**
	(0.224)	(0.429)	(0.182)	(0.970)	(0.597)	(0.021)
ROA	-0.9207	-3.4268**	0.3275	0.5115	77.5754	67.3172
	(0.776)	(0.023)	(0.549)	(0.559)	(0.628)	(0.422)
Performance	-0.0091**	-0.0031	0.0088	0.0004	2.4556**	4.7450
	(0.024)	(0.294)	(0.356)	(0.947)	(0.046)	(0.180)
GDP growth	0.0003	-0.0002	0.0011	0.0007	0.1959	0.3530
	(0.770)	(0.753)	(0.243)	(0.328)	(0.373)	(0.517)
Inflation	0.0004	0.0019	-0.0003	-0.0024	0.2310	-0.4832*
	(0.656)	(0.107)	(0.801)	(0.143)	(0.320)	(0.058)
Stock market turnover	0.0085	-0.0319*	0.0667**	0.0590**	4.2736	34.6236**
	(0.679)	(0.068)	(0.018)	(0.035)	(0.654)	(0.012)
Insurer-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Time-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	130	239	387	788	379	772
Adj. R^2	0.787	0.847	0.575	0.470	0.244	0.155

the same, we only find a statistically significant impact on systemic risk for non-life insurers. The economic significance of this effect is, however, moderate with a one standard deviation increase in leverage causing a change of almost minus one percent in ΔCoVaR during the crisis period (23.42 $\times$ -0.0003). In the cross-section of non-life insurers' MES during the crisis period, a one standard deviation increase in leverage is associated with an 1.4% higher exposure to systemic risk (23.42 $\times$ 0.0006).

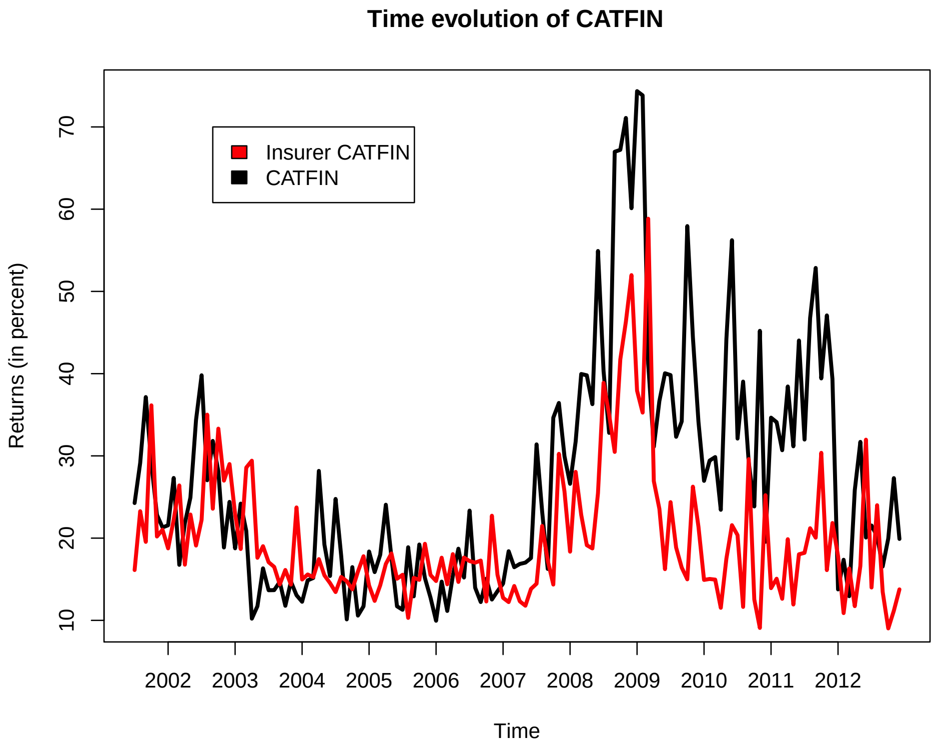
3.3.3 Insurers and the systemic risk in the financial sector

While we have investigated the factors influencing the marginal systemic risk of insurers at the micro-level, we have not yet addressed the overall level of systemic risk that emanates from the insurance sector (and its possible macroeconomic consequences). In our final analysis, we therefore employ a macro-level measure of systemic risk to capture the insurance sector's propensity to cause real macroeconomic downturns. More, specifically, we employ the CATFIN measure introduced by Allen et al. (2012) and compare their results with the CATFIN measure estimated for our sample of insurers. CATFIN is defined as the average of three Value-at-Risk estimates of monthly stock returns in excess of the 1-month treasury bill rate. We fit the Generalized Pareto Distribution and the Skewed Generalized Error Distribution to generate Value-at-Risk estimates from the cross-section of our insurers' monthly stock returns at the 99% level. Additionally, the third estimate is from the cross-sectional 1% sample quantile. The resulting CATFIN measures are plotted in Figure 3.3 for the time period 07/2001 to 12/2012.

From the figure, we can see that the time evolution of the two time series of CATFIN estimates are very similar, but vary in magnitude. Before the crisis, the estimated index values are closely together until the beginning of the crisis. While the insurer CATFIN peaks at around 60% in the beginning of 2009, the original estimates from Allen et al. (2012) reach a maximum of over 70%. The monthly values for the original CATFIN index seem to be higher than the insurer CATFIN for the most part after the crisis.

Figure 3.3: Time evolution of CATFIN.

This figure plots the time evolution of the CATFIN measure introduced in Allen et al. (2012). CATFIN is calculated by averaging the three Value-at-Risk estimates from the Generalized Pareto Distribution, the Skewed Generalized Error Distribution, and the nonparametric sample quantiles for the cross-section of stock returns of financial institutions in excess of the 1-month treasury bill rate. The red line represents the CATFIN measure for the cross section of insurers in our sample and the black line is the original CATFIN measure calculated in Allen et al. (2012) taken from the authors' website at http://faculty.msb.edu/tgb27/workingpapers.html. The sample used for calculating the CATFIN of the insurance sector consists of 253 international life and non-life insurers.



Despite the small difference in the magnitude of the peaks of both CATFIN time series, the plot in Figure 3.3 underlines the finding that the overall level of systemic risk in the insurance sector was significant and high, especially during the crisis. However, another important insight from Figure 3.3 is that the overall level of systemic risk in the insurance sector fails to predict economic downturns, since insurer stocks seem to lag behind the overall financial sector.

3.3.4 Robustness checks

We also estimate regressions in which we employ alternative measures of an insurer's size (net revenues instead of total assets), profitability (ROE instead of ROA) and investment activity (ratio of the insurers investment income to net revenues instead of the ratio of the insurers absolute investment income to the sum of absolute investment income and absolute earned premiums), respectively. Additional regressions using the beta of an insurer's stock yield no change in our results. As mentioned before, we also replace total assets with premiums earned in the calculation of our variable operating expenses. However, our previous conclusions remain valid.

Next, it could be argued that our results are driven by the specific manner in which we estimate the Marginal Expected Shortfall and the other systemic risk measures. To control for this potential bias, we recalculate MES and ΔCoVaR using three alternative indexes. To be precise, we employ the World DS Full Lin Insurer Index, the MSCI World Banks Index and the MSCI World Insurance Index taken from *Datastream*. The results show that our conclusions remain unchanged.

Another potential concern with our analysis could be that some of the insurers in our sample might in fact just be locally rather than internationally active market participants. Consequently, the presence of local insurers in our sample could bias our results on systemic risk as the systemic relevance of locally active insurers should generally lower than for globally important insurers. However, we believe that the inclusion of locally active insurers in the context of our analysis is sensible for the following reasons. First, we cannot rule out the possibility that insurers with insurance activities in only their home country contribute to global systemic risk due to off-balance sheet and non-insurance activities. Second, sheer size and relevance in an insurer's home country might be enough to destabilize a nation's economy and thus cause global financial stability.[60] Nevertheless, we perform an additional robustness check in which we include in our baseline regressions the variable Foreign sales, which is the ratio of an insurer's

[60] The anecdotal evidence of the inclusion of the Ping An Insurance Group in the list of the nine G-SIIs underlines this notion.

international sales to its total sales, to control for business activities abroad. Including this factor does neither change our main results, nor is the variable significant in any of the regressions.

Additionally, we employ GMM-sys regressions (see Blundell and Bond, 1998) that include one lag of our dependent variables and explanatory variables lagged by one quarter. In these regressions, double-lagged values of the insurer characteristics are used as instruments for estimation. In doing so, we mitigate concerns on possible endogeneity in our regression models. Our main results, however, remain valid.

Finally, we winsorize all data at the 1% and 99% quantiles to minimize a possible bias due to outliers and reestimate all our regressions using winsorized data. The results of these alternative regressions are qualitatively and quantitatively similar to those reported in the paper.

3.4 Conclusion

In this paper, we analyze the exposure and contribution of 253 international life and non-life insurers to global systemic risk in the period from 2000 to 2012. As our main result, we find systemic risk in the international insurance sector to be small in comparison to previous findings in the literature for banks in our full sample. During the financial crisis, however, insurers did contribute significantly to the instability of the financial sector. Further, we conclude that systemic risk of insurers is determined by various factors including an insurer's interconnectedness and leverage, the magnitudes and significances of these effects, however, differ depending on the systemic risk measure used and with the analyzed insurer line and geographic region. Most interestingly, we find the interconnectedness of large insurers with the insurance sector to be a significant driver of the insurers' exposure to systemic risk. In contrast, the contribution of insurers to systemic risk appears to be driven by (among others) leverage, loss ratios, and the insurer's funding fragility.

Our results also show that life insurers do not contribute significantly more to global systemic risk than non-life insurers. In addition, there seems to be little difference in the interconnectedness of life and non-life insurers. In our study, we find no convincing evidence in support of the hypothesis that insurer size is a fundamental driver of the contribution of an insurer to systemic risk. In contrast to the banking sector, we show that the insurance sector predominantly suffers from being exposed to systemic risk, rather than adding to the financial system's fragility. Finally, our study reveals that both the systemic risk exposure and the contribution of international insurers were limited prior to the financial crisis with all measures of systemic risk increasing significantly during the crisis. In contrast to the banking sector, however, systemic risk in the insurance sector does not appear to lead but rather follow macroeconomic downturns as evidenced by our analysis of the insurers' CATFIN estimates.

Chapter 4

Size is Everything: Explaining SIFI Designations

4.1 Introduction

At the climax of the financial crisis of 2007-2009, American International Group (AIG) became the first international insurer that required (and ultimately received) a bailout as regulators considered AIG to be too systemically important to default. At the time, AIG's near-collapse came to the surprise of most analysts and financial economists as systemic risk was considered to be a problem confined to banking, but not insurance. As a response to this wakeup-call, regulators have recently started to realign the regulation of international insurance companies towards a macroprudential supervision. Most prominently, on July 18, 2013, the Financial Stability Board (FSB) in collaboration with the International Association of Insurance Supervisors (IAIS) published a list of nine Global Systemically Important Insurers (G-SIIs) which will ultimately face higher capital and loss absorbency requirements. In essence, regulators deem insurers to be globally systemically important in the views of regulators if they are of such size and global interconnectedness that their default would trigger severe adverse effects on the financial sector. Previously, in November 2011, the FSB had similarly identified a set of 29 banks as Global Systemically Important Financial Institutions (G-SIFIs).

However, the validity of these classifications and the actual determinants of the decision of regulators to designate a financial institution as global systemically important remain relatively unknown.

Until the financial crisis, economists had never expected systemic risks to arise from the insurance sector. In contrast to banking, insurance companies are not vulnerable to runs by customers and thus are not subject to sudden shortages in liquidity. Although theoretically, one could think of runs on life insurance policies, there has not been a single example in history for such a run to take place and cause systemwide defaults of insurers (see, e.g., Eling and Pankoke, 2014).[61] Furthermore, even the largest international insurers are significantly smaller in size, less interconnected, and hold more capital (see Harrington, 2009) than the largest global banks. In light of this, the case of AIG seems to have been a major exception to the rule that insurers do not cause systemic risks.

As insurers do not accept customer deposits, they do not face the risk of a sudden shortage in liquidity due to a bank run. In addition, insurers in contrast to banks often rely more strongly on long-term liabilities thus further decreasing their exposure to liquidity risk. Furthermore, insurers are said to be less interconnected than banks resulting in a lower probability of contagion among insurers (see Bell and Keller, 2009). Based on the experiences from the financial crisis, the IAIS (2013) published a methodology for assessing the systemic risk of international insurers. In this methodology, the key determinants of systemic risk in insurance are non-core and non-insurance activities, insurer size and interconnectedness.[62]

However, the empirical evidence on the questions whether insurers can become systemically relevant and whether these factors drive systemic risk is limited. Shortly after the financial crisis, Acharya et al. (2009), Harrington (2009), and

[61] An "insurer run" is regarded as unlikely by most economists as customers are often protected by guarantees that are similar to explicit deposit insurance schemes in banking.

[62] The non-core activities listed by the IAIS include credit default swaps (CDS) transactions for non-hedging purposes, leveraging assets to enhance investment returns, as well as products and activities that concern bank-type (or investment bank-type) activities. Furthermore, the IAIS argues that insurance companies which engage in non-traditional insurance activities are more affected to financial market developments and contribute more to systemic risk of the insurance sector.

Cummins and Weiss (2014) discussed the role of insurers during the financial crisis.[63] More recently, due to the increased attention regulators are giving this topic, several studies have analyzed different aspects of systemic risk in insurance. For example, Cummins and Weiss (2014) and Weiß and Mühlnickel (2014) study the effect of different factors from the IAIS methodology on the systemic risk of U.S. insurers. In addition, Weiß and Mühlnickel (2015) support the too-big-to-fail conjecture for insurers by showing that insurer mergers tend to increase the systemic risk of the acquiring insurers.

In this paper, we analyze the question whether common measures of systemic risk are significantly driven by the size, the interconnectedness, and the leverage of global banks and insurers. As systemic risk measures, we employ the institutions' Marginal Expected Shortfall (MES) (see Acharya et al., 2010) and their ΔCoVaR (see Adrian and Brunnermeier, 2015). We then perform separate quantile regressions for both a sample of the world's largest banks and insurers of these two measures of systemic risk on size, interconnectedness, leverage, and a set of control variables. For both banks and insurers, the results of these quantile regressions are inconclusive and counterintuitive. The extreme quantiles of both MES and ΔCoVaR (i.e., institutions that are most exposed and contribute the most to systemic risk) are not significantly affected by size. Higher leverage and interconnectedness counterintuitively seem to decrease systemic risk. We then turn to probit regressions of the probability of membership in the groups of G-SIFIs and G-SIIs. Our results are extremely revealing: the decision of regulators to declare a financial institution (bank or insurer) as systemically relevant is only driven by the institution's size.

The rest of this paper is structured as follows. Related literature is presented in Section 4.2. The data and variables used in our empirical study are discussed in Section 4.3. The outline and the results of our empirical study are given in Section 4.4. Section 4.5 concludes.

[63]Additional analyses of systemic risk in insurance are due to Eling and Schmeiser (2010), Lehmann and Hofmann (2010), and van Lelyveld et al. (2011).

4.2 Related literature

The case of systemic risk in the banking sector has been discussed extensively in the recent literature. However, the question whether insurers can actually become systemically relevant for the financial system and the question whether the IAIS's proposed methodology is suitable for identifying G-SIIs remain relatively unanswered in the literature so far. Only few studies focus on the exposure and contribution of insurers to systemic risk and the key determinants that could cause severe consequences for insurers. Reviewing the academic literature, Trichet (2005) argued that the traditional insurance business is not vulnerable to "insurance runs" and that interconnectedness in the insurance sector is weak in contrast to the banking sector. After the financial crisis this view changed significantly. For example, Baluch et al. (2011) conclude that systemic risks exist in the insurance sector even though they are smaller than in banking. More importantly, systemic risk in insurance appears to have grown partially as a consequence of the increasing interconnectedness of insurers to other financial institutions and their activities outside of the traditional insurance business. Further, Trichet (2005) argues that new non-traditional insurance activities, for example, writing credit derivatives, can cause contagion in the financial sector. A warning that came almost three years before the near-collapse of AIG.

In the empirical literature, several studies have focused on the the interconnectedness of insurers as a primary driver of systemc risk. Billio et al. (2012) analyze the interconnectedness of global financial institutions based on their stock prices. They argue that illiquid assets of insurers could create systemic risks in times of financial crisis. In a related study, Chen et al. (2014) analyze the interconnectedness of banks and insurers but find in their analysis of credit default swap and intraday stock price data that the insurance sector is exposed to but does not contribute to systemic risks in the banking sector.

While the former two studies only address the interconnectedness of banks and insurers, the effect of additional factor like size, leverage, and profitability on systemic risk in the insurance sector is studied by Weiß and Mühlnickel (2014).[64] Most importantly, they find that insurer size has been a major driver of the systemic risk exposure and contribution of U.S. insurers. Several of the IAIS indicators (e.g., geographical diversification), however, do not appear to be significantly related to the systemic risk of insurers. The hypotheses behind these suspected causal relations are similar to arguments brought forward in banking. Insurer size, for example, could have an increasing effect on systemic risk in the insurance sector, because larger insurance companies have a wider range of different risks covered and thus are less prone to suffer from cumulative losses (see Hagendorff et al., 2014). Yet, larger insurance companies could become too-interconnected-to-fail and thus systemically relevant (see Acharya et al., 2009).

Additionally, the IAIS has also argued that high leverage could increase the systemic importance of individual insurers (especially in combination with size and interconnectedness). High leverage incentivizes managers into excessive risk-taking to increase a firm's profitability (see, e.g., Acharya et al., 2010, Fahlenbrach et al., 2012). However, leverage is obviously not bad per se. For example Vallascas and Hagendorff (2011) stress the disciplining function of leverage as it pressures managers into securing the payments of interest to investors and to secure a firm's liquidity. In addition, insurers that engage too heavily in non-core activities such as derivatives trading could also single-handedly destabilize the financial sector. For example, one of these non-traditional activities identified by the IAIS is the use of catastrophe bonds to hedge against severe losses induced by natural catastrophes. The assumption that these hedging vehicle could make insurers more interconnected with financial markets and thus more systemically relevant is confuted in Weiß et al. (2013). Concerning derivatives trading, Cummins and Weiss (2014) note that excessive derivatives trading by insurers was a major source of systemic risk in insurance during the financial crisis.

Probably the most fundamental question, however, remains whether systemic risk in

[64] In a related study, Cummins and Weiss (2014) also analyze the characteristics of U.S. insurers that are systemically important.

insurance companies (if it even exists) is large enough to destabilize the whole financial sector. In this respect, Bierth et al. (2015) find systemic risk in the international insurance sector to be small in comparison to previous findings in the literature for banks. However, confirming the results of Baluch et al. (2011), they find a strong upward trend in both the exposure and contribution of insurers to the fragility of the global financial sector during the financial crisis. In further panel regressions, they find the interconnectedness of large insurers with the financial sector to be a significant driver of the insurers' exposure to systemic risk. In contrast, the contribution of insurers to systemic risk appears to be primarily driven by the insurers' size and leverage.

4.3 Data

This section describes the construction of our sample of banks and insurers and presents the choice of our dependent and main independent variables as well as descriptive statistics of our data.

4.3.1 Sample construction

Balance sheet and income statement data are retrieved from the *Thomson Worldscope* database and all stock market and accounting data are collected in U.S. dollars to minimize a possible bias as a result from currency risk.

To construct our sample, we select all publicly listed international insurers from the dead and active firm list in *Thomson Reuters Financial Datastream* and omit all firms for which stock price data are unavailable in *Datastream*. We exclude Berkshire Hathaway due to its unusual high stock price, although it is listed as an insurer in *Datastream*. For our analysis we restrict our dataset to the one hundred largest insurance companies, measured by their total assets at the end of the fiscal year 2006.

A similar procedure is used for the construction of our international sample of banks. Initially, we start with a sample of all firms in the active and dead-firm "banks" and "financial services" lists in *Thomson Reuters Financial Datastream*. [65] As in Fahlenbrach and Stulz (2011), we then select all companies with SIC codes between 6000 and 6300 (i.e., we eliminate insurers, real estate operators, holding and investment offices as well as other non-bank companies in the financial service industry from our sample of banks). It is crucial for our analysis that we have accounting price and stock price data available in *Thomson Worldscope* and *Datastream*. Therefore, we exclude firms for which these data are not available. We exclude a stock from our sample if it is identified in *Datastream* as a non-primary quote or if it is an American Depositary Receipt (ADR). All OTC traded stocks and preference shares are also removed. Similar to the insurer sample, we restrict our data set to the 150 largest banks, measured by their total assets at the end of the fiscal year 2006. Due to secondary listings, we have to remove another two banks and two insurers from the samples. The geographical distribution of our sample banks and insurers covers 36 countries with most banks (25 out of 148) and insurers (27 out of 98) being from the United States. Following the U.S., the four most prominent countries in our samples are China (10 banks/2 insurers), Japan (16/6), the United Kingdom (11/8), and Germany (8/11). The geographical spread of our sample firms is shown in Table 4.1. [66] For increased transparency, the names of the 98 insurers and 148 banks in our final sample can be found in Appendix C.2 and C.1.

[65] Since we cannot rule out that some banks are erroneously listed in the "financial services" instead of the "banks" category in *Datastream*, we use both lists to generate our final sample.

[66] The names of the 98 insurers and 148 banks in our final sample are available upon request.

Table 4.1: Geographic sample distribution.

The table shows the geographic spread for the sample of the largest 148 banks and for the 98 largest international insurers. The minimum and maximum values for the total assets in 2006 are given in billion US-$.

	Banks			Insurer		
Country	Number	Min	Max	Number	Min	Max
AT	4	65.81	213.96	2	25.86	26.98
AU	5	77.73	453.41	4	19.04	72.99
BE	3	97.64	667.95	1	979.41	979.41
BM	-	-	-	1	19.55	19.55
BR	1	123.21	123.21	-	-	-
CA	6	99.94	458.57	7	19.48	326.43
CH	3	84.34	1815.56	6	25.1	327.94
CN	10	56.62	930.42	2	61.96	96.71
DE	8	76.7	1324.18	11	24.24	1311.58
DK	1	433.14	433.14	-	-	-
ES	5	85.01	972.82	1	28.07	28.07
FI	-	-	-	1	58.96	58.96
FR	5	252.57	1697.21	4	20.38	907.91
GB	10	77.85	1841.03	7	22.03	527.71
GR	3	58.42	90.01	-	-	-
HK	1	86.29	86.29	-	-	-
IE	4	86.41	262.94	2	59.49	94.49
IL	2	61.37	62.59	-	-	-
IN	2	61.48	154.75	-	-	-
IS	1	64.03	64.03	-	-	-
IT	6	80.59	963.16	7	23.68	454.27
JP	15	58.02	1578.76	5	26.12	143.65
KR	6	70.71	209.69	-	-	-
LU	1	72.85	72.85	-	-	-
MY	1	59.01	59.01	-	-	-
NG	1	130.39	130.39	-	-	-
NL	1	1160.22	1160.22	2	404.42	1318.22
NO	1	194.97	194.97	1	33.67	33.67
PT	2	69.66	92.84	-	-	-
RU	1	120.62	120.62	-	-	-
SE	4	170	393.23	-	-	-
SG	3	90.91	118.69	1	25.83	25.83
TR	1	63.15	63.15	-	-	-
TW	3	68.09	72.33	3	44.97	107.62
US	25	56.62	1841.03	27	17.91	985.44
ZA	3	78.04	152.69	3	29.89	51.96

Next, we define and discuss the main dependent and independent variables for our analysis in the subsequent sections. Appendix C.1 gives an overview of all variable definitions and data sources in our empirical study. To minimize the possibly biasing effect of extreme outliers in our sample on our results, all data are winsorized at the 1% and 99% levels.

4.3.2 Systemic risk measures

This study employs two different measures of systemic risk that proxy for an institution's sensitivity or exposure and contribution to systemic risk in a larger financial system. Systemic risk is calculated for the crisis period which we define as the period between July 2007 and the end of december 2008 (see Fahlenbrach et al., 2012). Similar to the recent literature (see, e.g., Anginer and Demirgüç-Kunt, 2014, Anginer et al., 2014a, Weiß and Mühlnickel, 2014), we use as our measures of systemic risk the unconditional ΔCoVaR as defined by Adrian and Brunnermeier (2015) and the Marginal Expected Shortfall as defined by Acharya et al. (2010).

One of the more established measures of systemic risk that is also used by regulators is the unconditional ΔCoVaR measured as the difference of the Value-at-risk (VaR) of a financial sector index[67] conditional on the distress of a particular insurer and the VaR of the sector index conditional on the median state of the insurer. Therefore, ΔCoVaR can be interpreted as the actual contribution to systemic risk in the financial system by the respective observed company.

In contrast, the Marginal Expected Shortfall is defined as the negative average return on a firm's stock on the days an index (in our case the MSCI World index) experienced its 5% worst outcomes. [68] A positive MES thus indicates a positive exposure to systemic risk rather than a stabilizing effect.

[67] In our main analysis, we employ the MSCI World Index. For further robustness checks, we also employ the the World DS Full Line Insurer Index, the MSCI World Banks Index, and the MSCI World Insurance index for the calculation of ΔCoVaR and Marginal Expected Shortfall.

[68] Additionally, we employ the Dynamic Marginal Expected Shortfall calculated following the procedure laid out by Brownlees and Engle (2015) for robustness checks later on.

4.3.3 Explanatory variables

The focus of our analyses is to shed more light on the interplay of systemic risk and possible determining factors proposed by the Financial Stability Board and the IAIS (2013). Thus, we concentrate on size, leverage, and the interconnectedness of banks and insurers. We intend to show whether these factors can explain the decisions of regulators to propose global systemic relevance for some of the banks and insurers in the financial system. Furthermore, we compare the predictive power of these factors for explaining the cross-sectional variation in both the institutions' MES and ΔCoVaR.

As a standard proxy for size we employ the natural logarithm of an institution's total assets at the end of the fiscal year 2006. The effect of size on systemic risk could be ambiguous. On the one hand, if a bank or insurer is deemed "too-big-to-fail", and hence might receive subsidies from safety net policies in a situation of undercapitalization, this could incentivize managers to take more risks than socially optimal. Consequently, large banks or insurers are more likely to contribute significantly more to systemic risk than smaller institutions (see, e.g., O'Hara and Shaw, 1990, Acharya and Yorulmazer, 2008, Anginer et al., 2014a). Additionally, Gandhi and Lustig (2015) find that, in contrast to non-financial firms, size is a priced factor in the cross-section of bank stock return. According to their study this is due to the pricing of implicit bailout guarantees by stock market investors. On the other hand, a larger firm generally has more opportunities to diversify and thus hedge against times of financial turmoil, which could decrease the firm's systemic risk.

As the next main variable of interest, we measure a firm's leverage as the book value of assets minus the book value of equity plus the market value of equity, divided by the market value of equity (see Acharya et al., 2010). High leverage is a factor that incentivizes managers into excessive risk-taking to increase a firm's profitability.[69] In contrast, managers could be disciplined by higher leverage since they could feel

[69] Support for this view is found by Acharya et al. (2010), Fahlenbrach et al. (2012) and Hovakimian et al. (2012) who empirically show that banks with low leverage during the crisis performed better and had less contribution to systemic risk than firms with high leverage ratios.

more pressured to provide enough liquid assets to cover interest payments (see, e.g., Vallascas and Hagendorff, 2011). This could in turn decrease a bank's or insurer's total risk. We therefore include leverage as a main independent variable in our regressions with no prediction for the sign of the coefficient.

The third important factor entering our analyses is the interconnectedness of banks and insurers within the financial system. Since we do not have information on, e.g., interbank lending markets, we make use of the measure of interconnectedness of a financial institution proposed by Billio et al. (2012) based on standardized stock returns of individual banks and insurers.

Billio et al. (2012) propose an univariate measure *PCAS* of an institution's interconnectedness with the system (using all types of financial institutions) which is based on a principal component analysis of the correlations between all institutions' stocks. The measure then computes the contribution of an individual institution to the overall risk of the financial system. The more interconnected an insurer or bank is with the rest of the financial sector, the higher its systemic relevance will be. We therefore suspect PCAS to enter our regressions with a significant increasing effect on systemic risk (see Arnold et al., 2012, Black et al., 2013, IAIS, 2013). An interconnected financial institution will be more exposed to shocks within the system. However, being more intertwined with the system does not automatically translate into a higher contribution to the systemic risk itself. Furthermore, similar to the too-big-to-fail argument, the too-interconnected-to-fail hypothesis (see Arnold et al., 2012, Black et al., 2013, IAIS, 2013) states that institutions that are too-interconnected-to-fail are guaranteed a safety net by governments to fall back on. Consequently, our expectations for the impact of the interconnectedness variable are unrestricted.

In addition to our three main independent variables that cover the most important (presumed) driving factors of systemic relevance, we include in our regressions several firm-specific characteristics that have shown to be significant drivers of performance and systemic risk of banks and insurers in the recent literature. An overview of all the variable definitions, data sources and our hypotheses regarding the analyses is given in

Appendix C.1.

We include a firm's annual buy-and-hold stock returns in 2006, since institutions that took on too many risks in the past could also stick to their culture of risk-taking (see Fahlenbrach et al., 2012) and increase their exposure and contribution to systemic risk. Next, we include standard proxys for a firm's valuation (market-to-book ratio) and its profitability (return on assets) and expect them to decrease a bank's and insurer's systemic risk. The literature suggests that banks and insurers that relied heavily on short-term funding were exposed to liquidity risks during the recent financial crisis and increased their overall systemic risk (see Brunnermeier and Pedersen, 2009, Cummins and Weiss, 2014, Fahlenbrach et al., 2012). Consequently, we control for the degree to which an insurer or bank relied on long-term debt before the crisis (debt maturity).

Turning to the variables specifically related to the insurance business, we control for the success of an insurer's asset management (investment success) and whether the form of generated income (fixed income) influences systemic risk. If an insurance company relies more on asset management rather than underwriting it could be more intertwined with the global financial markets and could thus contribute and be more exposed to global systemic risk. To check for other possible non-core activities we also include the variables non-policyholder liabilities and other income. Additional risk could arise in the form of poor management of the company which could also manifest itself in the quality of the insurance portfolio. We therefore include the variables loss ratio and operating expenses. Regarding our sample of banks, we use the composition of the bank's liabilities (deposits) to control whether banks with more deposit financing are in fact more stable. Next, we include the natural logarithm of expenses set aside as an allowance for uncollectable or troubled loans (loan loss provisions) to proxy for a bank's credit risk. A larger buffer against troubled loans should serve as a stabilizing factor for a bank's systemic risk. Also, we control for the loans-to-assets ratio (loans) of a bank, since it could indicate a business model that focuses on lending rather than more risky activities, which reduces systemic risk. With a similar reasoning, we include the ratio of non-interest income to total interest income (non-interest income) as a variable in our analysis. A bank relying more on non-deposit taking activities like, e.g., investment banking, could also be riskier than banks with a focus on traditional lending (see, e.g., Brunnermeier et al., 2012). Finally, we employ a bank's Tier-1-capital ratio (tier-1-capital) to check whether higher regulatory bank capital acts as a buffer against losses and stabilizes the individual bank within the financial sector.

4.3.4 Descriptive statistics

Table 4.2 shows summary statistics for our two dependent variables for the time period July 2007 to the end of 2008 (crisis period) and for our three main explanatory variables of interest, total assets, leverage and interconnectedness in the year 2006.[70]

The summary statistics for the banks in our sample are given in Panel A and for the insurers in Panel B of Table 4.2. First, we notice that the means of the variables of the banking sector differ substantially from the insurance sector. The average MES is higher for insurers than for banks while the opposite is true for ΔCoVaR. One explanation for this finding could be the fact that both measures are purely based on stock market data. As insurers will most likely have a higher sensitivity of their asset side to downturns in equity markets, so will their own equity. Consequently, the higher estimates for MES of insurers could be indicative of a) a higher overall (average) systemic importance of insurers or b) a higher sensitivity of their equity to market crashes (which in part could also indicate a higher systemic risk). Conversely, the sheer size of the asset management activities of the larger insurance companies and crisis-related shifts in their asset portfolios could also explain the lower average ΔCoVaR in our sample.

Insurers have a mean of total assets of \$ 158 billion while banks are significantly larger with a mean of total assets of \$ 350 billion. Furthermore, the leverage of banks is on average 13.430 whereas the insurers have a mean leverage of 9.285, which un-

[70] Note that the sample size is slightly reduced by the unavailability of some balance sheet items for smaller banks and insurers in *Worldscope*.

Table 4.2: Descriptive statistics: banks and insurers.

The table shows summary statistics for the sample of the largest 148 banks and for the 98 largest international insurers. The values for the systemic risk measures MES and ΔCoVaR are given for the crisis period (July 2007 to December 2008) and the values for the three independent variables are calculated for the fiscal year 2006. Variable definitions and data sources are documented in Appendix C.1. All data are winsorized at the 1% and 99% levels.

					Banks				
	No. Obs.	Min.	10%	25%	Median	Mean	75%	90%	Max.
MES	148	-0.166	-0.048	0.001	0.033	0.025	0.064	0.097	0.137
ΔCoVaR	148	-0.021	-0.015	-0.010	-0.001	-0.005	0.000	0.000	0.001
Total assets (in billions)	148	56.620	65.278	85.010	151.200	350.800	345.500	1046.447	1841.000
Leverage	146	4.071	5.221	6.585	9.046	13.430	14.110	22.114	96.060
Interconnectedness (in 10^{-9})	148	0.000	0.000	0.012	15950.000	108900.000	149556.000	328951.000	1211000.000

					Insurers				
	No. Obs.	Min.	10%	25%	Median	Mean	75%	90%	Max.
MES	98	0.009	0.020	0.034	0.051	0.056	0.073	0.098	0.150
ΔCoVaR	98	-0.021	-0.019	-0.018	-0.015	-0.015	-0.013	-0.011	-0.004
Total assets (in billions)	98	17.910	23.187	27.080	56.390	158.700	147.300	405.449	131.000
Leverage	98	1.729	3.322	5.273	7.309	9.285	11.350	17.265	42.260
Interconnectedness (in 10^{-9})	98	0.000	0.003	0.012	0.078	0.078	0.211	0.368	1.001

derlines the increased leverage in banking compared to other industries. As expected, on average, banks had significantly higher total assets, leverage and were more interconnected than insurers. Additionally, we find only little evidence of strong interconnectedness of the insurers in our sample compared to the bank sample. Based on the univariate analysis, we hypothesize that size and leverage are the driving systemic risk while interconnectedness does not play such an important role for explaining differences in MES and ΔCoVaR.

4.4 The determinants of systemic relevance

This section investigates which (possibly differential) factors determine the systemic relevance of banks and insurers. We first present the results of our cross-sectional OLS and quantile regressions of the institutions' MES and ΔCoVaR during the crisis. Afterwards, we report and comment on the results of our probit regressions for the determination of factors that influence systemic relevance as stated by regulators.

4.4.1 Cross-sectional regressions

Instead of only using the standard OLS approach for cross-sectional regressions, we perform the multivariate analysis of the determinants of extreme values of MES and ΔCoVaR in two ways. In particular, we employ cross-sectional quantile regressions with bootstrapped standard errors[71] and simple OLS regressions with robust standard errors of our systemic risk proxies during the crisis on our (lagged) main independent and the various control variables in 2006. The use of quantile regressions benefits us with reasonable benefits compared to OLS regressions. OLS models the relationship between the conditional mean of the dependent variable and the independent variables. We do not include all active Banks and insurance companies with available data in *Datastream* because the values of our systemic risk measures (or the dummy

[71] By using bootstrapped standard errors, we are able to partially obviate possible biases by the non-i.i.d. character of our data.

variables for our probit regressions) would be distorted by the inclusion of too many firms in a mechanical way. The quantile regression approach by Koenker and Basset (1978) circumvents the problems that arise in OLS due to heteroskedasticity in the data by estimating the change in a specified quantile of the dependent variable given the covariates produced by the independent variables. Quantile regression models the quantiles of the dependent variable's distribution and therefore does not suffer from the usual heteroskedasticity problem. For the MES, we analyze the 95%-percentile and for ΔCoVaR we analyze in the 5%-percentile, with both indicating extreme systemic risk. The results of our cross-sectional analysis for banks are shown in Table 4.4 and 4.3.

Table 4.3: Cross-sectional regression of systemic risk (ΔCoVaR) of banks.

The table shows the OLS and quantile regression results using a sample of the 148 largest banks. Independent variables are calculated for the fiscal year 2006 and the systemic risk measures are calculated for the crisis period (July 2007 to December 2008). Regressions on MES are on the 95%-percentile. The OLS regressions are estimated using heteroskedasticity-robust standard errors and the quantile regression uses bootstrapped standard errors. P-values are given in parentheses. ***,**, and * denote statistical significance at the 1%-,5%- and 10%-level respectively. Variable definitions and data sources are documented in Appendix C.1. Interconnectedness is given in millions. Test statistics and p-values for Breusch-Pagan tests on heteroskedasticity are reported below.

Dependent variable:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
Estimation:	OLS regression				Quantile regression			
Log(Total assets)	0.0008			0.0022	0.0008			0.0034*
	(0.121)			(0.100)	(0.527)			(0.090)
Leverage		0.0000		0.0000		0.0000		-0.0006
		(0.529)		(0.986)		(0.914)		(0.178)
Interconnectedness			0.0118***	0.0000**			0.0153	0.0061
			(0.001)	(0.049)			(0.410)	(0.259)
Performance				-0.0040				-0.0096*
				(0.176)				(0.082)
ROA				-0.0019				-0.0012
				(0.177)				(0.528)
Debt maturity				-0.0021				-0.0033
				(0.469)				(0.647)
Deposits				-0.0016				-0.0037
				(0.761)				(0.709)
Loan loss provision				-0.0016				-0.0031
				(0.346)				(0.283)
Loans				0.0048				-0.0036
				(0.371)				(0.839)
Tier-1-capital				0.0939				0.1515
				(0.175)				(0.115)
Non-interest income				-0.0024				-0.0074**
				(0.340)				(0.045)
No. Obs.	148	146	148	92	148	146	148	92
R^2	0.0169	0.0025	0.1360	0.3204	-	-	-	-
Pseudo R^2	-	-	-	-	0.0108	0.0012	0.1066	0.4826
χ^2	1.01	0.05	4.02	23.23	-	-	-	-
p-value	0.316	0.817	0.045	0.000	-	-	-	-

Table 4.4: Cross-sectional regression of systemic risk (MES) of banks.

The table shows the OLS and quantile regression results using a sample of the 148 largest banks. Independent variables are calculated for the fiscal year 2006 and the systemic risk measures are calculated for the crisis period (July 2007 to December 2008). Regressions on ΔCoVaR are on the 5%-percentile. The OLS regressions are estimated using heteroskedasticity-robust standard errors and the quantile regression uses bootstrapped standard errors. P-values are given in parentheses. ***,**, and * denote statistical significance at the 1%-,5%- and 10%-level respectively. Variable definitions and data sources are documented in Appendix C.1. Interconnectedness is given in millions. Test statistics and p-values for Breusch-Pagan tests on heteroskedasticity are reported below.

Dependent variable:	MES	MES	MES	MES	MES	MES	MES	MES
Estimation:	OLS regression				Quantile regression			
Log(Total assets)	0.0042			0.0062	0.0071			0.0022
	(0.389)			(0.669)	(0.311)			(0.888)
Leverage		-0.0002		-0.0007		-0.0003		-0.0046
		(0.475)		(0.530)		(0.589)		(0.205)
Interconnectedness			-0.1150**	-0.2070***			0.0192	-0.1920*
			(0.018)	(0.000)			(0.483)	(0.069)
Performance				-0.0030				-0.0267
				(0.889)				(0.385)
ROA				-0.0132				-0.0451**
				(0.196)				(0.027)
Debt maturity				0.0153				0.0382
				(0.592)				(0.462)
Deposits				-0.0422				-0.2903*
				(0.383)				(0.051)
Loan loss provision				0.0040				0.0254
				(0.844)				(0.333)
Loans				-0.0287				0.1026
				(0.704)				(0.197)
Tier-1-capital				0.5999				1.3814
				(0.196)				(0.173)
Non-interest income				-0.0122				-0.0283
				(0.567)				(0.281)
No. Obs.	148	146	148	92	148	146	148	92
R^2	0.0047	0.0028	0.1409	0.2975	-	-	-	-
Pseudo R^2	-	-	-	-	0.0212	0.0053	0.0003	0.2319
χ^2	5.71	0.02	34.21	0.14	-	-	-	-
p-value	0.017	0.895	0.000	0.713	-	-	-	-

The first three regressions in all settings are concerned with the individual effects of our three main dependent variables: size, leverage, interconnectedness with the financial system, as well as systemic risk.

In the OLS regressions of banks we find no significant effect of the variables total assets and leverage on our systemic risk measures except for a strong significance at the 1% level of interconnectedness on ΔCoVaR. Surprisingly, the variable enters the quantile regression with a positive coefficient and thus increases the value of ΔCoVaR, which we interpret as a decrease in the systemic risk contribution of the bank, since smaller values of ΔCoVaR indicate a higher contribution to systemic risk. However, by adding our control variables, we only lose some of the significance of the coefficient of interconnectedness and find no statistically significant influence of any other variable on ΔCoVaR. Looking at the respective quantile regressions on the 5%-quantile of ΔCoVaR reveals that only bank size is a slightly statistically significant predictor of extreme contribution of banks to systemic risk. The variable enters the quantile regression with a positive sign of the coefficient at a 10% level, which indicates the unintuitive impression that larger banks contribute less to systemic risk.

The OLS regressions of MES on our main variables of interest show that only the interconnectedness influenced the exposure of banks to external shocks during the crisis. The coefficient of interconnectedness enters both the OLS and the quantile regression with a negative sign that is significant at the 1% level in the regression of the conditional mean and at the 10% level for the regression of the 95%-quantile. Thus, at least for this sample, we find the counterintuitive result that being more interconnected does not necessarily increase the exposure of banks to systemic risk. Interestingly, we note a slightly significant decreasing effect of the variable deposits on MES which leaves us with the interpretation that banks with higher deposit financing were more stable and less sensitive to external shocks during the financial crisis.

The regressions of banks' systemic risk on the indicators of systemic relevance reveal that only the interconnectedness of banks with the financial sector helps in explaining the magnitude of the contribution or exposure to systemic risk. In Tables 4.5 and 4.6, we show the results from the OLS and quantile regressions of ΔCoVaR and MES on the proposed factors of systemic relevance for insurers.

Table 4.5 shows that an insurer's size decreases ΔCoVaR (significant at the 10% level) and thus, indicates a higher contribution to systemic risk by larger insurers. This significance, however, vanishes when including other control variables and is also never significant when regressing the conditional quantile of systemic risk. A very similar pattern can be found in Table 4.6 concerning insurer size, where total assets to increase the exposure to systemic risk. On the other hand, we find that a higher leverage induces a lower systemic risk contribution. Again, this counterintuitive result

Table 4.5: Cross-sectional regression of systemic risk (ΔCoVaR) of insurers.

The table shows the OLS and quantile regression results using a sample of the 98 largest insurance companies. Independent variables are calculated for the fiscal year 2006 and the systemic risk measures are calculated for the crisis period (July 2007 to December 2008). Regressions on ΔCoVaR are on the 5%-percentile. The OLS regressions are estimated using heteroskedasticity-robust standard errors and the quantile regression uses bootstrapped standard errors. P-values are given in parentheses. ***,**, and * denote statistical significance at the 1%-,5%- and 10%-level respectively. Variable definitions and data sources are documented in Appendix C.1. Test statistics and p-values for Breusch-Pagan tests on heteroskedasticity are reported below.

Dependent variable:	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR	ΔCoVaR
Estimation:	OLS regression				Quantile regression			
Log(Total assets)	-0.0006*			-0.0009	0.0003			0.0007
	(0.082)			(0.408)	(0.367)			(0.237)
Leverage		0.0001*		0.0002**		0.0001		0.0002*
		(0.063)		(0.043)		(0.214)		(0.078)
Interconnectedness			0.0032*	0.0022			0.0021	0.0058*
			(0.089)	(0.468)			(0.344)	(0.087)
Performance				-0.0003				0.0006
				(0.873)				(0.743)
ROA				0.0006				0.0011***
				(0.237)				(0.000)
Debt maturity				0.0014				-0.0006
				(0.550)				(0.804)
Investment success				0.0064				0.0063
				(0.305)				(0.094)
Loss ratio				0.0000				0.0000**
				(0.651)				(0.015)
Non-policyholder liab.				-0.0004				0.0000
				(0.283)				(0.974)
Operating expenses				-0.0124				-0.0036
				(0.111)				(0.353)
Other income				0.0000				0.0000
				(0.623)				(0.853)
Fixed income				0.0000				-0.0012**
				(0.999)				(0.025)
No. Obs.	98	98	98	71	98	98	98	71
R^2	0.0307	0.0307	0.0315	0.1973	-	-	-	-
Pseudo R^2	-	-	-	-	0.0092	0.0283	0.0332	0.3263
χ^2	0.01	0.37	0.40	0.75	-	-	-	-
p-value	0.909	0.544	0.53	0.385	-	-	-	-

could be due to our proxies of systemic risk not being able to fully capture all facets of an institution's systemic relevance. For the interconnectedness variable, we find the same effects on systemic risk as in the models involving our sample of banks, although with statistically less significant results.

Turning to the quantile regressions for our insurer sample, we notice that interconnectedness exhibits a strong influence on systemic risk. Although the actual values of interconnectedness of insurers are much lower than those for the sample of banks, we notice that being interconnected with the financial system as an insurer has a much

Table 4.6: Cross-sectional regression of systemic risk (MES) of insurers.

The table shows the OLS and quantile regression results using a sample of the 98 largest insurance companies. Independent variables are calculated for the fiscal year 2006 and the systemic risk measures are calculated for the crisis period (July 2007 to December 2008). Regressions on MES are on the 95%-percentile. The OLS regressions are estimated using heteroskedasticity-robust standard errors and the quantile regression uses bootstrapped standard errors. P-values are given in parentheses. ***,**, and * denote statistical significance at the 1%-,5%- and 10%-level respectively. Variable definitions and data sources are documented in Appendix C.1. Test statistics and p-values for Breusch-Pagan tests on heteroskedasticity are reported below.

Dependent variable:	MES	MES	MES	MES	MES	MES	MES	MES
Estimation:	OLS regression				Quantile regression			
Log(Total assets)	0.0095***			0.0019	0.0111			-0.0106
	(0.000)			(0.806)	(0.269)			(0.442)
Leverage		-0.0006		-0.0009		-0.0009		-0.0013
		(0.131)		(0.204)		(0.752)		(0.575)
Interconnectedness			-0.0275**	0.0156			-0.0734	-0.0141
			(0.020)	(0.453)			(0.179)	(0.795)
Performance				-0.0390***				-0.0594**
				(0.001)				(0.012)
ROA				0.0024				-0.0018
				(0.551)				(0.805)
Debt maturity				0.0048				-0.0022
				(0.762)				(0.967)
Investment success				0.1042*				0.1318
				(0.063)				(0.199)
Loss ratio				-0.0001**				-0.0001
				(0.025)				(0.363)
Non-policyholder liab.				0.0006				-0.0055
				(0.858)				(0.651)
Operating expenses				-0.0934				-0.1014
				(0.277)				(0.497)
Other income				0.0000				0.0000
				(0.422)				(0.691)
Fixed income				0.0077				0.0188
				(0.210)				(0.206)
No. Obs.	98	98	98	71	98	98	98	71
R^2	0.1128	0.0154	0.0339	0.4932	-	-	-	-
Pseudo R^2	-	-	-	-	0.0432	0.0098	0.0394	0.4905
χ^2	0.88	0.02	1.55	5.13	-	-	-	-
p-value	0.347	0.880	0.213	0.024	-	-	-	-

stronger impact on the systemic risk of the insurer than for banks. The coefficients in the quantile regressions are positive for ΔCoVaR and negative for MES which indicates a decrease in the contribution and the exposure to systemic risk. This holds true at the 1% level. Again, this counterintuitive result could be due to our proxies of systemic risk not being able to fully capture all facets of an institution's systemic relevance.

Additionally, we find that profitability and higher loss ratios also have a decreasing effect on the contribution to systemic risk. Throughout all of the regressions neither size nor leverage consistently enter the analysis with a significant coefficient. Consequently, a simple analysis of MES and ΔCoVaR could lead to the conclusion that both size and leverage are not significant drivers of systemic risk in banking and insurance.

4.4.2 Probit regressions

In this section, we explain the probability of being declared a global systemically important bank or insurer by regulators. Employing a probit regression model allows us to explain the probability that a bank or an insurer will be declared systemically relevant or not. To this end, we employ the same set of explanatory variables as before in our quantile regressions.

The results of the probit regressions for the 148 largest banks, measured by their total assets in 2006, are presented in Table 4.7.

Table 4.7: Systemic relevance of banks: probit regressions.

The table shows the results of several probit regressions on a dummy variables that is one if a bank was nominated as global systemically important by the Financial Stability Board and zero otherwise. Our sample consists of the 148 largest banks measured by their total assets at the end of the fiscal year 2006. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. P-values are given in parentheses and ***,**,* denote statistical significance at the 1%,5% and 10% level. Definitions of variables as well as descriptions of the data sources are given in Table C.1 in the Appendix.

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log(Total assets)	1.5630***					1.5620***	1.8896***
	(0.000)					(0.000)	(0.000)
Leverage		0.0020				-0.0157	0.0336
		(0.811)				(0.574)	(0.480)
Interconnectedness			0.0000			0.0000	
			(0.939)			(0.743)	
MES				5.1186**		3.0310	3.4083
				(0.031)		(0.327)	(0.325)
ΔCoVaR					14.5811		
					(0.462)		
Market-to-book ratio							0.2961
							(0.532)
Performance							-0.0411
							(0.975)
ROA							0.4492
							(0.304)
Debt maturity							0.5344
							(0.685)
Deposits							0.9625
							(0.621)
Non-interest income							1.4046*
							(0.052)
Observations	146	144	146	146	146	141	108
AIC	55.43	140.74	141.57	136.36	141.02	59.68	55.14

Table 4.7 shows the results of several probit regressions on dummy variables that

take on the value of one if a bank was declared global systemically important by the Financial Stability Board and zero otherwise.

Starting with probit regressions (1) to (3) of systemic relevance of banks, we can see that neither the banks' leverage nor their interconnectedness are significant indicators of an institution's systemic importance. This first finding is in striking contrast to the hypotheses formulated by the Financial Stability Board on the pivotal role of leverage and interconnectedness for a bank's systemic relevance. Interestingly, our results in regression (4) imply that the banks' Marginal Expected Shortfalls has a significant influence on the global importance of a bank as perceived by regulators (from model (5) we see that ΔCoVaR is not statistically significant). In model specifications (6) and (7), we include several control variables in our regressions but only find size to be a driving factor for systemic importance. More precisely, the MES of the banks which previously entered the regression with a significant positive coefficient now loses all its statistical significance. Consequently, we find strong evidence that the nomination as a G-SIFI is only driven by the institution's size.

The probit regression results for the sample of insurers are shown in Table 4.8.

Similar to the results for the banks, we can see from the probit regressions (1) to (5) that neither the insurers' leverage nor their interconnectedness are significant indicators of the nomination as a G-SII by the FSB and the IAIS. These findings are also in striking contrast to the hypotheses of the pivotal role of leverage and interconnectedness for an insurer's systemic importance. In regression (5) we find an insurer's ΔCoVaR to be a significant determinant of the probability to be included in the list of G-SIIs. However, this effect vanishes as soon as we add total assets and other controls to our regression model. Similar to the probit regressions for banks, we find in regression (6) that size is the only reliable predictor of systemic relevance according to regulators. This holds true even when we include various control variables.

In summary, the results of our probit regression analyses show that the inclusion of an institution in the list of G-SIFIs or G-SIIs is only a question of size. While MES and ΔCoVaR do appear to capture some of aspects of systemic risk, these measures

Table 4.8: Systemic relevance of insurers: probit regressions.

The table shows the results of several probit regressions on a dummy variables that is one if an insurer was nominated as global systemically important by the Financial Stability Board and zero otherwise. Our sample consists of the 98 largest insurers measured by their total assets at the end of the fiscal year 2006. Stock market data are retrieved from *Thomson Reuters Financial Datastream* while financial accounting data are taken from the *Worldscope* database. P-values are given in parentheses and ***,**,* denote statistical significance at the 1%,5% and 10% level. Definitions of variables as well as descriptions of the data sources are given in Table C.1 in the Appendix.

Model:	(1)	(2)	(3)	(4)	(5)	(6)
Log(Total assets)	0.9546***					1.526***
	(0.000)					(0.005)
Leverage		0.0287				-0.0760
		(0.188)				(0.482)
Interconnectedness			-0.1704			1.468
			(0.844)			(0.567)
MES				7.0939		
				(0.177)		
ΔCoVaR					-145.0350**	-64.3375
					(0.032)	(0.526)
Market-to-book ratio						-0.027
						(0.950)
Performance						1.9750
						(0.227)
ROA						-0.354
						(0.672)
Debt maturity						-0.3316
						(0.810)
Observations	96	96	96	96	96	96
AIC	37.95	62.67	64.08	62.51	58.28	41.86

cannot explain the methodology proposed by regulators. They determine the systemic importance of a financial institution (regardless whether it is a bank or insurer) only by the institutions' size.

4.4.3 Robustness checks

To underline the validity of our results, we perform additional robustness checks. First, our results could be biased by the manner in which we calculate the systemic risk measures ΔCoVaR and Marginal Expected Shortfall. Reestimating the measures using the MSCI World Banks Index and MSCI World Insurance Index does not significantly change our main results. For our cross-sectional analysis, we reestimate the OLS and quantile regression models with alternative definitions of our key variables leverage (ratio of total liabilities to total assets) and size (natural logarithm of net revenues). Except for the OLS regression for banks of MES on control variables, where we find a statistical significance of leverage at the 10% level, our main inferences are robust to these changes. Also, to control for an insurer's line of business, we include a dummy variable in our cross-sectional analyses that is one if the company is a life insurer (SIC code 6311), and zero otherwise. Including this variable neither changes our main inferences, nor do we find it to be significant in most of the regressions. However, in the regression of an insurer's ΔCoVaR on the control variables, we find a positive relation of the life insurer dummy and ΔCoVaR that is significant at the 10% level indicating that life insurers in our sample have a lower contribution to systemic risk than non-life insurers. Finally, we reestimate our probit regressions for banks and insurers using data from later years, i.e., 2009 and 2010 (if available) as it could be argued that regulators identified systemically relevant financial institutions based on post-crisis data rather than data from 2006. Our additional analyses, however, reveal no new information and also suggest that size was the most common factor when constructing the list of systemically relevant institutions.

4.5 Conclusion

In this paper, we study the determinants of the systemic importance of the world's largest banks and insurers during the financial crisis. Using a sample of the largest 148 banks and 98 insurers in the world, we analyze the cross-sectional variation in two popular measures of systemic risk of financial institutions during the crisis. In the second step of our analysis, we try to explain the decision of regulators to include certain banks and insurers in the lists of global systemically important financial institutions and global systemically important insurers.

Our results show that our quantile regressions of banks' and insurers' MES and ΔCoVaR as our systemic risk proxies mainly produce counterintuitive results. We find little to no evidence that higher leverage and interconnectedness increase the exposure or contribution of individual institutions to systemic risk.

As our second main finding, we show that regulators only seem to care about an institution's size proxied by its total assets in their decision to declare the institution global systemically important. We find some correlation between the probability of being a G-SIFI and G-SII, and the institution's MES (banks) and ΔCoVaR (insurers). Nevertheless these proxies of systemic risk cannot explain the classification by regulators as soon as size is included in our probit regressions. We thus conclude that despite the methodologies published by regulators themselves, the decision to include a bank in the G-SIFI list was purely a question of bank size. Global systemically important insurers are clearly identifiable by a simple look at the total assets in their balance sheet.

Chapter 5

Non-life Insurer Solvency and Default Risk

5.1 Introduction

Reinvigorated by the financial crisis of 2007-2009, academics and regulators have taken a renewed interest in the impact of higher capital requirements for financial institutions on the stability of the financial sector. For example, the Financial Stability Board (FSB), the Basel Committee on Banking Supervision (BCBS), and the International Association of Insurance Supervisors (IAIS) all have designed new rules and frameworks to warrant the safety of the financial system including banks, insurers, and other financial intermediaries. Among other approaches and concepts, they propose a framework to identify global systemically important financial institutions (SIFIs), focusing not only on banks but also on globally active insurance companies. Institutions identified as SIFIs are required to fulfill stricter solvability or capital requirements and are more likely to be monitored more closely by supervisors. In fact, regulators and academics alike are demanding higher capital restrictions on financial institutions to decrease the likelihood of a firm defaulting. The effectiveness of higher capital requirements, however, is debatable as such requirements might weaken an institution's profitability and could tempt managers to engage in excessive risk-taking and regulatory arbitrage (see, e.g., Kashyap et al., 2008, Matutes and Vives, 2000, Berger and Bouwman, 2013, Jiménez et al., 2015, Ongena et al., 2013).

In the light of these recent discussions, the study of idiosyncratic default risk and its determinants in the insurance sector is important and of high relevance to regulators. Especially the interplay of required solvency capital (which is the main instrument of regulators to improve financial stability) and the default risk of institutions is of great interest to both regulators and managers. Although higher capital requirements are the most favorite tools for regulators to support financial stability, they are also viewed by managers as being counterproductive as they reduce profits thereby increasing financial instability. However, the effects of higher solvency of insurers is also of great importance to policyholders since they could be affected by increases in insurance premia or could demand more protection from the contract's issuer.

In this paper, we investigate the question whether higher capital leads to a significant reduction in the default risk of insurers. More precisely, we study the effects of an insurer's solvency on its default probability for an international sample of non-life insurance companies. The question whether the idiosyncratic default risk of insurers can be explained by idiosyncratic fundamentals or rather by country-specific determinants is relatively unexplored in the literature. Most studies on an insurer's likelihood to default focus on the U.S. sector only or employ relatively short time frames from several decades ago.[72] One approach to explain the variation in insurers' default risk around the globe is to look at the differences in regulation across countries. We extend the existing empirical literature on the determinants of insurers' default risk by performing panel regression analyses for an international sample of non-life insurers from 2000 to 2013. In particular, we are interested in the question which idiosyncratic factors are able to explain a non-life insurer's default risk and how the explanatory power of firm fundamentals relates to the one of country-specific factors.

[72]For example, Shiu (2011) analyzes a panel of non-life insurance companies from 1985 to 2002 focusing on the interplay of reinsurance and leverage and argues that highly levered companies are more likely to become insolvent and thus, instead of raising costly capital, are more inclined to buy reinsurance.

Our study is related to Pasiouras and Gaganis (2013) who use information obtained from surveys on insurance regulation to analyze the default risk of insurance sectors in different countries. Similar to the work of Barth et al. (2004, 2005, 2013) on banking regulation, they derive indexes for, e.g., capital requirements or supervisory power standards in a given country and use these indicators to explain the z-score of an insurance company from 2005 to 2007. Related to this issue, Altuntas et al. (2015) decompose insurers' capital structure into idiosyncratic and country-specific factors and find that the capital structure of insurers is not homogenous across countries but rather driven by institutional environments.[73] Additionally, financial distress in a given year or insurance firm might simply be the result of current economic downturns or increased market competition.

Instead of identifying factors to explain idiosyncratic default risk of insurers, recent studies have shifted their attention towards the determinants of the systemic risk and the systemic relevance of the insurance sector. While some of the authors concentrate on the interconnectedness of the insurance sector with the global financial network and consequently its contribution to or relevance for systemic (in-)stability (see, e.g., Baluch et al., 2011, Billio et al., 2012, Chen et al., 2014, Cummins and Weiss, 2014), other contributions focus on the determinants of proposed measures of systemic risk (see, e.g., Weiß and Mühlnickel, 2014, 2015, Bierth et al., 2015).[74] Moreover, one of the more recent analyses given by Rauch et al. (2014) reveals that idiosyncratic default risk is a significant driver of systemic risk measures for banks and insurers.[75]

To answer our main question concerning the relation between an insurer's solvency and its default risk, we pursue two approaches. As a first step, we run dynamic panel regressions of an insurer's inverse z-score on idiosyncratic characteristics and country-effects. As independent variables, we employ different measures of short-term and

[73] Also, e.g., U.S. regulators rely more heavily on a free-market and competition to discipline insurers in comparison to other country environments.

[74] Eling and Pankoke (2014) provide an overview of the recent work on systemic risk in the insurance sector.

[75] For the discussion on such measures see, e.g., Acharya et al. (2010), Adrian and Brunnermeier (2015), Brownlees and Engle (2015) or Benoit et al. (2013). Other proposed indicators of systemic relevance are given by the IAIS (2011, 2013).

long-term solvency as well as control variables that proxy for, e.g., the insurers' efficiency or quality of its risk portfolio. As our main result, we find long-term capital to be significantly negatively related to the default risk of insurers. In a second step, we decompose a non-life insurer's inverse z-score to determine to which extent individual insurer characteristics explain the variance in default risk. In order to compare individual and country- and time-specific effects on default risk, we perform a standard analysis of covariance.

Based on an international sample of 308 non-life insurers, we find that long-term solvency significantly reduces default risk across all countries in our sample. Short-term solvency does not play a significant role in most of our regressions. Furthermore, we observe that operating efficiency and an insurer's loss ratio are suitable indicators of financial distress for non-life insurance companies. However, compared to country-specific effects, the explanatory power of idiosyncratic indicators of financial distress is small. Supporting the findings in Pasiouras and Gaganis (2013), we find that differences across countries and thus, regulatory environments play an important role for the financial soundness of insurance companies. As our main policy implication, we find that capital requirements related to an insurer's long-term solvency are well suited for increasing the financial soundness of insurers. Furthermore, we find that the regulatory environment of insurers is more important for reducing the default risk of non-life insurers.

The remainder of this article is structured as follows. Section 5.2 explains the construction of the data set. The subsequent section 5.3 explains the methodology and variables used in our empirical study. Section 5.4 presents the results of our analysis on the determinants of non-life insurers' default risk. Concluding remarks are given in Section 5.5.

5.2 Data and variables

This section presents the construction of our data sample. Our empirical study focuses on a panel of non-life insurance companies around the world. Thus, we begin to construct our data sample by first selecting all publicly listed international insurers from the dead and active firm lists in *Thomson Reuters Financial Datastream* from 2000 to 2013. As a next step, we exclude all secondary listings and non-primary issues from our sample. The industry classification of insurance companies in *Datastream* is, in parts, inconclusive[76] and therefore, we use the following method in order to identify non-life insurers. The classification given in *Datastream* is cross-checked with the firms' SIC codes (Worldscope data item WC07021, SIC codes 6311, 6321, 6331) and the Industry Classification Benchmark (ICB) code (Worldscope data item WC07040, ICB supersector 8500) to exclude firms which cannot be clearly classified as non-life insurance companies.[77] Next, we match the classification of *Datastream* and ICB. If these classifications match, an insurance company is clearly identified as a non-life insurer. Otherwise the company is excluded from our sample. Additionally, all company names are manually screened for companies with a non-insurance focus in their line of business. For our initial list of non-life insurers, we obtain balance sheet and income statement data from the *Thomson Worldscope* database. All stock market and accounting data are collected in U.S. dollars to minimize a possible bias due to currency risk. The names of the 308 non-life insurance firms included in our final sample are listed in Appendix D.1.

In the following section, we introduce and discuss our empirical strategy as well as the dependent and independent variables used in our model.

[76]For example, several medical service plans and medical wholesale companies are listed as life insurance companies in *Datastream*'s company lists.
[77]Consequently, HMOs, managed care, and title insurance companies are not included in the final sample.

5.3 Empirical strategy

In our empirical study, we focus on the determinants of default risk for an international sample of 308 non-life insurers for the period from 2000 to 2013. As a proxy for default risk, we employ an insurer's inverse z-score defined as the standard deviation of an insurer's return on assets from the previous five years over the sum of the equity ratio and return on assets.[78] Qualitatively, the z-score measures by how many standard deviations profits have to decrease below the mean profits in order to equal a firm's equity. Measuring the financial default risk of financial institutions using the z-score methodology is widely utilized in the finance literature (see, e.g., Anginer et al., 2014b).[79] Additionally, the z-score of an insurer could also be calculated by using (stock) market data or a combination of accounting and stock market data. In theory, the calculation of a firm's z-score based on accounting variables should be equivalent to using the average of stock returns and stock return volatility (see, e.g., Schäfer et al., 2015). In our study, we use the approach based on balance-sheet data as it does not reduce our sample size due to problems with data availability (see also, e.g., Boyd et al., 2006, Tykvova and Borell, 2012). For the sake of an easier interpretation, we employ the inverse of a firm's z-score as our main dependent variable, where higher values of the inverse z-score indicate a greater degree of financial distress of the insurance company. The following subsections describe our empirical model and introduce the explanatory variables.

5.3.1 Econometric design

In our empirical study, we investigate the relation between an insurer's default risk, measured by the inverse of the z-score, and firm characteristics with a focus on mea-

[78] Using a five-year rolling window for the estimation of the standard deviation provides more variation and thus, the z-score calculation is not entirely dependent on the equity ratio and annual return on assets. However, some studies employ only, e.g., three-year rolling windows in order to minimize a possible loss of observations due to a lack of data availability (see, e.g., Pasiouras and Gaganis, 2013, Schaeck et al., 2012).

[79] The first multivariate insolvency measure based on accounting data is introduced in Altman (1968).

sures of the insurer's solvency. To do so, we analyze annual data for an international panel of non-life insurers for the time period from 2000 to 2013. We include one-year lags of our dependent variable to account for persistence of an insurer's default risk in our analysis. To model such persistence in insurers' default risk, we estimate dynamic panel regressions of the following type:

$$\begin{aligned} \text{DEFAULT RISK}_t^i &= \alpha^i + \nu_t + \beta_1 \times \text{DEFAULT RISK}_{t-1}^i \\ &+ \beta_2 \times \text{SOLVENCY}_t^i + \Theta \times \text{CONTROLS}_t^i + \varepsilon_t^i \end{aligned} \tag{5.1}$$

where DEFAULT RISK$_t^i$ is the inverse z-score of insurer i in year t, SOLVENCY$_t^i$ is one of our respective solvency measures and CONTROLS$_t^i$ are firm characteristics. Further, we run all regressions using the (one-step) GMM estimator (see Blundell and Bond, 1998) and employ double-lagged values of the dependent variable as instruments. We include insurer-fixed effects α^i and year-dummies ν_t to capture unobserved heterogeneity across our sample.

5.3.2 Explanatory variables

We include various idiosyncratic and country-specific explanatory variables as controls in our regressions. An overview of all variables and their definitions and data sources is given in Appendix D.2. Our main variables of interest proxy for the solvency of insurance companies. Naturally, we would expect that the ability to pay short-term and long-term liabilities is most vital to the default probability of a firm. However, especially insurance companies are inclined to reserve enough capital to cover the risk arising from future claims with stochastic occurrence (both short-term and long-term).[80] The non-life insurance business is rather short-term orientated compared to the life insurance business where contracts have a longer maturity. Therefore, we

[80] Also, short-term and long-term solvency have been proposed by IAIS (2007) to be key indicators for an insurer's default risk.

assume that non-life insurers' default risk depends on short-term rather than long-term solvency.

There are several ways to measure different facets of solvency for an insurance company. For example, the solvency ratio of an insurer describes the size of its capital relative to the premiums written, and measures an insurer's risk of experiencing uncovered claims. Other solvency ratios include debt to equity, total debt to total assets, and interest coverage ratios. Further, the solvency of an insurance company could be assessed using regulatory capital, which is often determined using prescribed rules by, e.g., regulators. In practice, insurance companies hold higher levels of capital and economic capital is assessed using risk-based models. Alternative methods to determine regulatory and economic capital have been proposed to capture the insurance default risk adequately.[81]

In our study, we include two different proxies for the solvency of a non-life insurance company. We calculate the current solvency by the insurer's net income divided by the sum of short-term debt and portion of long-term debt. Furthermore, to estimate the solvency for a longer time frame, we calculate an insurer's long-term solvency by taking its total long-term insurance reserves divided by its total liabilities. For a longer time frame, we focus on the insurers' capital which includes technical reserves, accounting provisions, and capital for losses in asset positions. Higher values of each of the two proxies indicate better an improved ability of an insurer to pay back its liabilities and thus, are expected to decrease the level of default risk of an insurance company.

While the two variables above proxy for an insurer's active operating cash flow and solvency, we are also interested in whether the sheer size of capital buffers against unexpected high losses is relevant in determining default risk. We include the natural logarithm of capital surplus as an additional explanatory variable in our analysis and expect it to be negatively related to the inverse z-score (see also, e.g., Carson and Hoyt,

[81]For example, Mayers and Smith (2010) calculate solvency ratios by the insurers' market value and price of the insurance contracts written. Other authors use different methods based on the economic value of the balance sheet to measure the allocation of solvency capital (see, e.g., Cummins, 2000).

2000).

In addition to our measures of insurer solvency, we employ several other insurer-specific characteristics that may be significant drivers of individual default risk. We include the variable debt maturity which is defined as the ratio of total long-term debt to total debt. It exists a wide consensus among economists and regulators that the dependence of certain banks and insurers on short-term funding exposed these institutions to liquidity distress during the financial crisis (see, e.g., Brunnermeier and Pedersen, 2009, Cummins and Weiss, 2014, Fahlenbrach et al., 2012).[82] In our analysis, we assume that the variable debt maturity not only influences an insurer's systemic relevance (see, e.g., Bierth et al., 2015), but also the idiosyncratic default risk.

To characterize the quality of the risk portfolio, we obtain information on the insurers' loss ratio by employing the sum of claim and loss expenses and long-term insurance reserves dividing by premiums earned. In the absence of non-traditional business activities of insurers, the composition of their risk portfolio should be the determining factor for the probability of default. Whenever the claim and loss expenses exceed the earned premiums by a large magnitude, it is an indicator of either poor risk management or underwriting abilities and reflect the overall profitability and soundness of the insurance firm. Thus, we expect that higher loss ratios are associated with higher default risk and therefore should enter our regression analyses with a positive signed coefficient.

Next, we are interested in whether the quality and efficiency of an insurer's management affects its overall default risk. In order to proxy for such inefficiencies, we calculate an insurer's operating expense ratio given by the ratio of operating expenses to total assets. Higher values of the operating expense ratio express a less efficient management of the insurance company and thus, is very likely to decrease the overall soundness of the insurer.

Also, we proxy for an insurer's leverage by taking the sum of earned and unearned

[82] Also, the (IAIS) includes the ratio of the absolute sum of short-term borrowing to total assets in its methodological framework as a key indicator of systemic relevance of an insurance company (see IAIS, 2011, 2013).

premiums divided by capital surplus. Many studies argue that high leverage may increase the overall risk of a firm if the leverage ratio has reached values beyond a certain optimum, after which it decreases firm value (see, e.g., Carson and Hoyt, 2000).

As another idiosyncratic variable, we employ an insurer's annual premium growth (in percent) in booked premiums. A positive and higher growth rate increases the insurers' leverage in case of constant equity and thus, can be risky beyond a certain optimum. On the other hand, a strong growth in booked premiums might also indicate that an insurer's business is in demand. Thus, we argue that premium growth could have both, a positive and negative impact on default risk. Therefore, we have no expectations regarding the sign of its coefficient in our regressions.

Finally, to control for country-specific factors (such as the business climate) that generally influence the well-being of an insurance company in different countries, we also include a country's annual real GDP growth rate (in %) and the log of the annual change of the GDP deflator.

5.3.3 Descriptive statistics

We start our empirical analysis by presenting selected descriptive statistics for both full sample and sub-samples. To minimize possible biases stemming from extremely high or low values in our data, we winsorize each of our variables at the 1% and 99% level.

To describe our data sample in more detail, Table 5.1 shows the number of observations for our main independent variables of insurer solvency for each country.

Table 5.1: Number of observations per country.

The table presents the number of observations of the two variables that describe a non-life insurer's solvency per country. The sample consists of 308 international non-life insurers and runs from 2000 to 2013. Solvency is an insurer's net income divided by the sum of short-term debt and portion of long-term debt. Long-term solvency is defined as the total long-term insurance reserves divided by total liabilities. Data sources are given in Appendix D.2.

Country	**Solvency**	**Long-term solvency**	**Country**	**Solvency**	**Long-term solvency**
AUSTRALIA	30	10	MALAYSIA	19	26
AUSTRIA	0	19	MALTA	0	8
BAHRAIN	4	13	MEXICO	0	11
BERMUDA	60	108	NIGERIA	9	20
BRAZIL	19	14	NORWAY	3	4
CANADA	37	49	OMAN	13	15
CAYMAN ISLANDS	1	8	PAKISTAN	26	94
CHINA	15	5	PERU	3	14
CROATIA	4	16	POLAND	13	18
CYPRUS	4	7	QATAR	19	18
DENMARK	26	43	RUSSIAN FEDERATION	0	8
EGYPT	2	0	SAUDI ARABIA	0	53
FINLAND	9	22	SINGAPORE	0	5
FRANCE	20	21	SOUTH AFRICA	6	0
GERMANY	19	62	SPAIN	0	18
GREECE	4	24	SWITZERLAND	28	68
HONG KONG	17	5	TAIWAN	5	30
INDONESIA	5	80	THAILAND	118	27
IRELAND	17	13	TUNISIA	0	17
ISRAEL	20	18	TURKEY	9	41
ITALY	57	143	UNITED ARAB EMIRATES	56	103
JAPAN	62	165	UNITED KINGDOM	76	64
JORDAN	13	72	UNITED STATES	585	479
SOUTH KOREA	35	129	VIETNAM	2	24
KUWAIT	14	30			
LUXEMBOURG	15	14			

First, we notice that the number of observations differs substantially for long-term solvency and for the solvency variable. We find more data points for the insurers' long-term solvency than for the solvency variable in the whole sample. Second, the maximum number of available observations per country for both variables is given by 479 for the United States, followed by 165 for Japan. We later address this finding by performing analyses that compare the impact of idiosyncratic variables on the default risk of U.S. and non-U.S. non-life insurers. Overall, we include non-life insurers from 50 different countries.

Next, we turn to the more detailed description of our sample by reporting relevant statistics for selected variables. Table 5.2 presents descriptive statistics for the main variables used in our empirical study.

Summary statistics for data values used in our baseline regressions are given separately in two panels for our full sample and for the sub-sample of large insurers, respectively. Since data availability for the solvency and long-term solvency variables differs across countries, it is reasonable to report descriptive statistics for both samples used in the regressions.

First, we notice that the mean of the annual default risk variable is higher for the samples with long-term solvency and the standard deviation is almost twice as high. For the panel of large non-life insurers, we find qualitatively the same relation. Turning to the solvency variable, we observe a maximum of 2,755.96, which is significantly higher as the average value of 116.96 indicating the presence of few outliers. As expected, large insurers have a significantly higher average solvency ratio.

For the long-term solvency, we find no relevant differences for the mean and standard deviation besides that a maximum value of 0.853 can be found among the smaller and medium sized insurers. The average loss ratio of large insurers is similar for both samples and we find a lower quality of the insurers' risk portfolio among the full sample. Since the operating expense ratio for large insurers is significantly smaller, we argue that larger insurers might in fact have a more efficient management than their smaller counterparts (this is in line with larger insurers being able to generate

Table 5.2: Summary statistics of the full sample.

The table presents descriptive statistics of the inverse z-score and the main explanatory variables for a sample of 308 international non-life insurers (corresponding to our baseline regressions including the variables solvency and long-term solvency). The sample period runs from 2000 to 2013. Additionally, the table presents descriptive statistics for our set of explanatory variables for non-life insurers in the fourth quartile of total assets (large). We report the number of observations *N*, minimum and maximum values, mean and standard deviation. All variables and data sources are defined in Appendix D.2.

Sample	Full					Full			
N=790	Mean	St. Dev.	Min	Max	N=720	Mean	St. Dev.	Min	Max
Inverse z-score	0.728	1.204	0.034	15.864		1.084	2.226	0.034	15.864
Solvency	116.957	411.821	0.028	2755.960		-	-	-	-
Long-term solvency	-	-	-	-		0.036	0.071	0.000	0.853
Loss ratio	67.991	17.483	4.501	128.617		70.200	15.878	4.501	128.617
Operating efficiency	0.282	0.160	0.015	0.957		0.285	0.138	0.038	0.810
Debt maturity	0.545	0.391	0.000	1.000		0.728	0.375	0.000	1.000

Sample	Large					Large			
N=364	Mean	St. Dev.	Min	Max	N=338	Mean	St. Dev.	Min	Max
Default risk	0.732	1.168	0.034	9.979		0.952	2.050	0.034	15.864
Solvency	157.395	496.694	0.028	2755.960		-	-	-	-
Long-term solvency	-	-	-	-		0.039	0.061	0.000	0.284
Loss ratio	75.956	14.469	14.950	128.617		75.570	14.889	14.950	128.617
Operating efficiency	0.247	0.124	0.048	0.692		0.247	0.114	0.038	0.599
Debt maturity	0.715	0.326	0.000	1.000		0.780	0.331	0.000	1.000

economies of scale).

In addition to the summary statistics for our full sample, we also present descriptive statistics separately for samples in which the insurers are either above and below the median values of the respective solvency measure. The descriptive statistics are presented in Table 5.3.

Panel A of Table 5.3 shows descriptive statistics for the observations above and below of the median value of the solvency variable. For the values of default risk with observations below the median of solvency, we find a higher mean (1.19) and standard deviation (2.19) than in the sample with values above the median solvency (0.68 and 1.23). Also, the t-test of the equality of means is highly significant for every variable except size. Furthermore, higher solvency is associated with a lower mean in operating expense ratio and thus, higher operating efficiency.

Turning to the statistics for observations above and below the median values of our long-term solvency variable (Panel B), we find a statistically significant difference in the means of the inverse z-score for the two samples. Less long-term solvency is associated with a higher value of the inverse z-score and thus, a higher probability of default for the firm, which is intuitive. Looking at the loss ratio of non-life insurers, we find that more long-term solvency, on average, is associated with lower loss ratios and thus, a higher quality of the the company's risk portfolio. Although this is intuitive, we find the reverse relation in Panel A, where short-term solvency is associated with higher loss ratios. Thus, we find slight differences between the dynamics of solvency and long-term solvency.[83]

In Panel C, we present descriptive statistics for the main variables of interest with our sample being split up using the median value of capital surplus as the cut-off. Obviously, the overall number of observations is higher for capital surplus than for the other two variables, mainly due to data availability. Splitting the full sample according to this variable, however, does not reveal any significant differences in default risk. The findings for the loss ratios are similar to those in Panel B. In contrast to the other

[83] Also, note that the number and distribution of observations for these two variables differ substantially.

Table 5.3: Descriptive statistics for observations above and below the median values of solvency measures.

The table compares the characteristics of an international sample of non-life insurers for the time period from 2000 to 2013 for observations that are above or below the median values for three different solvency measures. We report the number of observations, minimum, maximum, mean, median, and the standard deviation of an insurer's inverse z-score and selected control variables. We test the equality of means of the two samples using Welch's t-test for unequal sample sizes. ***,**,* denote estimates that are significant at the 1%, 5%, and 10% level, respectively. All variables and data sources are defined in Appendix D.2.

Panel A: Solvency	Above						Below						t-value	
	N	Mean	St. Dev.	Median	Min	Max	N	Mean	St. Dev.	Median	Min	Max		
Inverse z-score	527	1.19	2.19	0.52	0.04	17.59	539	0.68	1.23	0.35	0.04	17.59	4.73	***
Size	577	21.77	2.73	21.86	15.63	26.61	577	21.66	2.47	21.88	15.63	26.61	0.72	
Loss ratio	533	70.39	18.31	70.36	2.20	129.25	561	64.58	19.71	67.48	2.20	129.25	5.05	***
Operating efficiency	519	0.27	0.15	0.24	0.01	0.91	548	0.30	0.18	0.26	0.01	0.96	-3.38	***
Panel B: Long-term solvency	Above						Below							
	N	Mean	St. Dev.	Median	Min	Max	N	Mean	St. Dev.	Median	Min	Max		
Inverse z-score	776	1.11	2.45	0.46	0.04	17.59	676	1.45	2.89	0.42	0.04	17.59	-2.37	**
Size	947	21.17	2.37	21.33	15.63	26.61	947	20.48	2.69	19.99	15.63	26.61	5.90	***
Loss ratio	939	63.11	20.42	64.28	2.20	129.25	946	73.46	22.77	76.55	2.20	129.25	-10.39	***
Operating efficiency	919	0.29	0.16	0.26	0.01	0.96	589	0.38	0.20	0.32	0.04	0.96	-8.43	***
Panel C: Capital surplus	Above						Below							
	N	Mean	St. Dev.	Median	Min	Max	N	Mean	St. Dev.	Median	Min	Max		
Inverse z-score	919	1.23	2.76	0.39	0.04	17.59	949	1.02	2.16	0.43	0.04	17.59	1.78	*
Size	1,116	19.73	1.94	19.77	15.63	25.99	1,116	22.89	1.75	22.81	17.85	26.61	-40.48	***
Loss ratio	1,070	63.72	19.94	65.23	2.20	129.25	1,068	70.24	17.56	70.13	2.20	129.25	-8.03	***
Operating efficiency	1,116	0.37	0.21	0.32	0.01	0.96	1,106	0.26	0.14	0.24	0.01	0.96	15.36	***

solvency ratios, we find lower operating efficiency for observations above the median of capital surplus.

5.4 Empirical results

In this section, we investigate which factors determine a non-life insurer's default risk. First, we comment on the evolution of the idiosyncratic default risk of insurers in our data during the sample period. Then, we discuss the results of our baseline panel regressions. Subsequently, we report and comment on further results of additional multivariate analyses.

5.4.1 Insurer default risk

The following Figure 5.1 presents the time evolution of insures' default risk. More precisely, the figure plots the time evolution of the mean, the 10%- and 90%-quantile of the inverse z-score of the international sample of non-life insurer, outside of the United States, as well as for the sample of U.S. non-life insurers for the sample period from 2000 to 2013.

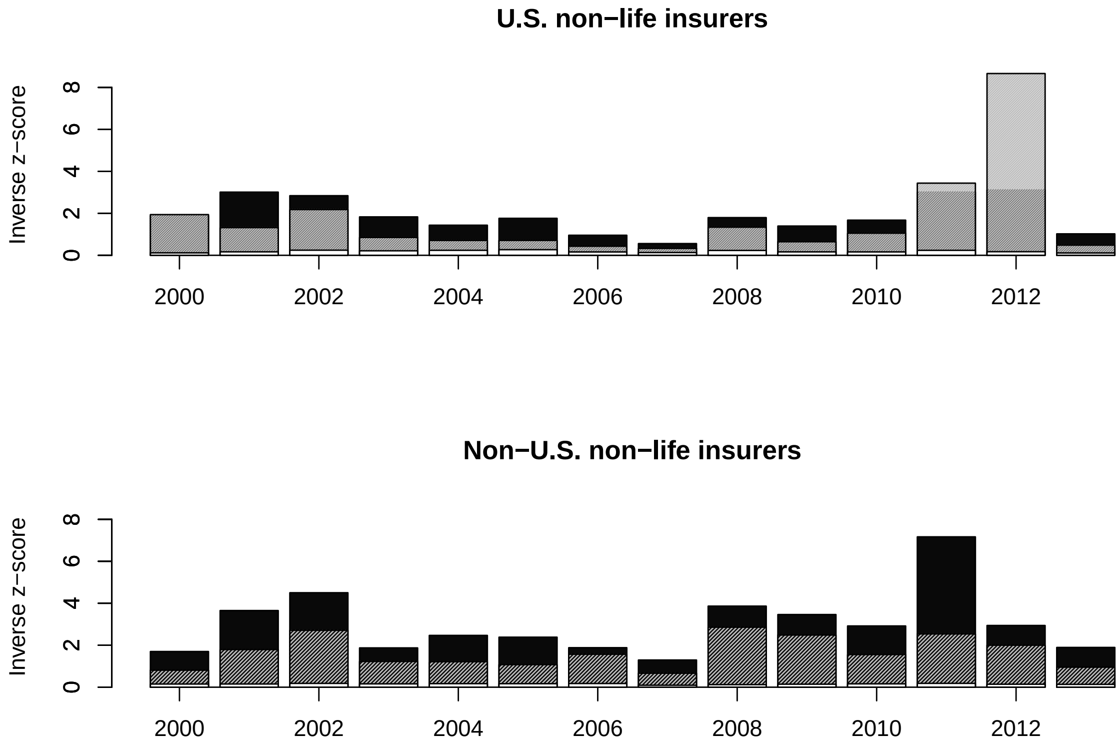
The first panel shows the time evolution of the U.S. non-life insurers. As shown in the figure, U.S. non-life insurers' average default risk (grey-shaded area) increased immensely during the dot-com crisis in 2002 and during the years 2010 and 2012.[84] Interestingly, the mean of the inverse z-score in 2011 and 2012 is above the 90%-quantile, probably due to outliers in that year. Before the recent financial crisis, the default risk of U.S. non-life insurers declined over the years but stayed on a relatively low level.

Turning to the time evolution of the non-U.S. non-life insurers illustrated in the second panel, it is not surprising that the average default risk increased steeply during the financial crisis. In contrast to the U.S. sub-sample, the level of default risk for the

[84] Since we calculate the z-score using balance sheet data, we can see an effect of variation in balance sheet data due to the recent financial crisis in 2010 up to 2012.

Figure 5.1: Time evolution of insurers' default risk for the period from 2000 to 2013.

The figure illustrates the time evolution of U.S. and non-U.S. non-life insurers' inverse z-score. Z-score is defined as the sum of an insurer's equity ratio and its return on assets over the standard deviation of return on assets during the previous five years. White areas present the values of the 10%-quantile and black bars present the 90%-quantile of insurer's inverse z-score per year. Grey shaded areas indicate the mean values of inverse z-score per year.



time period from 2000 to 2010 is considerably higher. However, we find no evidence for such high statistical outliers in 2011 and 2012 as for the other sample. The evolution of the inverse z-score values before the crisis period is comparable to those found for the U.S. sample. Finally, we notice that the level of default risk in the U.S. is lower in comparison with the non-U.S. non-life insurers.

5.4.2 Determinants of insurers' default risk

Following our univariate investigation of insurers' default risk, we now describe the results of our multivariate analyses. First, we run panel regressions for the time period from 2000 to 2013 using firm-fixed effects and year dummies. The estimates resulting from the (one-step) GMM-sys approach are given in Table 5.4.

Columns (1) - (6) present the results of regressions using the full sample of non-life insurers while (7) - (12) show analyses with observations in the fourth quartile of insurers' total assets.

In the first three regressions, we include the variable solvency among other idiosyncratic factors and a country's GDP growth and inflation rate. Most strikingly, we observe that the solvency measure does not seem to play a significant role in any of these regressions. Thus, the short-term ability to pay off debt is not the determining factor when assessing an insurer's default risk. The same conclusion is valid for the regressions of default risk on solvency for the sample of large insurers in (7) - (9).

In contrast to these results, we find a strong negative relation between our measure of long-term solvency and an insurer's inverse z-score. The larger the ratio of long-term insurance reserves and total liabilities in a non-life insurance company, the lower is its default risk as measured by the inverse z-score. Although the non-life insurance business is more volatile than, e.g., the business of life insurance contracts, the ability to meet long-term liabilities is nonetheless an essential component to preserve firm stability. It equips the insurance company with sufficient buffers to compensate unexpected high losses in the future. We conclude that although we would expect short-term solvency to be the determining factor of non-life insurers' default risk (since their claims are rather short-term and more volatile), long-term solvency significantly reduces default risk over the full sample. The effect of long-term solvency is also economically significant with a one standard deviation increase of the insurers long-term solvency being associated with a minus 43.35% (-6.108×0.071) decrease of the insurers' inverse z-score.

However, when we restrict our sample to large insurers, this significance vanishes. One explanation for this might be the higher level of long-term solvency of larger non-life insurers in general. Thus, the effect of this variable is not relevant for the sample of large insurers. Our observations from Table 5.2 support this view in the

Table 5.4: Panel regressions of non-life insurers' default risk (2000-2013).

The table shows the results of the (one-step) GMM-sys estimation of the inverse z-score on solvency measures of insurers and control variables. Regressors are defined in Appendix D.2. The lagged dependent variable is included in the regressions. We employ double-lagged values of the dependent variable as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Sample	**Full**						**Large**					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Inverse z-score$_{t-1}$	0.106***	0.113***	0.164***	-0.058	-0.067*	-0.044	0.215***	0.201***	0.212***	0.147**	0.116**	0.147**
	(0.000)	(0.000)	(0.000)	(0.122)	(0.066)	(0.249)	(0.000)	(0.000)	(0.000)	(0.010)	(0.024)	(0.012)
Solvency	0.000	0.000	0.000				0.000	0.000	0.000			
	(0.188)	(0.159)	(0.247)				(0.313)	(0.412)	(0.455)			
Long-term solvency				-6.098***	-6.108***	-6.443**				-4.133	-2.756	-4.063
				(0.001)	(0.000)	(0.024)				(0.297)	(0.408)	(0.347)
Loss ratio	0.010***	0.009**	0.017***	0.019**	0.026***	0.031***	0.032***	0.033***	0.038***	0.023**	0.023***	0.026**
	(0.009)	(0.012)	(0.000)	(0.030)	(0.001)	(0.003)	(0.000)	(0.000)	(0.000)	(0.025)	(0.007)	(0.020)
Operating efficiency	0.897*	0.573	0.601	8.518***	7.248***	7.871***	1.163*	1.260**	1.783**	4.518**	2.897	4.782**
	(0.072)	(0.214)	(0.254)	(0.000)	(0.000)	(0.000)	(0.079)	(0.036)	(0.017)	(0.039)	(0.112)	(0.042)
Debt maturity	0.171	0.205	-0.063	0.470	0.377	0.444	0.219	0.278	0.246	-0.149	-0.203	-0.305
	(0.342)	(0.230)	(0.711)	(0.175)	(0.285)	(0.254)	(0.333)	(0.183)	(0.323)	(0.739)	(0.615)	(0.521)
Premium growth		0.036			0.240			0.114			0.376	
		(0.798)			(0.401)			(0.531)			(0.263)	
GDP growth			-0.045			0.140**			-0.033			-0.031
			(0.114)			(0.041)			(0.341)			(0.749)
Inflation			0.016			0.099			-0.001			0.087
			(0.544)			(0.133)			(0.972)			(0.309)
Observations	790	725	590	720	677	628	364	324	328	338	312	322
Wald	250.64	310.66	296.14	255.19	299.93	280.10	230.47	284.63	230.5	143.38	166.26	139.61
p-value	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

way that large insurers have a slightly higher average value of long-term solvency, but also less dispersion. In this case, it shows that there is less variation in the values of solvency among the sub-sample of large non-life insurers and thus, these variables do not play a significant role in this specific analysis. Another reason might be that the observations in the fourth quartile of insurers' total assets are those tied to a specific group of countries. For example, U.S. non-life insurers are on average larger in size and make up the largest part of our sample. To understand this finding in detail, we run additional analyses that are concerned with the question whether insurers' default risk is driven by country-specific differences rather than idiosyncratic ones. Before we turn to these analyses, we highlight a few more findings from Table 5.4. First, we find that a non-life insurer's loss ratio, as a proxy for the quality of an insurer's risk portfolio, is positively related to its inverse z-score. Second, the less efficient the insurance company operates, the higher its default risk. The effect of the proportion of long-term debt on an insurer's default risk, however, is insignificant.

As a first step towards a cross-country analysis of insurers' default risk, we include a country's respective GDP growth and inflation rate in regressions (3) and (6). While we find a significant positive relation between GDP growth and default risk in (6), this effect vanishes in (3), where we have other restrictions on our observations due to differences in data availability for the two solvency measures.

To further investigate possible differences in default risk across our sample insurers due to country-specific effects, we split our sample into U.S. and non-U.S. insurers. U.S. insurers are different in the way that regulation does not require them to maintain higher solvency capital standards in contrast to what, e.g., the Solvency II framework in the European Union demands of European insurers.[85] We repeat our baseline regressions for these two separate samples. The results are shown in Table 5.5.

[85] Further, one of the main key differences between the two systems is that Solvency II has a stricter approach than the U.S. regulatory system.

In an effort to protect the interests of all stakeholders, the EU prescribes a strict provision for capital adequacy that may require a higher level of capitalization than in the United States. In contrast, the U.S. regulation focuses on free-markets and competition to discipline insurers.

Table 5.5: Panel regressions of default risk: U.S. and non-U.S. non-life insurers.

The table shows the results of the (one-step) GMM-sys estimation of the inverse z-score on solvency measures of insurers and control variables for U.S.-based and insurers outside of the United States. Regressors are defined in Appendix D.2. The lagged dependent variable is included in the regressions and we employ double-lagged values of the dependent variable as instruments. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Sample	**U.S.**				**Non-U.S.**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inverse z-score$_{t-1}$	0.0018	0.0133	-0.1861***	-0.1474***	0.2577***	0.2723***	0.1310***	0.1303***
	(0.892)	(0.283)	(0.001)	(0.004)	(0.000)	(0.000)	(0.001)	(0.001)
Solvency	-0.0001	-0.0001			-0.0001	-0.0001		
	(0.428)	(0.224)			(0.281)	(0.390)		
Long-term solvency			-5.7025	-5.1100			-4.0805***	-4.2808***
			(0.498)	(0.516)			(0.006)	(0.004)
Loss ratio	0.0087***	0.0126***	0.0488***	0.0530***	0.0053	0.0067*	0.0114*	0.0140**
	(0.000)	(0.000)	(0.001)	(0.000)	(0.152)	(0.063)	(0.057)	(0.017)
Operating efficiency	0.1644	0.5262**	4.5160***	5.1076***	2.3139***	1.9488***	7.5607***	6.7316***
	(0.574)	(0.031)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt maturity	-0.0171	0.0473	0.7247	0.1578	-0.0441	0.0005	-0.1611	-0.2213
	(0.856)	(0.548)	(0.136)	(0.727)	(0.811)	(0.998)	(0.562)	(0.426)
Premium growth		0.0940		0.1325		-0.5102***		-0.3446
		(0.112)		(0.717)		(0.003)		(0.145)
Observations	446	394	288	260	613	569	664	630
Wald	514.48	666.95	176.44	141.47	453.27	466.1	292.22	324.8
p-value	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

First, we notice that in the case of U.S. non-life insurers, none of the two measures of solvency enters the regressions with a statistically significant coefficient. For non-U.S. insurers, however, we find similar results as in our baseline regressions. Different from the findings in the regressions using the U.S. sample, we find that the loss ratio is a less significant factor when explaining default risk of non-U.S. insurers. We conclude that U.S. non-life insurers' default risk is not as dependent on the level of long-term and short-term solvency as for their non-U.S. counterparts. This substantial difference in the decomposition of insurers' default risk underlines the findings in Pasiouras and Gaganis (2013), who reveal that institutional differences across countries significantly drive differences in insurers' z-score.

5.4.3 Country effects and further analyses

As our next step, we disaggregate effects in our analysis that are due to differences in idiosyncratic and economic or regulatory environments in the home countries of insurers in our sample. Fundamental distress could be caused by current economic downturns or could be systematically influenced by, e.g., a stricter regulation of business activities or capital requirements.

Having pointed out that there are indeed differences in the non-life insurers' default risk across countries (see Pasiouras and Gaganis, 2013), we are interested in the explanatory power of such country effects. In order to do so, we estimate additional pooled OLS regressions using country dummies instead of firm-level effects and run standard analyses of covariances. The estimates for the pooled OLS regressions (with clustered standard errors on the country-level) are given in Table 5.6.

In columns (1) - (5), we report the OLS estimates for the regressions that include single variables and which are estimated with country-fixed and time-fixed effects. First, we include an insurer's natural logarithm of total assets as a proxy for its size. We observe a negative relation to the inverse z-score and thus, a decreasing effect on default risk[86]. Similar to the results above, an insurer's loss ratio and its operating

[86]Note that we do not report regressions with an insurer's size in our baseline regression since it is highly

Table 5.6: Pooled OLS regressions of non-life insurers' default risk on country dummies (2000-2013).

The table shows the results of pooled OLS regressions of the inverse z-score on solvency measures of insurers, country dummy variables, and control variables. Results for selected country dummy variables are reported in the table while the other dummies are suppressed. Regressors are defined in Appendix D.2. Standard errors are corrected for clustering on the firm level, p-values are given in parentheses, and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Size	-0.1433***						
	(0.007)						
Leverage		0.0000					
		(0.805)					
Surplus			-0.0151				
			(0.718)				
Loss ratio				0.0184***		0.0091	0.0266**
				(0.001)		(0.152)	(0.036)
Operating efficiency					0.8472**	1.3080*	3.6157***
					(0.031)	(0.060)	(0.001)
Solvency						-0.0001**	
						(0.029)	
Long-term solvency							-6.4534*
							(0.062)
Debt maturity						-0.0424	0.2308
						(0.826)	(0.378)
Constant	4.5404***	1.4625***	1.5501***	0.1657	1.1710***	-0.3954	-1.3675
	(0.000)	(0.000)	(0.000)	(0.707)	(0.000)	(0.462)	(0.121)
Country-fixed effects	YES	YES	YES	YES	YES	YES	YES
Time-fixed effects	YES	YES	YES	YES	YES	YES	YES
Observations	2,684	1,650	1,786	2,514	2,360	933	859
R^2	0.1241	0.1022	0.1156	0.1347	0.118	0.2034	0.1798

expense ratio enter the respective regressions with a statistically significant positive sign.[87]

Additionally, we estimate pooled OLS regressions employing the two additional variables capital surplus and leverage. Beyond a certain optimal point, high leverage is expected to increase the likelihood of a firm's default and thus, we assume that our variable leverage enters the regressions with a positive sign. While this is the case in our sample, the coefficient is statistically insignificant. Similarly, we find an intuitive negative relation of the logarithm of capital surplus and an insurer's inverse z-score, but no statistical significance.

correlated with some of our main variables and would bias the estimates. Instead, we opted for more granular insurer characteristics than size.

[87] Note that the number of observations in these regressions is reasonably higher than in our baseline regressions due to data availability for other variables.

Columns (6) and (7) report estimates using our baseline model (without the lagged dependent variable). For long-term solvency, we find qualitatively similar results as in our previous analyses with the difference that the estimate of the coefficient of long-term solvency is only statistically significant at the 10% level. In the absence of firm-fixed effects, which capture unobserved heterogeneity in our sample, our measure for short-term solvency becomes a significant driver for an insurer's default risk. The coefficient enters the regression with a statistically significant negative sign and thus, reduces the default risk in this model.

Finally, we analyze the decomposition of our default risk measure by employing a standard analysis of covariance (ANCOVA) (see, e.g., Altuntas et al., 2015). We include several firm-level determinants as well as country and year dummies to explore the degree to which each factor contributes to the variance of insurers' inverse z-score. For each variable, we calculate the ratio of the Type III partial sum of squares and the sum across all effects (times 100) in the model. The results are given in Table 5.7.

Table 5.7: Variance decomposition of non-life insurer default risk (2000-2013).

The table shows the variance decomposition of insurers' inverse z-score obtained from an analysis of covariance. Numbers represent the partial sum of squares for each variable in the model divided by the sum of squares of all effects (the total sum is 100). Explanatory variables include firm-level determinants, country dummies, and time dummies. All variables are defined in Appendix D.2.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Size	-	5.40	-	-	-	-	-	-	-
Leverage	-	-	0.02	-	-	-	-	-	-
Surplus	-	-	-	0.10	-	-	-	-	-
Loss ratio	-	-	-	-	10.16	2.63	8.86	0.88	9.00
Operating efficiency	-	-	-	-	-	3.98	9.40	2.25	7.87
Debt maturity	-	-	-	-	-	0.03	0.44	0.96	4.89
Solvency	-	-	-	-	-	0.53	-	0.40	-
Long-term solvency	-	-	-	-	-	-	4.06	-	1.71
Inverse z-score$_{t-1}$	-	-	-	-	-	-	-	24.47	5.10
Country-fixed effects	76.41	72.10	67.55	73.56	71.17	82.00	56.52	57.57	41.79
Time-fixed effects	23.59	22.51	32.43	26.34	18.67	10.83	20.71	13.48	29.63
Observations	2,684	2,684	1,650	1,786	2,514	933	859	790	720
Adjusted R^2	0.10	0.10	0.07	0.09	0.11	0.15	0.12	0.28	0.08

In column (1), we include year dummy variables and country-fixed effects and observe that in this simple setting the country effects account for over 75% of the variation of an insurer's inverse z-score. We continue like in our pooled OLS regressions by including single variables in our models to see what fraction is determined by idiosyncratic factors. The size of an insurance company explains about 5.4% of the dependent variable's variance while the capital surplus and leverage variables, which were insignificant in the OLS regressions, account for less than one percent. When we employ a non-life insurer's loss ratio as the only idiosyncratic variable in the model, we find that it determines almost twice as much of the fraction than the proxy for an insurer's size.

Next, we include all variables from our baseline analyses (which also significantly reduces the sample size in these models) and run separate analyses with and without one lag of inverse z-score. The results are reported in columns (6) - (9). For the models including our long-term solvency variable, we observe that the loss ratio and operating expense ratio both account for a little less than 10% of the variation in default risk and thus, possess a relatively high explanatory power compared to other firm-specific factors. Interestingly, we find that the lag of inverse z-score explains a relatively high proportion of the variance in these models. Still, we find that country effects and also time dummies explain most of the variations in our settings. In terms to the previous analysis we find that the long-term solvency capital endowment is the main buffer to reduce financial distress. Additionally we find no evidence in our study for the U.S. non-life insurance industry with the respective as a low stands regulatory guidelines for a reducing effect of financial distress in interaction with long-term solvency.

5.5 Conclusion

In this paper, we analyze the determinants of default risk of 308 international non-life insurers in the period from 2000 to 2013. As our main result, we find that default risk as measured by the inverse z-score is negatively related to non-life insurers' long-term solvency and positively related to the insurers' loss ratios. Interestingly, we find only little evidence that higher short-term solvency is associated with lower default risk.

Restricting our sample to only large insurers (with total assets in the fourth quartile of the full sample) reveals that none of the solvency measures is a significant driver of the default risk in that sub-sample. Also, when we compare the samples of U.S. and non-U.S. non-life insurers, we find that there are differences in the determinants of default risk across countries. While we confirm the results of our full sample analysis for non-U.S. insurers, we find no significant relation of any solvency measure for the insurers from the United States. One Reason might be for example the European Union with it's new insurer regulation system Solvency II and the corresponding capital requirement rules. The country specific regulation systems and the corresponding requirements affect the model of insurer business in different ways including the respective government specific intention.

Further, we explore the explanatory power of single indicators of distress in comparison to country effects and find that default risk is to a large extent driven by country-specific factors. The fraction of the variance of the inverse z-score explained by two different measures of solvency is small compared to other variables. Of all idiosyncratic insurer characteristics used in this study, we observe that an insurer's loss ratio and operating expense ratio are among the best predictors of a firm's financial distress.

Our study contributes to the discussion on solvency capital requirements in the insurance sector and stresses the importance of an insurer's regulatory environment for its default risk. Most importantly, regulation aiming at increasing an insurer's mid- and long-term solvency appear to be a powerful tool for significantly decreasing an insurer's default risk.

Chapter 6

Derivatives Usage and Default Risk in the U.S. Insurance Sector

6.1 Introduction

Financial and non-financial companies employ derivative instruments for a variety of reasons. Most obviously, companies use derivatives for hedging risky positions on their balance sheet. In contrast, companies could also use financial derivatives for other reasons, like lowering their expected costs of defaulting, lowering expected taxes, or reducing the volatility of executive compensations (see, e.g., Smith and Stulz, 1985, Froot et al., 1993, DeMarzo and Duffie, 1995). Finally, some firms might simply be using financial derivatives in their trading business, thereby increasing rather than decreasing their total firm risk. For insurance companies, which are by definition exposed to a variety of risks, hedging should be the prime motive for using derivative instruments. However, the literature still lacks an empirical investigation into the effects the usage of derivatives by insurers has on the institutions' default and systemic risk.

In the wake of the financial crisis of 2007-2009 and mainly due to the near-collapse of American International Group (AIG), regulators have become increasingly careful not to rule out a destabilizing effect of individual systemically important insurers on the financial sector.[88] In the context of regulators' endeavour to implement a macroprudential regulatory regime for insurers (see, e.g., IAIS, 2013), especially derivatives trading and usage have been named as a potential source of systemic risk. The allegedly adverse effect of derivatives usage on an insurer's firm risk, however, is not as obvious as regulators sometimes claim it to be. While derivatives trading for risk-taking should obviously increase firm risk, the use of derivatives for hedging purposes should (at least in theory) have a decreasing effect on an insurer's default risk. Insurers often employ derivatives to hedge various risks stemming from both sides of the balance sheet. For example, insurers are exposed to interest rate risk (due to guarantees for their policies) and via their debt financing. Also, insurers are often considerably exposed to foreign currency and market risk on their investments and liabilities. Derivatives may also substitute assets as part of an insurer's asset-liability-management (ALM).[89] On the other hand, some insurers could engage in derivatives trading simply for generating profit, a possibility which has been heavily criticized by, e.g., the IAIS (2011, 2013). An empirical test of the unknown relation between an insurer's derivatives usage (and its intended purpose) on the insurer's default risk and systemic risk exposure, however, has not yet been executed in the literature.

Motivated by the view of the IAIS (2013) that derivative usage and trading constitute a source of systemic risk in the insurance industry, this paper investigates the relation between the individual default risk of insurance companies and their disclosed information on derivatives usage. More precisely, we evaluate the 10-K filings of U.S. insurance companies to obtain information on the firms' disclosed derivatives usage, the intended purpose, and the variety of derivatives used in the insurers' risk management. For a sample of 171 U.S. insurers for the period from 1999 to 2014, we then perform panel regressions of quarterly default risk estimates on a set of variables that

[88] Several discussions on measuring systemic risk are given in, e.g., Acharya et al. (2010), Adrian and Brunnermeier (2015), Brownlees and Engle (2015), or Benoit et al. (2013). An overview of the recent literature on systemic risk and systemic relevance in the insurance industry is given in Eling and Pankoke (2014).

[89] For instance, insurers may use simple interest rate swaps to lengthen their assets' duration and match it with the duration of their liabilities.

proxy for the insurers' use of derivatives and a set of control variables taken from the literature (see, e.g., Bartram et al., 2011, Cummins et al., 1997, 2001). To control for the endogenous nature of an insurer's decision to use derivatives, we match derivative users with a control group of non-users using nearest neighbor matching based on the insurers' size and market-to-book ratios.

The main result in our empirical study is that insurers that employ financial derivatives have a significantly lower risk of defaulting than matched non-using insurers. We also find empirical evidence that the decreasing effect of derivatives usage on default risk is reversed in case insurers use derivatives for risk-taking and non-hedging purposes. Moreover, we find a more pronounced use of derivatives to increase an insurer's exposure to systemic market shocks as proxied by the insurer's Marginal Expected Shortfall. Our results thus corroborate current views by insurance regulators that derivatives usage for trading negatively affects financial stability. However, our findings also underline the risk-reducing and thereby stabilizing effect of using derivatives for hedging purposes.

This paper is related to, and complements several previous studies in the empirical financial economics literature. In the classical work of Modigliani and Miller (1958), hedging should not add value to a firm in case capital markets are perfect. In the presence of market frictions, however, risk management can have a beneficial effect on firms as shown, e.g., in the studies of Smith and Stulz (1985), Froot et al. (1993), Nance et al. (1993), Leland (1998), and Whidbee and Wohar (1999). Not surprisingly, the empirical results in this literature (see, e.g., Mian, 1996) are also ambiguous with the expected effects of (and motives for) using financial derivatives still being unclear. For example, Bartram et al. (2011) find empirical evidence that the use of financial derivatives significantly reduces both total firm risk and systematic risk. Yet at the same time, several studies have also stressed the finding that derivatives usage does not significantly lower firm risk even if it is used for hedging purposes (see, e.g., Tufano, 1996, Allayannis and Weston, 2001, Graham and Rogers, 2002). Guay (1999) also finds that systematic risk is unaffected by the use of derivatives. Underlining this result, Hentschel and Kothari (2001) find that derivative usage is not significantly related to a firm's stock return volatility. In addition, the results by Guay and Kothari (2003) and Jin and Jorion (2006) further reveal that firm market values are relatively unaffected by hedging activities. For banks during the financial crisis, Trapp and Weiß (2014) even find an increasing effect of derivatives usage by U.S. banks on the institutions' systemic equity tail risk.[90]

Our paper is also related to several studies in the risk management and insurance literature. To start with, the study by Bartram (2015) finds that derivative users have higher gross exposures to financial risks compared to non-users. There is no evidence of speculation with derivatives for sub-samples of firms in individual countries or for different types of derivatives. Firms use derivatives for hedging independent of access to derivatives or country-level governance. However, users have larger reductions in risk compared to non-users if shareholder rights are strong, creditor rights are weak, and if derivatives are readily available. Further, Cummins and Danzon (1997) find that insurers use derivatives to hedge their costs of financial distress and interest rate, liquidity, and exchange rate risks. Cummins et al. (2001) analyze the derivatives holdings of U.S. insurers to explain why widely held, value-maximizing firms engage in risk management. They suggest that although measures of risk and illiquidity will be positively associated with an insurer's decision to engage in risk management. The same measures of risk will be negatively related to the volume of hedging for the set of firms, who choose to hedge using derivatives.[91] Cummins and Song Drechsler (2008) study the usage of two common hedging tools, reinsurance and derivatives. In a simple mean-variance efficient optimization model, the two hedging tools display substitutive effects when assets and liabilities do not display strong natural hedging.

Furthermore, Peréz-González and Yun (2013) show that active risk management policies lead to an increase in firm value. To identify the effect of hedging, they exploit the introduction of weather derivatives as an exogenous shock to firms' ability to hedge

[90]The effects of derivatives usage by banks is also studied, e.g., by Géczy et al. (1997).
[91]A related study in this respect is the work of Colquitt and Hoyt (1997).

weather risks. Their main result is that risk management has real consequences on firm outcomes. Cummins et al. (1995) develop a model of price determination in insurance markets. They find that the price may increase or decrease following a loss shock that depletes the insurer's capital, depending on factors such as the effect of the shock on the price elasticity of demand. Also, their study shows that the price of insurance is inversely related to insurer default risk.[92] Finally, there also exist several studies in the literature that analyze the use of reinsurance for risk management as an alternative to derivatives (see, e.g., Cole and McCullough, 2006, Garven et al., 2014). However, no study has analyzed the effects of derivatives usage on the default risk of insurers so far.

The remainder of this article is structured as follows. Section 6.2 introduces the construction of our data sample. The following Section 6.3 describes the econometric methodology and the main variables used in our empirical study. Section 6.4 presents the results of our empirical analysis. Concluding remarks are given in Section 6.5.

6.2 Data sources and sample construction

This section describes the construction of our data sample, which is constructed from data taken from the *Morningstar Document Research*, the *Center for Research in Security Prices* (CRSP), and the *Compustat* databases, respectively.

We start the construction of our data sample by first selecting all publicly listed U.S. insurance companies with SIC codes 6311, 6321, 6331 from the dead and active lists in *CRSP* for the time period from Q1 1999 to Q3 2014.

Financial market data are retrieved from *CRSP*, while accounting data are collected from *Compustat*. We then collect the 10-K filings for all firms in our sample from the *Morningstar Document Research* database. Information on the insurers' risk management, hedging activities, as well as their usage of financial derivatives are collected manually from the insurers' respective 10-K filings. In addition to these qualitative variables concerning the insurers' risk management, we also extract from the 10-K

[92]They also provide evidence that prices declined in response to the loss shocks of the mid-1980s.

filings for each insurance company the fair value gains and losses on derivatives positions. In our process of screening the insurers' 10-K filings, we include only those insurance companies in our final sample, for which at least one 10-K filing is available during the course of our sample period. Furthermore, we manually screen the 10-K filings for clear identification of the firms as an insurance company and exclude a respective firm from our sample if its 10-K filing indicates a non-insurance business or if the filing identifies it as a secondary listing.

Finally, we end up with a full sample of 171 U.S. insurers. For increased transparency, the names of all insurers in our final sample are listed in Appendix E.1. In the next section, we define and discuss the different dependent and independent variables that we use in our empirical study. In this discussion, emphasis is given to the variables constructed from the insurers' 10-K filings which we use to proxy for the firms' derivatives usage. An overview of all variable definitions and data sources is given in Appendix E.2.

6.3 Empirical strategy

In this section, we describe the setup of our empirical analysis. First, we introduce our main dependent variable, with which we try to capture the financial distress of an insurer. Next, we describe our main independent variables that are used to proxy for an insurer's derivatives usage. We continue by discussing our set of insurer-specific control variables as well as the econometric setup of our analysis. We conclude this section by presenting selected descriptive statistics on our variables.

6.3.1 Dependent variable

The goal of our empirical analysis is an investigation of the relation between an insurer's default risk and its use of financial derivatives. As a proxy for an insurer's default risk, we use the inverse z-score calculated on the basis of the insurer's stock returns.[93] In the literature, the z-score is regularly used to proxy for the default risk of firms and has been discussed in several previous papers (see, e.g., Boyd et al., 2006, Berger et al., 2009, Uhde and Heimeshoff, 2009, Laeven and Levine, 2009, De Nicolo, 2001, Anginer et al., 2014b). As our dependent variable, we employ the insurers' inverse z-scores, which are defined as one divided by the average quarterly stock return divided by the respective insurer's stock return volatility over the last five quarters.

Theoretically, the calculation of the z-score based on accounting variables should be equivalent to using average stock returns and stock return volatilities (see, e.g., Schäfer et al., 2015). To capture an insurer's default risk in a more comprehensive way, we use the stock based version of the inverse z-score in our empirical analyses. Since we employ the inverse of the z-score, higher values will indicate a higher degree of financial distress for a respective insurance company.

6.3.2 Main explanatory variables on an insurer's derivatives usage

We are interested in the effects of the usage of derivative contracts on our sample insurers' default risk. To obtain information on the disclosure of derivatives usage of insurance companies, we use their respective (quarterly) 10-K filings. For each firm with an available 10-K filing in a given quarter, we manually screen the filing for disclosures on the insurer's derivatives usage. If an insurer discloses information on derivatives, we define the firm as a "derivatives-user". Consequently, we define our first variable *Derivatives-user* as a dummy variable, that is one for derivatives users, and zero otherwise. Since insurers can have different motives for using financial derivatives in turn leading to different risk exposures stemming from the insurers' derivatives positions, we have no expectation regarding the sign of the coefficient in our regressions. Next, we test whether insurers simply use derivatives as an instrument for hedging, or alternatively, for taking on additional risks. When hedging is the only purpose of derivatives

[93]There exist other methods for capturing the financial distress of firms like, e.g., using Merton's distance-to-default. In our analysis, we opted to use the z-score measure because of its fewer data requirements. As a consequence, our sample size is not unnecessarily reduced due to missing data for our sample insurers.

usage, it should have a decreasing effect on a firm's default probability since it is employed to reduce remaining risks. We include in our analysis a more nuanced dummy variable *Hedging* that is one, when derivatives are used for hedging purposes (as stated by the insurer's disclosed information on the firm's risk management activities), and zero otherwise.[94] For our variable *Hedging*, the relation between the insurer's motive to use derivatives for hedging purposes and its default risk should consistently be a negative one. To get a clearer picture of the differential effects of the various types of financial derivatives on an insurer's default risk, we also employ dummy variables that indicate whether an insurer uses *options*, *swaps*, *forwards*, and/or *futures*. The corresponding dummy variables are set to one, if an insurer discloses the use of the respective type of derivative in its 10-K filing, and zero otherwise. We argue that the sign of the coefficient on these variables is unrestricted in our regressions and expect different signs for the four different derivative types.

In addition to our dummy variables, we count the disclosed number of different derivative types used by an insurer. The resulting number is the variable *Derivatives Intensity*, which ranges from zero to four. This variable proxies for the intensity with which an insurer uses derivative contracts (and should thus, have a similar effect on an insurer's default risk as our dummy variable *Derivatives-user*) (see also Bartram et al., 2011, for a similar approach to measure the extent of a company's derivatives usage).

Finally, we collect the net fair value gains and losses on the insurers' derivatives positions as disclosed in the insurers' 10-K filings. By doing so, we attempt to measure the actual exposure of an insurance firm to risks emanating from the firm's derivatives positions.

6.3.3 Control variables

In our regression analyses, in addition to the variables on an insurer's derivatives usage, we control for a variety of firm characteristics. We use proxies for the insurers' size,

[94] If an insurer disclosed that it does not use any kind of financial derivative, we set the variable *Hedging* to not available (NA).

profitability, solvency, capital structure, and liabilities. In the following, we define the control variables used in our empirical study. As a common measure of a firm's size, we employ the natural logarithm of the insurers' total assets. We expect insurer size to be an economically significant driver of an insurer's default risk, although the expected sign on the estimated coefficients in our regressions is unrestricted. On the one hand, larger insurers are less likely to suffer from cumulative losses due to its broader range of pooled risks and better risk diversification. On the other hand, larger insurers could also be more complex, which in turn could increase its default probability.

Next, we include the variable *Solvency* in our regressions defined as the ratio of capital surplus and the insurers' total assets. We expect an insurer's solvency to have a decreasing effect on the default risk of the respective insurer as a higher solvency improves the firm's ability to repay short-term liabilities and addresses a liquidity shortage. Furthermore, we include the insurers' return on assets (ROA) as a proxy for the insurers' profitability as an explanatory variable in our regressions. To be precise, we calculate ROA by dividing an insurer's pre-tax return by its total assets. We expect ROA to have a decreasing effect on the default risk of insurance companies as higher profits can shield insurers from the adverse effects of impending financial distress.

We also make use of the insurers' market-to-book ratios, defined as the market values of common equity divided by the book values of common equity. Additionally, we employ the insurers' leverage, which we compute as total debt divided by total assets, as a proxy for the insurers' level of indebtedness and expect a positive impact of leverage on our measure of an insurer's financial distress.[95] Finally, we also control for an insurer's debt maturity by taking the insurer's ratio of total long-term debt to total debt. Here, we expect a more fragile funding structure of an insurer to be positively correlated with the probability of the insurer defaulting.

[95] In our robustness checks, we alternatively employ an insurer's (log) total liabilities as a proxy for its extent of financial leverage.

6.3.4 Econometric design

After the discussion of the variables used in our empirical analysis, we now shortly comment on the econometric design employed in our regressions.

In our empirical study, we investigate the relation between an insurer's default risk, measured by the inverse of the z-score, and its derivatives usage. We employ a panel data sample with quarterly observations for our sample of U.S. insurers over the time frame from Q1 1999 to Q3 2014. To account for possible persistence in our dependent variable, we estimate dynamic panel regressions that include the first lag of the inverse z-score as an independent variable. As our main independent variables of interests, we include regressors that reflect information on the insurers' use of derivative contracts in the previous quarter. In particular, panel regressions are estimated using the (one-step) GMM-sys estimator as proposed by Blundell and Bond (1998) (with double-lagged values of the dependent variable as instruments). The estimated baseline model is

$$\begin{aligned} \text{INVERSE Z-SCORE}_{i,t} &= \alpha_i + \mu_t + \beta_1 \times \text{INVERSE Z-SCORE}_{i,t-1} \\ &+ \beta_2 \times \text{DERIVATIVE-USER}_{i,t-1} + \boldsymbol{\beta} \times \text{CONTROLS}_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{6.1}$$

where DERIVATIVE-USER$_{i,t}$ is a dummy variable that is one when insurer i uses derivatives contracts (options, swaps, futures, forwards) in quarter t, α_i and μ_t are insurer-fixed and quarter-fixed effects that capture unobserved heterogeneity across our sample insurers and across time, CONTROLS$_{i,t}$ is the vector of control variables, where $\varepsilon_{i,t}$ are the model residuals.

6.3.5 Descriptive statistics

In this subsection, we present selected descriptive statistics for the dependent and independent variables used in our empirical analysis. Table 6.1 provides summary statistics for the full sample.

First, we comment on the distribution of our dependent variable in our data sample.

Table 6.1: Descriptive statistics (full sample).

The table presents descriptive statistics of the quarterly values of the inverse z-score and control variables for firm-quarter observations with available information on derivative use. The sample includes the 171 U.S. insurers shown in Appendix E.1 and the sample period runs from Q1 1999 to Q3 2014. We report the number of observations, minimum and maximum values, first and fourth quartile, mean and median values. All variables and data sources are defined in Appendix E.2 and all variables except for *Derivatives intensity* are winsorized at the 5% level.

	N	Min	1st quartile	Median	Mean	3rd quartile	Max
Inverse z-score	4,308	0.008	0.013	0.018	0.023	0.027	0.078
Derivatives intensity	3,745	0.000	1.000	2.000	2.313	4.000	4.000
Gains/losses (in million US-$)	1,840	-767.500	-14.440	-0.100	-14.060	8.129	645.200
Debt maturity	5,656	0.000	0.023	0.054	0.086	0.101	0.587
Leverage	3,699	0.001	0.001	0.002	0.440	0.008	5.747
Market-to-book ratio	3,152	0.278	0.732	0.951	1.038	1.244	2.511
ROE	4,193	-0.447	-0.062	0.016	0.007	0.097	0.337
Total assets (in million US-$)	6,114	98.600	1,210.000	5,562.000	31,900.000	21,190.000	356,500.000
Solvency	3,693	0.000	0.031	0.105	0.411	0.315	4.838
Volatility	4,314	0.008	0.012	0.018	0.023	0.027	0.077

Insurers in our sample have an average inverse z-score of approximately 0.023 and a median inverse z-score of 0.018. Estimates for our proxy of the insurers' default risk range from a minimum value of 0.008 to the maximum of 0.078.

On average, an insurer disclosed the use of at least two different types of financial derivatives as can be seen from the mean and median values of our variable *Derivatives intensity*. Moreover, we can see from Table 6.1 that our sample includes both insurers, which do not use derivatives at all, as well as insurers for which *Derivatives intensity* takes on the maximum value of four.

Looking at the duration of an insurers' liabilities, the variable *Debt maturity* ranges from the minimum value of 0.000 to a maximum value of 0.587. However, the first and last quartile are 0.023 and 0.101, respectively. Thus, it appears as if the maximum value constitutes an outlier in our sample. Consequently, we find that most of the insurance firms in our sample do not rely too heavily on long-term debt in their capital structure.

The insurers in our sample have a mean leverage of around 44%. In contrast, the median value is only around 0.2%. In addition, few insurance companies are highly levered with values of up to 574.7% for our variable *Leverage*. Moreover, the firms in our sample have a mean market-to-book ratio of 1.024 with the median ratio being

0.945. Looking at the firm size of our sample insurers, we can see that our sample is composed of both small and large insurers with the median firm size being approx. $ 5.562 billion. Firms in the first quartile of size have total assets between $ 98.6 million and $ 1.15 billion. Firm size between the first and third quartile is quite homogeneous across insurers. In contrast, the largest insurers in our sample have total assets between $ 21.190 and $ 356.500 billion.

The proxy for the insurers' solvency has an average value of approx. 0.411 with the median solvency ratio being 0.105 and the maximum value being 4.838. As a result, the summary statistics indicate only a medium level of solvency at the vast majority of insurers with only a few institutions having higher, ample levels of solvency. Turning to our measure of an insurer's idiosyncratic equity volatility, we find the volatility of the insurers' stock returns to be low, on average, with the mean and median values for our variable *Volatility* being 2.3% and 1.8%, respectively. With 7.7%, even the maximum value of the insurers' stock volatility is quite low and 75% of our sample insurers have an equity volatility that is lower than 2.7%.

After this first discussion of the composition and the main characteristics of our data sample, we now turn to an univariate analysis of the disclosed information on the insurers' derivatives usage. In Panel A of the following Table 6.2, we present summary statistics for the two sub-samples of derivative-users and -non-users. In Panel B, we present similar summary statistics for the two sub-samples of insurers that employ derivatives (predominantly) for hedging or non-hedging purposes.

As can be seen from Panel A in Table 6.2, insurance companies that employ financial derivatives have, on average, a statistically lower default risk than non-users of derivatives (mean inverse z-scores of 0.020 vs. 0.026). In addition, derivatives users also have a shorter debt maturity, a considerably higher leverage, and a higher market-to-book ratio on average. Non-users of derivatives are also, on average, significantly smaller than derivatives users. Interestingly, non-users appear to have a better mean solvency than insurers, which employ derivatives.

Turning to Panel B of Table 6.2, we find that insurers that employ derivatives primarily for hedging purposes possess lower mean default risk than insurers that presumably use financial derivatives for risk-taking. This difference, however, is not statistically significant. Interestingly, we find the stock return volatility of hedging insurers to be statistically significantly lower than the volatility of insurers that use derivatives for non-hedging purposes. Thus, it appears as if either the use of derivatives for hedging exerts a stabilizing effect on the insurers' stock volatility and/or that the use of derivatives for speculation significantly increases an insurer's stock volatility.

Next, we turn to an analysis of the question whether insurers that report high gains in fair values of derivative positions differ significantly from their peers that report low fair value gains or even losses on derivatives. To this end, Table 6.3 reports summary statistics for insurers in the top and bottom quartiles of fair value gains/losses on derivative positions.

The statistics presented in Table 6.3 show that insurers that report the highest gains on their derivative positions are, on average, smaller and employ fewer types of financial derivatives than insurers in the bottom quartile of gains/losses on derivatives. Apart from these two results, however, insurers in both quartiles do not appear to differ significantly with respect to their balance sheet and income statement variables.

In the following section 6.4, we perform a deeper empirical analysis and present the results on the nexus between the default risk and derivatives usage of insurers.

Table 6.2: Descriptive statistics for users versus non-users of derivatives.

The table presents descriptive statistics of the quarterly values of the inverse z-score and control variables used in this study for sub-samples of derivative-users and -non-users (Panel A). In Panel B, summary statistics are shown for the two sub-samples of insurers that use derivatives for hedging or non-hedging purposes. The sample includes the 171 U.S. insurers shown in Appendix E.1 and the sample period runs from Q1 1999 to Q3 2014. We report the number of observations, minimum and maximum values, first and fourth quartile, mean and median values. The equality of means of the different variables is tested using Welch's t-test for unequal sample sizes and possibly unequal variances of the two samples (t-statistics and p-values are reported). All variables and data sources are defined in Appendix E.2 and all variables except for Derivatives intensity are winsorized at the 5% level. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Panel A:	Derivatives usage							No derivatives usage								
	N	Min	1st quartile	Median	Mean	3rd quartile	Max	N	Min	1st quartile	Median	Mean	3rd quartile	Max	t-value	p-value
Inverse z-score	2,368	0.008	0.012	0.016	0.020	0.024	0.078	1,940	0.008	0.015	0.021	0.026	0.031	0.078	-11.754	0.000***
Debt maturity	3,323	0.000	0.030	0.057	0.095	0.101	0.587	2,333	0.000	0.000	0.046	0.073	0.101	0.587	7.203	0.000***
Leverage	2,245	0.001	0.001	0.002	0.124	0.004	5.747	1,454	0.001	0.001	0.006	0.929	1.227	5.747	-18.868	0.000***
Market-to-book ratio	1,958	0.278	0.713	0.917	0.996	1.196	2.511	1,194	0.278	0.759	1.005	1.109	1.322	2.511	-6.404	0.000***
ROE	2,315	-0.447	-0.058	0.018	0.008	0.094	0.337	1,878	-0.447	-0.072	0.015	0.005	0.103	0.337	0.788	0.431
Total assets (in million US-$)	3,488	103.000	6,054.000	16,650.000	53,650.000	50,450.000	356,500.000	2,626	98.570	392.200	1,209.000	3,002.000	35,69.000	52,180.000	33.579	0.000***
Solvency	2,239	0.000	0.028	0.092	0.335	0.234	4.838	1,454	0.000	0.043	0.139	0.528	0.440	4.838	-5.868	0.000***
Volatility	2,429	0.008	0.012	0.017	0.023	0.027	0.077	1,885	0.008	0.013	0.018	0.023	0.027	0.077	-0.163	0.871
Panel B:	Hedging							Non-hedging purpose								
	N	Min	1st quartile	Median	Mean	3rd quartile	Max	N	Min	1st quartile	Median	Mean	3rd quartile	Max	t-value	p-value
Inverse z-score	2,229	0.008	0.012	0.016	0.020	0.024	0.078	155	0.008	0.011	0.016	0.022	0.024	0.078	-1.138	0.257
Debt maturity	3,151	0.000	0.030	0.056	0.093	0.098	0.587	188	0.000	0.025	0.083	0.121	0.144	0.587	-2.493	0.013**
Leverage	2,145	0.001	0.001	0.002	0.102	0.004	5.747	116	0.001	0.001	0.002	0.497	0.002	5.747	-2.624	0.010**
Market-to-book ratio	1817	0.278	0.707	0.898	0.988	1.187	2.511	158	0.278	0.932	1.078	1.082	1.246	2.511	-3.168	0.002***
ROE	2,179	-0.447	-0.058	0.018	0.008	0.093	0.337	152	-0.447	-0.060	0.021	0.016	0.098	0.337	-0.649	0.517
Total assets (in million US-$)	3,294	103.000	6,532.000	17,490.000	56,150.000	53,310.000	356,500.000	210	196.200	1,866.000	6,048.000	10,950.000	16,810.000	52,170.000	24.862	0.000***
Solvency	2,139	0.000	0.029	0.091	0.333	0.227	4.838	116	0.000	0.009	0.208	0.363	0.335	3.936	-0.462	0.645
Volatility	2,294	0.008	0.012	0.017	0.022	0.027	0.077	135	0.008	0.016	0.021	0.028	0.034	0.077	-3.678	0.000***

Table 6.3: Descriptive statistics for insurers in the top and bottom quartiles of fair value gains/losses on derivative positions.

The table compares descriptive statistics of insurers whose gains/losses on derivatives positions were in the bottom quartile with the characteristics of insurers whose gains/losses on derivatives positions were in the top quartile. The sample includes the 171 U.S. insurers shown in Appendix E.1 and the sample period runs from Q1 1999 to Q3 2014. We report the number of observations, minimum and maximum values, first and fourth quartile, mean and median values. The equality of means of the different variables is tested using Welch's t-test for unequal sample sizes and possibly unequal variances of the two samples (t-statistics and p-values are reported). All variables and data sources are defined in Appendix E.2 and all variables except for *Derivatives intensity* are winsorized at the 5% level. P-values are given in parentheses and *, **, and *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

	1st quartile of net derivative gains and losses							4th quartile of net derivative gains and losses								
	N	Min	1st quartile	Median	Mean	3rd quartile	Max	N	Min.	1st	Median	Mean	3rd	Max.	t-value	p-value
Inverse z-score	262	0.008	0.013	0.020	0.026	0.030	0.078	270	0.008	0.011	0.016	0.023	0.026	0.078	1.646	0.100
Derivatives intensity	445	1.000	2.000	4.000	3.115	4.000	4.000	453	1.000	2.000	3.000	2.932	4.000	4.000	2.391	0.017**
Debt maturity	375	0.000	0.030	0.048	0.088	0.078	0.587	394	0.000	0.029	0.051	0.085	0.079	0.587	0.270	0.788
Leverage	308	0.001	0.001	0.002	0.003	0.002	0.047	330	0.001	0.001	0.002	0.002	0.002	0.023	1.174	0.241
Market-to-book ratio	319	0.278	0.619	0.840	0.908	1.064	2.511	328	0.278	0.599	0.811	0.911	1.050	2.511	-0.081	0.935
Total assets (in million US-$)	406	2,285.000	21,620.000	56,580.000	109,100.000	156,600.000	356,500.000	421	1,624.000	16,290.000	40,240.000	93,150.000	127,900.000	356,500.000	1.990	0.047**
Solvency	308	0.000	0.029	0.066	0.200	0.164	4.777	330	0.000	0.027	0.064	0.166	0.158	1.832	1.115	0.265
Volatility	281	0.007	0.012	0.018	0.025	0.031	0.077	283	0.007	0.012	0.018	0.025	0.032	0.077	0.295	0.768

6.4 Empirical results

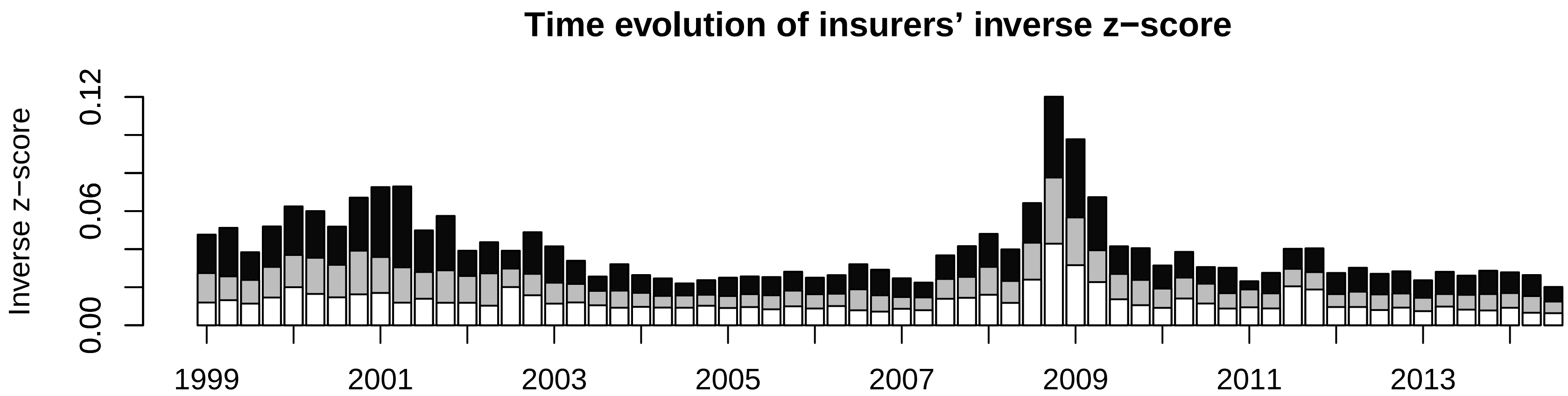
In this section, we report the results from our empirical analyses to answer the question whether derivatives usage is a significant driver of an insurer's default risk. We start our empirical analysis by first commenting on the time evolution of our major dependent and independent variables. We then address the endogenous nature of an insurer's decision to use financial derivatives. We follow Bartram et al. (2011) and control for endogeneity by matching users and non-users of derivatives based on variables known from the literature to drive the decision to employ derivatives. After matching users and non-users of derivatives, we perform several panel regressions of the insurer's inverse z-score on various variables related to derivatives usage.

6.4.1 Default risk

First, we analyze how the values of our main dependent variable evolve for our sample of insurers over time. Figure 6.1 illustrates the time evolution of the U.S. insurers' mean default risk (and respective quantiles) over the full sample period.

Figure 6.1: Time evolution of U.S. insurers' default risk for the period from 1999 to 2014.

This figure plots the time evolution of U.S. insurers' default risk over our full sample period from 1999 to 2014. The sample consists of 171 U.S. insurers shown in Appendix E.1. In each plot, the mean of the respective risk measure (grey area) is plotted against the corresponding 10% and 90% percent quantiles (white and black areas).



The time evolution of default risk is characterized by a short peak during the dotcom-crisis in 2001. Further, we notice a high peak during the recent financial crisis, which underlines that the inverse z-score is a suitable proxy for an insurer's degree of financial distress. After the crisis, average default risk in the U.S. insurance sector returns to its pre-crisis level. Looking at the 90%-quantiles, we can again see the extreme surge in our sample insurers' default risk after the onset of the financial crisis in 2008. Next, we shortly comment on the time evolution of derivatives usage in the U.S. insurance sector.

6.4.2 Derivatives usage

As a first step, we analyze the structure of the derivatives usage in the U.S. insurance sector by looking at the annual derivative reports of the National Association of Insurance Commissioners (NAIC).[96] Figure 6.2 presents the percentage of each of the four (major) derivative types used in the U.S. insurance sector (option, swaps, forwards, and futures) for the years 2011, 2012, and 2013.

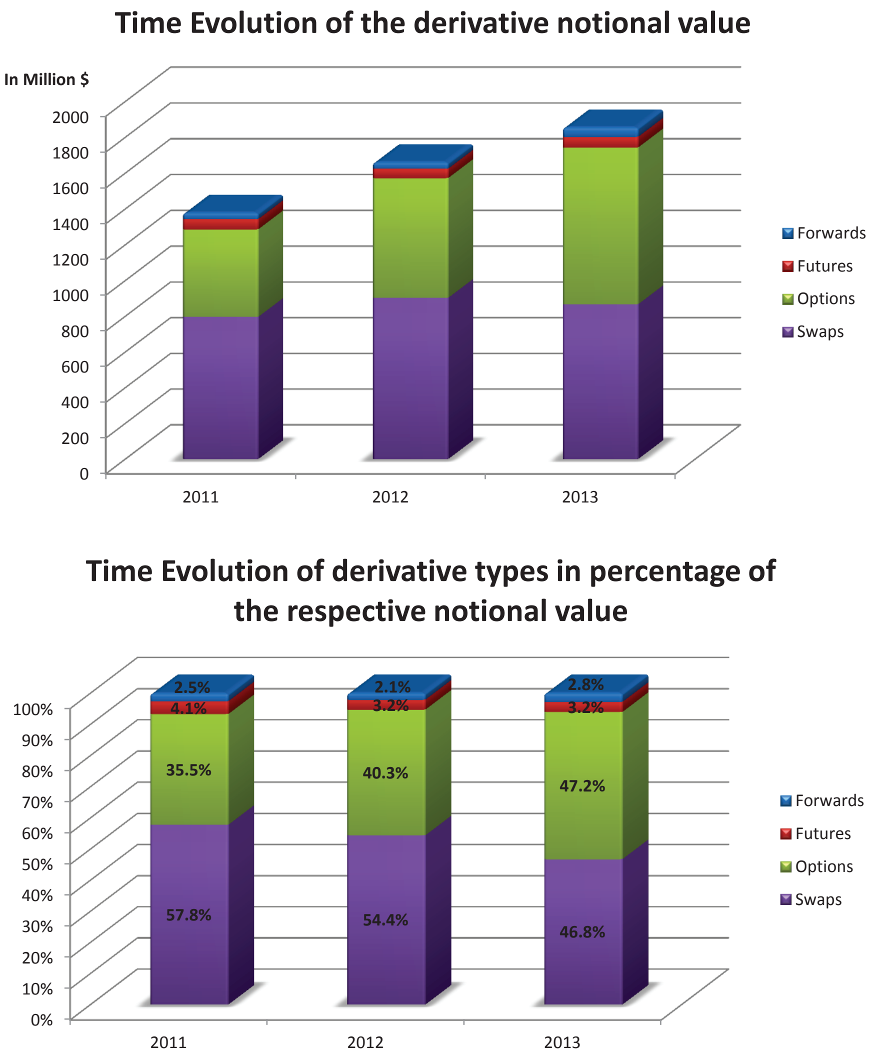
The plots in Figure 6.2 show that forwards and futures are used only to a negligible extent by insurers. Moreover, as can be seen from the lower panel, the percentages of both futures and forwards do not vary much over time. In contrast, the total notional value of the derivatives used by insurers is primarily composed of options and swaps. We see a strong increase in the use of options over the short time period from 2011 to 2013, which drives the overall trend of increased derivatives usage by insurers. The volume of options used in the U.S. insurance industry increases by over 10% from 2011 to 2013. Furthermore, the fraction of swaps in the derivative portfolio decreases by more than 10% during this period. This shows a clear trend towards the use of options instead of swaps by U.S. insurers.

However, as revealed by both the disclosed information in the insurers' 10-K filings and the NAIC reports, the majority of insurers states hedging rather than risk-taking

[96] The used reports are published and available on the following web-page: `http://www.naic.org/capital_markets_archive/131023.htm`.

Figure 6.2: Structure of the derivative usage in the U.S. insurance sector.

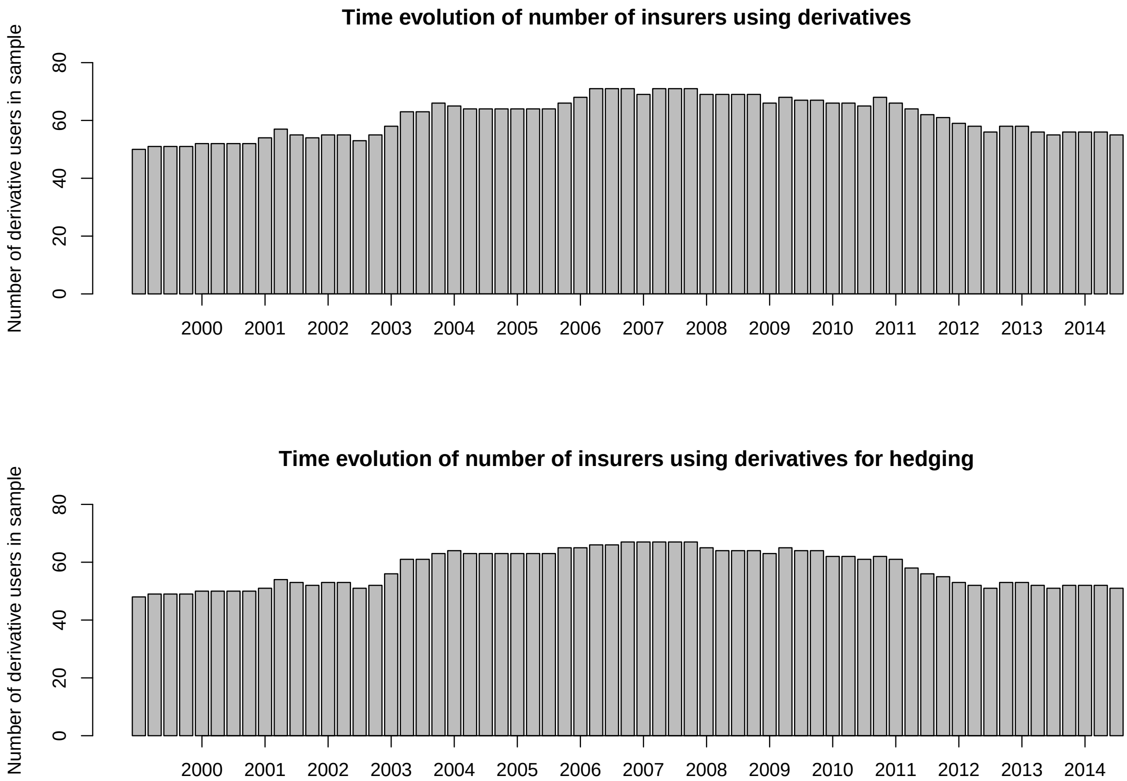
The figure plots the notional values of the types of derivatives (option, swaps, forwards, futures) used in the U.S. insurance sector for the years 2011, 2012, and 2013. The data are received from the disclosed NAIC derivative reports for the respective years. The upper panel shows the total sum of the notional value of all derivative types. The lower panel illustrates the relative distribution of the notional values across the four types of derivatives.



as the main reason for using derivatives. Next, we contrast the findings taken from the NAIC reports with the data from our sample. The upper panel in Figure 6.3 displays the time evolution of the number of insurers in our sample using derivatives, while the lower panel shows the time evolution of the number of sample insurers that use derivatives for hedging purposes.

Figure 6.3: Number of derivatives users.

The figure shows the number of insurers using derivatives over our full sample period from 1999 to 2014. The sample consists of 171 U.S. insurers shown in Appendix E.1. The upper panel shows the total number of derivatives users while the lower panel focuses on the number of insurers that employ derivatives for hedging purposes.



On average, around 35% of our sample insurers use derivatives. The number of insurers that employ derivatives increases slowly over time until 2003, from where it remains on a high level until the onset of the recent financial crisis. After the crisis, the number of derivatives users decreases significantly to pre-crisis levels. The second panel focuses on the number of insurers that use derivatives for hedging purposes.

Here, we find that around 30% of our sample insurers use derivatives for hedging. The number increases until 2004, from when it continues to exhibit a similar pattern as the total number of derivatives users shown in the upper panel. It appears that most of our sample insurers use derivatives for hedging purposes rather than for other reasons. Similarly, we plot the time evolution of the number of derivative users for each of the four derivative types. The plots are shown in Figure 6.4 and 6.5.

Figure 6.4: Number of swap and option derivatives users.

The figure shows the number of insurers using swaps (upper panel) and options (lower panel) over our full sample period from 1999 to 2014. The sample consists of 171 U.S. insurers shown in Appendix E.1.

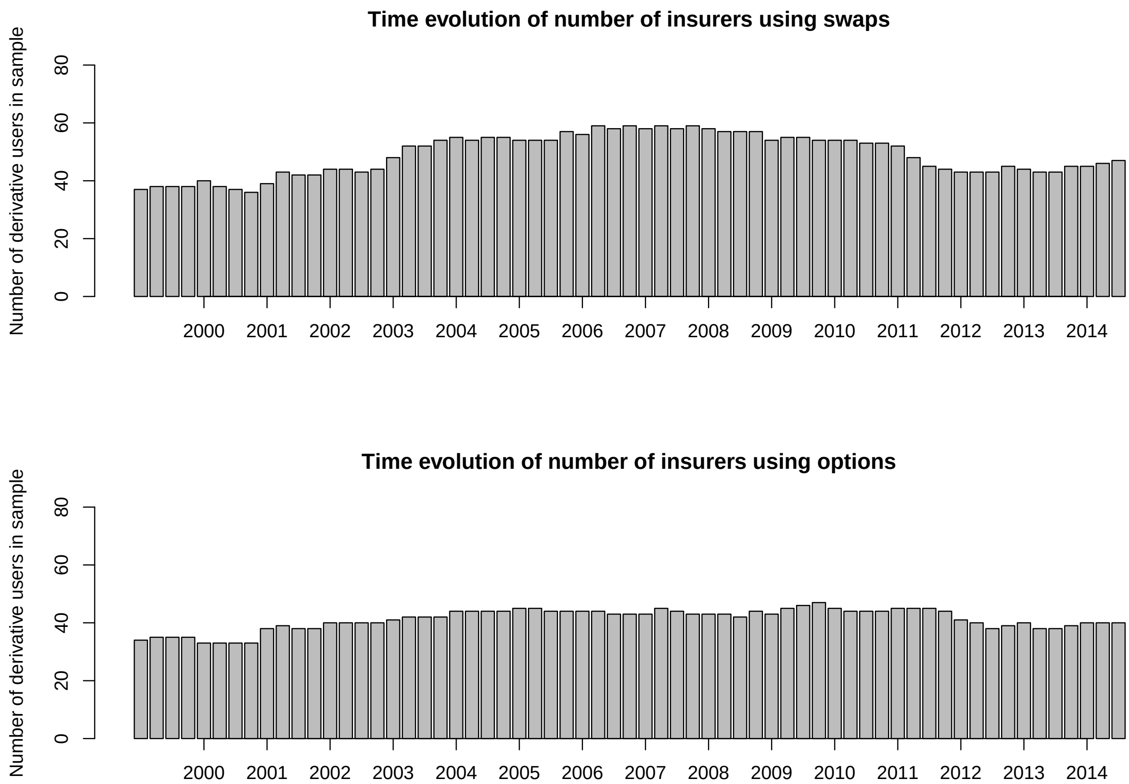
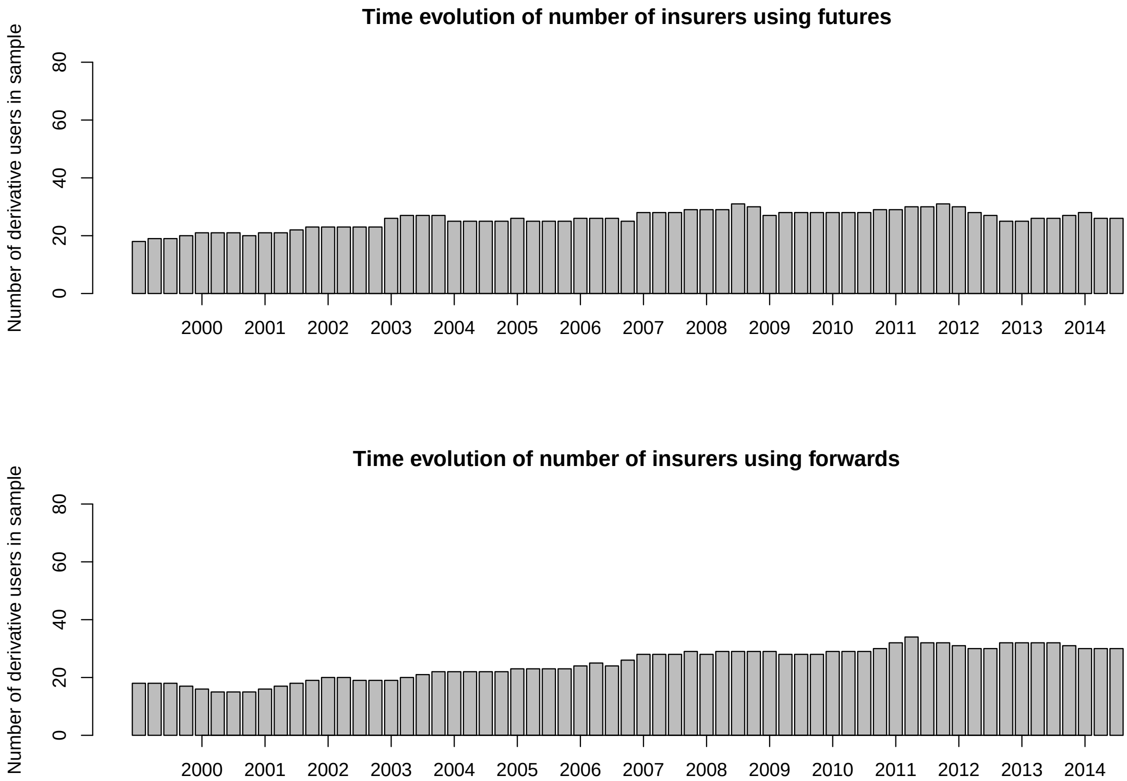


Figure 6.4 shows the number of insurers using swaps (first panel) and options (second panel) during our sample period while Figure 6.5 shows the usage of forwards and futures, respectively. As before, the number of swap users increases until the beginning of the financial crisis and then decreases slowly, which is in line with the

Figure 6.5: Number of futures and forwards derivatives users.

The figure shows the number of insurers using futures (upper panel) and forwards (lower panel) over our full sample period from 1999 to 2014. The sample consists of 171 U.S. insurers shown in Appendix E.1.



generally decreasing use of swaps observed above in Figure 6.2. Note that not all of the insurance companies in our sample use swaps, since the number of swap users is significantly lower than the total number of derivative users. The number of option users is even lower but remains relatively constant over time. Compared to the number of users of options and swaps, the number of insurers that use forwards and futures is significantly lower. However, the number of insurers using forwards and futures has increased steadily over time.

6.4.3 Matching of derivatives users and non-users

In this part of our analysis, we address the endogeneous nature of the relation between derivatives usage and default risk and match users of derivatives with non-using insurers. We compare the mean values of the inverse z-score for a group of derivatives users (treatment group) with corresponding mean values of non-users (control group). In each quarter from Q1 2006 to Q4 2010, we perform nearest neighbor propensity score matching procedures based on the insurers' size and market-to-book ratios.[97] We match users and non-users on the insurers' size and market-to-book ratio as these firm characteristics are known to drive a firm's decision to employ financial derivatives (see also Bartram et al., 2011). After matching, we run t-tests and Wilcoxon tests on the equality of the mean values for the two groups. The results of our matching analyses are shown in Table 6.4.

Table 6.4: Matching of derivatives users and non-users.

This table reports mean values for the inverse z-score of insurers that use derivatives in a given quarter matched with non-users from Q1 2006 to Q4 2010. Nearest neighbor matching (with replacement) of derivative users and non-users is performed on the insurers' size and market-to-book ratios. The columns "Yes" and "No" report average values for the user and non-user group and "Difference" is their difference. The statistical significance of the difference of mean values is tested with t-tests and Wilcoxon tests, for which corresponding t-statistics and p-values are reported. Bolded values indicate a statistical significance at the 10% level.

	Inverse z-score				
Time	Yes	No	Difference	t-stat	Wilcoxon
Q1 2006	0.014	0.017	-0.003	-0.938	0.268
Q2 2006	0.016	0.016	0.000	0.079	0.696
Q3 2006	0.015	0.012	0.003	1.464	0.317
Q4 2006	0.015	0.012	0.003	1.453	0.354
Q1 2007	0.013	0.012	0.001	0.514	0.788
Q2 2007	0.013	0.019	-0.007	-0.790	0.893
Q3 2007	0.026	0.023	0.003	0.895	0.732
Q4 2007	0.024	0.028	-0.004	-0.846	0.205
Q1 2008	0.026	0.033	-0.008	-1.624	0.026
Q2 2008	0.023	0.025	-0.002	-0.470	0.279
Q3 2008	0.051	0.046	0.005	0.414	0.510
Q4 2008	0.083	0.055	**0.028**	3.464	0.148
Q1 2009	0.063	0.048	0.015	1.480	0.324
Q2 2009	0.043	0.040	0.003	0.398	0.876
Q3 2009	0.031	0.025	0.006	1.127	0.743
Q4 2009	0.023	0.025	-0.002	-0.433	0.378
Q1 2010	0.019	0.015	0.004	0.971	0.551
Q2 2010	0.026	0.029	-0.004	-1.158	0.175
Q3 2010	0.020	0.021	-0.001	-0.235	0.940
Q4 2010	0.015	0.020	-0.005	-1.087	0.487

[97] Since the number of observations is relatively small for each quarter, the matching of users and non-users is performed with replacements.

Overall, we observe only little to no significant differences between users and non-users. During the crisis (Q4 2008), however, we find that the treatment group of derivatives users had a statistically significant larger inverse z-score . These estimates, however, have to be taken with care, since the number of observations in each quarter is quite low.

Next, we analyze whether we can find significant differences in the default risk of users of options and swaps vs. non-users. To this end, we perform further matchings of users and non-users with swap and option users forming the treatment groups. The results of these two analyses are reported in Tables 6.5 and 6.6.

Table 6.5: Matching of swap users and non-users.

This table reports mean values for the inverse z-score of insurers that use swaps in a given quarter matched with non-users from Q1 2006 to Q4 2010. Nearest neighbor matching (with replacement) of swap users and non-users is performed on the insurers' size and market-to-book ratios. The columns "Yes" and "No" report average values for the user and non-user group and "Difference" is their difference. The statistical significance of the difference of mean values is tested with t-tests and Wilcoxon tests, for which corresponding t-statistics and p-values are reported. Bolded values indicate a statistical significance at the 10% level.

	Inverse z-score				
Time	Yes	No	Difference	t-stat	Wilcoxon
Q1 2006	0.012	0.010	0.002	1.464	0.322
Q2 2006	0.013	0.010	**0.003**	2.711	0.071
Q3 2006	0.012	0.018	-0.007	-0.899	0.767
Q4 2006	0.011	0.013	-0.002	-0.500	0.862
Q1 2007	0.012	0.015	-0.004	-0.616	0.705
Q2 2007	0.011	0.010	0.000	0.464	0.900
Q3 2007	0.025	0.018	**0.007**	2.232	0.157
Q4 2007	0.022	0.034	-0.012	-0.858	0.631
Q1 2008	0.025	0.024	0.001	0.354	0.336
Q2 2008	0.021	0.031	-0.011	-1.574	0.112
Q3 2008	0.050	0.042	0.008	0.740	0.589
Q4 2008	0.081	0.081	-0.001	-0.031	0.942
Q1 2009	0.063	0.044	0.019	1.912	0.139
Q2 2009	0.039	0.048	-0.008	-0.498	0.959
Q3 2009	0.031	0.022	0.009	1.216	0.431
Q4 2009	0.020	0.033	-0.013	-1.192	0.254
Q1 2010	0.016	0.018	-0.002	-0.269	0.767
Q2 2010	0.024	0.020	0.004	0.967	0.600
Q3 2010	0.020	0.016	0.004	1.131	0.547
Q4 2010	0.017	0.011	**0.005**	2.184	0.280

Table 6.6: Matching of option users and non-users.

This table reports mean values for the inverse z-score of insurers that use options in a given quarter matched with non-users from Q1 2006 to Q4 2010. Nearest neighbor matching (with replacement) of option users and non-users is performed on the insurers' size and market-to-book ratios. The columns "Yes" and "No" report average values for the user and non-user group and "Difference" is their difference. The statistical significance of the difference of mean values is tested with t-tests and Wilcoxon tests, for which corresponding t-statistics and p-values are reported. Bolded values indicate a statistical significance at the 10% level.

	Inverse z-score				
Time	Yes	No	Difference	t-stat	Wilcoxon
Q1 2006	0.012	0.011	0.001	0.402	0.978
Q2 2006	0.013	0.011	0.002	1.604	0.640
Q3 2006	0.013	0.011	0.003	1.346	0.314
Q4 2006	0.012	0.010	0.002	1.150	0.365
Q1 2007	0.012	0.012	0.000	0.138	0.705
Q2 2007	0.011	0.011	0.000	0.068	0.753
Q3 2007	0.025	0.018	**0.007**	2.232	0.374
Q4 2007	0.027	0.015	**0.012**	2.361	0.039
Q1 2008	0.026	0.022	0.004	0.915	0.527
Q2 2008	0.025	0.016	**0.010**	2.078	0.091
Q3 2008	0.050	0.040	0.010	0.944	0.880
Q4 2008	0.087	0.057	**0.030**	3.352	0.027
Q1 2009	0.061	0.046	0.015	1.407	0.575
Q2 2009	0.043	0.036	0.007	0.777	0.771
Q3 2009	0.030	0.025	0.005	0.839	0.650
Q4 2009	0.023	0.021	0.002	0.460	0.787
Q1 2010	0.018	0.010	**0.008**	2.837	0.096
Q2 2010	0.024	0.015	**0.009**	3.871	0.125
Q3 2010	0.020	0.013	**0.008**	2.925	0.125
Q4 2010	0.016	0.013	0.003	1.224	0.813

Again, we can see that the disclosed usage of swaps has no pervasive effect on default risk over our sample period. Instead, the default risk of swap users appears to be significantly higher only during selected quarters. In contrast, users of options consistently had higher inverse z-scores than non-users during our sample period with the differences being statistically significant especially during the crisis years from Q3 2007 to Q4 2008. We thus find empirical evidence that particularly insurers that employ options in their risk management, at times, have a significantly higher default risk than comparable non-users. Even more surprising, however, is the fact that the usage of financial derivatives does not exert a decreasing effect on the insurers' default risk.

6.4.4 Panel regressions of default risk on derivative usage

We now turn to our multivariate analyses of default risk for our sample of U.S. insurers. First, we perform several GMM-sys panel regressions (see Blundell and Bond, 1998) of the inverse z-score on the various variables on the insurers' derivatives usage. The resulting estimates are shown in Table 6.7.

In the first column of Table 6.7, we only include our main dummy variable that is one, if an insurer discloses the usage of derivatives in its 10-K filing, and zero otherwise. Additionally, we employ insurer- and time-fixed effects and one lag of the dependent variable as regressors. The sign of the coefficient of the derivative dummy variable is negative and also statistically significant at the 1% level. In contrast to the cross-sectional matching analysis, we find a decreasing effect of derivatives usage on the default risk of U.S. insurers. As a consequence, we find empirical evidence pointing at a beneficial effect of using financial derivatives on the average default probability of an insurer. Next, we include the hedging dummy variable in regression (2) to test whether the purpose of hedging has a significant effect on default risk. The hedging dummy variable, however, is not significant in this regression specification (note that the number of observations in this regression is considerably smaller than in the first regression).

To get a more nuanced picture of the effects the different types of derivatives have on default risk, we include the respective dummy variables one by one in our regressions and report the results in columns (3) - (6). The dummy variables for options, futures, and forwards are highly significant with a negative sign. Again, we find the result that the use of the different derivatives significantly decreases the level of default risk. The swap dummy variable, however, is not a statistically significant driver of default risk. Using all four dummy variables simultaneously in regression (7) yields no reliable results as all four dummies are highly correlated. Finally, in regression (8), we perform a regression in which we interact the hedging dummy with the dummy for the usage of derivatives. The latter is now statistically significant and positive, showing that the usage of derivatives for non-hedging purposes exerts a destabilizing effect on the default risk of insurers.

6.4.5 Robustness and further analyses

To validate our main results, we perform additional panel regressions that include control variables and regressions on sub-samples. First, one could argue that the positive effect of derivatives on an insurer's default risk could change in times of crisis or when derivative markets experience a downturn. Therefore, we repeat our baseline regressions for a sub-sample of observations during the financial crisis. The results are reported in Table 6.8.

In column (1) and (2), we observe that both the dummy variables on an insurer's derivatives use and hedging purpose have no significant impact on insurers' default risk. Consistent with our previous findings, we find a decreasing effect of the use of future contracts on insurers' default risk. This variable remains significant in all settings of our analysis. Column (7) reports the estimation result of the regression in which we use all dummy variables. The results underline our previous findings from models (3)-(6). Finally, note that the use of swaps appears to significantly increase the default risk of insurers.

Table 6.7: GMM-sys regressions of default risk on derivative usage variables.

The table shows the results of panel regressions of quarterly values of the inverse z-score for a sample of U.S. insurers on lagged indicators of derivative usage. All panel regressions are estimated using the (one-step) GMM-sys estimator in Blundell and Bond (1998) (with double-lagged values of the dependent variable as instruments) and include insurer- and quarter-fixed effects. The estimated model is

$$\text{INVERSE Z-SCORE}_{i,t} = \alpha^i + \mu_t + \beta_1 \times \text{INVERSE Z-SCORE}_{i,t-1} + \beta_2 \times \text{DERIVATIVES}_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is the inverse z-score (winsorized at the 5% level). DERIVATIVES$_{i,t}$ is a dummy variable that is one when insurer i uses derivatives contracts (options, swaps, futures, forwards) in quarter t. α^i and μ_t are insurer fixed- and quarter fixed effects. The sample includes insurer-quarter observations of 171 U.S. insurers over the time period from Q1 1999 to Q3 2014. P-values are reported in parentheses. Variable definitions and data sources are provided in Table E.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Inverse z-score$_{t-1}$	**0.304*****	**0.394*****	**0.393*****	**0.386*****	**0.386*****	**0.385*****	**0.382*****	**0.394*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Derivatives	**-0.006*****							**0.025*****
	(0.000)							(0.000)
Hedging		-0.003						0.011
		(0.303)						(0.214)
Options			**-0.003****				-0.001	
			(0.039)				(0.609)	
Swaps				0.002			0.002	
				(0.273)			(0.147)	
Futures					**-0.004*****		-0.002	
					(0.008)		(0.256)	
Forwards						**-0.004*****	-0.003	
						(0.008)	(0.129)	
Derivatives × Hedge								-0.014
								(0.125)
N	4,242	2,343	2,309	2,317	2,297	2,318	2,261	2,343

Table 6.8: GMM-sys regressions and derivative use during the crisis (2006-2010).

The table shows the results of panel regressions of quarterly values of the inverse z-score for a sample of U.S. insurers on lagged indicators of derivative usage for the crisis period (2006-2010). All panel regressions are estimated using the (one-step) GMM-sys estimator in Blundell and Bond (1998) (with double-lagged values of the dependent variable as instruments) and include insurer- and quarter-fixed effects. The estimated model is

$$\text{INVERSE Z-SCORE}_{i,t} = \alpha^i + \mu_t + \beta_1 \times \text{INVERSE Z-SCORE}_{i,t-1} + \beta_2 \times \text{DERIVATIVES}_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is the inverse z-score (winsorized at the 5% level). DERIVATIVES$_{i,t}$ is a dummy variable that is one when insurer i uses derivatives contracts (options, swaps, futures, forwards) in quarter t. α^i and μ_t are insurer fixed- and quarter fixed effects. The sample includes insurer-quarter observations of 171 U.S. insurers over the time period from Q1 2006 to Q4 2010. P-values are reported in parentheses. Variable definitions and data sources are provided in Table E.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Inverse z-score$_{t-1}$	**0.441*****	**0.544*****	**0.545*****	**0.528*****	**0.526*****	**0.537*****	**0.498*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Derivatives	0.002						
	(0.507)						
Hedging		-0.007					
		(0.203)					
Options			-0.003				0.001
			(0.435)				(0.727)
Swaps				**0.008***			**0.009****
				(0.050)			(0.026)
Futures					**-0.007****		**-0.007***
					(0.014)		(0.063)
Forwards						**-0.006****	-0.004
						(0.036)	(0.233)
N	1,557	881	864	866	852	866	842

Next, we run regressions that include several insurer characteristics as control variables in addition to the derivatives usage dummy. We report the respective estimates in Table 6.9.

In all regressions, we include the variables *Leverage*, *Debt maturity*, and *Solvency*. Columns (1)-(4) show results employing the inverse z-score as our dependent variable. In (1) and (4), we include the derivatives usage dummy variable and find that it enters the regressions with a highly significant negative sign. Next, we also employ two alternative variables that capture an insurer's usage of financial derivatives. In (2), we include the derivatives intensity, which describes the number of different derivative types used in an insurer's risk management. However, this test is not successful as this variable is not significant in any of the two regressions. Complementing this finding, the insurers' net gains and losses on derivative positions are also not significantly correlated with the insurers' average default risk. Also note that an insurer's solvency is always significantly positively correlated with the default risk of insurers. Finally, including an insurer's stock return volatility as an independent variable in regression model (8) does not change our conclusions.

Table 6.9: GMM-sys regressions of default risk on derivative usage and control variables.

This table shows the results of panel regressions of quarterly estimates of three systemic risk measures for a sample of international insurers on key indicators of systemic relevance and various control variables. All panel regressions are estimated with insurer- and quarter-fixed effects and with robust standard errors. The estimated model is

$$\text{INVERSE Z-SCORE}_{i,t} = \alpha^i + \mu_t + \beta_1 \times \text{INVERSE Z-SCORE}_{i,t-1} + \beta_2 \times \text{DERIVATIVES}_{i,t-1} + \Theta \times \text{CONTROLS}_{i,t-1} + \varepsilon_{i,t}$$

The dependent variable in Panel A is the inverse z-score based on balance sheet data and Panel B employs the alternative specification of the inverse z-score. $\text{DERIVATIVES}_{i,t}$ is a dummy variable that is one when insurer i uses derivatives contracts (options, swaps, futures, forwards) in quarter t. $\text{CONTROLS}_{i,t}$ are various firm-specific control variables winsorized at the 5% level. α^i and μ_t are insurer fixed- and quarter fixed effects. The sample includes insurer-quarter observations of 171 U.S. insurers over the time period from Q1 1999 to Q3 2014. P-values are reported in parentheses. Variable definitions and data sources are provided in Table E.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

	Inverse z-score			
	(1)	(2)	(3)	(4)
Inverse z-score$_{t-1}$	**0.289*****	**0.387*****	**0.571*****	**0.382*****
	(0.000)	(0.000)	(0.000)	(0.000)
Derivatives	**-0.004*****			**-0.004*****
	(0.008)			(0.010)
Leverage $(\times 10^{-3})$	0.462	-0.816	**-2.740****	-0.009
	(0.416)	(0.314)	(0.010)	(0.989)
Debt maturity	**-0.016****	0.005	**0.022****	-0.004
	(0.037)	(0.638)	(0.011)	(0.631)
Solvency $(\times 10^{-3})$	**4.240*****	**2.530*****	**1.830*****	**4.480*****
	(0.000)	(0.000)	(0.009)	(0.000)
Derivatives intensity $(\times 10^{-3})$		-0.180		
		(0.772)		
Gains/Losses $(\times 10^{-3})$			-0.001	
			(0.563)	
Volatility				**-0.214*****
				(0.000)
Quarter fixed effects	x	x	x	x
Insurer fixed effects	x	x	x	x
N	2,567	1,542	778	2,010

6.4.6 Systemic risk and derivative usage

The results so far emphasize the stabilizing role of using financial derivatives on the default risk of insurers in case derivatives are primarily used for hedging and not for risk-taking. In this part of our analysis, we try to answer the related question whether the effect of derivatives usage on default risk also translates to the systemic risk of insurers.

The bailout of AIG during the financial crisis has spurred numerous discussions on the potential threat the insurance sector poses to financial stability. Complementing the Financial Stability Board's list of globally systemically important banks, the IAIS recently published a list of nine global systemically important insurers (GSII) that are subject to increased monitoring by regulators.[98] To identify systemic relevance, they employ several indicators such as an insurer's size, leverage, or interconnectedness with the rest of the financial system. They argue that non-traditional and non-insurance activities could cause an insurer to become systemically relevant to the rest of the financial system. While several authors analyze this question by relating common systemic risk measures to an insurer's leverage, funding constraints, or its interconnectedness (see, e.g., Weiß and Mühlnickel, 2014, 2015, Bierth et al., 2015, Chen et al., 2014, Cummins and Weiss, 2014), the interplay between an insurer's derivatives use and its systemic risk has not been analyzed yet.

Consequently, we perform further panel regressions involving two common systemic risk measures proposed in the literature. As explanatory variables, we employ our derivatives usage dummy variables.[99]

In our study, we use quarterly estimates of the *Marginal Expected Shortfall* (MES) and *SRISK*. The MES is defined by Acharya et al. (2010) as the negative average return

[98] The GSIIs are Allianz SE, American International Group, Inc., Assicurazioni Generali S.p.A., Aviva plc, Axa S.A., MetLife, Inc., Ping An Insurance (Group) Company of China, Ltd., Prudential Financial Inc. and Prudential plc.

[99] The systemic risk measures that we employ share the property that both are based on economic theory and capture different aspects of systemic risk. Since the recent financial crisis, several other measures of systemic risk have been proposed in the literature. Further examples for such measures apart from those used in this study are due to De Jonghe (2010), Huang et al. (2012), Schwaab et al. (2011), Hautsch et al. (2015), Hovakimian et al. (2012) and White et al. (2015).

on an individual insurer's stock on the days the *S&P 500* index experienced its 5% worst outcomes and measures an individual insurer's *exposure* to systemic risk.[100] The second systemic risk measure is SRISK, which is the quarterly estimate of the Systemic Risk Index as proposed by Acharya et al. (2012) and Brownlees and Engle (2015).[101]

Table 6.10 shows the results of panel regressions of MES on our variables describing an insurer's derivatives usage.

Column (1) reports the regressions in which we test the isolated impact of derivatives usage on MES. The coefficient enters the regression with a positive sign and is significant at the 5% level. Thus, derivatives usage is associated with a higher exposure of the insurer to tail events in the financial market and potential systemic risks. This result underlines in part the conjecture proposed by regulators that engaging in derivatives trading may bear additional risk for an otherwise unexposed insurance company. In the second regression, we find the complementing result that using derivatives for hedging significantly reduces the MES and thus an insurer's exposure to systemic risk in the financial sector. Turning to the four derivatives classes in (3)-(7), we can observe a positive and significant influence of the use of future contracts. In column (8), we show the results for the regression that includes the interaction of derivatives usage and hedging purpose to test whether the use of derivatives for risk-taking increases an insurer's systemic risk exposure. Again, we find the coefficient for derivatives usage to be statistically significant and positive, meaning that the use of derivatives for non-hedging purposes significantly increases an insurer's vulnerability to tail risks in the financial sector.

In the following Table 6.11, we illustrate the results using SRISK as a proxy for an insurer's *contribution* (rather than its *exposure*) to systemic risk as our dependent variable.

[100] The return on the S&P 500 is a proxy for the return on the market portfolio in our analysis.

[101] For an insurer i at time t, the SRISK measure is given by $SRISK_{i,t} = k\,(Debt_{i,t}) - (1-k)\,(1 - LRMES_{i,t})\,Equity_{i,t}$, where k is a regulatory capital ratio (set to 8%), $Debt_{i,t}$ is the insurer's book value of debt, $LRMES_{i,t}$ is the long run Marginal Expected Shortfall defined as $1 - \exp(-18 \cdot MES)$, MES is the estimated Marginal Expected Shortfall and $Equity_{i,t}$ is the insurer's market value of equity.

The results from models (1) and (2) show that derivatives usage exerts an increasing, and the use of derivatives for hedging exerts a decreasing effect on an insurer's SRISK. Both results, however, are not statistically significant at the 10% level. The four derivative usage dummies used in the regressions in columns (3)-(6) all have a positive and statistically significant sign. SRISK has larger values for insurers that use the different derivatives and thus, the insurer has a larger capital shortfall and contribution to systemic instability. When all four variables are used together in model (7), only the use of forwards remains a significant driver of an insurer's contribution to systemic risk. Interacting our variables *Derivatives* and *Hedging* does not yield any new insights and it appears as if the overall usage of derivatives by an insurer does not increase its contribution to systemic risk.[102]

[102] This finding is in line with the results of Chen et al. (2014), Cummins and Weiss (2014), who view insurers as "victims" rather than "perpetrators" of systemic risk.

Table 6.10: GMM-sys regressions of MES on derivative usage variables.

The table shows the results of panel regressions of quarterly values of the *MES* for a sample of U.S. insurers on lagged indicators of derivative usage. All panel regressions are estimated using the (one-step) GMM-sys estimator in Blundell and Bond (1998) (with double-lagged values of the dependent variable as instruments) and include insurer- and quarter-fixed effects. The estimated model is

$$\mathrm{MES}_{i,t} = \alpha^i + \mu_t + \beta_1 \times \mathrm{MES}_{i,t-1} + \beta_2 \times \mathrm{DERIVATIVES}_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is the MES as in Acharya et al. (2010). $\mathrm{DERIVATIVES}_{i,t}$ is a dummy variable that is one when insurer i uses derivatives contracts (options, swaps, futures, forwards) in quarter t. α^i and μ_t are insurer fixed- and quarter fixed effects. The sample includes insurer-quarter observations of 171 U.S. insurers over the time period from Q1 1999 to Q3 2014. P-values are reported in parentheses. Variable definitions and data sources are provided in Table E.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MES_{t-1}	**0.059*****	**0.102*****	**0.103*****	**0.111*****	**0.111*****	**0.108*****	**0.110*****	**0.102*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Derivatives	**0.005****							**0.028*****
	(0.020)							(0.000)
Hedging		**-0.009****						-0.003
		(0.029)						(0.829)
Options			0.001				-0.002	
			(0.639)				(0.498)	
Swaps				-0.001			-0.002	
				(0.584)			(0.412)	
Futures					**0.004****		**0.006****	
					(0.042)		(0.027)	
Forwards ($\times 10^{-3}$)						-0.214	-0.002	
						(0.934)	(0.522)	
Derivatives $\times$ Hedge								-0.006
								(0.663)
N	4,213	2,337	2,303	2,311	2,291	2,312	2,255	2,337

Table 6.11: GMM-sys regressions of SRISK on derivative usage variables.

The table shows the results of panel regressions of quarterly values of the *SRISK* for a sample of U.S. insurers on lagged indicators of derivative usage. All panel regressions are estimated using the (one-step) GMM-sys estimator in Blundell and Bond (1998) (with double-lagged values of the dependent variable as instruments) and include insurer- and quarter-fixed effects. The estimated model is

$$\text{SRISK}_{i,t} = \alpha^i + \mu_t + \beta_1 \times \text{SRISK}_{i,t-1} + \beta_2 \times \text{DERIVATIVES}_{i,t-1} + \varepsilon_{i,t}.$$

The dependent variable is the SRISK as in Brownlees and Engle (2015). $\text{DERIVATIVES}_{i,t}$ is a dummy variable that is one when insurer i uses derivatives contracts (options, swaps, futures, forwards) in quarter t. α^i and μ_t are insurer fixed- and quarter fixed effects. The sample includes insurer-quarter observations of 171 U.S. insurers over the time period from Q1 1999 to Q3 2014. P-values are reported in parentheses. Variable definitions and data sources are provided in Table E.2 in the Appendix. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SRISK_{t-1}	**0.875*****	**0.871*****	**0.851*****	**0.864*****	**0.848*****	**0.826*****	**0.814*****	**0.870*****
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Derivatives	115.2							997.5
	(0.546)							(0.281)
Hedging		-71.8						1,603.0
		(0.932)						(0.292)
Options			**1,431.1*****				655.5*	
			(0.000)				(0.070)	
Swaps				**738.9****			388.1	
				(0.032)			(0.266)	
Futures					**1,206.0*****		535.4	
					(0.000)		(0.105)	
Forwards						**1,640.6*****	**1,308.9*****	
						(0.000)	(0.000)	
Derivatives $\times$ Hedge								-1,671.5
								(0.336)
N	2,647	1,577	1,556	1,551	1,531	1,552	1,515	1,577

6.4.7 Which insurers use derivatives?

The results from our regression analyses so far show that the use of derivatives may have a differential effect on the default risk and also on the exposure and contribution of insurers to systemic risk. Therefore, the question arises which insurers engage in derivative activities and also, why they use such tools.[103] To get an overview of the characteristics of derivative users, we run additional logistic regressions with the derivatives usage dummies as binary dependent variables. The results from our regressions of the derivative dummy on insurer characteristics are shown in Table 6.12.

Our first result is that derivatives usage is more likely for larger insurers, a result which is in line with our intuition. Insurers with higher leverage ratios, however, seem to be less likely to use derivatives, since the coefficient enters the regressions with a negative sign. Market-to-book ratios or solvency proxies do not seem to play a major role in explaining an insurer's decision to use derivatives. When we include all of the four variables together, instead of using each one of them separately, we find that insurer size is the only factor to explain the derivatives usage dummy. These results also hold true, when we employ quarter dummies to account for unobserved time effects.

Table 6.13 and 6.14 present the results of logistic regressions using the option and swap usage dummies as dependent variables.

Qualitatively, the results from Table 6.12 also remain true for the option and swap dummies with a minor exception. In the regressions including the leverage ratio, we do not find any significant influence of this variable in the decision to use options. Surprisingly, the size of an insurer does not explain the decision to disclose swap usage when all of the variables are included and thus, the sample size is reduced. However, we conclude that the sheer size of an insurance firm determines its decision to employ financial derivatives.

[103] For example, highly levered insurers may be inclined to lengthen the duration of their liabilities through derivatives usage.

Table 6.12: Logistic regression of derivative usage on insurer characteristics.

This table shows the results of logistic regressions of derivative usage indicators on insurer characteristics. The estimated model is:

$$\text{DERIVATIVES}_t^i = \alpha + \beta_1 \times \text{INSURER CHARACTERISTICS}_{t-1}^i + \varepsilon_t,$$

where DERIVATIVES_t^i is a dummy variable that is one if an insurer uses derivatives in a given quarter and zero otherwise. $\text{INSURER CHARACTERISTICS}_{t-1}^i$ include an insurer's size, leverage, market-to-book ratio and solvency. Variable definitions and data sources are provided in Table E.2 in the Appendix. P-values are reported in parentheses and calculated using clustered standard errors on the firm level. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Regressions in column (1) - (4) include only one variable while (5) uses all four characteristics. Columns (6) - (10) show results from regressions using quarter dummies.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	**1.057***				**0.938***	**1.073***				**0.943***
	(0.000)				(0.001)	(0.000)				(0.001)
Leverage		**-0.933***			-0.031		**-0.918***			-0.025
		(0.006)			(0.861)		(0.007)			(0.892)
Market-to-book ratio			-0.472		-0.555			-0.498		-0.665
			(0.105)		(0.129)			(0.196)		(0.167)
Solvency				-0.157	**0.463***				-0.142	**0.448***
				(0.164)	(0.072)				(0.204)	(0.088)
Constant	**-23.160***	**0.776***	**0.997***	**0.510***	**-20.210***	**-23.500***	**0.821***	**1.095***	0.306	**-19.870***
	(0.000)	(0.001)	(0.005)	(0.021)	(0.003)	(0.000)	(0.042)	(0.070)	(0.397)	(0.004)
Quarter dummies						x	x	x	x	x
N	6,019	3,600	3,042	3,593	2,108	6,019	3,600	3,042	3,593	2,108

Table 6.13: Logistic regression of option usage on insurer characteristics.

This table shows the results of logistic regressions of derivative usage indicators on insurer characteristics. The estimated model is:

$$\text{OPTION}_t^i = \alpha + \beta_1 \times \text{INSURER CHARACTERISTICS}_{t-1}^i + \varepsilon_t,$$

where OPTION_t^i is a dummy variable that is one if an insurer uses options in a given quarter and zero otherwise. $\text{INSURER CHARACTERISTICS}_{t-1}^i$ include an insurer's size, leverage, market-to-book ratio and solvency. Variable definitions and data sources are provided in Table E.2 in the Appendix. P-values are reported in parentheses and calculated using clustered standard errors on the firm level. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Regressions in column (1) - (4) include only one variable while (5) uses all four characteristics. Columns (6) - (10) show results from regressions using quarter dummies.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	0.423***				0.552**	0.425***				0.555**
	(0.001)				(0.014)	(0.001)				(0.015)
Leverage		-0.347			0.236		-0.350			0.246
		(0.297)			(0.392)		(0.283)			(0.387)
Market-to-book ratio			-0.435		-0.845			-0.519		-1.005
			(0.270)		(0.159)			(0.338)		(0.199)
Solvency				-0.086	0.290				-0.078	0.254
				(0.660)	(0.376)				(0.692)	(0.430)
Constant	-9.062***	0.986***	1.205**	0.975***	-11.190**	-8.944***	0.879*	1.448*	1.043*	-10.870**
	(0.002)	(0.000)	(0.010)	(0.001)	(0.032)	(0.002)	(0.072)	(0.073)	(0.051)	(0.041)
Quarter dummies						x	x	x	x	x
N	3,411	2,202	1,880	2,195	1,385	3,411	2,202	1,880	2,195	1,385

Table 6.14: Logistic regression of swap usage on insurer characteristics.

This table shows the results of logistic regressions of swap usage indicators on insurer characteristics. The estimated model is:

$$\text{SWAP}_t^i = \alpha + \beta_1 \times \text{INSURER CHARACTERISTICS}_{t-1}^i + \varepsilon_t,$$

where SWAP_t^i is a dummy variable that is one if an insurer uses swaps in a given quarter and zero otherwise. $\text{INSURER CHARACTERISTICS}_{t-1}^i$ include an insurer's size, leverage, market-to-book ratio and solvency. Variable definitions and data sources are provided in Table E.2 in the Appendix. P-values are reported in parentheses and calculated using clustered standard errors on the firm level. ***,**,* denote coefficients that are significant at the 1%, 5%, and 10% level, respectively. Regressions in column (1) - (4) include only one variable while (5) uses all four characteristics. Columns (6) - (10) show results from regressions using quarter dummies.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Size	**0.275****				0.103	**0.286****				0.107
	(0.012)				(0.542)	(0.013)				(0.533)
Leverage		**-0.399***			-0.229		**-0.429***			-0.201
		(0.081)			(0.425)		(0.078)			(0.473)
Market-to-book ratio			0.053		0.143			-0.090		-0.114
			(0.897)		(0.766)			(0.869)		(0.860)
Solvency				-0.252	-0.422				-0.294	-0.500
				(0.218)	(0.197)				(0.171)	(0.179)
Constant	**-5.024****	**1.557*****	**1.185****	**1.600*****	-1.112	**-5.423****	**1.779*****	**1.402***	**1.725*****	-0.463
	(0.045)	(0.000)	(0.011)	(0.000)	(0.788)	(0.040)	(0.006)	(0.082)	(0.007)	(0.916)
Quarter dummies						x	x	x	x	x
N	3,417	2,188	1,895	2,181	1,387	3,417	2,188	1,895	2,181	1,387

6.5 Conclusion

In this paper, we analyze the relation between the default risk of 171 U.S. insurance companies and their derivatives usage in the time period from 1999 to 2014. We hand-collect data on our sample insurers' derivatives usage by evaluating their respective 10-K filings and relate this information to the insurers' inverse z-score as a proxy of their idiosyncratic default risk. We then match users and non-users of derivatives using propensity score matching and thus alleviate in part the problematic endogeneous nature of an insurer's decision to use financial derivatives. Finally, we estimate panel regressions of the proxies of the insurers' default and systemic risk on various variables that capture their engagement in derivatives markets.

As our main empirical result, we find that insurers that employ financial derivatives have a significantly lower risk of defaulting than matched non-using insurers. We also find that the decreasing effect of derivatives usage on default risk is reversed in case insurers use derivatives for risk-taking and non-hedging purposes. Perhaps not surprisingly, this adverse effect of using derivatives for non-hedging purposes on default risk also translates to an insurer's exposure to tail risk in the financial system. Consequently, insurers that employ derivatives for risk-taking appear to be more vulnerable to turmoil in financial markets. However, we do not find any evidence in favor of a destabilizing effect of an insurer's derivatives usage on the stability of the financial system itself.

Our results complement current views by insurance regulators that derivatives usage for trading negatively affects an insurer's financial health and might ultimately lead to financial instability. However, our findings also underline the risk-reducing and thereby stabilizing effect of using derivatives for hedging purposes.

In future work, one could think about extracting more detailed information on the insurers' derivatives usage from their 10-K filings. One could also think about using the notional values of the insurers' derivatives positions. Both approaches, however, do not come without caveats as the information given in the insurers' 10-K filings is quite fuzzy and inconsistent across insurers.

Appendix A

Supplementary Material for Chapter 2

Dynamic pair-copulas

This appendix presents the dynamic pair-copulas used in the construction of our dynamic R-vine copula model. The dynamization of the standard elliptical and Archimedean copulas is based on Patton (2006), who incorporates time variation by estimating appropriate dynamic processes for the evolution of the copula parameters. We discuss the most important properties and show the (log) likelihoods for statistical inference.

Normal copula

The bivariate normal copula, $\boldsymbol{C}_N$, is given by

$$\boldsymbol{C}_N(u_{1,t}, u_{2,t}; \rho_t) = \boldsymbol{\Phi}_{\rho_t}\left(\Phi^{-1}(u_{1,t}), \Phi^{-1}(u_{2,t})\right), \tag{A.1}$$

where $\boldsymbol{\Phi}_{\rho_t}$ and Φ^{-1} denote the bivariate Gaussian distribution function with correlation parameter ρ_t and the univariate Gaussian quantile function, respectively, and $u_{1,t}, u_{2,t} \in [0,1]$, $t = 1, ..., T$. The correlation parameter, ρ_t, follows the dynamic

$$\rho_t = \tilde{\Lambda}\left(c + b\rho_{t-1} + a\frac{1}{10}\sum_{i=1}^{10}\Phi^{-1}(u_{1,t-i})\Phi^{-1}(u_{2,t-i})\right), \tag{A.2}$$

where $\tilde{\Lambda}(x) \equiv (1 - e^{-x})(1 + e^{-x})^{-1}$ ensures that $\rho_t \in [-1, 1]$ at all times. The normal copula allows for equal degrees of positive and negative dependence and is independent in the tails, i.e., the asymptotic probabilities

$$\begin{aligned}
\lambda_L &= \lim_{\xi \to 0} \Pr\left[U_1 \leqslant \xi | U_2 \leqslant \xi\right] = \lim_{\xi \to 0} \frac{C_N(\xi, \xi)}{\xi}, \\
\lambda_U &= \lim_{\xi \to 1} \Pr\left[U_1 \geqslant \xi | U_2 \geqslant \xi\right] = \lim_{\xi \to 1} \frac{1 - 2\xi + C_N(\xi, \xi)}{1 - \xi}
\end{aligned} \tag{A.3}$$

are equal to zero. With $x_{i,t} = \Phi^{-1}(u_{i,t})$ for $i = 1, 2$ and T denoting the sample size, the log likelihood, $\mathcal{L}$, is given by

$$\mathcal{L} = \sum_{t=1}^{T} \frac{1}{2} \left[x_{1,t}^2 + x_{2,t}^2 - \log(1 - \rho_t^2) - \frac{x_{1,t}^2 - 2\rho_t x_{1,t} x_{2,t} + x_{2,t}^2}{1 - \rho_t^2} \right]. \tag{A.4}$$

t -copula

The bivariate t copula, $\boldsymbol{C}_t$, is given by

$$\boldsymbol{C}_t(u_{1,t}, u_{2,t}; \nu, \rho_t) = \boldsymbol{t}_{\nu,\rho_t}(t_\nu^{-1}(u_{1,t}), t_\nu^{-1}(u_{2,t})), \tag{A.5}$$

where $\boldsymbol{t}_{\nu,\rho_t}$ and t_ν^{-1} denote the bivariate distribution and univariate quantile function of a (standard) Student's t distribution with degrees of freedom parameter ν and correlation ρ_t, and $u_{1,t}, u_{2,t} \in [0, 1]$, $t = 1, ..., T$. The correlation parameter, ρ_t, follows the dynamic

$$\rho_t = \tilde{\Lambda} \left(c + b\rho_{t-1} + a \frac{1}{10} \sum_{i=1}^{10} t_\nu^{-1}(u_{1,t-i}) t_\nu^{-1}(u_{2,t-i}) \right), \tag{A.6}$$

where $\tilde{\Lambda}(x) \equiv (1 - e^{-x})(1 + e^{-x})^{-1}$ ensures that $\rho_t \in [-1, 1]$ at all times. The t copula allows for equal degrees of positive and negative dependence and is asymptotically dependent in the tails, with the coefficients of lower and upper tail dependence, $\lambda_{L,t}$

and $\lambda_{U,t}$, being equal and given by

$$\lambda_{L,t} = \lambda_{U,t} = 2t_{\nu+1}\left(-\frac{\sqrt{\nu+1}\sqrt{1-\rho_t}}{\sqrt{1+\rho_t}}\right). \tag{A.7}$$

With $x_{i,t} = t_\nu^{-1}(u_{i,t})$ for $i = 1, 2$, $\nu_j = \frac{1}{2}(\nu + j)$ for $j = 0, 1, 2$, and T denoting the sample size, the log likelihood, $\mathcal{L}$, is given by

$$\begin{aligned}\mathcal{L} = \sum_{t=1}^{T} \log \Bigg[&\frac{\Gamma(\nu_2)\Gamma(\nu_0)}{\sqrt{1-\rho_t^2}\,\Gamma(\nu_1)^2}\left(1+\frac{x_{1,t}^2 - 2\rho_t x_{1,t}x_{2,t} + x_{2,t}^2}{\nu(1-\rho_t^2)}\right)^{-\nu_2} \\ &\cdot \left(\left[1+\frac{x_{1,t}^2}{\nu}\right]\left[1+\frac{x_{2,t}^2}{\nu}\right]\right)^{\nu_1}\Bigg].\end{aligned} \tag{A.8}$$

Clayton and rotated Clayton copula

The bivariate Clayton copula, $\boldsymbol{C}_C$, is given by

$$\boldsymbol{C}_C(u_{1,t}, u_{2,t}; \theta_t) = \left(u_{1,t}^{-\theta_t} + u_{2,t}^{-\theta_t} - 1\right)^{-\frac{1}{\theta_t}}, \tag{A.9}$$

where $\theta_t \in [-1, \infty)\backslash\{0\}$ and $u_{1,t}, u_{2,t} \in [0, 1]$, $t = 1, ..., T$. The Clayton copula is an asymmetric copula and implies greater dependence for joint negative events than for joint positive events. While being asymptotically independent in the upper tail, its lower tail dependence coefficient, $\lambda_{L,t}$, can be calculated according to

$$\lambda_{L,t} = 2^{-\frac{1}{\theta_t}} \tag{A.10}$$

Since the parameter of the Clayton copula, θ_t, has little economic interpretation, Patton (2006) suggests using the tail dependence coefficients as the forcing variable for the time dynamics equation. Using (A.10), we assume that θ_t evolves according to

$$\begin{aligned}\lambda_{L,t} &= \Lambda\left(c + b\lambda_{L,t-1} + a\frac{1}{10}\sum_{i=1}^{10}\left|u_{1,t-i} - u_{2,t-i}\right|\right), \\ \theta_t &= -\frac{\log(2)}{\log(\lambda_{L,t})}\end{aligned} \tag{A.11}$$

where $\Lambda(x) \equiv (1 + e^{-x})^{-1}$ ensures that $\lambda_{L,t} \in [0, 1]$ at all times. With T denoting the sample size, the log likelihood of the dynamic Clayton copula, $\mathcal{L}$, is given by

$$\mathcal{L} = \sum_{t=1}^{T} \log\left(1 + \theta_t\right) - \left(1 + \theta_t\right) \log\left(u_{1,t} u_{2,t}\right) - \left(2 + \theta_t^{-1}\right) \log\left(u_{1,t}^{-\theta_t} + u_{2,t}^{-\theta_t} - 1\right). \tag{A.12}$$

The rotated Clayton copula, C_{rC}, is defined via $C_{rC}(u_{1,t}, u_{2,t}; \theta_t) = C_C(1 - u_{1,t}, 1 - u_{2,t}; \theta_t)$, where $\lambda_{L,t} = 0$ and $\lambda_{U,t} = 2^{-\frac{1}{\theta_t}}$. The time evolution equation and the log likelihood for the rotated version of the dynamic Clayton copula can be derived using (A.11) and (A.12).

Gumbel and rotated Gumbel copula

The bivariate Gumbel copula, $\boldsymbol{C}_G$, is given by

$$\boldsymbol{C}_G(u_{1,t}, u_{2,t}; \theta_t) = \exp\left(-\left[(-\log(u_{1,t}))^{\theta_t} + (-\log(u_{2,t}))^{\theta_t}\right]^{\frac{1}{\theta_t}}\right), \tag{A.13}$$

where $\theta_t \in [1, \infty)$ and $u_1, u_2 \in [0, 1]$, $t = 1, ..., T$. The Gumbel copula is an asymmetric copula and implies greater dependence for joint positive events than for joint negative events. While being asymptotically independent in the lower tail, its upper tail dependence coefficient, $\lambda_{U,t}$, can be calculated according to

$$\lambda_{U,t} = 2 - 2^{\frac{1}{\theta_t}}. \tag{A.14}$$

Since the parameter of the Gumbel copula, θ_t, has little economic interpretation, Patton (2006) suggests using the tail dependence coefficients as the forcing variable for the time dynamics equation. Using (A.14), we assume that θ_t evolves according to

$$\begin{aligned} \lambda_{U,t} &= \Lambda\left(c + b\lambda_{U,t-1} + a\frac{1}{10}\sum_{i=1}^{10}|u_{1,t-i} - u_{2,t-i}|\right), \\ \theta_t &= \frac{\log(2)}{\log(2-\lambda_{U,t})} \end{aligned} \tag{A.15}$$

where $\Lambda(x) \equiv (1+e^{-x})^{-1}$ ensures that $\lambda_{U,t} \in [0,1]$ at all times. With $x_{i,t}^{j} = (-\log(u_{i,t}))^{\theta_t - j}$ for $i = 1,2;\ j = 0,1$, and T denoting the sample size, the log likelihood of the dynamic Gumbel copula, $\mathcal{L}$, is given by

$$\begin{aligned} \mathcal{L} = \sum_{t=1}^{T} \log\left(\frac{x_{1,t}^{1}x_{2,t}^{1}}{u_{1,t}u_{2,t}}\right) &- \left(x_{1,t}^{0} + x_{2,t}^{0}\right)^{\frac{1}{\theta_t}} \\ + \log\left(\left(x_{1,t}^{0} + x_{2,t}^{0}\right)^{\frac{2}{\theta_t}-2} + (\theta_t - 1)\left(x_{1,t}^{0} + x_{2,t}^{0}\right)^{\frac{1}{\theta_t}-2}\right). \end{aligned} \tag{A.16}$$

The rotated Gumbel copula, C_{rG}, is defined via $C_{rG}(u_{1,t}, u_{2,t};\theta_t) = C_G(1-u_{1,t}, 1-u_{2,t};\theta_t)$, where $\lambda_{U,t} = 0$ and $\lambda_{L,t} = 2 - 2^{\frac{1}{\theta_t}}$. The time evolution equation and the log likelihood for the rotated version of the dynamic Gumbel copula can be derived using (A.15) and (A.16).

Joe and rotated Joe copula

The bivariate Joe copula, $\boldsymbol{C}_J$, is given by

$$\boldsymbol{C}_J(u_{1,t}, u_{2,t};\theta_t) = 1 - \left((1-u_{1,t})^{\theta_t} + (1-u_{2,t})^{\theta_t} - (1-u_{1,t})^{\theta_t}(1-u_{2,t})^{\theta_t}\right)^{\frac{1}{\theta_t}}, \tag{A.17}$$

where $\theta_t \in [1,\infty)$ and $u_{1,t}, u_{2,t} \in [0,1]$, $t = 1,...,T$. The Joe copula is an asymmetric copula and implies greater dependence for joint positive events than for joint negative events. While being asymptotically independent in the lower tail, its upper tail dependence coefficient, $\lambda_{U,t}$, can be calculated according to

$$\lambda_{U,t} = 2 - 2^{\frac{1}{\theta_t}}. \tag{A.18}$$

Since the parameter of the Joe copula, θ_t, has little economic interpretation, Patton (2006) suggests using the tail dependence coefficients as the forcing variable for the time dynamics equation. Using (A.18), we assume that θ_t evolves according to

$$\begin{aligned}\lambda_{U,t} &= \Lambda\left(c + b\lambda_{U,t-1} + a\frac{1}{10}\sum_{i=1}^{10}|u_{1,t-i} - u_{2,t-i}|\right)\\ \theta_t &= \frac{\log(2)}{\log(2-\lambda_{U,t})},\end{aligned} \tag{A.19}$$

where $\Lambda(x) \equiv (1+e^{-x})^{-1}$ ensures that $\lambda_{U,t} \in [0,1]$ at all times. With $x^j_{i,t} = (1-u_{i,t})^{\theta_t - j}$ for $i = 1,2$; $j = 0,1$, and T denoting the sample size, the log likelihood of the dynamic Joe copula, $\mathcal{L}$, is given by

$$\mathcal{L} = \sum_{t=1}^{T}\log\left[\left(x^0_{1,t} + x^0_{2,t} - x^0_{1,t}x^0_{2,t}\right)^{\frac{1}{\theta_t}-2} x^1_{1,t}x^1_{2,t}\left(\theta_t - 1 + x^0_{1,t} + x^0_{2,t} - x^0_{1,t}x^0_{2,t}\right)\right]. \tag{A.20}$$

The rotated Joe copula, C_{rJ}, is defined via $C_{rJ}(u_{1,t}, u_{2,t}; \theta_t) = C_J(1-u_{1,t}, 1-u_{2,t}; \theta_t)$, where $\lambda_{U,t} = 0$ and $\lambda_{L,t} = 2 - 2^{\frac{1}{\theta_t}}$. The time evolution equation and the log likelihood for the rotated version of the dynamic Joe copula can be derived using (A.19) and (A.20).

Table A.1: Sample of S&P 500 companies.

The table lists a total of 209 companies included in the S&P 500 stock market index as reported by *Thomson Reuters Datastream* between January 2008 and December 2013. Starting with an initial sample of all constituents of the S&P 500 index, we exclude firms with missing/incomplete stock price data and further restrict the sample to firms with traded credit default swaps (CDS). The stock price and CDS spread data of the remaining 209 companies are retrieved from *Datastream* and used to document linear and non-linear dependences between stock returns, bid-ask spreads, and default intensities. The six companies printed in bold type are included in our Value-at-Risk (VaR) study and are used to forecast liquidity- and credit-adjusted VaR.

3M Company	Abbott Laboratories	ACE Limited	Aetna Inc	Air Products & Chemicals Inc
Allegheny Technologies Inc	Allergan Inc	Allstate Corp	Ameren Corp	American Electric Power
American Express Co	American International Group, Inc.	Amerisource Bergen Corp	Anadarko Petroleum Corp	Apache Corporation
Archer-Daniels-Midland Co	Assurant Inc	Automatic Data Processing	AutoZone Inc	AvalonBay Communities, Inc.
Avery Dennison Corp	Avon Products	Baker Hughes Inc	Ball Corp	Bank of America Corp
Baxter International Inc.	BB&T Corporation	Becton Dickinson	Bemis Company	Best Buy Co. Inc.
BorgWarner	Boston Properties	Boston Scientific	Bristol-Myers Squibb	Cameron International Corp.
Campbell Soup	Capital One Financial	Cardinal Health Inc.	Caterpillar Inc.	CBS Corp.
CenterPoint Energy	CenturyLink Inc	Chesapeake Energy	Chevron Corp.	The Clorox Company
CMS Energy	Coca-Cola Enterprises	Computer Sciences Corp.	ConAgra Foods Inc.	ConocoPhillips
Constellation Brands	Corning Inc.	CVS Caremark Corp.	D. R. Horton	Danaher Corp.
Darden Restaurants	DaVita Inc.	Devon Energy Corp.	DirecTV	Dover Corp.
Dow Chemical	Dr Pepper Snapple Group	DTE Energy Co.	Eastman Chemical	Eaton Corp.
Edison Int'l	EMC Corp.	Emerson Electric	Ensco plc	Entergy Corp.
EOG Resources	Equifax Inc.	Exelon Corp.	Exxon Mobil Corp.	FedEx Corporation
Fluor Corp.	FMC Technologies Inc.	Freeport-McMoran Cp & Gld	Gannett Co.	Gap (The)
General Mills	Genworth Financial Inc.	Halliburton Co.	Harris Corporation	Hartford Financial Svc.Gp.
Hasbro Inc.	HCP Inc.	Health Care REIT, Inc.	Hess Corporation	**Hewlett-Packard**
Honeywell Int'l Inc.	Hospira Inc.	Host Hotels & Resorts	Humana Inc.	Illinois Tool Works
International Bus. Machines	International Game Technology	Interpublic Group	Iron Mountain Incorporated	Jabil Circuit
Johnson & Johnson	Johnson Controls	Joy Global Inc.	JPMorgan Chase & Co.	KeyCorp
Kimberly-Clark	Kimco Realty	Kohl's Corp.	Leggett & Platt	Lennar Corp.
Lilly (Eli) & Co.	Lincoln National	Lockheed Martin Corp.	Lowe's Cos.	Marathon Oil Corp.
Marriott Int'l.	Marsh & McLennan	Masco Corp.	Mattel Inc.	McDonald's Corp.
McKesson Corp.	MeadWestvaco Corporation	Medtronic Inc.	Merck & Co.	MetLife Inc.
Molson Coors Brewing Company	The Mosaic Company	Murphy Oil	Mylan Inc.	Newell Rubbermaid Co.
Newmont Mining Corp.	NIKE Inc.	Noble Energy Inc	Norfolk Southern Corp.	Northrop Grumman Corp.
NRG Energy	Nucor Corp.	Occidental Petroleum	Omnicom Group	ONEOK
P G & E Corp.	Pentair Ltd.	Pepco Holdings Inc.	PepsiCo Inc.	PerkinElmer
Pfizer Inc.	Pioneer Natural Resources	Pitney-Bowes	PNC Financial Services	PPG Industries
Principal Financial Group	Progressive Corp.	Prologis	Prudential Financial	Pulte Homes Inc.
PVH Corp.	Quest Diagnostics	Raytheon Co.	Republic Services Inc	Reynolds American Inc.
Rockwell Automation Inc.	Safeway Inc.	SCANA Corp	Schlumberger Ltd.	Seagate Technology
Sealed Air Corp.	Sempra Energy	Sherwin-Williams	Simon Property Group Inc	SLM Corporation
Snap-On Inc.	Southwest Airlines	Stanley Black & Decker	Starwood Hotels & Resorts	Sysco Corp.
Target Corp.	**Tenet Healthcare Corp.**	Tesoro Petroleum Co.	Texas Instruments	**Textron Inc.**
The Hershey Company	The Travelers Companies Inc.	Time Warner Inc.	TJX Companies Inc.	Torchmark Corp.
Transocean	Tyson Foods	Tyco International	U.S. Bancorp	Union Pacific
United Health Group Inc.	United Parcel Service	United Technologies	Unum Group	V.F. Corp.
Valero Energy	Vornado Realty Trust	**Wal-Mart Stores**	The Walt Disney Company	WellPoint Inc.
Wells Fargo	Western Digital	Whirlpool Corp.	Williams Cos.	Windstream Communication
Wisconsin Energy Corporation	Xerox Corp.	Yum! Brands Inc	Zimmer Holdings	

Table A.2: Summary statistics for level data of firms included in the Value-at-Risk study.

The table reports descriptive statistics on the time-series distribution of daily mid prices, bid-ask spreads, default intensities, and default probablities (at a monthly horizon) for the six firms investigated in our Value-at-Risk (VaR) study. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The summary statistics refer to the in- and out-of-sample time periods in the VaR study, which cover the period from January 2010 to November 2011 resulting in 499 daily observations. Mid prices and bid-ask spreads are denominated in US dollar, where the latter are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 2.3 and have a horizon of one year. Default probabilities are derived from the intensities using the formula in (2.15) and thus have a horizon of one month.

		Percentiles								Moments				
	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.	AC(1)
Panel A: Mid prices														
3M Company	70.93	73.586	76.855	81	84.72	89.615	95.388	96.9258	97.97	85.3225	5.739	0.1499	-0.7167	0.9749
American Express	36.79	37.709	38.384	41.465	44.17	46.94	51.258	52.3412	53.59	44.4242	3.8702	0.2353	-0.7618	0.9729
Hewlett-Packard	22.2	22.6486	24.439	36.4125	42.1	47.075	53.069	53.8702	54.52	41.0519	8.4451	-0.6218	-0.3825	0.992
Tenet Healthcare	14.36	16	16.72	18.12	21.52	25.46	28.168	30.0424	30.52	21.978	4.006	0.2134	-1.2524	0.9814
Textron	14.88	15.259	16.719	18.91	21.42	23.49	27.171	27.9612	28.5	21.4874	3.1636	0.2213	-0.6451	0.9827
Wal-Mart Stores	48	48.5668	50.274	52.105	53.6	54.625	56.73	58.1308	59.32	53.4569	1.9611	-0.0272	0.2277	0.9583
Panel B: Bid-ask spreads														
3M Company	0.01	0.01	0.01	0.01	0.02	0.04	0.08	0.11	1.12	0.0329	0.0537	16.7505	334.9984	0.0784
American Express	0.01	0.01	0.01	0.01	0.02	0.03	0.05	0.1002	0.18	0.0228	0.018	3.8209	24.1701	0.2213
Hewlett-Packard	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.06	0.14	0.0195	0.0135	3.7733	25.9914	0.2291
Tenet Healthcare	0.04	0.04	0.04	0.04	0.04	0.04	0.08	0.08	7.76	0.0615	0.3456	22.2102	492.1938	-0.0033
Textron	0.01	0.01	0.01	0.01	0.01	0.02	0.03	0.04	7.6	0.0319	0.3396	22.2527	493.4575	-0.0036
Wal-Mart Stores	0.01	0.01	0.01	0.01	0.02	0.02	0.04	0.0502	0.34	0.0195	0.0207	10.466	145.0211	0.1117
Panel C: Default intensities														
3M Company	0.0041	0.0042	0.0044	0.0048	0.0051	0.0055	0.007	0.0074	0.0075	0.0053	0.0007	1.2603	0.9934	0.9845
American Express	0.0092	0.0098	0.0101	0.0108	0.0121	0.0148	0.0181	0.0206	0.0221	0.013	0.0027	0.976	0.0338	0.9709
Hewlett-Packard	0.0037	0.0037	0.0043	0.0055	0.0061	0.0093	0.0183	0.0212	0.0217	0.0079	0.0042	1.7035	1.9721	0.9876
Tenet Healthcare	0.0584	0.059	0.0613	0.0695	0.078	0.0845	0.1074	0.1167	0.1279	0.0798	0.014	0.8984	0.4018	0.9837
Textron	0.0152	0.0153	0.0167	0.0204	0.0242	0.0325	0.0378	0.0391	0.0406	0.0262	0.0069	0.3656	-1.1715	0.9908
Wal-Mart Stores	0.0048	0.0051	0.0052	0.0061	0.0064	0.0069	0.0079	0.0083	0.0088	0.0065	0.0008	0.3221	-0.1403	0.9788
Panel D: Monthly default probabilities														
3M Company	0.0003	0.0004	0.0004	0.0004	0.0004	0.0005	0.0006	0.0006	0.0006	0.0004	0.0001	1.2602	0.993	0.9845
American Express	0.0008	0.0008	0.0008	0.0009	0.001	0.0012	0.0015	0.0017	0.0018	0.0011	0.0002	0.9757	0.0328	0.9709
Hewlett-Packard	0.0003	0.0003	0.0004	0.0005	0.0005	0.0008	0.0015	0.0018	0.0018	0.0007	0.0004	1.703	1.97	0.9876
Tenet Healthcare	0.0049	0.0049	0.0051	0.0058	0.0065	0.007	0.0089	0.0097	0.0106	0.0066	0.0012	0.8956	0.3957	0.9837
Textron	0.0013	0.0013	0.0014	0.0017	0.002	0.0027	0.0031	0.0033	0.0034	0.0022	0.0006	0.365	-1.1719	0.9908
Wal-Mart Stores	0.0004	0.0004	0.0004	0.0005	0.0005	0.0006	0.0007	0.0007	0.0007	0.0005	0.0001	0.3219	-0.1405	0.9788

Table A.3: Summary statistics for log-differenced data of firms included in the Value-at-Risk study.

The table reports descriptive statistics on the time-series distribution of monthly log-differences of mid prices, bid-ask spreads, and default intensities for the six firms investigated in our Value-at-Risk (VaR) study. The six firms include *3M Company*, *American Express*, *Hewlett-Packard*, *Tenet Healthcare*, *Textron*, and *Wal-Mart Stores*. The summary statistics refer to the in- and out-of-sample time periods in the VaR study, which cover the period from January 2010 to November 2011 resulting in 460 daily observations. For each day, t, in the sample period, log-differences are calculated using the prices, spreads, and intensities at days t and $t-30$. Bid-ask spreads are calculated as the difference between ask and bid quotes. Default intensities are extracted from CDS spreads according to the procedure discussed in Section 2.3 and have a horizon of one year.

		Percentiles								Moments				
	Min	1st	5th	25th	Median	75th	95th	99th	Max	Mean	St. Dev.	Skewness	Exc. Kurt.	AC(1)
Panel A: Stock returns														
3M Company	-0.4987	-0.4059	-0.2380	-0.0831	0.0198	0.0884	0.1669	0.2208	0.2902	-0.0042	0.1282	-0.9150	1.2774	0.9525
American Express	-0.1108	-0.0898	-0.0667	-0.0250	0.0024	0.0232	0.0545	0.0704	0.0727	-0.0009	0.0367	-0.3641	-0.2060	0.9271
Hewlett-Packard	-0.2302	-0.1791	-0.1339	-0.0438	0.0168	0.0639	0.1125	0.1383	0.1528	0.0062	0.0759	-0.4930	-0.3404	0.9298
Tenet Healthcare	-0.2214	-0.1975	-0.1191	-0.0386	0.0085	0.0351	0.0778	0.1046	0.1249	-0.0041	0.0599	-0.9563	1.2339	0.9434
Textron	-0.4119	-0.3703	-0.2261	-0.0982	-0.0207	0.0339	0.0902	0.1199	0.1400	-0.0389	0.1034	-1.1114	1.5305	0.9521
Wal-Mart Stores	-0.3858	-0.3013	-0.2063	-0.0808	-0.0162	0.0392	0.2651	0.4786	0.5059	-0.0109	0.1410	1.3039	3.6138	0.9374
Panel B: Log-differences of bid-ask spreads														
3M Company	-5.9402	-1.0986	-1.0986	-0.4055	0.0000	0.0000	1.0986	1.2194	6.6333	-0.0316	0.6936	0.6742	28.4284	-0.0005
American Express	-2.5257	-1.6094	-1.0986	-0.4055	0.0000	0.4055	0.9163	1.3863	3.2189	-0.0318	0.6301	0.1000	2.7220	0.0278
Hewlett-Packard	-2.4849	-1.7918	-1.3863	-0.6931	0.0000	0.4055	1.2661	1.7918	2.8904	-0.0347	0.7884	0.1789	0.5025	0.1207
Tenet Healthcare	-3.6199	-1.6860	-1.1066	-0.6931	0.0000	0.4055	1.0986	1.6495	3.1091	-0.0690	0.7414	0.0842	1.4815	0.0662
Textron	-1.9459	-1.5694	-1.0986	-0.6931	0.0000	0.4055	1.0986	1.6094	2.6391	-0.0470	0.6397	0.1725	0.6715	-0.0033
Wal-Mart Stores	-5.2679	-0.6931	-0.6931	0.0000	0.0000	0.0000	0.6931	0.6931	5.2679	-0.0115	0.4942	-0.0074	54.6338	0.0038
Panel C: Log-differences of default intensities														
3M Company	-0.1282	-0.0833	-0.0422	-0.0150	-0.0016	0.0112	0.0456	0.0986	0.1351	-0.0005	0.0290	0.3665	3.8761	-0.0621
American Express	-0.0688	-0.0366	-0.0164	-0.0056	-0.0002	0.0046	0.0144	0.0522	0.1072	-0.0001	0.0142	2.3588	20.5839	-0.2622
Hewlett-Packard	-0.0941	-0.0607	-0.0321	-0.0093	-0.0002	0.0101	0.0327	0.0622	0.1199	0.0004	0.0221	0.3707	5.8719	-0.1556
Tenet Healthcare	-0.0610	-0.0502	-0.0272	-0.0073	-0.0005	0.0074	0.0239	0.0566	0.1106	-0.0001	0.0177	0.9112	7.3419	-0.2213
Textron	-0.2241	-0.0679	-0.0348	-0.0099	-0.0010	0.0090	0.0258	0.0557	0.1690	-0.0015	0.0249	-0.7232	20.8471	-0.0782
Wal-Mart Stores	-0.1922	-0.0948	-0.0489	-0.0159	-0.0017	0.0127	0.0508	0.0854	0.4379	-0.0007	0.0375	3.0806	42.2552	-0.0904

Table A.4: Variable pairs and parametric pair-copulas selected in first R-vine trees.

The table reports the (unconditional) variable pairs and bivariate parametric pair-copulas selected in the first tree of the R-vine copula model for each estimation period included in our Value-at-Risk (VaR) study. The R-vine copula model is estimated on pseudo-observations of standardized log-differences of mid prices (m), bid-ask spreads (s), and default intensities (h) for six firms from the S&P 500, resulting in 17 variable pairs and parametric pair-copulas that need to be specified in the first tree. The six firms include *3M Company* (MMM), *American Express* (AXP), *Hewlett-Packard* (HPQ), *Tenet Healthcare* (THC), *Textron* (TXT), and *Wal-Mart Stores* (WMT). The candidate copulas include dynamic versions of the standard normal (C_N), t (C_t), (rotated) Clayton (C_C and C_{rC}), (rotated) Gumbel (C_G and C_{rG}), and (rotated) Joe copula (C_J and C_{rJ}), where we follow the dynamization approach suggested by Patton (2006) (as outlined in Appendix A). The selection of the variable pairs and the bivariate pair-copulas is based on the sequential method as proposed by Dißmann et al. (2013), where the former results from some maximum spanning tree algorithm based on Kendall's tau and the latter is conducted using Akaike's Information Criterion (AIC) as the selection criterion to be minimized.

01/2010 - 01/2011			02/2010 - 02/2011			03/2010 - 03/2011			04/2010 - 04/2011			05/2010 - 05/2011		
Pair		Copula	Pair		Copula	Pair		Copula	Pair		Copula	Pair		Copula
MMM(m)	AXP(m)	C_N	MMM(m)	MMM(h)	C_N	MMM(m)	MMM(h)	C_{rG}	MMM(m)	MMM(s)	C_N	MMM(m)	MMM(s)	C_N
MMM(m)	AXP(h)	C_N	MMM(m)	AXP(m)	C_N	MMM(m)	AXP(m)	C_N	MMM(m)	MMM(h)	C_{rG}	MMM(m)	AXP(m)	C_{rG}
MMM(s)	AXP(s)	C_N	MMM(m)	AXP(h)	C_N	MMM(m)	AXP(s)	C_N	MMM(m)	AXP(m)	C_N	MMM(m)	AXP(s)	C_N
MMM(h)	AXP(s)	C_N	MMM(s)	AXP(s)	C_N	MMM(m)	AXP(h)	C_N	MMM(m)	AXP(s)	C_N	MMM(m)	AXP(h)	C_N
AXP(s)	AXP(h)	C_N	AXP(s)	AXP(h)	C_N	MMM(s)	AXP(s)	C_N	MMM(m)	AXP(h)	C_N	MMM(s)	MMM(h)	C_N
AXP(s)	WMT(s)	C_{rJ}	AXP(s)	WMT(s)	C_C	AXP(s)	WMT(s)	C_{rJ}	MMM(m)	HPQ(m)	C_G	MMM(s)	THC(m)	C_t
HPQ(m)	THC(m)	C_{rJ}	HPQ(m)	THC(m)	C_N	HPQ(m)	THC(m)	C_N	AXP(s)	WMT(s)	C_{rJ}	AXP(s)	WMT(s)	C_N
HPQ(s)	HPQ(h)	C_{rG}	HPQ(s)	HPQ(h)	C_{rG}	HPQ(s)	HPQ(h)	C_{rG}	HPQ(m)	THC(m)	C_N	HPQ(m)	THC(m)	C_G
HPQ(s)	THC(s)	C_{rJ}	HPQ(s)	THC(s)	C_N	HPQ(s)	THC(s)	C_N	HPQ(s)	HPQ(h)	C_{rJ}	HPQ(s)	HPQ(h)	C_{rJ}
HPQ(s)	THC(h)	C_G	HPQ(s)	THC(h)	C_{rJ}	HPQ(h)	THC(m)	C_J	HPQ(s)	THC(s)	C_{rG}	HPQ(s)	THC(s)	C_{rG}
HPQ(h)	THC(m)	C_N	HPQ(h)	THC(m)	C_J	THC(s)	TXT(s)	C_N	HPQ(h)	THC(m)	C_{rC}	HPQ(h)	THC(m)	C_G
THC(s)	TXT(s)	C_{rG}	THC(s)	TXT(s)	C_{rG}	THC(s)	WMT(h)	C_{rG}	THC(s)	THC(h)	C_{rG}	THC(s)	THC(h)	C_{rG}
THC(s)	WMT(h)	C_{rJ}	THC(s)	WMT(h)	C_{rG}	THC(h)	TXT(m)	C_G	THC(s)	TXT(s)	C_{rC}	THC(s)	TXT(s)	C_{rG}
TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t	TXT(m)	TXT(s)	C_{rG}	TXT(m)	TXT(s)	C_N	TXT(m)	TXT(s)	C_N
TXT(s)	TXT(h)	C_t	TXT(s)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t
WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t
WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t

06/2010 - 06/2011			07/2010 - 07/2011			08/2010 - 08/2011			09/2010 - 09/2011			10/2010 - 10/2011		
Pair		Copula	Pair		Copula	Pair		Copula	Pair		Copula	Pair		Copula
MMM(m)	AXP(m)	C_{rG}	MMM(m)	AXP(m)	C_{rJ}	MMM(m)	AXP(m)	C_{rJ}	MMM(m)	AXP(m)	C_{rG}	MMM(m)	AXP(s)	C_N
MMM(m)	AXP(s)	C_N	MMM(m)	AXP(s)	C_N	MMM(m)	AXP(s)	C_N	MMM(m)	AXP(s)	C_N	MMM(s)	MMM(h)	C_{rG}
MMM(m)	AXP(h)	C_N	MMM(m)	AXP(h)	C_N	MMM(m)	AXP(h)	C_N	MMM(m)	AXP(h)	C_N	MMM(s)	AXP(s)	C_N
MMM(s)	MMM(h)	C_G	MMM(s)	MMM(h)	C_N	MMM(m)	HPQ(m)	C_G	MMM(s)	MMM(h)	C_{rG}	MMM(h)	AXP(m)	C_N
MMM(s)	AXP(s)	C_N	MMM(s)	AXP(m)	C_{rG}	MMM(s)	MMM(h)	C_{rG}	MMM(s)	AXP(s)	C_N	AXP(m)	AXP(h)	C_N
MMM(s)	THC(m)	C_N	AXP(s)	WMT(s)	C_N	MMM(s)	AXP(s)	C_N	AXP(s)	WMT(s)	C_{rG}	AXP(s)	WMT(s)	C_N
AXP(s)	WMT(s)	C_N	HPQ(m)	THC(m)	C_{rJ}	AXP(s)	WMT(s)	C_N	HPQ(m)	THC(s)	C_{rG}	HPQ(m)	TXT(m)	C_{rJ}
HPQ(m)	THC(m)	C_{rJ}	HPQ(s)	HPQ(h)	C_{rG}	HPQ(s)	HPQ(h)	C_{rG}	HPQ(s)	TXT(s)	C_J	HPQ(s)	HPQ(h)	C_N
HPQ(s)	HPQ(h)	C_{rG}	HPQ(h)	THC(m)	C_N	HPQ(s)	TXT(s)	C_t	HPQ(h)	THC(m)	C_{rG}	HPQ(s)	TXT(s)	C_G
HPQ(s)	THC(s)	C_{rJ}	THC(m)	THC(s)	C_{rJ}	HPQ(h)	THC(m)	C_{rG}	HPQ(h)	THC(h)	C_{rG}	HPQ(h)	THC(m)	C_G
HPQ(h)	THC(m)	C_N	THC(s)	THC(h)	C_N	THC(m)	THC(s)	C_{rJ}	THC(m)	THC(s)	C_{rJ}	THC(m)	THC(s)	C_{rG}
THC(s)	THC(h)	C_{rJ}	THC(s)	TXT(s)	C_N	THC(s)	THC(h)	C_{rJ}	THC(s)	WMT(h)	C_G	THC(s)	THC(h)	C_{rG}
THC(s)	TXT(s)	C_{rG}	THC(s)	WMT(h)	C_N	THC(s)	WMT(h)	C_N	TXT(m)	TXT(s)	C_t	TXT(m)	TXT(s)	C_{rG}
TXT(m)	TXT(s)	C_{rG}	TXT(m)	TXT(s)	C_t	TXT(m)	TXT(s)	C_G	TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_t
TXT(m)	TXT(h)	C_t	TXT(m)	TXT(h)	C_G	TXT(m)	TXT(h)	C_t	TXT(s)	WMT(s)	C_N	TXT(s)	WMT(s)	C_{rG}
WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_t	WMT(m)	WMT(s)	C_{rG}
WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_t	WMT(m)	WMT(h)	C_{rG}	WMT(s)	WMT(h)	C_{rG}	WMT(m)	WMT(h)	C_t

Appendix B

Supplementary Material for Chapter 3

Sample insurance companies

Table B.1: Sample insurance companies.

The appendix lists all international insurance companies that are used in the empirical study. The sample is constructed by first selecting all international insurers from the country and dead-firm lists of *Thomson Reuters Financial Datastream*. The list is then corrected for all companies for which stock price and balance sheet data are not available from *Thomson Reuters Financial Datastream* and *Worldscope*. The names of the companies are retrieved from the *Worldscope*database (item WC06001).

ALEA GROUP HOLDINGS	AXA ASIA PACIFIC	ERGO PREVIDENZA
CHAUCER HOLDINGS PLC	AXA LEBENSVERSICH	ERGO-VERSICHERUNG
21ST CENTURY INS	AXA KONZERN AG	ERIE FAMILY LIFE INS
ACE LIMITED	AXA PORTUGAL SEGUROS	ERIE INDEMNITY
AEGON N.V.	AXA VERSICHERUNG AG	ETHNIKI GREEK INS
AFFIN-ACF HOLDINGS	AXIS CAPITAL HLDG	EULER HERMES
AFLAC INCORPORATED	BALOISE HOLDING AG	EVEREST RE GROUP
AFRICAN LIFE	BENFIELD GROUP LTD	FAIRFAX FIN'L HLDGS
AGEAS SA	BRIT INSURANCE HOLD	FBD HOLDINGS PLC
ASSURANCES GENERALES	CAPITAL ALLIANCE	FBL FINANCIAL GROUP
AIOI INSURANCE	CASH.LIFE AG	FINANCIAL INDUSTRIES
ALFA CORPORATION	CATHAY FINANCIAL	FINAXA SA
ALLEANZA ASSICUR.	CATLIN GROUP LTD	FIRST FIRE & MARINE
ALLEGHANY CORP	CATTOLICA ASS	FONDIARIA - SAI SPA
ALLIANZ SE	CESKA POJISTOVNA A.S	FOYER S.A.
ALLIANZ LEBENSVERS.	CHALLENGER FIN'L SVC	FPIC INSURANCE GROUP
ALLSTATE CORPORATION	CHESNARA PLC	FRIENDS PROVIDENT
ALM BRAND AS	CHINA LIFE INSURANCE	FUBON FINANCIAL
ALTERRA CAPITAL	CHINA TAIPING INSU	FUJI FIRE& MARINE INS
AMBAC FINANCIAL	CHUBB CORP (THE)	GENERALI (SCHWEIZ)
AMERICAN NATIONAL	CINCINNATI FINL CORP	GENERALI DEUTSCH
AMERICAN PHYSICIANS	CLAL INSURANCE ENT	GENERALI HOLDING VIE
AMERICAN EQUITY INV	CNA FINANCIAL CORP	GENWORTH FIN'L, INC.
AMERICAN FIN'L GROUP	CNA SURETY CORP	GLOBAL INDEMNITY
AMERICAN INT'L GROUP	CNO FINANCIAL	GRUPO NACIONAL
AMERUS GROUP CO	CNP ASSURANCES	GRUPO PROFUTURO
AMLIN PLC	CODAN A/S	GREAT EASTERN HLDGS
AMP LIMITED	GROUPE COFACE	GREAT WEST LIFECO
ANN & LIFE RE HLDGS	COMMERCE GROUP, INC.	GRUPO CATALANA
AON PLC	MILANO ASSICURAZIONI	GREAT AMERICAN FIN'L
ARAB INSURANCE GROUP	COX INSURANCE	HANNOVER RUECK SE
ARCH CAPITAL GROUP	DAI-ICHI LIFE INSU	HANOVER INSURANCE
ARGONAUT GROUP, INC.	DAIDO LIFE INSURANCE	HAREL INSUR INVEST
ARTHUR J GALLAGHER	DBV WINTERTHUR	HARLEYSVILLE GROUP
ASIA FINANCIAL HLDGS	DELPHI FINANCIAL GRP	HARTFORD FINL SRVC
ASPEN INSURANCE HOLD	DELTA LLOYD LEBENS	HCC INS HOLDINGS
ASSICUR GENERALI SPA	DONGBU INSURANCE CO.	HELVETIA HOLDING
ASSURANT INC	DEUTSCHE AERZTEVERS	HILB, ROGAL & HOBBS
ASSURED GUARANTY LTD	E-L FINANCIAL CORP.	HILLTOP HOL
AVIVA PLC	EMPLOYERS HOLDINGS	HISCOX PLC
AXA SA	ENDURANCE SPECIALTY	HORACE MANN EDUCATRS

Table B.1: Sample insurance companies (continued).

HYUNDAI M & F INS.	OLD REPUBLIC INTL	SWISS RE
INDUSTRIAL ALLIANCE	PARTNERRE LTD.	TAIWAN LIFE INSURANC
INFINITY PROP & CAS	PENN TREATY AMERICAN	TAIYO LIFE INSURANCE
ING GROEP N.V.	PERMANENT TSB GROUP	TOKIO MARINE
INSURANCE AUSTRALIA	PHILADELPHIA CORP	TONG YANG LIFE INS
INTACT FINANCIAL	PHOENIX COMPANIES	TOPDANMARK A/S
IPC HOLDINGS, LTD.	PHOENIX HOLDINGS	TORCHMARK CORP
JARDINE LLOYD	PICC PROPERTY	TORO ASSICURAZIONI
JEFFERSON-PILOT CORP	PING AN INSURANCE	TOWER LTD
JOHN HANCOCK FIN SVC	PLAT UNDERWRITERS	TRANSATLANTIC HLDGS
KANSAS CITY LIFE INS	PMA CAPITAL CORP	TRAVELERS COS
KEMPER	POHJOLA-YHTYMA OYJ	TRAVELERS PROPERTY
KINGSWAY FINANCIAL	POWER CORP OF CANADA	TRYG A/S
KOELNISCHE RUECKVER.	POWER FINANCIAL CORP	UICI
KOREAN REINSURANCE	PREMAFIN FINANZIARIA	UNIPOL GRUPPO FIN
LANDAMERICA FINL GRP	PRESIDENTIAL LIFE	UNIQA INSUR
LEGAL & GEN’L GRP	PRINCIPAL FINL GROUP	UNITED FIRE
LIBERTY GROUP LTD	PROASSURANCE CORP	PROVIDENT COMPANIES
LIBERTY HOLDINGS	PROGRESSIVE CORP	WAADT VERSICHERUNGEN
LIG INSURANCE CO LTD	PROMINA GROUP	VESTA INSURANCE GRP
LINCOLN NAT’L CORP	PROTECTIVE LIFE CORP	VIENNA INSURANCE
LOEWS CORPORATION	PRUCO LIFE INSURANCE	VITTORIA ASSICURAZIO
MAA GROUP	PRUDENTIAL PLC	W R BERKLEY CORP.
MANULIFE FINANCIAL	PRUDENTIAL FINANCIAL	WELLINGTON
MAPFRE SA	QBE INSURANCE GROUP	WESCO FINANCIAL CORP
MARKEL CORP	RIUNIONE ADRIATICA	WHITE MOUNTAIN INSUR
MARSH & MCLENNAN CO.	REINSURANCE GROUP	WILLIS GROUP
MBIA INC	RENAISSANCERE HLDGS	WUERTTEMBERGISCHE LE
MEDIOLANUM	RHEINLAND HOLDING	XL GROUP PLC
MENORAH MIVTACHIM	RLI CORP	ZENITH NATIONAL
MERCURY GENERAL CORP	RSA INSURANCE GROUP	ZURICH INSURANCE
METLIFE INC	SAFECO CORPORATION	
MIDLAND COMPANY	SAFETY INSURANCE GP	
MIGDAL INSURAN & FIN	SAMPO OYJ	
MIIX GROUP, INC	SAMSUNG FIRE & MARINE	
MNI HOLDINGS BHD	SOUTH AFRICAN NAT’L	
MONTPELIER RE HLDGS	SCHWEIZERISCHE NAT	
MONY GROUP INC.	SCOR SE	
MS& AD INSURANCE	SCOTTISH RE GROUP	
MUENCHENER	SELECTIVE INSURANCE	
NATIONAL WESTERN	SHIN KONG FINANCIAL	
NATIONWIDE FIN’L	SKANDIA FORSAKRINGS	
NAVIGATORS GROUP INC	SOMPO JAPAN INSURANC	
NIPPONKOA INS	SAINT JAMES’S PLACE	
NISSAY DOWA GEN	STANCORP FINANCIAL	
NISSHIN FIRE/MAR INS	STATE AUTO FINANCIAL	
NUERNBERGER BET.-AG	STOREBRAND ASA	
ODYSSEY RE	SUL AMERICA SEGUROS	
OHIO CASUALTY CORP	SUN LIFE FINANCIAL	
OLD MUTUAL PLC	SWISS LIFE HOLDING	

Variable definitions and data sources

Table B.2: Variable definitions and data sources.

The appendix presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study. The insurer characteristics were retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Variable name	*Definition*	*Data source*
Dependent variables		
ΔCoVaR	Unconditional ΔCoVaR as defined by Adrian and Brunnermeier (2015), measured as the difference of the Value-at-risk (VaR) of a financial sector index conditional on the distress of a particular insurer and the VaR of the sector index conditional on the median state of the insurer.	Datastream, own calc.
MES	Quarterly Marginal Expected Shortfall as defined by Acharya et al. (2010) as the average return on an individual insurer's stock on the days the *World Datastream Bank* index experienced its 5% worst outcomes.	Datastream, own calc.
SRISK	Average quarterly estimate of the Systemic Risk Index as proposed by Acharya et al. (2012) and Brownlees and Engle (2015). The SRISK estimate for insurer i at time t is given by $SRISK_{i,t} = k\,(Debt_{i,t}) - (1-k)\,(1 - LRMES_{i,t})\,Equity_{i,t}$ where k is a regulatory capital ratio (set to 8%), $Debt_{i,t}$ is the insurer's book value of debt, $LRMES_{i,t}$ is the long run Marginal Expected Shortfall defined as $1 - \exp(-18 \cdot MES)$, MES is the estimated Marginal Expected Shortfall and $Equity_{i,t}$ is the insurer's market value of equity.	Datastream, Worldscope (WC03351, WC08001), own. calc.
Insurer characteristics		
Beta	Beta of the capital asset pricing model measuring the market sensitivity of a firm and a local market index of the insurer's country.	Worldscope (WC09802).
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251, WC03255).
Foreign sales	International sales divided by net revenues (times 100)	Worldscope (WC08731).
Investment success	Ratio of insurer's investment income to net revenues.	Worldscope (WC01001, WC01006), own calc.
Interconnectedness	PCAS measure as defined in Billio et al. (2012). PCAS is constructed using a decomposition of the variance-covariance matrix of the insurers' daily, standardized stock returns.	Datastream, own calc.
Leverage	Book value of assets minus book value of equity plus market value of equity, divided by market value of equity.	Worldscope (WC02999, WC03501, WC08001), own calc.
Loss ratio	Ratio of claim and loss expenses plus long term insurance reserves to earned premiums.	Worldscope (WC15549).

Table B.2: Variable definitions and data sources (continued).

The appendix presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study. The insurer characteristics were retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Variable name	*Definition*	*Data source*
Insurer characteristics		
Market-to-book	Market value of common equity divided by book value of common equity.	Worldscope (WC07210, WC03501).
Net revenues	Log value of total operating revenue of the insurer.	Worldscope (WC01001).
Non-Policyholder Liabilities	Total on balance sheet liabilities divided by total insurance reserves.	Worldscope (WC03351, WC03030).
Operating expenses	Ratio of operating expenses to total assets.	Worldscope (WC01249, WC02999).
Other income	Other pre-tax income and expenses besides operating income.	Worldscope (WC01262).
Performance	Quarterly buy-and-hold return on an insurer's stock.	Datastream, own calc.
Return on Assets	Return of the insurer on it's total assets after taxes (in %).	Worldscope (WC08326).
Return on Equity	An insurer's earnings per share during the last 12 months over the prorated book value per share times 100 (in %).	Worldscope (WC08372).
Total assets	Natural logarithm of a insurer's total assets.	Worldscope (WC02999).
Country characteristics		
GDP growth	Annual real GDP growth rate (in %).	WDI database (World Bank).
Inflation	Log of the annual change of the GDP deflator.	WDI database (World Bank)
Stock market turnover	Total value of shares traded in a given country divided by the average market capitalization.	WDI database (World Bank).

Appendix C

Supplementary Material for Chapter 4

Sample firms

Table C.1: Sample banks.

The table shows the names of the 148 international banks used in our study. Banks were selected by their respective total assets at the end of the fiscal year 2006 and availability of stock price data from *Datastream*.

ABN AMRO HOLDING N.V.	DANSKE BANK AS	NATIONAL CITY CORPORATION
ALLIANCE & LEICESTER PLC	DBS GROUP HOLDINGS LTD	NATIXIS
ALLIED IRISH BANKS PLC	DEPFA BANK PLC	NIKKO CORDIAL CORPORATION
ALPHA BANK SA	DEUTSCHE BANK AKTIENGESELLSCHAFT	NISHI-NIPPON CITY BANK LIMITED (THE)
AMERIPRISE FINANCIAL, INC.	DEUTSCHE BOERSE AG	NOMURA HOLDINGS INCORPORATED
ANGLO IRISH BANK CORPORATION PLC	DEUTSCHE POSTBANK AG	NORDEA BANK AB
AUSTRALIA AND NEW ZEALAND BANKING GROUP LIMITED	DEXIA SA	NORTHERN ROCK PLC
BANCO BILBAO VIZCAYA ARGENTARIA SA	DNB ASA	NORTHERN TRUST CORPORATION
BANCO COMERCIAL PORTUGUES, S.A.	ECOBANK NIGERIA PLC	OVERSEA-CHINESE BANKING CORPORATION LIMITED
BANCO DO BRASIL SA	ERSTE GROUP BANK AG	PNC FINANCIAL SERVICES GROUP INCORPORATED
BANCO ESPANOL DE CREDITO, S.A.	ESPIRITO SANTO FINANCIAL GROUP S.A.	RAIFFEISEN BANK INTERNATIONAL AG
BANCO ESPIRITO SANTO SA	EUROBANK ERGASIAS SA	REGIONS FINANCIAL CORPORATION
BANCO POPOLARE	FIFTH THIRD BANCORP	RESONA HOLDINGS INC
BANCO POPULAR ESPANOL	FIRSTRAND LIMITED	ROYAL BANK OF CANADA
BANCO SABADELL	GOLDMAN SACHS GROUP INC	ROYAL BANK OF SCOTLAND GROUP PLC (THE)
BANCO SANTANDER SA	HANA FINANCIAL GROUP	SAN PAOLO IMI SPA
BANK AUSTRIA CREDITANSTALT AG	HANG SENG BANK LIMITED	SBERBANK ROSSII OAO
BANK HAPOALIM B.M.	HBOS PLC	SCHWEIZERISCHE NATIONALBANK
BANK LEUMI LE-ISRAEL B.M.	HSBC HOLDINGS PLC	SHANGHAI PUDONG DEVELOPMENT BANK
BANK OF AMERICA CORPORATION	HUA XIA BANK COMPANY LTD	SHINHAN FINANCIAL GROUP COMPANY LIMITED
BANK OF CHINA LIMITED	HYPO REAL ESTATE HOLDING	SHINSEI BANK LIMITED
BANK OF COMMUNICATIONS CO LTD	HYPOTHEKENBANK FRANKFURT AG	SHIZUOKA BANK LTD (THE)
BANK OF IRELAND	ICAP PLC	SKANDINAVISKA ENSKILDA BANKEN
BANK OF MONTREAL	ICICI BANK LIMITED	SLM CORPORATION
BANK OF NEW YORK MELLON CORP.	INDUSTRIAL AND COMMERCIAL BANK OF CHINA LTD	SOCIETE GENERALE
BANK OF NOVA SCOTIA (THE)	INDUSTRIAL BANK CO LTD	SOVEREIGN BANCORP INCORPORATED
BANK OF YOKOHAMA LIMITED (THE)	INDUSTRIAL BANK OF KOREA	ST. GEORGE BANK LIMITED
BANQUE NATIONALE DE BELGIQUE	INTESA SANPAOLO SPA	STANDARD BANK GROUP LIMITED
BARCLAYS AFRICA GROUP LTD	JAPAN SECURITIES FINANCE CO LTD	STANDARD CHARTERED PLC
BARCLAYS PLC	JOYO BANK LIMITED (THE)	STATE BANK OF INDIA
BAYERISCHE HYPO- UND VEREINSBANK AG	JPMORGAN CHASE & CO.	STATE STREET CORPORATION
BB & T CORPORATION	KAUPTHING BANK HF	SUMITOMO MITSUI FINANCIAL GROUP INC
BNP PARIBAS SA	KB FINANCIAL GROUP INCORPORATION	SUMITOMO TRUST AND BANKING COMPANY LIMITED (THE)
BRADFORD & BINGLEY PLC	KBC GROUP NV	SUNTRUST BANKS, INC.
CANADIAN IMPERIAL BANK OF COMMERCE	KEYCORP	SVENSKA HANDELSBANKEN AB
CAPITAL ONE FINANCIAL CORPORATION	KOREA EXCHANGE BANK	SWEDBANK AB
CAPITALIA SPA	LANDESBANK BERLIN HOLDING AG	TAISHIN FINANCIAL HOLDING COMPANY LIMITED
CHIBA BANK LTD (THE)	LLOYDS BANKING GROUP PLC	TAIWAN COOPERATIVE BANK
CHINA CITIC BANK CORPORATION LIMITED	M & T BANK CORPORATION	TORONTO-DOMINION BANK (THE)
CHINA CONSTRUCTION BANK CORP	MACQUARIE GROUP LIMITED	TURKIYE IS BANKASI A.S.
CHINA MERCHANTS BANK CO LTD	MALAYAN BANKING BERHAD	U.S. BANCORP
CHINA MINSHENG BANKING CORPORATION LIMITED	MARSHALL & ILSLEY CORPORATION	UBI BANCA
CITIGROUP INC.	MEGA FINANCIAL HOLDING COMPANY LIMITED	UBS AG
COMERICA INCORPORATED	MITSUBISHI UFJ FINANCIAL GROUP INCORPORATED	UNICREDIT SPA
COMMERZBANK AKTIENGESELLSCHAFT	MIZUHO FINANCIAL GROUP INC	UNITED OVERSEAS BANK LIMITED
CREDIT AGRICOLE SA	MORGAN STANLEY	WACHOVIA CORPORATION
CREDIT INDUSTRIEL ET COMMERCIAL SA	NATIONAL AUSTRALIA BANK LIMITED	WELLS FARGO & COMPANY
CREDIT SUISSE GROUP AG	NATIONAL BANK OF CANADA	WESTPAC BANKING CORPORATION
DAIWA SECURITIES GROUP INCORPORATED	NATIONAL BANK OF GREECE, S.A.	WOORI FINANCE HOLDINGS

Table C.2: Sample insurers.

The table shows the names of the 98 international insurers used in our study. Insurers were selected by their respective total assets at the end of the fiscal year 2006 and availability of stock price data from *Datastream*.

ACE LIMITED	LOEWS CORPORATION
AEGON N.V.	MANULIFE FINANCIAL CORPORATION
AFLAC INCORPORATED	MAPFRE SA
AGEAS SA	MARSH & MCLENNAN COMPANIES, INC.
AIOI INSURANCE COMPANY LIMITED	MBIA INC.
ALLEANZA ASSICURAZIONI S.P.A.	MEDIOLANUM S.P.A
ALLIANZ LEBENSVERSICHERUNG-AG	METLIFE, INC.
ALLIANZ SE	MS & AD INSURANCE GROUP HOLDINGS, INCORPORATED
ALLSTATE CORPORATION (THE)	MUENCHENER RUCKVERSICHERUNGS-GESELLSCHAFT AG
AMBAC FINANCIAL GROUP, INC.	NATIONWIDE FINANCIAL SERVICES INC
AMERICAN FINANCIAL GROUP, INC.	NIPPONKOA INSURANCE COMPANY LIMITED
AMERICAN INTERNATIONAL GROUP, INC.	NUERNBERGER BETEILIGUNGS-AG
AMERICAN NATIONAL INSURANCE COMPANY	OLD MUTUAL PLC
AMP LIMITED	PERMANENT TSB GROUP HOLDINGS PLC
AON PLC	PHOENIX COMPANIES INC
ASSICURAZIONI GENERALI SPA	PING AN INSURANCE (GROUP) COMPANY OF CHINA LTD
ASSURANCES GENERALES DE FRANCE (AGF) SA	POWER CORPORATION OF CANADA
ASSURANT, INC.	POWER FINANCIAL CORP
AVIVA PLC	PREMAFIN FINANZIARIA SPA
AXA ASIA PACIFIC HOLDINGS LIMITED	PRINCIPAL FINANCIAL GROUP, INCORPORATED
AXA KONZERN AG	PROGRESSIVE CORPORATION (THE)
AXA LEBENSVERSICHERUNG AG	PROTECTIVE LIFE CORPORATION
AXA SA	PRUCO LIFE INSURANCE COMPANY
BALOISE HOLDING AG	PRUDENTIAL FINANCIAL, INCORPORATED
CATHAY FINANCIAL HOLDING COMPANY LIMITED	PRUDENTIAL PLC
CATTOLICA ASSICURAZIONI S.C.A.R.L.	QBE INSURANCE GROUP LIMITED
CHALLENGER FINANCIAL SERVICES GROUP LTD	REINSURANCE GROUP OF AMERICA, INC.
CHINA LIFE INSURANCE CO LTD	RSA INSURANCE GROUP PLC
CHUBB CORPORATION (THE)	SAMPO OYJ
CNA FINANCIAL CORPORATION	SANLAM LIMITED
CNO FINANCIAL GROUP, INCORPORATION	SCOR SE
CNP ASSURANCES	SHIN KONG FINANCIAL HOLDING COMPANY LIMITED
DBV-WINTERTHUR HOLDING AG	SOMPO JAPAN INSURANCE INC
ERGO VERSICHERUNGSGRUPPE AG	ST. JAMES'S PLACE PLC
FAIRFAX FINANCIAL HOLDINGS LIMITED	STOREBRAND ASA
FUBON FINANCIAL HOLDING COMPANY LIMITED	SUN LIFE FINANCIAL INCORPORATED
GENERALI DEUTSCHLAND HOLDING AG	SWISS LIFE HOLDING AG
GENWORTH FINANCIAL, INC.	SWISS RE LTD
GREAT EASTERN HOLDINGS LTD	TOKIO MARINE HOLDINGS INCORPORATED
GREAT-WEST LIFECO INC	TRAVELERS COMPANIES, INC. (THE)
HANNOVER RUECK SE	UNIPOL GRUPPO FINANZIARIO SPA
HARTFORD FINANCIAL SERVICES GROUP, INC. (THE)	UNIPOLSAI ASSICURAZIONI SPA
HELVETIA HOLDING AG	UNIQA INSURANCE GROUP AG
INDUSTRIAL ALLIANCE INSURANCE AND FINANCIAL SERVICES INCORPORATED	UNUM GROUP
ING GROEP N.V.	VIENNA INSURANCE GROUP
LEGAL & GENERAL GROUP PLC	WHITE MOUNTAINS INSURANCE GROUP LTD
LIBERTY GROUP LIMITED	WURTTEMBERGISCHE LEBENSVERSICHERUNG AG
LIBERTY HOLDINGS LIMITED	XL GROUP PLC
LINCOLN NATIONAL CORPORATION	ZURICH INSURANCE GROUP LIMITED

Variable definitions and data sources

Table C.1: Variable definitions and data sources.

The appendix presents data sources, definitions and expected signs in our regression analyses for all dependent and independent variables that are used in the empirical study. The expected sign of each independent variable on the systemic risk of a bank or insurer is shown in the last column with a "+" indicating an expected increasing (and a "-" a decreasing) impact on systemic risk. The bank and insurer controls were taken from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Variable name	Definition	Data source	Hypotheses	Expected sign
Panel A: Systemic risk measures				
ΔCoVaR	Unconditional ΔCoVaR as defined by Adrian and Brunnermeier (2015), measured as the difference of the Value-at-risk (VaR) of a financial sector index conditional on the distress of a particular insurer and the VaR of the sector index conditional on the median state of the firm.	Datastream, own calc.		
MES	Marginal Expected Shortfall as defined by Acharya et al. (2010) as the negative average return on an individual firm's stock on the days the *MSCI World* index experienced its 5% worst outcomes.	Datastream, own calc.		
Panel B: Main independent variables				
Interconnectedness	PCAS measure as defined in Billio et al. (2012). PCAS is constructed using a decomposition of the variance-covariance matrix of the firms' daily, standardized stock returns.	Datastream, own calc.	More exposure to other banks and insurers.	+
Market-to-book	Market value of common equity divided by book value of common equity.	Worldscope (WC07210, WC03501)	Greater charter value incentivizes bank managers to keep their bank's capital ratio and to limit their risk-taking (see Keeley, 1990 and Fahlenbrach et al. (2012)).	-
Total assets	Natural logarithm of a firm's total assets.	Worldscope (WC02999)	Too-big-to-fail vs. more diversification.	+/-
Leverage	Book value of assets minus book value of equity plus market value of equity, divided by market value of equity.	Worldscope (WC02999, WC03501, WC08001), own calc.	Disciplining effect of leverage vs. greater vulnerability during financial crises (see Adrian and Shin, 2010).	+/-
Performance	Annual buy-and-hold stock returns computed from the first and last trading day in the year 2006.	Datastream, own calc.	Firms that performed well in the past will continue to perform well over time VS. institutions that took on too many risks in the past could also stick to their culture of risk-taking (see Fahlenbrach et al., 2012) and increase their exposure and contribution to systemic risk.	+/-
Return on assets	Return of the firm on it's total assets after taxes (in %).	Worldscope (WC08326).	Higher profits can shield banks from the adverse effects of a financial crisis	-
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251, WC03255).	A less fragile funding structure of a bank makes it less vulnerable to sudden shortages in liquidity during a crisis (see Brunnermeier and Pedersen, 2009).	

Table C.1: Variable definitions and data sources (continued).

Variable name	Definition	Data source	Hypotheses	Expected sign
Panel C: Bank characteristics				
Deposits	Total deposits divided by total liabilities.	Worldscope (WC03019, WC03351).	Banks with more deposit financing are more stable in times of crises.	-
Loan loss provisions	Natural logarithm of expenses set aside as an allowance for uncollectable or troubled loans.	Worldscope (WC01271).	A larger buffer against troubled loans should serve as a stabilizing factor reducing a bank's total risk.	-
Loans	Ratio of total loans to total assets.	Worldscope (WC02271, WC02999).	A higher loans-to-assets ratio of a bank could indicate a business model that focuses on lending rather than more risky activities.	-
Tier-1-capital	Ratio of a bank's Tier-1-Capital to total assets.	Worldscope (WC18228, WC02999).	Higher regulatory bank capital acts as a buffer against losses and should stabilize both an individual bank and the financial sector.	-
Non-interest income	Non-interest income divided by total interest income.	Worldscope (WC01021, WC01016).	Higher values of non-interest income relative to total interest income could be indicative of a business model that concentrates more on non-deposit taking activities (like, e.g., investment banking) and thus more risk-taking (see, e.g., Brunnermeier et al., 2012).	+
Panel D: Insurer characteristics				
Investment success	Ratio of insurer's investment income to net revenues.	Worldscope (WC01001, WC01006), own calc.	Insurers become more intertwined with financial markets through asset management.	+
Loss ratio	Ratio of claim and loss expenses plus long term insurance reserves to earned premiums.	Worldscope (WC15549).	High loss ratio indicates bad quality of the insurance portfolio and increases default risk.	+
Non-Policyholder Liabilities	Total on balance sheet liabilities divided by total insurance reserves.	Worldscope (WC03351, WC03030).	Non-core insurance activities increase the risk to suffer from other sources in the financial market (see IAIS, 2013).	+
Operating expenses	Ratio of operating expenses to total assets.	Worldscope (WC01249, WC02999).	Poor management reflects the total risk of the insurance company.	+
Other income	Other pre-tax income and expenses besides operating income.	Worldscope (WC01262).	Non-core insurance activities increase the risk to suffer from other sources in the financial market (see IAIS, 2013).	+
Fixed income	Natural logarithm of fixed income.	Worldscope (WC01262).	Engagement in other asset classes than fixed income could suffer more profoundly from plummeting asset prices.	-

Appendix D

Supplementary Material for Chapter 5

Sample firms

Table D.1: Sample non-life insurance companies.

The table lists all international non-life insurance companies that are used in the empirical study. The sample is constructed by first selecting all international non-life insurance companies from the dead- and active-firm list in *Thomson Reuters Worldscope*. Further, the list is adjusted for all companies for which stock price and balance sheet data are not available from *Thomson Reuters Financial Datastream* and *Worldscope*. The names of the companies are retrieved from the *Worldscope* database (item WC06001).

21ST CENTURY INSURANCE GROUP
ABBEY PROTECTION PLC
ABU DHABI NATIONAL TAKAFUL CO PSC
ABU DHABI NATIONAL INSURANCE COMPANY
ACE LIMITED
ACE ARABIA COOPERATIVE INSURANCE COMPANY
ADAMJEE INSURANCE COMPANY LIMITED
ADMIRAL GROUP PLC
ADVENT CAPITAL (HOLDINGS) PLC
AGF BRASIL SEGUROS S.A.
AGROTIKI INSURANCE S.A.
AIOI INSURANCE COMPANY LIMITED
AKSIGORTA ANONIM SIRKETI
AL AHLIA INSURANCE COMPANY BSC
AL AIN AHLIA INSURANCE CO PSC
AL ALAMIYA FOR COOPERATIVE INSURANCE COMPANY
AL BARAKAH TAKAFUL PLC
AL BUHAIRA NATIONAL INSURANCE COMPANY
AL DHAFRA INSURANCE COMPANY P.S.C.
AL MANARA INSURANCE CO PSC
AL SAGR NATIONAL INSURANCE CO PSC
AL WATHBA NATIONAL INSURANCE COMPANY
AL-AHLEIA INSURANCE CO SAK
AL RAJHI FOR COOPERATIVE INSURANCE
ALFA CORPORATION
AL KHALEEJ TAKAFUL GROUP QSC
ALLEGHANY CORPORATION
ALLIANZ SE
ALLIANZ SAUDI FRANSI COOPERATIVE INSURANCE COMPANY
ALLIED COOPERATIVE INSURANCE GROUP
ALLIED WORLD ASSURANCE COMPANY HOLDINGS, LTD
ALLSTATE CORP
ALM BRAND AS
ALTERRA CAPITAL HOLDINGS LIMITED
AMERICAN FINANCIAL GROUP, INC.
AMERICAN INTERNATIONAL GROUP, INC.
AMLIN PLC
AMTRUST FINANCIAL SERVICES, INC.
ANADOLU ANONIM TURK SIGORTA SIRKETI
ARAB ORIENT INSURANCE CO. LTD
ARAB UNION INTERNATIONAL INSURANCE
ARABIA INSURANCE COOPERATIVE COMPANY
ARABIAN SCANDINAVIAN INSURANCE COMPANY
ARABIAN SHIELD COOPERATIVE INSURANCE
ARCH CAPITAL GROUP LTD.
ARGONAUT GROUP INCORPORATED
ARGO GROUP INTERNATIONAL HOLDINGS LIMITED
ASKARI GENERAL INSURANCE CO.
ASPEN INSURANCE HOLDINGS LTD
ASURANSI BINTANG TBK PT
ASURANSI BINA DANA ARTA TBK PT
ASURANSI BINTANG TBK PT
ASURANSI DAYIN MITRA TBK PT
ASURANSI HARTA AMAN PRATAMA TBK PT
PT ASURANSI JASA TANIA TBK
ASURANSI MULTI ARTHA GUNA TBK PT
ASURANSI RAMAYANA TBK PT
ATLAS FINANCIAL HOLDINGS, INCORPORATION
ATLAS INSURANCE CO., LTD.
ATRIUM UNDERWRITING PLC
AVIVA SIGORTA AS
AXA COOPERATIVE INSURANCE COMPANY
AXA VERSICHERUNG AG
AXIS CAPITAL HOLDINGS LTD
BAHRAIN KUWAIT INSURANCE COMPANY BSC
BAHRAIN NATIONAL HOLDING COMPANY
BALDWIN & LYONS INCORPORATED
BANGKOK INSURANCE PUBLIC COMPANY LIMITED
BANGKOK UNION INSURANCE PUBLIC COMPANY LIMITED
BEAZLEY PLC
BERKSHIRE HATHAWAY INC.
BIDV INSURANCE CORPORATION
BURUJ COOPERATIVE INSURANCE CO
CALLIDEN GROUP LIMITED
CATLIN GROUP LTD
CENTRAL INSURANCE COMPANY LIMITED
CENTURY INSURANCE CO LTD
CHARAN INSURANCE PUBLIC COMPANY LIMITED
CHUBB CORP
CIE D'ASSURANCES ET DE REASSURAN. ASTREE
CINCINNATI FINANCIAL CORPORATION
CLAL INSURANCE ENTERPRISES HOLDINGS LIMITED
CNA FINANCIAL CORPORATION
COMMERCE GROUP INC
MILANO ASSICURAZIONI S.P.A.
COSMOS INSURANCE PUBLIC COMPANY LTD.
COX INSURANCE HOLDINGS PLC
CROATIA LLOYD D.D.
CUSTODIAN & ALLIED INSURANCE PLC
DELTA INSURANCE COMPANY
DEVES INSURANCE PUBLIC COMPANY LIMITED (THE)
DHIPAYA INSURANCE PUBLIC COMPANY LIMITED
DHOFAR INSURANCE COMPANY
DIRECT LINE INSURANCE GROUP PLC
DOHA INSURANCE
DONEGAL GROUP INC.
DONGBU INSURANCE CO., LTD.
DUBAI INSURANCE COMPANY
DUBAI ISLAMIC INSURANCE & REINSURANCE
DUBAI NATIONAL INSURANCE COMPANY
E-L FINANCIAL CORPORATION LIMITED
EFU GENERAL INSURANCE LTD
EGI FINANCIAL HOLDINGS INC.
EMC INSURANCE GROUP INC.
EMIRATES INSURANCE COMPANY P.S.C
ENDURANCE SPECIALTY HOLDINGS LTD.
ENSTAR GROUP LIMITED
ESURE GROUP PLC
EULER HERMES GROUP SA
EUROHERC OSIGURANJE D D
EVEREST RE GROUP, LTD.
FAIRFAX FINANCIAL HOLDINGS LIMITED
FBD HOLDINGS PLC
FEDERATED NATIONAL HOLDING CO
FIRST ACCEPTANCE CORPORATION
FIRST FIRE & MARINE INSURANCE CO., LTD.
FIRST INSURANCE COMPANY LIMITED (THE)
FIRST MERCURY FINANCIAL CORPORATION
FIRST TAKAFUL INSURANCE COMPANY KCSC
FLAGSTONE REINSURANCE HOLDINGS SA
UNIPOLSAI ASSICURAZIONI SPA
FOYER S.A.
AL FUJAIRAH NATIONAL INSURANCE CO P.S.C.
FUJI FIRE & MARINE INSURANCE COMPANY LIMITED
GABLE HOLDINGS INC
GENERALI HOLDING VIENNA AG
GENERAL DE SEGUROS SA
GJENSIDIGE FORSIKRING ASA
GLOBAL INDEMNITY PLC
GOSHAWK INSURANCE HOLDINGS PLC
GREENLIGHT CAPITAL RE, LIMITED.
GRUPO CATALANA OCCIDENTE SA
GULF INSURANCE CO KSC
HABIB INSURANCE COMPANY LIMITED
HANOVER INSURANCE GROUP INC
HANWHA GENERAL INSURANCE COMPANY LIMITED
HARDY UNDERWRITING BERMUDA LIMITED
HARLEYSVILLE GROUP INC.
HARTFORD FINANCIAL SERVICES GROUP INC
HCC INSURANCE HOLDINGS INC
HCI GROUP INC
HEUNGKUK FIRE & MARINE INSURANCE CO LTD
HIGHWAY INSURANCE GROUP PLC
HILLTOP HOLDINGS INC
HISCOX PLC
HOLYLAND INSURANCE
HORACE MANN EDUCATORS CORPORATION
HYUNDAI MARINE & FIRE INSURANCE COMPANY LIMITED
INDARA INSURANCE PUBLIC COMPANY LIMITED
INDEQUITY GROUP LIMITED
INFINITY PROPERTY & CASUALTY CORPORATION
INGOSSTRAKH OSAO
INSPLANET AB
INSURANCE AUSTRALIA GROUP LIMITED
INTACT FINANCIAL CORPORATION
IGI INSURANCE LTD

Table D.1: Sample non-life insurance companies (continued).

ISLAMIC ARAB INSURANCE COMPANY	QUANTA CAPITAL HOLDINGS LTD
JADRANSKO OSIGURANJE D.D.	RANDALL AND QUILTER INVESTMENT HOLDINGS PLC
JAMES RIVER GROUP, INC.	RENAISSANCERE HOLDINGS LTD.
JERUSALEM INSURANCE COMPANY	REPUBLIC COMPANIES GROUP, INC.
JORDAN EMIRATES INSURANCE PSC	RLI CORP.
JUBILEE GENERAL INSURANCE CO LTD	RSA INSURANCE GROUP PLC
KEMPER CORPORATION	RTW, INC.
KILN PLC	SABB TAKAFUL
KINGSWAY FINANCIAL SERVICES INC	SAFECO CORPORATION
KSK GROUP BHD	SAFETY INSURANCE GROUP, INC.
KUWAIT INSURANCE CO SAK	SAFETY INSURANCE PUBLIC COMPANY LIMITED (THE)
LANCASHIRE HOLDINGS LTD	SAMPO OYJ
LIG INSURANCE COMPANY LIMITED	SAMSUNG FIRE & MARINE INSURANCE COMPANY LIMITED
LINKAGE ASSURANCE PLC	SANTAM LIMITED
LOEWS CORPORATION	SALAMA COOPERATIVE INSURANCE CO
LOTTE NON-LIFE INSURANCE CO LTD	SAUDI UNITED COOPERATIVE INSURANCE COMPANY
LPI CAPITAL BERHAD	SCHWEIZERISCHE NATIONAL VERSICHERUNGS GESELLSCHAFT AG
MAIDEN HOLDINGS, LIMITED	SEABRIGHT HOLDINGS, INCORPORATION
MAPFRE PERU CIA DE SEGUROS Y REASEGUROS	SECREX SEGUROS DE CREDITO Y GARANTIAS SA
MARKEL CORPORATION	SELECTIVE INSURANCE GROUP, INCORPORATED
MEADOWBROOK INSURANCE GROUP INCORPORATED	SHAHEEN INSURANCE COMPANY LIMITED
MERCER INSURANCE GROUP.INC.	SHC INSURANCE PTE LIMITED
MERCHANTS GROUP, INC.	SHINKONG INSURANCE CO LTD
MERCURY GENERAL CORPORATION	SAMAGGI INSURANCE PCL
MERITZ FINANCIAL GROUP INC	SILVER STAR INSURANCE CO. LTD.
METHAQ TAKAFUL INSURANCE COMPANY	STE TUN D’ASSURANCES ET DE REASSURANCES
MIDDLESEA INSURANCE P.L.C.	SOLIDARITY SAUDI TAKAFUL
MIN XIN HOLDINGS LTD.	SOMPO JAPAN NIPPONKOA INSURANCE INC
MOHANDES INSURANCE COMPANY	SPECIALTY UNDERWRITERS ALLIANCE, INC.
MONTPELIER RE HOLDINGS LTD	SRI AYUDHYA CAPITAL PCL
MPHB CAPITAL BHD	STANDARD ALLIANCE INSURANCE PLC
MS&AD INSURANCE GROUP HOLDINGS, INCORPORATED	STATE AUTO FINANCIAL CORP
MUANG THAI INSURANCE COMPANY LIMITED	SYN MUN KONG INSURANCE PUBLIC COMPANY LIMITED
MUSCAT NATIONAL HOLDINGS COMPANY SAOG	TAIWAN FIRE & MARINE INSURANCE COMPANY LIMITED
MUTUAL & FEDERAL INSURANCE COMPANY LTD	DAR AL TAKAFUL PJSC
NAM SENG INSURANCE PUBLIC CO LIMITED	TAKAFUL INTERNATIONAL COMPANY
NATIONAL ATLANTIC HOLDINGS CORPORATION	TALANX AG
NATIONAL GENERAL INSURANCE COMPANY	THAI INSURANCE PUBLIC COMPANY LIMITED (THE)
NATIONAL INTERSTATE CORPORATION	THAI SETAKIJ INSURANCE PUBLIC COMPANY LIMITED (THE)
NAVAKIJ INSURANCE PUBLIC COMPANY LIMITED (THE)	THAIVIVAT INSURANCE PUBLIC COMPANY LIMITED
NAVIGATORS GROUP INC	ARAB ASSURERS INSURANCE CO PSC
NIGER INSURANCE PLC	THE ISLAMIC INSURANCE COMPANY
NIPPONKOA INSURANCE COMPANY LIMITED	THE MEDITERRANEAN & GULF INS CO - JORDAN
NISSAY DOWA GENERAL INSURANCE COMPANY LIMITED	TOKIO MARINE HOLDINGS INCORPORATED
NISSHIN FIRE & MARINE INSURANCE COMPANY LIMITED (THE)	TOPDANMARK A/S
SOMPO JAPAN NIPPONKOA HOLDINGS INC	TORO ASSICURAZIONI CIA ANOMIA D’ASSICU.
NORTH POINTE HOLDINGS CORPORATION	TOWER GROUP INTERNATIONAL LTD
NOVAE GROUP PLC	TRADE UNION COOPERATIVE INSURANCE CO
OHIO CASUALTY CORPORATION	TRANSATLANTIC HOLDINGS, INC.
OMAN INSURANCE COMPANY	TRAVELERS COMPANIES INC
OMAN UNITED INSURANCE CO. SAOG	TRYG A/S
ONEBEACON INSURANCE GROUP LTD	TOWARZYSTWO UBEZPIECZE EUROPA SA
OPTIMUM GENERAL INC	UNION GENERALE DU NORD
ORIENT INSURANCE COMPANY PSC	UNICO AMERICAN CORPORATION
PACIFIC & ORIENT BERHAD	UNION INSURANCE COMPANY P.S.C.
PENN MILLERS HOLDING CORPORATION	UNION INSURANCE COMPANY LIMITED
THE PEOPLE S INSURANCE CO (GROUP) OF CHINA LTD	UNIPOL GRUPPO FINANZIARIO SPA
PETROVIETNAM INSURANCE JOINT STOCK CORP	UNISON FORSIKRING ASA
PHILADELPHIA CONSOLIDATED HOLDINGS CORPORATION	UNITED COOPERATIVE ASSURANCE (UCA)
PHILADELPHIA INSURANCE COMPANY LTD	UNITED FIRE & CASUALTY CO
PHOENIX METROLIFE EMPORIKI	UNITED INSURANCE CO PSC
PICC PROPERTY AND CASUALTY COMPANY LTD	UNITED OVERSEAS INSURANCE LIMITED
PETROLIMEX INSURANCE CORP	UNIVERSAL INSURANCE HOLDINGS, INC
PLATINUM UNDERWRITERS HOLDINGS LIMITED	VALIDUS HOLDINGS, LIMITED
PMA CAPITAL CORPORATION	VAUDOISE ASSURANCES HOLDING
PORTO SEGURO SA	VITTORIA ASSICURAZIONI SPA
PREMAFIN FINANZIARIA SPA	W. R. BERKLEY CORP
PREMIER INSURANCE LIMITED	SAUDI INDIAN COMPANY FOR CO- OPERATIVE INSURANCE
PROASSURANCE CORPORATION	WATANIYA INSURANCE COMPANY
PROCENTURY CORPORATION	WESCO FINANCIAL CORPORATION
PROGRESSIVE CORP	WESTAIM CORPORATION (THE)
POWSZECHNY ZAKLAD UBEZPIECZEN SA	WETHAQ TAKAFUL INSURANCE CO KCSC
QATAR GENERAL INSURANCE & REINSURANCE	WHITE MOUNTAINS INSURANCE GROUP LTD
QATAR INSURANCE	WUERTTEMBERGISCHE UND BADISCHE VERS.AG
QATAR ISLAMIC INSURANCE COMPANY	ZUR SHAMIR HOLDINGS LTD
QBE INSURANCE GROUP LIMITED	ZURICH INSURANCE GROUP LIMITED

Variable definitions and data sources

Table D.2: Variable definitions and data sources.

The appendix presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study. The insurer characteristics are retrieved from the *Thomson Reuters Financial Datastream* and *Thomson Worldscope* databases.

Variable name	*Definition*	*Data source*
Inverse z-score	One divided by z-score. Z-score is the sum of an insurer's equity ratio and return on assets, divided by the standard deviation of an insurer's return on assets from the previous five years.	own calc.
Capital surplus	Natural logarithm of capital surplus. Capital surplus represents the amount received in excess of par value from the sale of common stock.	Worldscope (WC03481), own calc.
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Worldscope (WC03251, WC03255).
Equity ratio	Ratio of an insurer's equity to total assets.	Worldscope (WC01249, WC02999).
Leverage	Sum of earned and unearned premiums divided by capital surplus.	Worldscope (WC03010, WC01002, WC03351), own calc.
Long-term solvency	Total long-term insurance reserves divided by total liabilities.	Worldscope (WC03030,WC03351), own calc.
Loss ratio	Ratio of claim and loss expenses plus long term insurance reserves to earned premiums.	Worldscope (WC15549).
Operating expenses	Ratio of operating expenses to total assets.	Worldscope (WC01249, WC02999).
Premium growth	One year annual growth rate in booked premiums.	Worldscope (WC01004).
Return on Assets	Return of the insurer on its total assets after taxes (in %).	Worldscope (WC08326).
Size	Natural logarithm of an insurer's total assets.	Worldscope (WC02999).
Solvency	Net income divided by the sum of short-term debt and current portion of long-term debt.	Worldscope (WC07250,WC03051), own calc.
GDP growth	Annual real GDP growth rate (in %).	WDI database (World Bank).
Inflation	Natural logarithm of the annual change of the GDP deflator.	WDI database (World Bank).

Appendix E

Supplementary Material for Chapter 6

Sample firms

Table E.1: Sample U.S. insurers.

The appendix lists all insurers that are included in the empirical study. The sample is constructed by first selecting all firms with (TIC/CUSIP) SIC-codes 6311, 6321, and 6331 from the *Compustat/CRSP* databases. The list is then corrected for all insurance companies for which no 10-K filings could be found in the *Morningstar Document Research* database for the time period Q1 1999 until Q3 2014. All insurers in the *CRSP/Compustat* and *Morningstar Document Research* databases are matched using their TIC and CUSIP-Codes and we manually double-check those insurance companies that have non-matching names.

21ST CENTURY INS GROUP
ACA CAPITAL HOLDINGS INC
ACAP CORP
ACCEPTANCE INSURANCE COS INC
ACE LTD
AETNA INC
AFFIRMATIVE INS HOLDINGS INC
AFLAC INC
ALFA CORP
ALLEGHANY CORP
ALLIED WORLD ASSURANCE CO AG
ALLSTATE CORP
ALTERRA CAPITAL HOLDINGS LTD
AMBAC FINANCIAL GROUP INC
AMCOMP INC
AMER COUNTRY HOLDINGS INC
AMERICAN EQTY INVT LIFE HLDG
AMERICAN FINANCIAL CORP OH
AMERICAN FINANCIAL GROUP INC
AMERICAN GENERAL CORP
AMERICAN INDEPENDENCE CORP
AMERICAN INTERNATIONAL GROUP
AMERICAN NATIONAL INSURANCE
AMERICAN PHYSICIANS CAPITAL
AMERICAN RE CORP
AMERISAFE INC
AMWEST INSURANCE GROUP INC
ANNUITY AND LIFE RE HOLDINGS
ARCH CAPITAL GROUP LTD
ASPEN INSURANCE HOLDINGS LTD
ASSURANT INC
ASSURED GUARANTY LTD
ATHENE USA CORP
AXA FINANCIAL INC
AXIS CAPITAL HOLDINGS LTD
BERKLEY (W R) CORP
BERKSHIRE HATHAWAY
BLANCH E W HOLDINGS INC
BPO MANAGEMENT SERVICES/PA
BRISTOL WEST HOLDINGS INC
CAREMARK ULYSSES HOLDING CORP
CASTLEPOINT HOLDINGS LTD
CHUBB CORP
CITIZENS INC
CNA FINANCIAL CORP
CNA SURETY CORP
CNO FINANCIAL GROUP INC
COMMERCE GROUP INC/MA
CONSECO INC
DARWIN PROFESSIONAL UNDWRTS
DELPHI FINANCIAL GROUP INC
DIRECT GENERAL CORP
DONEGAL GROUP INC
EASTERN INSURANCE HLDGS INC
EMPLOYERS HOLDINGS INC
ENDURANCE SPECIALTY HOLDINGS
ENHANCE FINANCIAL SVCS GRP
ENSTAR GROUP INC
ENSTAR GROUP LTD
ESSENT GROUP LTD
EVEREST RE GROUP LTD
FARM FAMILY HOLDINGS INC
FBL FINANCIAL GROUP INC-CL A
FEDERATED NATIONAL HLDG CO
FIDELITY & GUARANTY LIFE
FIRST ACCEPTANCE CORP
FIRST MERCURY FINANCIAL CORP
FORTUNE FINANCIAL INC
FRONTIER INSURANCE GROUP INC
GAINSCO INC
GLOBAL INDEMNITY PLC
GREAT AMERN FINL RESOURCES
GREENLIGHT CAPITAL RE LTD
HALLMARK FINANCIAL SERVICES
HANOVER INSURANCE GROUP INC
HARTFORD FINANCIAL SERVICES
HCC INSURANCE HOLDINGS INC
HCI GROUP INC
HEALTHMARKETINC UICI
HIGHLANDS INSURANCE GRP INC
HILLTOP HOLDINGS INC
HORACE MANN EDUCATORS CORP
HSB GROUP INC
INDEPENDENCE HOLDING CO
INFINITY PROPERTY & CAS CORP
JAMES RIVER GROUP INC
JEFFERSON-PILOT CORP
KANSAS CITY LIFE INS CO
KEMPER CORP
KINGSWAY FINANCIAL SVCS INC
KMG AMERICA CORP
LANDAMERICA FINANCIAL GP
LINCOLN NATIONAL CORP
MAIDEN HOLDINGS LTD
MAJESTIC CAPITAL LTD
MARKEL CORP
MBIA INC
MEADOWBROOK INS GROUP INC
MERCER INSURANCE GROUP INC
MERCHANTS GROUP INC
MERCURY GENERAL CORP
METLIFE INC
MGIC INVESTMENT CORP/WI
MIIX GROUP INC
MONTPELIER RE HOLDINGS
MONY GROUP INC
MUTUAL RISK MANAGEMENT LTD
NYMAGIC INC
NATIONAL ATLANTIC HOLDINGS
NATIONAL INTERSTATE CORP
NATIONAL SEC GROUP INC
NATIONAL WESTERN LIFE -CL A
NATIONWIDE FINL SVCS -CL A
NORTH POINTE HOLDINGS CORP
ODYSSEY RE HOLDINGS CORP
OLD REPUBLIC INTL CORP

Table E.1: Sample U.S. insurers (continued).

ONEBEACON INSURANCE GROUP
PARTNERRE LTD
PAULA FINANCIAL/DE
PENN-AMERICA GROUP INC
PENN TREATY AMERN CORP
PHOENIX COMPANIES INC
PLATINUM UNDERWRITERS HLDG
PMI GROUP INC
PRESERVER GROUP INC
PRIMERICA INC
PRINCIPAL FINANCIAL GRP INC
PROASSURANCE CORP
PROCENTURY CORP
PROGRESSIVE CORP-OHIO
PROTECTIVE LIFE CORP
PRUDENTIAL FINANCIAL INC
QUANTA CAPITAL HOLDINGS LTD
RADIAN GROUP INC
RAM HOLDINGS LTD
REINSURANCE GROUP AMER INC
RELIANCE GROUP HOLDINGS
RELIASTAR FINANCIAL CORP
RENAISSANCERE HOLDINGS LTD
REPUBLIC COMPANIES GROUP
RLI CORP
RTW INC
SAFECO CORP
SAFETY INSURANCE GROUP INC
SCOTTISH RE GROUP LTD
SCPIE HOLDINGS INC
SEABRIGHT HOLDINGS INC
SOUTHWESTERN LIFE HLDGS INC
SPECIALTY UNDERWRITERS
STANCORP FINANCIAL GROUP INC
SUN LIFE FINANCIAL INC
SYMETRA FINANCIAL CORP
SYNCORA HOLDINGS LTD
TORCHMARK CORP
TOWER GROUP INTL LTD
TRANSATLANTIC HOLDINGS INC
TRAVELERS COS INC
TRAVELERS CORP
TRIPLE-S MANAGEMENT CORP
UNICO AMERICAN CORP
UNITED AMERICA INDEMNITY Ltd
UNITED FIRE GROUP INC
UNIVERSAL AMERICAN CORP
UNIVERSAL INSURANCE HLDGS
UNUM GROUP
US HEALTH GROUP INC
VALIDUS HOLDINGS LTD
VESTA INSURANCE GROUP INC
VOYA INSURANCE & ANNUITY CO
WHITE MTNS INS GROUP LTD
XL GROUP PLC
ZENITH NATIONAL INSURANCE CP

Variable definitions and data sources.

Table E.2: Variable definitions and data sources.

The appendix presents definitions as well as data sources for all dependent and independent variables that are used in the empirical study. Variables describing an insurer's use of financial derivatives are constructed using information from the respective insurer's 10-K filings retrieved from the *Morningstar Document Research* database. The insurer characteristics were retrieved from the *Compustat* and *CRSP* databases.

Variable name	*Definition*	*Data source*
Dependent variables		
Inverse z-score	One divided by z-score. Z-score is the average stock return divided by the respective stock return volatility.	CRSP, own calc.
MES	Quarterly Marginal Expected Shortfall defined in Acharya et al. (2010) as the average return on an individual insurer's stock on the days the *S&P 500* index experienced its 5% worst outcomes.	CRSP, own calc.
SRISK	Average quarterly estimate of the Systemic Risk Index as proposed by Acharya et al. (2012) and Brownlees and Engle (2015). The SRISK estimate for insurer i at time t is given by $SRISK_{i,t} = k\left(Debt_{i,t}\right) - (1-k)\left(1 - LRMES_{i,t}\right) Equity_{i,t}$, where k is a regulatory capital ratio (set to 8%), $Debt_{i,t}$ is the insurer's book value of debt, $LRMES_{i,t}$ is the long-run Marginal Expected Shortfall defined as $1 - \exp(-18 \cdot MES)$, MES is the estimated Marginal Expected Shortfall and $Equity_{i,t}$ is the insurer's market value of equity.	CRSP, Compustat, own. calc.
Insurer derivatives usage variables		
Derivative-user	Dummy variable with value 1 if an insurer uses derivatives, and 0 otherwise.	Morningstar.
Hedging	Dummy variable with value 1 if an insurer predominantly uses derivatives to hedge risks, and 0 otherwise.	Morningstar.
Derivatives intensity	The number of different types of derivatives used by an insurer (ranges from 0 to 4).	Morningstar.
Swaps	Dummy variable with value 1 if an insurer uses swaps, and 0 otherwise.	Morningstar.
Options	Dummy variable with value 1 if an insurer uses options, and 0 otherwise.	Morningstar.
Forwards	Dummy variable with value 1 if an insurer uses forwards, and 0 otherwise.	Morningstar.
Futures	Dummy variable with value 1 if an insurer uses futures, and 0 otherwise.	Morningstar.
Gains/Losses	Fair value gains/losses on an insurer's derivatives positions.	Morningstar.
Insurer-specific control variables		
Capital surplus	Natural logarithm of insurer's capital surplus.	Compustat.
Debt maturity	Total long-term debt (due in more than one year) divided by total debt.	Compustat, own calc.
Leverage	Total debt divided by total size	Compustat, own calc.
Market-to-book	Market value of common equity divided by book value of common equity.	Compustat, own calc.
ROA	Return on assets.	Compustat, own calc.
Total Liabilities	Natural logarithm of an insurer's liabilities.	Compustat.
Size	Natural logarithm of an insurer's total assets.	Compustat.
Solvency	Capital surplus divided by total assets.	Compustat, own calc.
Volatility	Standard deviation of an insurer's stock returns.	CRSP, own calc.

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Eidesstattliche Versicherung

Hiermit versichere ich, dass ich die vorliegende Dissertation selbstständig verfasst habe und mich ausschließlich der angegebenen Hilfsmittel bedient habe. Die Dissertation ist nicht bereits Gegenstand eines erfolgreich abgeschlossenen Promotions- oder sonstigen Prüfungsverfahrens gewesen.

Nettersheim, ... Januar 2016